

UCLA

UCLA Electronic Theses and Dissertations

Title

Towards Equitable Clean Transportation: Understanding Zero Emission Vehicle Adoption Trends, Air Quality and Public Health Benefits, and Public Access to Charging Infrastructure

Permalink

<https://escholarship.org/uc/item/8xq9q5tc>

Author

Yu, Qiao

Publication Date

2024

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA

Los Angeles

Towards Equitable Clean Transportation:

Understanding Zero Emission Vehicle Adoption Trends, Air Quality
and Public Health Benefits, and Public Access to Charging Infrastructure

A dissertation submitted in partial satisfaction
of the requirements for the degree Doctor of Philosophy
in Environmental Health Sciences

by

Qiao Yu

2024

© Copyright by

Qiao Yu

2024

ABSTRACT OF THE DISSERTATION

Towards Equitable Clean Transportation:

Understanding Zero Emission Vehicle Adoption Trends, Air Quality
and Public Health Benefits, and Public Access to Charging Infrastructure

by

Qiao Yu

Doctor of Philosophy in Environmental Health Sciences

University of California, Los Angeles, 2024

Professor Yifang Zhu, Chair

As California positions itself as a leader in climate mitigation, zero-emission vehicle (ZEV) adoption and the development of clean energy infrastructure hold promise for reducing air pollution and improving public health. However, disadvantaged communities (DACs) continue to experience disproportionate exposure to traffic-related air pollution, uneven access to clean energy infrastructure, and barriers to adopting environmentally sustainable technologies like ZEVs. As California approaches its target of achieving 100% ZEV sales by 2035 and long term carbon neutrality goal by 2045, there is a critical need to ensure that the benefits of this transition—improved air quality, reduced greenhouse gas emissions, and enhanced public health—are equitably distributed. This dissertation seeks to address these equity challenges by evaluating the

environmental justice implications of ZEV adoption, analyzing the regional air quality and health benefits in urban environments like Los Angeles, and assessing the equity and reliability of public electric vehicle charging stations (EVCSs) at the national level.

Through the use of multiple methods—including geospatial analysis, predictive modeling, integrated traffic, air quality modeling, health benefits assessment, qualitative data analysis and large language models—this work provides an in-depth exploration of how ZEV policies, transportation emissions, and charging infrastructure impact DACs and racially and ethnically minoritized communities. The findings of this dissertation offer a clearer understanding of the extent to which California's clean transportation policies are advancing equity, as well as identifying areas where additional policy interventions are required. The ultimate goal is to inform more targeted, action-oriented strategies for reducing pollution burdens and improving access to clean energy solutions in the most vulnerable communities. This work is divided into the following five chapters: an introduction (Chapter 1), three chapters of primary research (Chapters 2-4), and the conclusions and future research directions (Chapter 5).

In Chapter 2, we quantify ZEV adoption trends at the census tract level in California from 2015 to 2020 and project future adoption levels through 2035. Our analysis highlights significant disparities, showing that per capita ZEV ownership in non-DACs is nearly four times higher than in DACs, and that racially and ethnically minoritized populations own fewer ZEVs regardless of DAC designation. While pollutant reductions due to inter-community ZEV trips benefit DAC residents, these communities remain exposed to higher levels of traffic-related air pollutants. With a projected increase in ZEV adoption by 2035, exposure disparities narrow but persist, emphasizing the need for targeted ZEV policies to address inequities in pollution burdens among DACs.

Chapter 3 focuses on assessing the regional air quality and health benefits of increased ZEV adoption in Los Angeles. Through the application of transportation and emissions models, we evaluate future ZEV adoption scenarios and their impact on air quality. Our findings demonstrate that increased ZEV adoption can significantly improve air quality and yield substantial public health benefits, particularly for Hispanic populations in DACs. However, the study also highlights the complexities of managing air pollutants, as reductions in nitrogen oxides (NO_x) may lead to higher ozone (O₃) levels, necessitating a multi-faceted approach to emission control.

In Chapter 4, we conduct a national analysis of public EVCS equity and reliability, using data from user-generated content and reviews. Using data from over 470,000 user-generated reviews, we identify significant disparities in the distribution of public EVCSs, with DACs having 26% fewer EVCSs per capita compared to non-DACs. This disparity is more pronounced among renters in multi-dwelling units. Additionally, we find that EVCS users in DACs face more reliability issues than their counterparts in non-DACs, with hardware and technical failures being the most common complaints. These findings underscore the need for more investment in EVCS infrastructure and maintenance, particularly in underserved communities.

Together, these chapters highlight both the progress and remaining challenges in ensuring an equitable clean transportation transition. By identifying key areas for improvement in ZEV policies and EVCS infrastructure, this dissertation contributes to ongoing efforts to achieve environmental justice and a healthier, more sustainable future for all Californians and beyond.

The dissertation of Qiao Yu is approved.

Gregory S. Pierce

Jiaqi Ma

Lara J. Cushing

Yifang Zhu, Committee Chair

University of California, Los Angeles

2024

TABLE OF CONTENTS

LIST OF FIGURES	viii
LIST OF TABLES.....	xii
ACKNOWLEDGEMENTS.....	xiii
VITA.....	xvi
1. INTRODUCTION.....	1
1.1. ENVIRONMENTAL JUSTICE AND THE TRANSITION TO EQUITABLE CLEAN TRANSPORTATION.....	1
1.2. SUMMARY OF AIMS	3
2. CALIFORNIA'S ZERO-EMISSION VEHICLE ADOPTION BRINGS AIR QUALITY BENEFITS YET EQUITY GAPS PERSIST	6
2.1. ABSTRACT	6
2.2. INTRODUCTION.....	6
2.3. METHODS	10
2.3.1. DAC Designation.....	10
2.3.2. ZEV Adoption Trends.....	11
2.3.3. Integrated Transportation Model	12
2.3.4. ZEV Trip Assignment and Emission Calculation.....	14
2.4. RESULTS	19
2.5. DISCUSSION	45
CHAPTER 2 APPENDIX	51
3. ASSESSING THE REGIONAL AIR QUALITY AND HEALTH BENEFITS OF ZERO- EMISSION VEHICLE ADOPTION IN LOS ANGELES.....	54
3.1. ABSTRACT	54
3.2. INTRODUCTION.....	55
3.3. METHODS	57
3.3.1. Emission Inventory Development.....	57
3.3.2. Air Quality Modeling.....	60
3.4. RESULTS	65
3.4.1. Changes in Emission Inventory	65
3.4.2. Changes in Ambient Air Quality	67
3.5. DISCUSSION	82
CHAPTER 3 APPENDIX	85

4.	EQUITY AND RELIABILITY OF PUBLIC ELECTRIC VEHICLE CHARGING STATIONS IN THE UNITED STATES	90
4.1.	ABSTRACT	90
4.2.	INTRODUCTION.....	90
4.3.	Methods.....	94
4.3.1.	EV Charging Station Location and Review Data	94
4.3.2.	Environmental Justice Data	95
4.4.	RESULTS	104
4.4.1.	Public EVCSs in the United States	104
4.4.3.	EVCS Reliability	109
	CHAPTER 4 APPENDIX	117
5.	CONCLUSIONS AND FUTURE DIRECTIONS	120
6.	REFERENCES.....	125

LIST OF FIGURES

Figure 2.1. Lorenz curves of cumulative vehicle ownership and cumulative population for (a) internal combustion engine vehicles (ICEVs), (b) plug-in hybrid vehicles (PHEVs), and (c) battery electric vehicles (BEVs) from 2015 to 2020 in California. The cumulative population is sorted from highest CalEnviroScreen 4.0 percentiles to lowest percentiles. The red shaded area represents the 25% of the population most disadvantaged, and the blue shaded area represents the remaining 75% of the less disadvantaged population. The blue dashed line in each subfigure represents the ideal Lorenz curve with perfect equality.	20
Figure 2.2. Spatial distribution of zero-emission vehicle (ZEV) ownership from 2015 to 2020 in California and Los Angeles County. Census tract level spatial distribution for (a) the CalEnviroScreen 4.0 percentile, (b) 2015, and (c) 2020 ZEV ownership per 1,000 residents in California and for (d) the CalEnviroScreen 4.0 percentile, (e) 2015, and (f) 2020 ZEV ownership per 1,000 residents in Los Angeles County.	21
Figure 2.3. Spatial distribution of simulated daily traffic volumes in Los Angeles County in 2020 and 2035. Simulated link-level arterial and freeway traffic for (a) total traffic volume and (b) ZEV traffic volume as a percentage for Los Angeles County in 2020; (c) total traffic volume and (d) ZEV traffic volume as a percentage for Los Angeles County in 2035.	23
Figure 2.4. Racial and ethnic analysis on zero-emission vehicle (ZEV) ownership and simulated electric vehicle miles traveled (eVMT) in 2020. Share of county population, ZEV ownership, and eVMT per census tract for different racial and ethnic groups in (a) all communities, (b) disadvantaged communities (DACs), and (c) non-disadvantaged communities (non-DACs) in Los Angeles County. Hispanic: Hispanic or Latino. White: non-Hispanic white. AAPI: non-Hispanic Asian American and Pacific Islander. AfricanAm: non-Hispanic African	

American or black. **OtherMult**: non-Hispanic “other” or multiple races. **NativeAm**: non-Hispanic Native American. Racial and ethnic demographic data were obtained from CalEnviroScreen 4.0 for each census tract. 25

Figure 2.5. Spatial distribution of near-roadway nitrogen oxides (NO_x) reduction attributable to zero-emission vehicles (ZEVs) in Los Angeles County in 2020 and 2035. (a) NO_x in ppb, (b) NO_x as a percentage in 2020; (c) NO_x in ppb, (d) NO_x as a percentage in 2035. The percentage (relative reduction) is calculated by dividing the ZEV-attributable reduction by the total traffic-attributable pollutant concentration in each census tract. The deeper the blue color, the greater the reduction observed. 42

Figure 2.6. Spatial distribution of near-roadway fine particulate matter (PM_{2.5}) reduction attributable to zero-emission vehicles (ZEVs) in Los Angeles County in 2020 and 2035. (a) PM_{2.5} in µg/m³, (b) PM_{2.5} as a percentage in 2020; (c) PM_{2.5} in µg/m³, (d) PM_{2.5} as a percentage in 2035. The percentage (relative reduction) is calculated by dividing the ZEV-attributable reduction by the total traffic-attributable pollutant concentration in each census tract. The deeper the blue color, the greater the reduction observed. 43

Figure 3.1. Illustration of triple nested modeling domains used in this study 61

Figure 3.2. The total emission rates of all the source categories for PM_{2.5} and NO_x in LA City in 2035 relative to the 2017 Base. Black line marks LA City boundary. 66

Figure 3.3. Monthly mean daily PM_{2.5} concentrations for four representative months in LA City for Base, Disparity, Equity, and Equity_MSS 70

Figure 3.4 Monthly mean daily maximum 8-hour average O₃ concentration for four representative months in LA City for Base, Disparity, Equity, and Equity_MSS..... 71

Figure 3.5. Monthly mean of LA City region daily PM _{2.5} concentrations (A) and daily maximum 8-hour average O ₃ concentrations (B) for Base, Disparity, Equity, and Equity_MSS scenarios .	72
Figure 3.6. Annual mean daily PM _{2.5} concentrations in LA City for the Base scenario (A) and the differences between Disparity and Base (B), between Equity and Disparity (C), as well as between Equity_MSS and Disparity (D). Thick grey line marks the LA City boundary and hatch-filled areas denote disadvantaged communities in LA City.	76
Figure 3.7. Annual mean daily maximum 8-hour average O ₃ concentration in LA City for the Base scenario (A) and the differences between Disparity and Base (B), between Equity and Disparity (C), as well as between Equity_MSS and Disparity (D). Thick grey line marks the LA City boundary and hatch-filled areas denote the disadvantaged communities in LA City.....	77
Figure 3.8. Community means of PM _{2.5} (A) and O ₃ (B) concentrations averaged over DAC and non-DACs in LA City for Base, Disparity, Equity and Equity_MSS scenarios, as well as the relative differences between the Disparity, Equity, and Equity_MSS scenarios compared to the Base scenario (C)	78
Figure 3.9. Total avoided mortality in LA City for the differences between Disparity and Base (A), and between Equity_MSS and Base (B)	79
Figure 3.10. Differences in PM _{2.5} -related avoided mortality, comparing the use of uniform beta coefficients with racial/ethnic-specific beta coefficients.....	81
Figure 4.1. Schematic of Data Curation, LLM Model Validation and Application	98
Figure 4.2. Data comparison between the Department of Energy (DOE) database and the user-generated content (UGC) platform. (a) Electric vehicle charging stations (EVCSs), and (b) public electric vehicle supply equipment (EVSEs).....	105

Figure 4.3.: Mean public electric vehicle charging stations (EVCS) density in 2022, comparing disadvantaged and non-disadvantaged communities: (a) per 1 000 population and (b) per 100 renters living in multi-dwelling units..... 108

Figure 4.4. User experience rankings and problem categorization results for public EV charging stations. (a) Non-disadvantaged communities (non-DAC) and rural areas exhibit significantly higher average rankings of positive user experience, as compared to disadvantaged communities (DAC) and urban areas ($*** p < 0.001$). User experience is ranked by sentiment scores, which are derived from each user review. **(b)** Distribution of different categories of problems encountered by public EVCS users. The developed procedural equity framework ultimately guided our analysis of interview data. 109

LIST OF TABLES

Table 2.1. Zero-emission vehicle (ZEV) ownership, electric vehicle miles traveled (eVMT), and traffic-emitted air pollutants in disadvantaged communities (DACs) vs. non-DACs in Los Angeles County in 2020 and 2035.....	40
Table 3.1. Exposure-response Factors Used	64
Table 3.2. Valuation Functions Selected from BenMAP-CE v1.5	65
Table 3.3. Pollutant-specific Emissions (tons per day) Under Base, Disparity, Equity, and Equity_MSS Scenarios and Their Relative Changes for Los Angeles County	66
Table 3.4. Simulated LA Citywide Annual Average of Daily Maximum 8-hour O ₃ and Daily PM _{2.5} Concentrations for all Evaluated Scenarios	72
Table 3.5. Summary of Annual Health Changes Between Scenarios (Mortality and Morbidity)	80
Table 3.6. Monetized Health Benefits Between Scenarios for Both Mortality and Morbidity....	81
Table 4.1. Inequitable access to public electric vehicle charging stations (EVCS) and supply equipment (EVSE) between DACs and non-DACs in the United States.	108
Table 4.2. Summary of current issues for electric vehicle charging stations (EVCSs) based on negative user reviews.....	111

ACKNOWLEDGEMENTS

I would like to express my deepest gratitude to my doctoral advisor, Professor Yifang Zhu, for her constant intellectual enlightenment and kind guidance throughout these four years. Her leadership, composure, and calming presence have been a guiding light especially during the challenging times of the COVID-19 pandemic. In moments when I felt lost or adrift, her wisdom and support were a beacon, reminding me to press forward. Her confidence in me gave me the strength to overcome my doubt to myself, and her boundless encouragement touched not only my academic journey but also my personal growth. She helped me rediscover my potential and allowed me the freedom to be my true self in the pursuit of knowledge. For that, I will forever be grateful.

I would also like to extend my heartfelt thanks to my esteemed doctoral committee for all the resources and support you have generously provided throughout my journey. To Dr. Gregory S. Pierce, thank you for guiding me in thinking critically about how to make my research more relevant to policy, helping me bridge the gap between research and practical application in sustainable and equitable policy. To Dr. Jiaqi Ma, your expertise in transportation engineering and your insights into cutting-edge technologies have been invaluable, enabling my interdisciplinary work to be both impactful and forward-thinking. And to Dr. Lara J. Cushing, you have been a true model of what an equity scholar should aspire to be. Your mentorship has equipped me with the knowledge and passion to advocate for the underserved and to pursue equity in all facets of my work. I am deeply grateful to each of you for your support and guidance throughout my journey and your participation in all my dissertation chapters.

For Chapter 2, I would like to extend my gratitude to my colleague Dr. Brian Yueshuai He, whose expertise in the transportation demand forecasting model was instrumental. Without his

contributions, this work would not have been as impactful. I am also grateful for the financial support provided by several grants, including the California Statewide Transportation Research Program (SB 1) Program under grant number LA2205 awarded to Dr. Jiaqi Ma, the Center for Excellence on New Mobility and Automated Vehicles Project under Award No. 693JJ32350027 awarded to Dr. Jiaqi Ma, and the Zero Emission Healthy Communities project, supported by the Sustainable LA Grand Challenge and the Anthony and Jeanne Pritzker Family Foundation, awarded to Dr. Yifang Zhu. The views, opinions, findings, and conclusions or recommendations expressed in this paper are strictly those of the authors. They do not necessarily reflect the views of funding agencies.

Chapter 2 is a version of:

Yu, Qiao, He, Brian Yueshuai, Ma, Jiaqi, and Yifang Zhu. California's zero-emission vehicle adoption brings air quality benefits yet equity gaps persist. *Nat Commun* **14**, 7798 (2023).
<https://doi.org/10.1038/s41467-023-43309-9>

For Chapter 3, I would like to extend my gratitude to Dr. Yun Lin and Dr. Yu Gu for their invaluable expertise in atmospheric and air pollution modeling. Their contributions are an inseparable part of this research and greatly enhanced its quality and depth. Additionally, I am thankful for the financial support provided by the Los Angeles Department of Water and Power through the LA100 Equity Strategies Study, under grant number 20225060, awarded to Dr. Yifang Zhu.

Chapter 3 is a version of:

Yu, Q., Lin, Y., He, Y., Gu, Y., Ma, J., & Zhu, Y. LADWP LA100 Equity Strategies Chapter 15. Air Quality and Public Health. In *LADWP LA100 Equity Strategies* (2023).
<https://escholarship.org/uc/item/5qj6g9j1>

For Chapter 4, I would like to extend my thanks to my collaborators Tristan Que, Ke Shen, and Dr. Mayank Kejriwal. I am grateful for the financial support provided by the University of California Office of the President Climate Action under grant number R02CP6948, awarded to Dr. Yifang Zhu.

Chapter 4 is a version of:

Qiao Yu, Tristan Que, Lara J. Cushing, Gregory Pierce, Ke Shen, Mayank Kejriwal, Yuan Yao, Yifang Zhu. Equity and reliability of public electric vehicle charging stations in the United States. Submitted to *Nature Communications* (2024).

I would like to thank the UCLA Dr. Ursula Mandel Scholarship, the UCLA Center for Diverse Leadership in Science, and the UC Center for Climate, Health and Equity for their generous support. I am also grateful to my peers at Dr. Zhu's lab for the meaningful moments we shared and their support throughout this journey.

Finally, I would like to express my gratitude to my family and friends. To my grandmother, Yunxian, I feel your smile forever bright in my heart, guiding me endlessly. To my brother, Feng, your unwavering support has been a constant pillar in my life. To my parents, thank you for providing me with the opportunity to pursue this journey, for your sacrifices, and for believing in me every step of the way. And to my cat, Dorami, for putting up with my bad temper while I tolerate her attitude.

VITA

Education

- 2020 Duke University – Master of Environmental Management in Economics and Policy
2018 Rensselaer Polytechnic Institute – B.S. in Environmental Engineering

Awards and Grants

- 2023-2024 UC Center for Climate, Health, and Equity Fellowship
2023 UCLA Lester Breslow Public Health Impact Award
2022-2023 UCLA Dr. Ursula Mandel Scholarship
2021 ULCA Graduate Summer Research Mentorship Fellowship
2020-2024 UCLA Center for Diverse Leadership in Science Fellowship

Experience

- 2023-2024 Student Research Fellow, UC Center for Climate, Health, and Equity, UCSF, CA
2020-2024 Graduate Student Researcher, ULCA Department of Environmental Health Sciences, Los Angeles, CA
2019-2020 Graduate Research Assistant, Duke University, NC
2019 Intern to the Coordinator, United Nations Environment Programme, Jamaica
2018-2020 Outreach Coordinator, Duke Sustainability Board, Duke University, NC
2017 Research Assistant, Tsinghua University, China
2015-2018 Research Assistant, RPI Environmental Outreach Program, Rensselaer Polytechnic Institute, NY

Selected Publications

- Qiao Yu**, Tristan Que, Lara J. Cushing, Gregory Pierce, Ke Shen, Mayank Kejriwal, Yuan Yao, Yifang Zhu. Equity and reliability of public electric vehicle charging stations in the United States. Submitted to *Nature Communications* (2024).
Yao Y, Niu MC, Chen HX, **Yu Q**, Wu QY, Li YH, Zhang YJ, Ozcan A, Jerrett M, Zhu YF. Fine particulate matter emissions from electric vehicle fast charging stations. Preprint, doi: 10.21203/rs.3.rs-4535756/v1.
Qinhua Jiang, **Qiao Yu**, Yifang Zhu, Jiaqi Ma, Brian Yueshuai He. Are telework and teleservices the solution for reducing traffic congestion and emissions? Findings from a comprehensive activity-based modeling analysis. Submitted to *Transportation Research Part A* (2024).

- Wen, Yifan, **Yu, Qiao**, He, Yueshuai, Ma, Jiaqi, Zhang, Shaojun, Wu, Ye, and Yifang Zhu. Persistent environmental injustice due to brake and tire wear emissions and heavy-duty trucks in future California zero-emission fleets. *Environ Sci Technol* (2024).
- Yu, Qiao**, He, Brian Yueshuai, Ma, Jiaqi, and Yifang Zhu. California’s zero-emission vehicle adoption brings air quality benefits yet equity gaps persist. *Nat Commun* **14**, 7798 (2023).
- Connolly, Rachel, **Qiao Yu**, Zemin Wang, Yu-Han Chen, Jonathan Z. Liu, Ashley Collier-Oxandale, Vasileios Papapostolou, Andrea Polidori, and Yifang Zhu. “Long-term evaluation of a low-cost air sensor network for monitoring indoor and outdoor air quality at the community scale”. *Science of the Total Environment* 807: 150797 (2022).
- Huan L, Shuai L, Boru X, Zhaofeng L, Zhihang M, Xiaofan Y, Tao X, **Qiao Y**, Kebin H, Ground-level ozone pollution and its health impacts in China. *Atmospheric Environment*, Volume 173, Pages 223-230 (2018).
- Man, Hanyang, Liu, Huan, Xiao, Qian, Deng, Fanyuan, **Yu, Qiao**, Wang, Kai, Yang, Zhengjun, Wu, Ye, He, Kebin, and Jiming Hao. How ethanol and gasoline formula changes evaporative emissions of the vehicles. *Applied Energy*, Volume 222, 2018, Pages 584-594.

Selected Presentations

- National Academies Transportation Research Board Conference. “Environmental Justice Implications of Distributive Equity and Near-Roadway Air Quality from Zero-Emission Vehicle Adoption in California” [Poster Presentation]. Panel Title: Environment, Energy, and Livable Economies. Aug 2024.
- UCLA Downtown Los Angeles Forum on Transforming Transportation. “Environmental Justice On Air” [Oral Presentation]. Panel Title: TRACtion 2024 Research in Action. March 2024.
- American Association for Aerosol Research. “Environmental Justice Implications of Distributive Equity and Near-Roadway Air Quality from Zero-Emission Vehicle Adoption in California” [Oral Presentation]. October 2023.

1. INTRODUCTION

1.1. ENVIRONMENTAL JUSTICE AND THE TRANSITION TO EQUITABLE CLEAN TRANSPORTATION

The transportation sector is the largest contributor to greenhouse gas (GHG) emissions and a significant source of air pollution in California, accounting for nearly 50% of the state's GHG emissions and 90% of diesel particulate matter (PM) pollution¹. To mitigate climate change and improve air quality, California has been the leader of zero-emission vehicles (ZEVs) adoption. Unlike conventional internal combustion engine vehicles (ICEVs), ZEVs produce no tailpipe emissions and have the potential to dramatically reduce traffic-related air pollution (TRAP). As a result, ZEV policy is considered a critical tool for climate change mitigation and improving public health through reductions in air pollutants.

California has taken a leadership role in the global ZEV transition. Through initiatives such as Executive Order N-79-20, which mandates that all new passenger vehicles sold in the state must be ZEVs by 2035, California has set ambitious goals for a clean transportation future². Policies such as the Advanced Clean Cars II rule provide a roadmap for ZEV adoption³, and other regions, including New York⁴, the United Kingdom⁵, and the European Union⁶, are following California's lead in accelerating the shift to zero-emission vehicles. Despite these advancements, however, equity concerns persist. Disadvantaged communities (DACs) and racially and ethnically minoritized populations in California continue to experience disproportionate exposure to air pollution, and disparities in ZEV adoption remain significant. This raises critical questions about whether the benefits of clean transportation technologies are being distributed equitably across all communities.

While the policy-driven push for ZEVs presents an opportunity to address both air quality and climate change, its equity implications remain uncertain. Despite progress, many disadvantaged communities (DACs) in California continue to experience some of the worst air quality in the nation⁷. DAC residents, often comprising racially and ethnically minoritized populations, are disproportionately exposed to traffic emissions due to their proximity to roadways and other transportation infrastructure⁸. These communities are also more likely to experience cumulative vulnerabilities due to socioeconomic and biological factors, which exacerbate the health impacts of environmental pollutants. Moreover, DACs often have a higher concentration of older, more polluting vehicles and fewer ZEVs, further compounding their exposure to TRAP^{9,10}.

In urban areas like Los Angeles, where air pollution and health disparities are particularly pronounced, the transition to ZEVs offers a potential solution to reduce pollution and improve public health. However, the distribution of these benefits across the population is uneven, with DACs facing greater barriers to ZEV adoption and fewer opportunities to access clean transportation technologies. Although current ZEV policies could reduce overall emissions, the specific air quality and health outcomes for DACs, particularly near roadways, require further examination to ensure an equitable distribution of the benefits.

Building on the state's climate priorities, this dissertation investigates the environmental justice dimensions of ZEV adoption, the associated air quality and health benefits, and the equity of access to electric vehicle charging infrastructure. Chapter 2 explores the distributive equity of ZEV adoption in California, quantifying ZEV ownership disparities at the census tract level and projecting future adoption patterns through 2035. It highlights the continuing exposure of DACs to higher levels of air pollution despite increased ZEV adoption. Chapter 3 focuses on the regional air quality and public health benefits of ZEV adoption in Los Angeles, modeling future emissions

and air quality changes under various ZEV adoption scenarios. The chapter also assesses the health impacts of these changes, particularly among DACs, identifying both the potential benefits and complexities of reducing multiple pollutants. Chapter 4 examines the equity and reliability of public electric vehicle charging stations (EVCSs) in the United States, utilizing user-generated data to assess access disparities and the reliability of charging infrastructure across different communities. This chapter emphasizes the challenges faced by DACs in accessing reliable charging, particularly among renters in multi-dwelling units who lack access to at-home charging.

Taken together, these chapters provide a comprehensive analysis of the environmental and health implications of California's ZEV policies, the progress and challenges in achieving equitable access to clean transportation, and the role of EVCS infrastructure in supporting the transition to a carbon-neutral transportation system. By focusing on the intersection of air quality, public health, and environmental justice, this dissertation contributes to the ongoing conversation on how to ensure that the benefits of clean energy and climate mitigation strategies reach all communities, especially those that are most vulnerable to the impacts of air pollution and climate change.

1.2. SUMMARY OF AIMS

In this dissertation, we use a variety of methods from the different disciplines—including geospatial analysis, transportation modeling, air quality simulations, and qualitative analysis of user-generated data using artificial intelligence—to examine the public health and equity implications of ZEV adoption and EVCS accessibility in California and across the United States. This work provides evidence-based insights that can inform future policy interventions aimed at achieving environmental justice and equitable access to clean transportation technologies. Each of

the three aims in this dissertation, presented in Chapters 2, 3, and 4, explores different aspects of how ZEVs and EVCS infrastructure impact air quality, public health, and equity.

In Chapter 2, we examined the historical trend of ZEV adoption between 2015 and 2020 in DACs and non-DACs in California. Focusing on the Greater Los Angeles area, which has the largest ZEV population in the U.S., we conducted a near-roadway air quality analysis to assess the disparities in ZEV ownership and air pollution exposure. Using an integrated transportation model, we simulated ZEV trips at the census tract level and quantified changes in fine particulate matter and nitrogen oxide concentrations. Our findings show that while ZEV adoption has led to some reductions in pollutant exposure for DACs, these communities still face disproportionately higher levels of traffic-related air pollution. Racially and ethnically minoritized populations, regardless of DAC status, also face lower ZEV ownership rates. This chapter highlights the need for targeted ZEV policies that address the persistent inequities in pollution exposure and vehicle ownership among vulnerable populations.

In Chapter 3, we build upon the LA100 study by focusing on the potential environmental and public health benefits of ZEV adoption in Los Angeles, particularly for DACs. We developed three scenarios to model the effects of different ZEV adoption levels on air quality and health outcomes. We simulated changes in $PM_{2.5}$ and ozone concentrations using a high-resolution chemical transport model and assessed the related public health benefits using racial and ethnic-specific concentration-response data. Our results indicate that while ZEV adoption can substantially reduce $PM_{2.5}$ concentrations and improve public health outcomes for both DACs and non-DACs, the impact on O_3 levels is more complex. We observed temporary increases in O_3 concentrations, particularly in DACs, a phenomenon that requires further NO_x and VOC emissions reductions to fully realize the air quality benefits of ZEVs. This chapter underscores the importance of a multi-

faceted approach to emission reductions in order to maximize the health benefits of clean transportation policies.

In Chapter 4, we conducted the first national-level analysis of equity in access to public EVCSs, using a large dataset of user-generated reviews to assess both accessibility and reliability of EVCS infrastructure across the United States. We applied large language models to perform sentiment analysis on over 470,000 user reviews and conducted a qualitative analysis using grounded theory to identify the most common issues encountered by EVCS users. Our findings reveal that DACs and residents who lack at-home charging opportunities face significant barriers to accessing reliable public EVCS infrastructure. Despite several policies aimed at improving EVCS access in underserved areas, disparities in both availability and reliability persist nationwide. This chapter calls for increased investment in public EVCS infrastructure, particularly in DACs, and emphasizes the need for enhanced reliability to ensure that all communities can benefit from the clean energy transition.

In sum, the three aims of this dissertation address key issues in the intersection of ZEV adoption, air quality, public health, and environmental justice. The findings provide actionable insights for policymakers, stakeholders, and advocates working to ensure an equitable and sustainable transition to clean transportation technologies.

2. CALIFORNIA'S ZERO-EMISSION VEHICLE ADOPTION BRINGS AIR QUALITY BENEFITS YET EQUITY GAPS PERSIST

Published in Nature Communications [2023]

DOI: <https://doi.org/10.1038/s41467-023-43309-9>

2.1. ABSTRACT

Zero-emission vehicle (ZEV) adoption is a key climate mitigation tool, but its environmental justice implications remain unclear. Here, we quantify ZEV adoption at the census tract level in California from 2015 to 2020 and project it to 2035 when all new passenger vehicles sold are expected to be ZEVs. We then apply an integrated traffic model together with a dispersion model to simulate air quality changes near roads in the Greater Los Angeles. We found that per capita ZEV ownership in non-disadvantaged communities (non-DACs) as defined by the state of California is 3.8 times of that in DACs. racially and ethnically minoritized populations owned fewer ZEVs regardless of DAC designation. While DAC residents receive 40% more pollutant reduction than non-DACs due to intercommunity ZEV trips in 2020, they remain disproportionately exposed to higher levels of traffic-related air pollutants. With more ZEVs in 2035, the exposure disparity narrows. However, to further reduce disparities, the focus must include trucks, emphasizing the need for targeted ZEV policies that address persistent pollution burdens among DAC and racially and ethnically minoritized populations.

2.2. INTRODUCTION

In California, the transportation sector contributes to approximately 50% of total greenhouse gas (GHG) emissions and 90% of diesel particulate matter (PM) pollution¹. Unlike internal combustion engine vehicles (ICEVs), zero-emission vehicles (ZEVs) produce no tailpipe emissions and only generate non-exhaust emissions caused by brake and tire wear. ZEV policy, a

practical climate change mitigation tool, is expected to produce health co-benefits by reducing traffic-related air pollution (TRAP) while also reducing GHG emissions¹¹⁻¹⁵.

The California Air Resources Board (CARB) defines ZEVs as vehicle technologies including battery electric, plug-in hybrid, and hydrogen fuel cell vehicles. California was one of the first government bodies in the world to publish ZEV sales requirements: Executive Order N-79-20 of September 2020 requires all new passenger vehicles sold in California to be ZEVs by 2035². In 2022, the CARB approved the Advanced Clean Cars II rule, which establishes a year-by-year roadmap so that by 2035 100% of new cars and light trucks sold in California will be ZEVs³. An increasing number of regions across the globe are following California in accelerating ZEV adoption: New York State adopted California's ZEV rules in September 2022⁴; the United Kingdom announced a plan for new car and van sales to be fully zero-emitting by 2035⁵; and the European Union also reached an agreement to zero-out tailpipe emissions for both new cars and vans by 2035⁶. The International Energy Agency projects that there will be 200 million electric vehicles (EVs) in 2030 globally, 11 times the stock in 2022¹⁶. As the fifth largest economy in the world and the largest ZEV market in the United States, California has a total of 635,000 registered ZEVs at the end of 2020, which still only represents approximately 2.2% of the total vehicle fleet¹⁷. Nevertheless, California is expected to make 9.5 million more ZEV sales by 2035³.

Despite air quality improvements being made in the past few decades, many metropolitan areas and disadvantaged communities (DACs) in California, as defined by the state government, still experience the worst air quality in the country⁷. Here, we use the Senate Bill (SB) 535 DAC designation¹⁸ since it specifically targets greater air pollution reduction and climate change investments. The SB535 DAC designation is based on CalEnviroScreen, a tool developed by the California Environmental Protection Agency to identify California communities

disproportionately affected by pollution while considering health, socioeconomic, and population characteristic data. These data are then computed to derive an overall score, which is later utilized to rank communities and identify DACs. The designation comprises four categories: (1) Census tracts in the top 25% of overall scores in CalEnviroScreen 4.0; (2) Tracts with the highest 5% cumulative pollution burden scores lacking overall scores due to data gaps; (3) Tracts identified as disadvantaged in 2017, regardless of CalEnviroScreen 4.0 scores; (4) Lands under federally recognized tribes' control, with a consultation process for tribal designation requests. Over 9.3 million Californians live in DACs⁷. California also has the highest percentage of population living near-roadways (within 300 meters of a major road)⁸. In addition, many DAC residents are racially and ethnically minoritized populations who are often more susceptible to environmental pollutants due to cumulative vulnerabilities they encounter, including biological (epigenetic expression and preexisting health conditions) and social vulnerabilities (low socioeconomic status, ethnoracial discrimination, and physiological stressors)^{19–22}. While the term “racial and ethnic minorities” have been officially used by government agency such as the U.S. National Institutes of Health^{23,24}, there have been calls to replace the term with 'racially and ethnically minoritized' to recognize the active processes of marginalization and systemic discrimination that these groups experience^{25,26}. Moreover, due to historical and ongoing socioeconomic inequities, racially and ethnically minoritized populations often reside near transportation infrastructure^{27–31}. This is further compounded by the fact that the vehicle fleet passing through DACs and non-DACs differs considerably. There is a higher proportion of medium- and heavy-duty trucks and older vehicles that emit more pollutants in DACs, resulting in higher levels of TRAP exposure in these communities^{9,10}. Therefore, these communities are disproportionately exposed to higher levels of TRAP and other environmental pollutants, together contributing to health disparities^{32–36}. Thus,

there is a critical need to assess the distributive equity of ZEVs and associated air quality benefits through the lens of environmental justice. A lack of such knowledge will likely undermine the equity perspective during climate mitigation policy planning and aggravate health disparities among DAC residents.

Previous studies have quantified the ambient air quality and health benefits of ZEV adoption at the national and state levels: a 75% fleet electrification rate in the United States could prevent 3,000 PM_{2.5}-related premature deaths and bring ~\$70 billion in health benefits per year.¹⁵ Another study³⁷ simulating full electrification of light-duty vehicles and buses in California has demonstrated an average PM_{2.5} reduction of 0.13 µg/m³. More recent research³⁸ presenting various electrification scenarios has reported reductions in PM_{2.5} concentrations ranging from 0.08 to 0.98 µg/m³. Since traffic emissions often contribute most to ambient air pollution in urban environments^{39–41}, analyzing near-roadway TRAP exposure at the neighborhood level could be both insightful and indicative from an environmental justice perspective. In addition, epidemiological studies have also found linkages between near-roadway exposure to TRAP and a variety of adverse health outcomes, including birth effects and cardiorespiratory morbidity and mortality^{42–47}. Focusing on near-roadway TRAP exposure allows us to investigate how ZEV-related air quality benefits are distributed at the community level.

In this study, we analyzed the historical ZEV adoption trend for DACs and non-DACs in California between 2015 and 2020. We then chose the Greater Los Angeles area, which has the largest ZEV population in the United States¹⁷, and conducted a detailed near-roadway air quality analysis based on ZEV adoption data in 2020 to assess the disparities between DACs and non-DACs. To further analyze the extent to which ZEVs can reduce disparities, we conducted additional analysis based on the projected adoption of ZEVs in 2035. We first create an integrated

transportation model that combines ZEV ownership data, household travel demand data, and transportation supply data to predict ZEV trips in terms of electric vehicle miles traveled (eVMT) at the roadway link level. Here, eVMT represents the total miles driven by ZEVs in a given census tract. We then analyze ZEV ownership and eVMT per census tract among different racial and ethnic groups. Finally, we calculate emission changes associated with modeled eVMT at each link and use a dispersion model to project fine particulate matter (PM_{2.5}) and nitrogen oxide (NO_x) concentrations at the census tract level. These results provide evidence for policy-makers to design future ZEV policies to address environmental justice issues related to disproportionately higher exposure to TRAP found among DAC residents and racially and ethnically minoritized populations.

2.3. METHODS

2.3.1. DAC Designation

SB 535 DAC designation is based on CalEnviroScreen 4.0, a tool developed by the California Environmental Protection Agency to identify California communities that are disproportionately affected by pollution. CalEnviroScreen 4.0 assigns scores of different indicators to each census tract, and a final score is calculated by multiplying the pollution burden and population characteristics⁷. The final score is then expressed as a percentile ranking. The higher the percentile, the more risk is faced by the census tract residents. Compared to CalEnviroScreen 4.0, the final SB 535 DAC designation includes more DACs from previous CalEnviroScreen versions, recognized Tribes and tracts with high pollution burden scores but without population characteristics scores. Using SB 535 DAC designation allows us to provide more policy-relevant and readily applicable analysis.

2.3.2. ZEV Adoption Trends

To better understand light-duty ZEV adoption trends in different California communities from 2015 to 2020, we retrieve vehicle registration data from the CARB Fleet Database⁴⁸ which provides Census Block Group level vehicle population estimation based on registration data from the California Department of Motor Vehicles. Census block group data are then aggregated at the census tract level to facilitate environmental justice analysis.

To project the future ZEV adoption in 2035 when all new passenger vehicles sold are expected to be ZEVs, we applied different logistic growth models to estimate the number of light-duty ZEVs for each census tract within Los Angeles County based on census tract specific historical ZEV adoption data between 2015 to 2020. For medium- and heavy-duty vehicles, we used the ZEV penetration prediction directly from EMFAC2021 v1.0.2⁴⁹, an official emission and fleet inventory database developed by the CARB. The logistic growth model is a mathematical framework commonly used to predict the adoption rate of new technologies. It describes a sigmoidal, or S-shaped, curve, representing a slow initial adoption, followed by rapid growth as the technology becomes more prevalent, and eventually leveling off as the market becomes saturated. This model has been widely applied in various fields, including technology diffusion, population growth, and resource consumption, to forecast future trends and inform decision-making processes. We utilized light-duty ZEVs ownership data for each census tract from 2015 to 2020 to establish a growth trend from EMFAC2021 v1.0.2⁴⁹. After estimating the number of light-duty ZEVs for each census tract in 2035, we adjust the total light-duty ZEVs count in Los Angeles County to achieve a final ZEVs penetration rate of 50%, in accordance with the value used in the CARB Mobile Source

Strategy report^{50–52}. We then proportionally scale the ZEVs count for each census tract to reflect this target penetration rate.

To represent this methodology mathematically, we use the following logistic growth equation:

$$N(t) = \frac{K}{1 + \frac{K-N_0}{N_0}e^{-rt}} \quad (1)$$

where:

$N(t)$ is the number of ZEVs at time t (in our case, $t = 2035$),

K is the carrying capacity, representing the total light-duty vehicle population being zero-emissions in 2050,

N_0 is the initial number of ZEVs (at $t = 2015$),

r is the growth rate, estimated from the ZEVs ownership data from 2015 to 2020,

t is the time (in years) since the initial year.

The ZEVs fleet penetration rates at the census tract level in 2035 were subsequently utilized in both the transportation and air quality models to provide a comprehensive analysis of near-Green Space and Parks Exposure Metrics

2.3.3. Integrated Transportation Model

To estimate the distribution of eVMT, we adopted an integrated transportation model to predict the traffic volume distribution on a typical weekday. The integrated model employs agent-based simulation to simulate the dynamic interactions between travel demand and supply and predict the equilibrium state of the transportation system by leveraging synthetic and real data from multiple sources. Based on the ZEV adoption estimation, ZEV users can be selected from the population, and the associated eVMT distribution can be obtained.

Travel demand is derived from an activity-based model (ABM) developed by the Southern California Association of Government (SCAG) for both 2020 and 2035 scenarios, which is one of the largest models used in practice in the United States. Based on the principle that people's demand for travel is derived from the demand for activity⁵³, the ABM predicts people's decision-making regarding a series of interdependent travel-related choices and estimates the derived travel demand at the individual level in consideration of spatial-temporal constraints^{54,55}. While the ABM predicts the travel demand in six counties of Southern California, we filtered trips within Los Angeles County in this paper. For trips occurring inside or outside Los Angeles County, we aggregated the origins or destinations to the nearest zones on the border of Los Angeles County. Approximately 3,221,000 households (9,661,000 population) in Los Angeles County were incorporated with 43,850,000 trips in total. Additionally, the heavy-duty truck trips were also incorporated as part of the travel demand, including about 368,000 daily truck trips in Los Angeles County.

The ABM provides a realistic prediction of people's travel demand on a typical weekday, while the movement of travelers and vehicles in a transportation network is not explicitly captured. We adopted agent-based simulation toolkit Multi-Agent Transport Simulation v13 (MATSim)⁵⁶ to simulate the movement of travelers and vehicles in a multimodal network of Los Angeles County. In the simulation, we used a "Passenger Car Equivalent" of 3.5, indicating that a truck impacts traffic flow equivalently to 3.5 conventional cars⁵⁷. The traffic volume distribution across Los Angeles County can be obtained from the simulation results at a link-level spatial resolution and temporal resolution for each hour. The multimodal network consists of a road network and a transit network including approximately 354,000 links that are incorporated into the multimodal

network. The road network is generated from OpenStreetMap data⁵⁸, while the transit network is developed from General Transit Feed Specification (GTFS) data⁵⁹.

Considering the computational efficiency of large-scale simulation, 10% of the population was simulated in this paper. An iterative calibration approach was adopted to accommodate the road capacity to the 10% population sample⁶⁰. By selecting traffic count data from major freeways across Los Angeles County as the validation set, the simulated traffic volumes were compared to the validation set (Fig. A1). Good agreements were obtained between the simulated and real traffic volumes in Los Angeles County.

2.3.4. ZEV Trip Assignment and Emission Calculation

We calculate emissions in Los Angeles County for both 2020 and 2035, with and without ZEVs. For our 2020 estimate, we use real-world ZEV ownership data from CARB to determine traffic emissions. For 2035, we rely on the projected light-duty ZEV ownership data, which is anticipated to rise to 50% for light-duty vehicles, while medium-duty vehicles and heavy-duty vehicles are projected by the CARB META tool⁵² to reach 16% and 20%, respectively. We assume that both ICEVs and ZEVs have the same vehicle miles traveled (VMT), indicating similar driving behaviors and patterns for both vehicle types. To establish a baseline for our study, we consider all on-road light-duty vehicles to be ICEVs, thus excluding ZEVs. Based on the ZEV ownership percentage in a specific census tract, we assume that the same percentage of trips originating from the census tract will be ZEV trips. The ZEV trips are randomly selected from all trips originating from a census tract.

We then aggregate link-level hourly emission rates for PM_{2.5} and NO_x. On-road emission rates for Los Angeles County are retrieved from EMFAC2021 v1.0.2⁴⁹. Vehicle category-specific

emission rates from EMFAC are matched with vehicle types in the MATSIM model by vehicle weight class (Table A2). Unlike EMFAC, which uses a more detailed vehicle category classification, the MATSIM model only classifies vehicles into four vehicle weight-based categories. Thus, we calculate MATSIM-weighted emission rates from EMFAC using the equation below:

$$ER_MATSIM_j^i = \sum ER_EMFAC_k^i \times VP^k \quad (2)$$

where $ER_MATSIM_j^i$ stands for the emission rate of pollutant i for MATSIM weight class j , $ER_EMFAC_k^i$ stands for the emission rate of pollutant i for EMFAC vehicle category k that falls into MATSIM weight class j , and VP^k stands for the vehicle population proportion of EMFAC vehicle category k with regard to the total vehicle population that falls into MATSIM weight class j .

Emission rates are then matched with link-level hourly vehicle volumes and vehicle activities (starting or stopping a vehicle) to calculate emissions from different emission processes, including running exhaust emissions, start exhaust tailpipe emissions, idling emissions, and brake and tire wear emissions. The emissions from all processes are then aggregated together to reflect the total emissions of a specific link.

2.3.5. Near-Roadway Air Pollution Modeling

Air dispersion models are often used to evaluate TRAP exposure and associated health outcomes among near-roadway communities^{61–63}. Here, we use the R-LINE V1.2 model to calculate hourly PM_{2.5} and NO_x concentrations due to on-road vehicle emissions. R-LINE is a line-source dispersion model developed by the U.S. Environmental Protection Agency (EPA) using steady-state Gaussian formulation⁶⁴. It is specifically designed to take in mobile source emissions, which is in line with the link-level emission data we simulated from MATSIM.

R-LINE V1.2 takes in four input files: (a) run parameters, (b) a source file, (c) a receptor file, and (d) a surface meteorology file. We prepare these input files for each link segment simulated in the MATSIM model individually. For run parameters, we use default parameters except the lane width, which is changed to 3.75 m to match the MATSIM model parameter. For the source file, we convert link-specific parameters such as lane numbers and starting and ending coordinates into an R-LINE compatible format. For the receptor file, we created a receptor network for Los Angeles County including 6,423 receptors, each presenting the centroid of a census block group. We select the receptors within 1,500 meters for each source (each link segment in MATSIM) for the receptor file, as several studies show that 1,500 meters is the maximum length at which PM_{2.5} and NO_x directly emitted from traffic cannot be detected^{65–67}. Finally, for the surface meteorology file, we first collect hourly surface meteorological data for the area near Los Angeles International Airport from the National Centers for Environmental Information in the Integrated Surface Dataset format⁶⁸. Data for January, April, July and October (a total of 123 days) are collected to represent seasonal variations across the four seasons. We also collect upper air sounding data from the National Oceanic and Atmospheric Administration Radiosonde Database for the area near Los Angeles International Airport⁶⁹. Surface meteorology and upper air sounding data are then processed using AERMET v22112⁷⁰, a meteorological data preprocessor provided by the EPA, to generate R-LINE compatible meteorology files.

With the input files, R-LINE V1.2 generates PM_{2.5} and NO_x concentrations from each link segment to all related receptors at an hourly resolution. Since the receptors are of the Census Block Group level, we aggregate the concentrations to the census tract level to facilitate DAC-related analysis. The final concentrations at each receptor are then aggregated to daily concentrations. The

seasonal and yearly daily average concentrations are then calculated. We use the average annual daily average concentrations for our final analysis. Additional data processing, analyses, and geospatial visualization were performed using Python 3.9.13⁷¹, along with the Python modules Pandas 1.5.2⁷², NumPy 1.23.5⁷³, SciPy 1.8.1⁷⁴, GeoPandas 0.13.2⁷⁵, and QGIS 3.26.2⁷⁶. The census tract administrative boundary shapefile used in this study is from CalEnviroScreen 4.0⁷.

2.3.6. Method Limitations

Our analysis is subject to several limitations. First, we were unable to predict individual ZEV trip precisely. The prediction of ZEV trips requires additional survey data encompassing household-level choices and distinct driving patterns^{77,78}. This includes preferences related to ZEV purchase, the availability of private and public EV charging stations, information on the distribution of ZEV incentives, and actual ZEV trip data that could be used to validate our model. Future research is warranted to address these aspects to improve the accuracy of ZEV-trip simulations. Due to the abovementioned data gaps, ZEV trips were randomly selected from all trips originating from a census tract. To ensure that our random selection did not impact our analysis of pollution concentration reduction distribution in DACs and non-DACs, we repeated the entire simulation process four times. Pearson correlation coefficients of the dispersion model results were calculated using Python module SciPy 1.8.1⁷⁴ for each census tract between the first random ZEV trip selection results and the additional random selection results⁷⁹. For PM_{2.5} concentration reduction in each census tract, the average correlation coefficient is 0.99 for DACs and 0.98 for non-DACs. For NO_x concentration reduction, the average correlation coefficient is 0.95 for DACs and 0.90 for non-DACs. The correlation coefficients indicate that the results obtained from the four additionally simulated results using different random selections are highly correlated with the first. This could be because resident travel patterns in the same census tract

share certain homogeneities. Thus, we are confident that our conclusion is not affected by our random selection process.

Second, we assume that ZEVs and ICEVs have identical VMTs. Although we recognize potential variations in driving patterns between ZEV and ICEV drivers, current empirical data yield inconsistent conclusions, making it difficult to adjust our model. The average annual VMT for ICEV is between 11k and 12k miles, while for ZEVs, it ranges from 6k to 15k miles, depending on survey and modeling methods^{77,80}. Moreover, most existing empirical data are aggregated, typically at the annual level, which is inadequate to calibrate our agent-based simulation that requires detailed driving log data. Variations in eVMT might affect absolute pollution reduction values, but the relative shares of eVMT and disparities between DAC and non-DAC remain consistent. Thus, our equity-focused findings will not be affected.

Third, the estimated near-roadway air quality benefits are small for both PM_{2.5} and NO_x, as the ZEV fleet penetration rate was only 2.2% in 2020. However, these benefits increase substantially as ZEV fleet expands in 2035. While we confirm that the reductions with and without ZEVs are statistically significant using a paired t-test (p-value < 0.001), and that reductions in both PM_{2.5} and NO_x attributable to ZEVs are significant between DACs and non-DACs (p-value < 0.01), we acknowledge that some uncertainty persists. Thus, we conduct our analysis based on traffic-emitted pollutant concentrations alone instead of adding background pollutant concentrations. Moreover, our work aims to complement existing methodologies such as the CTM. It is important to note that the dispersion model has inherent limitations, including challenges in modeling secondary pollutants.

Fourth, while the utilization of annual average daily concentrations is a scientifically sound approach commonly employed in air pollution research and aligns with EPA's long-term exposure

standards, we acknowledge that air pollution is associated with both short-term and long-term health effects. Future studies could enhance our understanding by examining these effects at a more granular temporal scale, leveraging our transportation model, which has temporal resolution down to the hour.

Finally, we acknowledge the impacts of upstream emissions from electricity generating units resulting from increased electricity demand due to ZEVs. However, we anticipate that these upstream emissions would have minimal impact on TRAP near roadways. Nevertheless, studies have suggested that a clean energy portfolio is the key to reducing upstream emissions and ensuring environmental justice^{12,81}. Reducing emissions from electricity generating units could yield air quality benefits, even with the increased energy demand from ZEVs^{82,83}. Shifting from fossil fuels to clean energy sources has the potential to substantially reduce the exposure of disadvantaged populations to air pollutants emitted from these units, particularly those living in close proximity⁸⁴.

2.4. RESULTS

2.4.1. ZEV Ownership

The three Lorenz curves in Figure 2.1 show how plug-in hybrid vehicles (PHEVs) and battery electric vehicles (BEVs) ownership disparities changed from 2015 to 2020 relative to ICEVs. The Lorenz curve was initially developed to represent income inequality, where the horizontal axis represents the cumulative population, and the vertical axis represents the cumulative population income⁸⁵. Here, we adapt the Lorenz curve concept and plot cumulative vehicle ownership on the vertical axis. In 2015, the most disadvantaged population (top 25%) shared 23%, 7.6% and 6.6% of all ICEVs, PHEVs, and BEVs, respectively. After 5 years, these numbers are respectively 23%, 11%, and 6.6% for 2020. For ICEVs, the ownership share is almost the same as the cumulative

population share based on CalEnviroScreen ranking (Fig. 2.1a). For PHEVs, the Lorenz curve moves toward the perfect equality line, as ownership disparity has improved despite a large gap remaining: the PHEV share of the most disadvantaged population (top 25%) increases from 7.6% to 11% from 2015 to 2020 (Fig. 2.1b). For BEVs, the gap is even greater relative to PHEVs, and no change is observed: ownership for the most disadvantaged population (top 25%) stagnates at 6.6% over the five-year period (Fig. 2.1c).

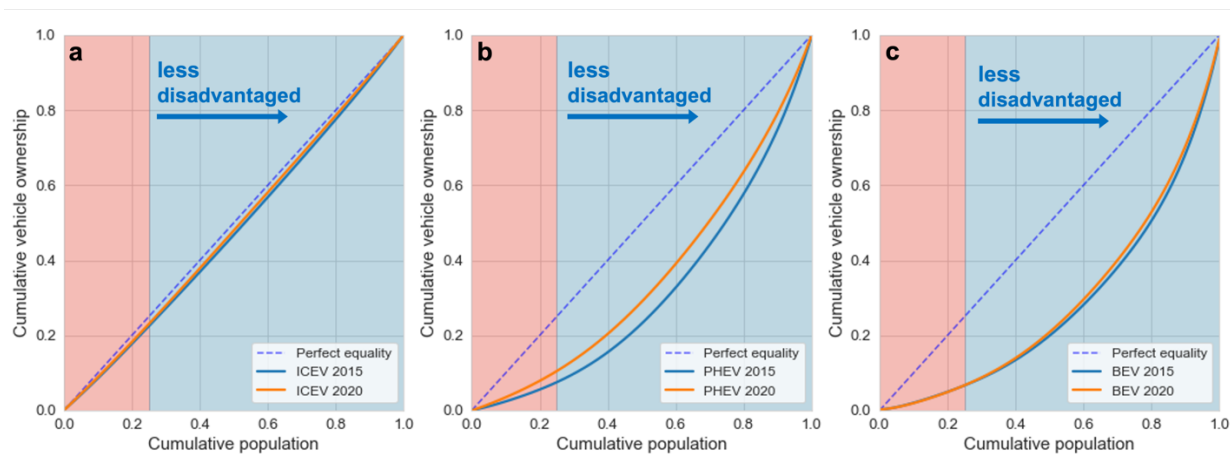


Figure 2.1. Lorenz curves of cumulative vehicle ownership and cumulative population for (a) internal combustion engine vehicles (ICEVs), (b) plug-in hybrid vehicles (PHEVs), and (c) battery electric vehicles (BEVs) from 2015 to 2020 in California. The cumulative population is sorted from highest CalEnviroScreen 4.0 percentiles to lowest percentiles. The red shaded area represents the 25% of the population most disadvantaged, and the blue shaded area represents the remaining 75% of the less disadvantaged population. The blue dashed line in each subfigure represents the ideal Lorenz curve with perfect equality.

Figure 2.2 shows how ZEV ownership changes spatially from 2015 to 2020. Figures 2.2a and 2.2d represent CalEnviroScreen 4.0 percentiles for California and Los Angeles County, respectively. Redder colors reflect more disadvantaged census tracts. In California, from 2015 to 2020, the average light-duty ZEV ownership per 1,000 residents increased from 4.3 to 16 (Figs. 2.2b, 2.2c). However, only a small amount of ZEV ownership increased in DACs, as marked in red in Figure 2.2a, especially for areas in northern, central, and southeastern California. Most ZEV ownership increases occur in non-disadvantaged census tracts located in the coastal area of

Southern California and the Bay Area. Figures 2.2d-f show a similar trend in Los Angeles County: most of the ZEV ownership increase took place in tracts with lower CalEnviroScreen 4.0 percentiles, while the disparity merely improved for tracts located in central Los Angeles County.

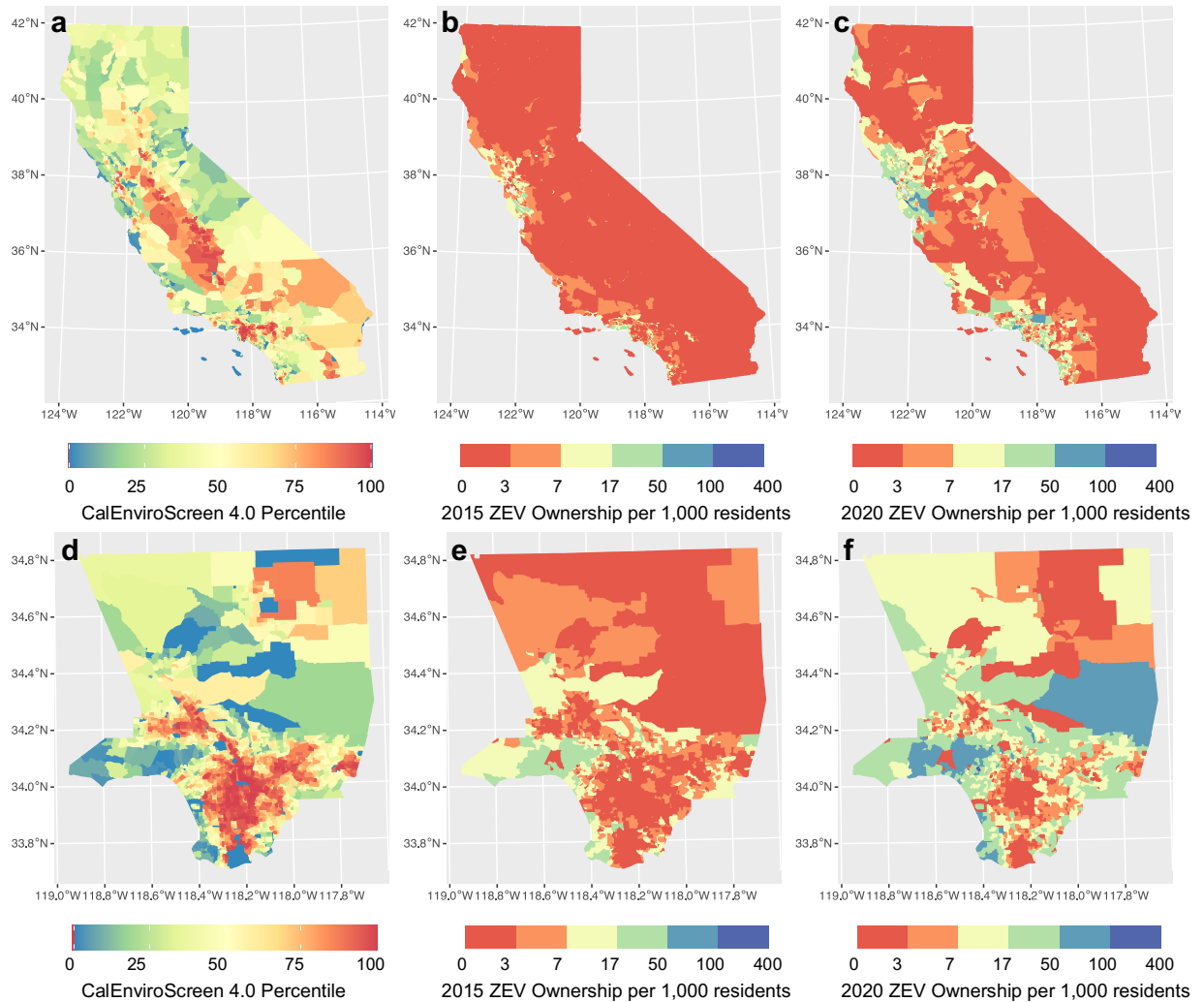


Figure 2.2. Spatial distribution of zero-emission vehicle (ZEV) ownership from 2015 to 2020 in California and Los Angeles County. Census tract level spatial distribution for (a) the CalEnviroScreen 4.0 percentile, (b) 2015, and (c) 2020 ZEV ownership per 1,000 residents in California and for (d) the CalEnviroScreen 4.0 percentile, (e) 2015, and (f) 2020 ZEV ownership per 1,000 residents in Los Angeles County.

2.4.2. ZEV Traffic

Figure 2.3 compares the spatial patterns between total (Figs. 2.3a, 2.3c) and ZEV traffic (Figs. 2.3b, 2.3d). The ZEV traffic volumes for both freeways and arterial roadways in 2020 (more local traffic activities) are affected by the ZEV ownership data for nearby communities, as presented in Figure 2.2f. For freeways, while I-405, one of the major freeways oriented north–south on the left side of Los Angeles County, has a higher percentage of ZEV traffic volume, other highways located in census tracts with lower levels of ZEV ownership have much lower ZEV traffic volumes (Fig. 2.3b). In addition, I-110, I-710, and CA-60, with more truck traffic^{86,87}, show lower ZEV traffic volumes since medium- and heavy-duty ZEV technology was still less developed in 2020. For arterial roads, links near or located in census tracts with higher levels of ZEV ownership have the highest ZEV traffic volumes. Links located in the lower middle part of Los Angeles County hardly have any ZEV traffic volumes greater than 1%. These links are located in the most disadvantaged communities, which also have the lowest per 1,000 ZEV ownership (Figs. 2.2d, 2.2f). Despite a modest increase in total traffic volume (Fig. 2.3c) and a spatial pattern similar to that of 2020 (Fig. 2.3b), there is a notably higher proportion of ZEV traffic observed in 2035 (Fig. 2.3d) due to increased ZEV adoption.

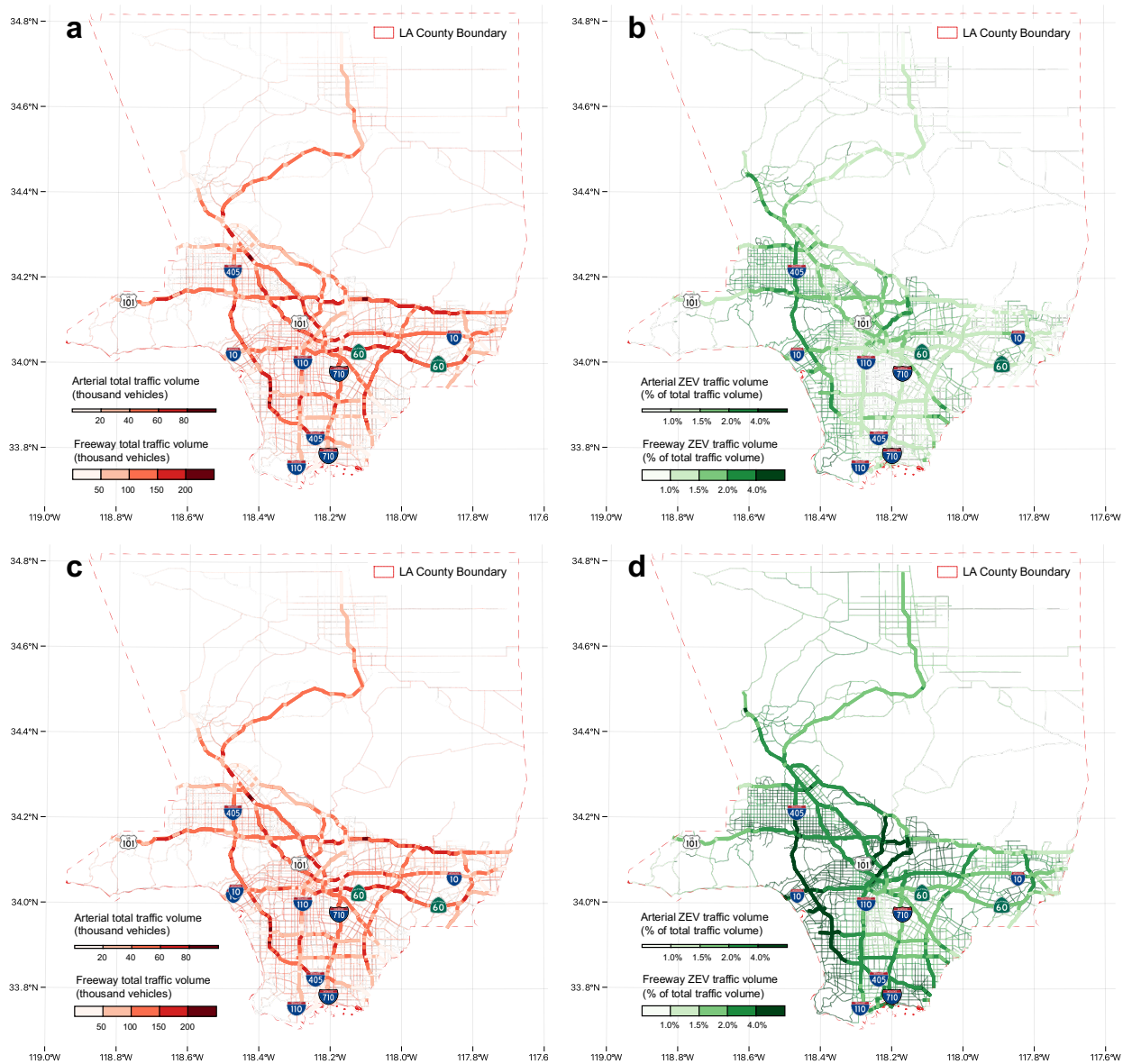


Figure 2.3. Spatial distribution of simulated daily traffic volumes in Los Angeles County in 2020 and 2035. Simulated link-level arterial and freeway traffic for (a) total traffic volume and (b) ZEV traffic volume as a percentage for Los Angeles County in 2020; (c) total traffic volume and (d) ZEV traffic volume as a percentage for Los Angeles County in 2035.

2.4.3. Racial and Ethnic Disparities

Figure 2.4 shows how ZEV ownership and eVMT which can also be viewed as a surrogate for traffic-attributable emission reduction are distributed among different racial and ethnic groups in Los Angeles County. As shown in Figure 2.4a, at the County level, the white population, while constituting only 26% of the total population, possesses 45% of the ZEV and 31% of the eVMT share. For the Hispanic population, despite showing low ZEV ownership levels of only 26%, the eVMT share is almost doubled at 44%, close to but still lower than its 48% population share. The non-Hispanic Asian American and Pacific Islander population has higher ZEV and eVMT shares than its population share. The non-Hispanic African American population has lower ZEV and eVMT shares than its population share. Populations identified as other races or as multiple races and the Native American population have similar ZEV and eVMT shares relative to their population shares. The ZEV ownership disparity persists regardless of the DAC designation (Figs. 2.4b, 2.4c): the Hispanic or Latino population owns fewer ZEVs relative to its population share even among non-DACs, whereas the non-Hispanic white population residing in DACs still has almost double the ZEV share relative to its population share. The higher eVMT share among Hispanics in DACs can be partially attributed to the more extensive network of highways and roads within their communities, which translates to more vehicle usage leading to a higher eVMT share. Racial and ethnic disparities are observed in both the DACs and non-DACs, suggesting that a more targeted ZEV policy should be developed for racially and ethnically minoritized populations to overcome potential barriers such as linguistic isolation.

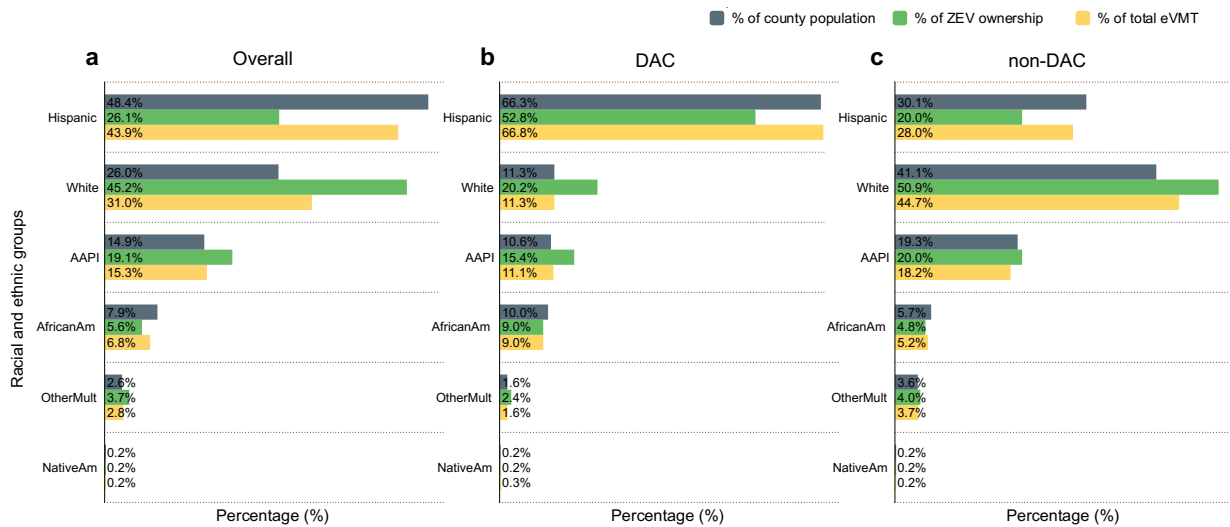


Figure 2.4. Racial and ethnic analysis on zero-emission vehicle (ZEV) ownership and simulated electric vehicle miles traveled (eVMT) in 2020. Share of county population, ZEV ownership, and eVMT per census tract for different racial and ethnic groups in (a) all communities, (b) disadvantaged communities (DACs), and (c) non-disadvantaged communities (non-DACs) in Los Angeles County. **Hispanic:** Hispanic or Latino. **White:** non-Hispanic white. **AAPI:** non-Hispanic Asian American and Pacific Islander. **AfricanAm:** non-Hispanic African American or black. **OtherMult:** non-Hispanic “other” or multiple races. **NativeAm:** non-Hispanic Native American. Racial and ethnic demographic data were obtained from CalEnviroScreen 4.0 for each census tract.

2.4.4. Near-Roadway Air Quality

Table 2.1 compares number of households, ZEV ownership, eVMT, associated emission reduction, and air pollutant levels of DACs and non-DACs within Los Angeles County for the years 2020 and 2035. It should be noted while residents in DACs constitute 25% of the total population state-wide, this number increases to approximately 45% in Los Angeles County. For year 2020, while ZEV ownership is not equally distributed among DACs and non-DACs, with DACs sharing only 18% of all ZEVs, the eVMT disparity is less prominent, indicating that many ZEVs purchased in non-DACs actually travel through DACs.

Table 2.1. Zero-emission vehicle (ZEV) ownership, electric vehicle miles traveled (eVMT), and traffic-emitted air pollutants in disadvantaged communities (DACs) vs. non-DACs in Los Angeles County in 2020 and 2035.

	2020		2035	
Variable	DAC (N=1173)	non-DAC (N = 1167)	DAC (N=1173)	non-DAC (N = 1167)
	Share (%)		Share (%)	
Number of Households	45%	55%	45%	55%
ZEV Ownership	18%	82%	30%	70%
eVMT	43%	57%	46%	54%
Pollutant emission reduction	(tons/year)		(tons/year)	
PM _{2.5}	0.39	0.51	11	13
NO _x	6.3	8.3	56	66
CO ₂	16,000	21,000	500,000	590,000
	Geometric Mean (IQR)		Geometric Mean (IQR)	
Traffic-emitted PM _{2.5} concentration (µg/m ³) ^a				
without ZEVs	0.42 (0.22-0.79)	0.20 (0.10-0.50)	0.39 (0.21-0.72)	0.18 (0.095-0.45)
with ZEVs ^b	0.41 (0.22-0.78)	0.19 (0.10-0.50)	0.32 (0.17-0.60)	0.14 (0.075-0.36)
reduction attributable to ZEVs	0.002 (0.001-0.004)	0.001 (0.001-0.004)	0.065 (0.034-0.12)	0.034 (0.017-0.093)
Traffic-emitted NO _x concentration (ppb)				
without ZEVs	5.0 (2.6-9.0)	2.4 (1.2-5.9)	1.6 (0.87-2.9)	0.72 (0.37-1.8)
with ZEVs ^b	4.9 (2.5-9.0)	2.3 (1.2-5.9)	1.1 (0.61-2.1)	0.45 (0.25-1.1)
reduction attributable to ZEVs	0.09 (0.05-0.18)	0.06 (0.03-0.16)	0.47 (0.25-0.85)	0.25 (0.12-0.70)

The upper part of the table reports the shares of the number of households, ZEV ownership, simulated eVMT, and corresponding aggregated emission reductions for PM_{2.5}, NO_x, and CO₂ in tons per year for 2020 and 2035. The lower part of the table reports model-simulated pollutant concentrations attributable to traffic for PM_{2.5} and NO_x and the reduction attributable to ZEVs in Los Angeles County SB535 DACs and non-DACs.

^aAverage annual daily concentration

^bZEVs accounted for 2.2% of the total light-duty vehicle fleet in 2020, projected to rise to 50% (light-duty vehicle), 16% (medium-duty vehicle), and 20% (heavy-duty vehicle) by

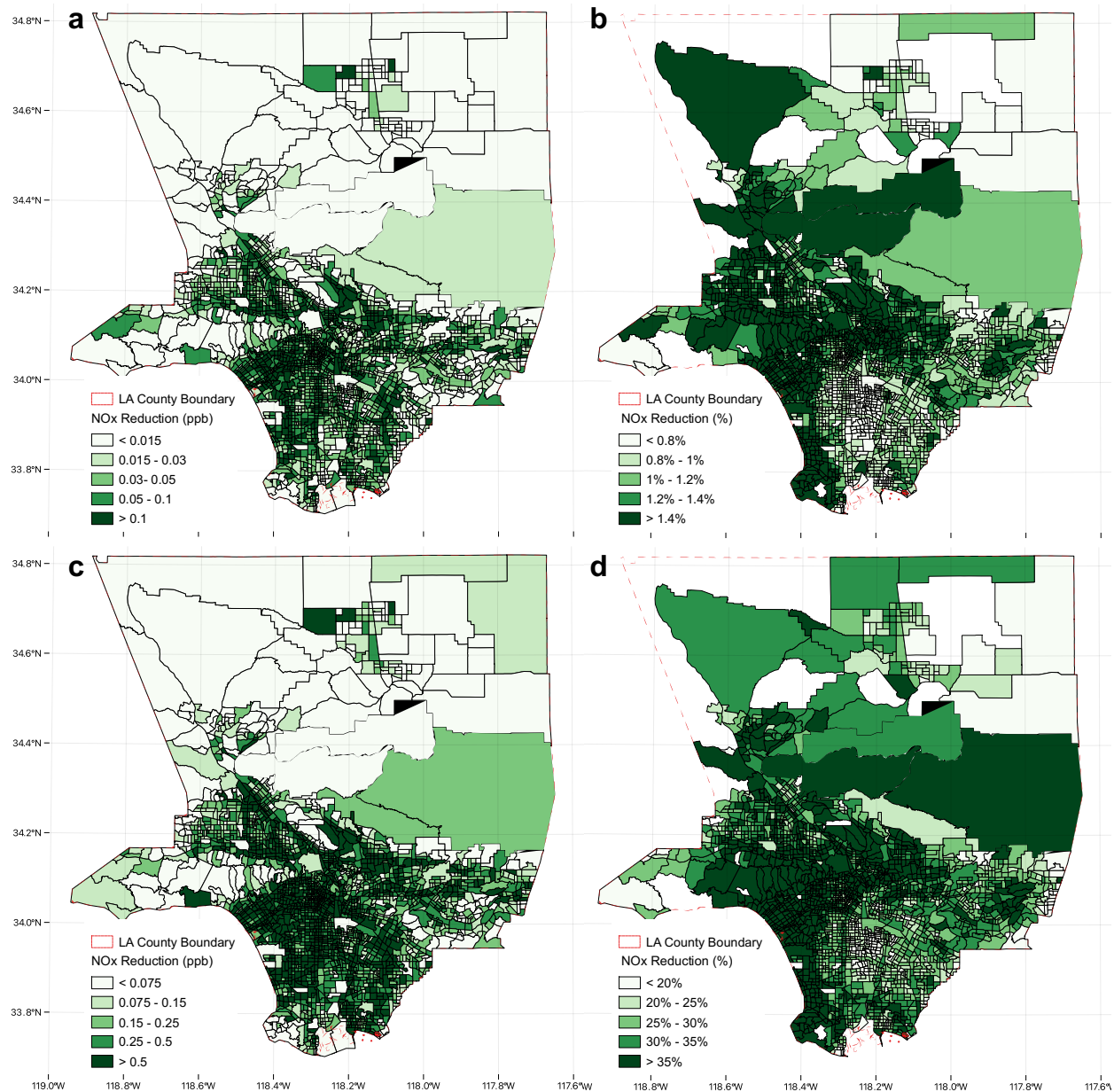


Figure 2.5. Spatial distribution of near-roadway nitrogen oxides (NO_x) reduction attributable to zero-emission vehicles (ZEVs) in Los Angeles County in 2020 and 2035. (a) NO_x in ppb, (b) NO_x as a percentage in 2020; (c) NO_x in ppb, (d) NO_x as a percentage in 2035. The percentage (relative reduction) is calculated by dividing the ZEV-attributable reduction by the total traffic-attributable pollutant concentration in each census tract. The deeper the blue color, the greater the reduction observed.

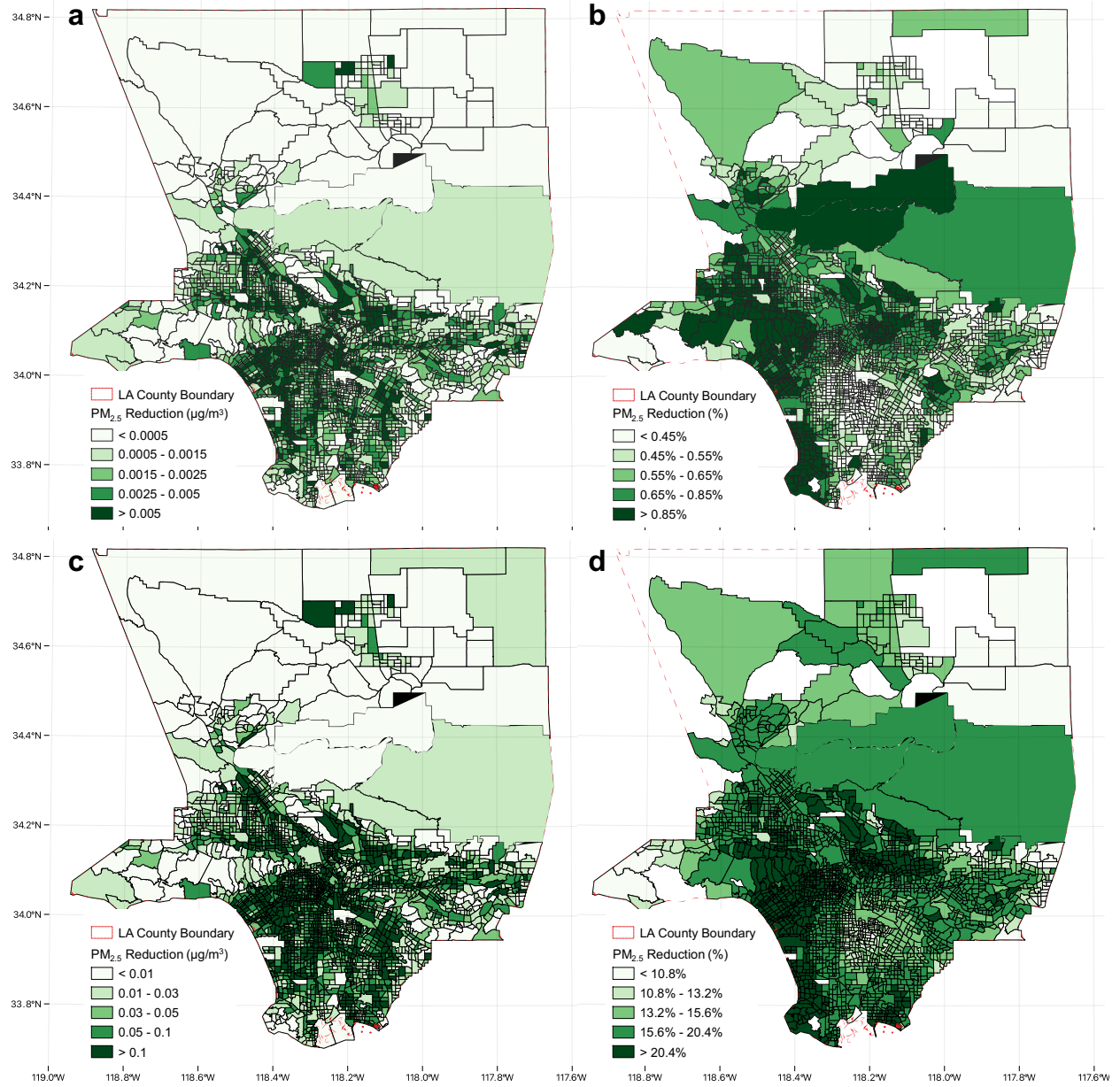


Figure 2.6. Spatial distribution of near-roadway fine particulate matter (PM_{2.5}) reduction attributable to zero-emission vehicles (ZEVs) in Los Angeles County in 2020 and 2035. (a) PM_{2.5} in $\mu\text{g}/\text{m}^3$, (b) PM_{2.5} as a percentage in 2020; (c) PM_{2.5} in $\mu\text{g}/\text{m}^3$, (d) PM_{2.5} as a percentage in 2035. The percentage (relative reduction) is calculated by dividing the ZEV-attributable reduction by the total traffic-attributable pollutant concentration in each census tract. The deeper the blue color, the greater the reduction observed.

The baseline concentration levels without ZEVs for traffic-emitted PM_{2.5} and NO_x are doubled in DACs, showing that DACs receive a much higher TRAP burden than non-DACs. The pollutant concentration reduction attributable to ZEVs is small, as the ZEV population in 2020 accounted for only 2.2% of the total vehicle fleet. However, these numbers increase as the ZEV penetration rate increases. By the year 2035, an anticipated increase in the ZEV population from 2.2% to 50% for light-duty vehicles based on CARB Mobile Source Strategy report^{50,51}, coupled with more stringent emission standards, further reduced traffic-emitted PM_{2.5} and NO_x.

As ZEV adoption expands, the gap in traffic-emitted PM_{2.5} concentrations between DACs and non-DACs narrows from 0.22 µg/m³ to 0.18 µg/m³. A recent study³⁷ simulating full electrification of light-duty vehicles and buses in California has demonstrated an average PM_{2.5} reduction of 0.13 µg/m³. These findings corroborate our results for the 100% ZEV scenario for light-duty vehicles in 2035, which results in an PM_{2.5} reduction of 0.10 µg/m³ for DAC (see Table A1). The reduction could be even greater if medium- and heavy-duty vehicles were also fully converted to ZEVs, as the aforementioned study reported an average PM_{2.5} reduction of 0.24 µg/m³ for a fully zero-emission fleet. Simultaneously, the traffic-emitted NO_x concentration gap between DACs and non-DACs is projected to decrease substantially from 2.6 ppb to 0.88 ppb, attributed to both the prevalence of ZEVs and the more rigorous emission standards enforced by 2035.

Figure 2.5 illustrates the spatial distribution of NO_x concentrations for the years 2020 and 2035. These results are consistent with those given in Table 1: the NO_x concentration reduction shares for both year 2020 and 2035 are greater in DACs, showing that the widespread adoption of ZEVs could reduce TRAP in DACs. While the NO_x concentration reductions in ppb (Figs. 2.5a, 2.5c) are more evenly distributed regardless of DAC designation, percentage reductions

(Figs. 2.5b, 2.5d) are more pronounced in tracts with higher ZEV traffic volumes (Figs. 2.3b, 2.3d). In DAC areas, such as downtown Los Angeles (located centrally at the lower part of the figure), percentage reductions increase from 2020 to 2035 with the rise of the ZEV population. However, these reductions remain relatively low when compared to those in non-DAC areas.

Figure 2.6 exhibits a similar pattern to Figure 2.5, but with a lower magnitude of $PM_{2.5}$ concentration reduction. In other words, even though DACs receive near-roadway air quality benefits from ZEV trips, the current reductions are simply not sufficient for the following reasons: (a) the ZEV-attributable reduction from vehicle start emissions from local trips cannot be shared relative to intercommunity ZEV trips, and (b) medium- and heavy-duty vehicles contribute more to TRAP exposure in DACs and ZEVs are mainly light-duty vehicles. The air quality benefits for $PM_{2.5}$ are also less than those of NO_x reduction, as ZEVs only reduce tailpipe emissions, and brake and tire wear emissions still occur.

2.5. DISCUSSION

This study examines the environmental justice implications of ZEV adoption by analyzing ZEV ownership distributions, simulating ZEV trips, and quantifying changes in near-roadway air pollutants using a bottom-up approach. Even with several targeted ZEV incentive programs and increased incentive allocation to DACs⁸⁸, we find that ZEV ownership gaps between DACs and non-DACs still remain, especially for BEVs. We also find a large ZEV ownership gap between white and racially and ethnically minoritized populations, regardless of DAC designation. This echoes findings from recent studies^{89,90}, which also concluded that racially and ethnically minoritized populations have lower electric vehicle ownership rates, regardless of income. One potential explanation for this disparity could be the purchasing behavior observed among DAC residents who often lean towards buying used vehicles⁹¹⁻⁹⁴. As of 2020, the market for used ZEVs

is somewhat limited, providing fewer opportunities for DAC residents to acquire these vehicles. Additionally, the higher subsidy elasticity of ZEV demand observed among low and medium-income consumers combined with the even greater disparities in rebate allocation could contribute to this discrepancy^{90,95}. Furthermore, a recent study⁹⁶ highlights that DAC residents encounter disparities in access to EV charging stations in California, which could further contribute to the lower ZEV penetration rate.

Despite the ZEV ownership disparities observed, we found that ZEVs travel across different communities. Thus, even communities with low ZEV ownership levels receive near-roadway air quality benefits from ZEV trips (Fig. 3). We find that DACs receive more near-roadway air quality benefits for NO_x and PM_{2.5} than non-DACs in 2020, and even more in 2035. This finding is encouraging in that ZEVs can offer near-roadway air quality benefits to various communities. Unlike previous research⁸¹ that focused on regional air quality benefits from ZEVs using a top-down approach—based on vehicle registration locations—our study employs a bottom-up methodology centered on ZEV trip routes. Consequently, we discovered that near-roadway air quality benefits can be distributed irrespective of DAC designation, an insight not addressed in the literature.

Nevertheless, when we compare the reduction to the baseline pollutant concentrations in DACs and non-DACs in 2020, we find that the gap persists: DACs receive 40% and 31% fewer relative air quality benefits for NO_x and PM_{2.5}, respectively, compared to non-DACs. In other words, although DACs may experience greater reductions in pollutant concentration in terms of µg/m³ or ppb, because the baseline concentrations in DACs are higher, their relative reductions, when considering the higher starting point, are much smaller compared to those of non-DACs. This could be explained by the fact that ZEVs not only reduce vehicle running emissions (for

which the benefits can be shared across different communities) but also reduce vehicle start emissions. In addition, DAC residents are exposed more to TRAP from medium- and heavy-duty trucks, while the current ZEVs are mainly light-duty vehicles. With more ZEVs on-road in the entire fleet, the disparity narrows in our 2035 scenario: DACs only receive 21% and 15% fewer relative air quality benefits for NO_x and PM_{2.5}, respectively. While this decline in disparity is promising near roadways, regional air quality and secondary pollutants such as ozone will require more attention in the future. Owing to the complex nature of ozone⁹⁷, ZEV adoption, which reduces NO_x emissions, could paradoxically increase ozone concentrations, especially in VOC-limited regions such as Los Angeles County. This has been reported both in the LA100 study⁹⁸ conducted by the National Renewable Energy Laboratory and another recent study³⁷. Future strategies will need to consider ozone concentrations in a region-specific context.

Similar to our findings, a previous study has shown that Hispanic and African-American populations are much more likely to live in counties with the worst air quality in the United States⁹⁹. A recent study focused on Los Angeles County delivers a similar message: white residents drive more and traverse communities with a higher proportion of racially and ethnically minoritized populations²⁷. Consequently, this results in disproportionately high TRAP burdens on these racially and ethnically minoritized residents. This agrees with the results of our study: the racially and ethnically minoritized populations share more eVMT, which are primarily driven by the ZEV trips initiated by white population. Historically, phenomena such as “white flight”, in which white families moved from cities to suburbs to avoid increasing diversity, and the highway construction boom of the 1960s, which connected urban and suburban areas, shaped commuting patterns substantially^{29–31}. As a result, non-DAC/white populations in metropolitan regions, including Los Angeles, have contributed substantially to commuting emissions due to their

tendency to travel more. Beyond exposure, it's important to recognize the cumulative impact where socio-economic, environmental, and health-related factors converge, increasing the susceptibility of DAC residents, especially the racially and ethnically minoritized populations, to the adverse effects of TRAP. While our primary focus is on exposure, addressing the underlying determinants of this increased susceptibility can amplify the benefits of reducing TRAP exposure. To comprehensively evaluate the synergy between reducing exposure and susceptibility, future studies specifically focusing on susceptibility within DAC and racially and ethnically minoritized populations are warranted. In addition to the distributive equity issue, DAC residents, especially the racially and ethnically minoritized populations, are often excluded from collective decision-making processes in contemporary history^{100,101}. As a result, unjust redlining investment practices, transportation policies, and urban planning force DAC residents to host unwanted transportation structures in their communities and disproportionately bear higher exposure to TRAP¹⁰². Policy-makers should also focus on capacity building and procedural equity when developing future targeted ZEV policies.

Different climate mitigation policies could potentially lead to spatial heterogeneities of ambient air quality across communities^{103,104}. In terms of spatial resolution, each level of granularity, from near-road to the regional, provides distinct insights and implications. For more accurate environmental justice analyses, considering that individual communities have unique characteristics, it is beneficial to use the finest resolution possible. However, this granularity often requires extensive data collection and computational resources, which might not always be readily available. Thus, adjustments tailored to specific research projects may be needed.

While regional air quality improvements from ZEVs using chemical transport model (CTM) are well studied, a community-level ZEV-related air quality benefit analysis framework has not

yet been established. Our work begins this process and can be further developed into a more comprehensive analysis framework by integrating high-resolution data from other sources (e.g., commercial and residential building emissions) to address environmental justice issues related to climate change and air pollution. Previously, a study¹⁰⁵ reported an association between zip code level ZEV adoption and lower ambient nitrogen dioxide concentrations albeit not statistically significant. By tracking individual trip and utilizing link-level emission data specifically from traffic, our approaches allow us to model the near-roadway air quality benefits attributable to ZEVs, finding statistically significant differences. Our methodology and findings are generalizable to other metropolitan areas, especially those with urban planning histories and demographic distributions similar to those of Los Angeles County. Our results suggest that ZEVs could bring cross-community near-roadway air quality benefits, yet the air quality disparity persists between DACs and non-DACs at present.

To reduce this disparity, it is critical to ensure a just transition to clean transportation^{106,107}. As shown in our 2035 simulation results, the disparity can be reduced with more light-duty ZEVs. Although a universal ZEV incentive program can boost ZEV adoption and benefit DACs, targeted policies are needed to reduce the TRAP exposure gap between DACs and non-DACs, a result of historically unjust land-use policies. Recognizing and rectifying these historical injustices is a cornerstone of a just transition. This can be achieved by directing more rebates and incentives towards disadvantaged communities, providing them with opportunities to access clean transportation.

Addressing the disparities inherent in environmental and health outcomes requires persistent and targeted efforts. As we move forward, future policies and incentive programs should take a comprehensive approach. Trucks, given their substantial emissions and frequent routes through

DACs, pose a considerable health risk. It is therefore important to prioritize the transition of trucks to zero-emission alternatives. In addition, addressing non-tailpipe emissions can provide transformative air quality improvements for the most vulnerable communities^{103,108,109}. By adopting this holistic approach, we are taking a decisive step towards achieving ZEV distributive justice and ensuring a just transition to clean transportation.

CHAPTER 2 APPENDIX

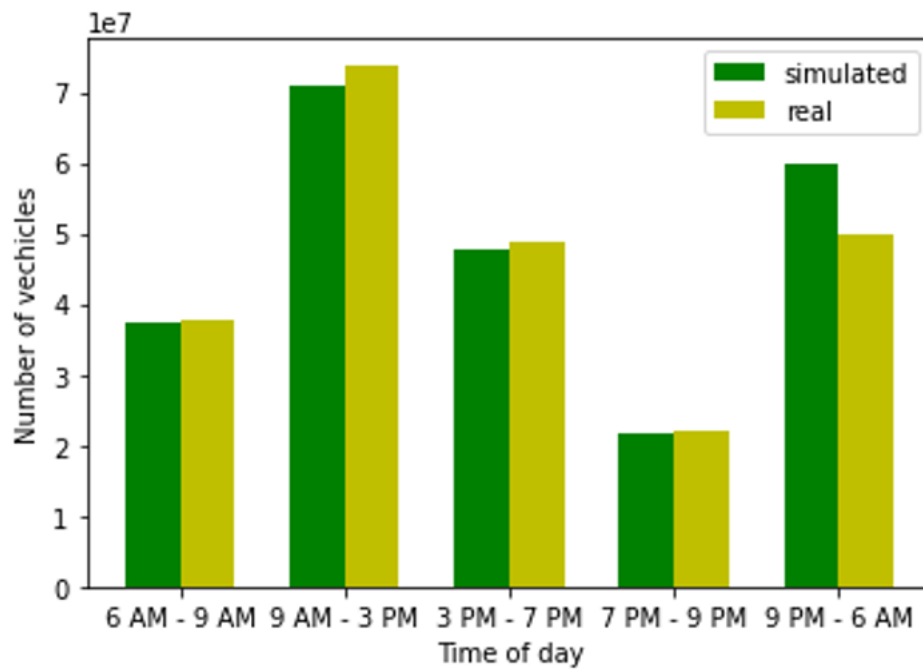


Figure A.1. Comparison of simulated and real traffic volumes in Los Angeles County.

Table A.1. Zero-emission vehicle (ZEV) ownership, electric vehicle miles traveled (eVMT), and traffic-emitted air pollutants in disadvantaged communities (DACs) vs. non-DACs in Los Angeles County in 2035 assuming 100% ZEV for light-duty vehicle.

	2035 Clean	
Variable	DAC (N=1173)	non-DAC (N = 1167)
	Share (%)	
Number of Households	45%	55%
ZEV Ownership	46%	54%
eVMT	47%	53%
Pollutant emission reduction	(tons/year)	
PM_{2.5}	26	29
NO_x	134	150
CO₂	1,200,000	1,340,000
	Geometric Mean (IQR)	
Traffic-emitted PM_{2.5} concentration (µg/m³)^a		
without ZEVs	0.39 (0.21-0.72)	0.18 (0.095-0.45)
with ZEVs^b	0.29 (0.15-0.54)	0.13 (0.068-0.32)
reduction attributable to ZEVs	0.10 (0.053-0.18)	0.049 (0.025 -0.13)
Traffic-emitted NO_x concentration (ppb)		
without ZEVs	1.6 (0.87-2.9)	0.72 (0.37-1.8)
with ZEVs^b	0.12 (0.060-0.23)	0.05 (0.024-0.13)
reduction attributable to ZEVs	1.5 (0.79-2.7)	0.66 (0.34-1.7)

The upper part of the table reports the shares of the number of households, ZEV ownership, simulated eVMT, and corresponding aggregated emission reductions for PM_{2.5}, NO_x, and CO₂ in tons per year for 2020 and 2035. The lower part of the table reports model-simulated pollutant concentrations attributable to traffic for PM_{2.5} and NO_x and the reduction attributable to ZEVs in Los Angeles County SB535 DACs and non-DACs.

^aAverage annual daily concentration

^bZEVs accounted for 100% of the total light-duty vehicle fleet, 16% medium-duty vehicle, and 20% heavy-duty vehicle in 2035

Table A.2. MATSIM and EMFAC Vehicle Category

MATSIM Vehicle Type	Passenger Vehicles	Light-heavy Truck	Medium-heavy Truck	Heavy-heavy Truck
Corresponding Weight Class	< 8,500 lbs GVW	8,500 to 14,000 lbs. GVW	14,001 to 33,000 lbs. GVW	>33,000 lbs. GVW
EMFAC Vehicle Category	"LDA", "LDT1", "LDT2", "MDV"	"LHD1", "LHD2"	"T6 CAIRP Class 4", "T6 CAIRP Class 5", "T6 CAIRP Class 6", "T6 CAIRP Class 7", "T6 Instate Delivery Class 4", "T6 Instate Delivery Class 5", "T6 Instate Delivery Class 6", "T6 Instate Delivery Class 7", "T6 Instate Other Class 4", "T6 Instate Other Class 5", "T6 Instate Other Class 6", "T6 Instate Other Class 7", "T6 Instate Tractor Class 6", "T6 Instate Tractor Class 7", "T6 OOS Class 4", "T6 OOS Class 5", "T6 OOS Class 6", "T6 OOS Class 7", "T6 Public Class 4", "T6 Public Class 5", "T6 Public Class 6", "T6 Public Class 7", "T6 Utility Class 5", "T6 Utility Class 6", "T6 Utility Class 7", "T6TS"	"T7 CAIRP Class 8", "T7 NNOOS Class 8", "T7 NOOS Class 8", "T7 POAK Class 8", "T7 POLA Class 8", "T7 Public Class 8", "T7 Single Concrete/Transit Mix Class 8", "T7 Single Dump Class 8", "T7 Single Other Class 8", "T7 SWCV Class 8", "T7 Tractor Class 8", "T7 Utility Class 8", "T7IS"

3. ASSESSING THE REGIONAL AIR QUALITY AND HEALTH BENEFITS OF ZERO-EMISSION VEHICLE ADOPTION IN LOS ANGELES

Published in LA100 Equity Strategies Chapter 15. Air Quality and Public Health [2023]
DOI: <https://doi.org/10.2172/2221858>

3.1. ABSTRACT

For dense urban environment such as Los Angeles in California, air pollution continues to disproportionately impact disadvantaged communities, especially those near roadways. As the city aims for 100% renewable electricity by 2035, zero-emission vehicles offer a promising solution to reduce pollution and improve public health. This study evaluates the potential environmental and health benefits of increased ZEV adoption by modeling future transportation patterns, emissions, air quality, and associated health outcomes. The results from this study indicate that transitioning to ZEVs significantly improves regional air quality, although areas with high levels of fine particulate matter (PM_{2.5}) persist in central and southern Los Angeles. The greatest health benefits are seen in DACs, particularly among the Hispanic population, with potential economic gains exceeding \$2 billion, of which a substantial portion would directly benefit DACs. However, reductions in nitrogen oxides (NO_x) emissions may contribute to increased ozone (O₃) levels. To maximize public health and environmental benefits, we recommend accelerating vehicle electrification, focusing on medium- and heavy-duty trucks, and continuing efforts to reduce both NO_x and volatile organic compound (VOC) emissions. These strategies are crucial to ensuring an equitable distribution of cleaner air and improved health outcomes for all Los Angeles residents.

3.2. INTRODUCTION

The transportation sector is the largest contributor to climate change and air pollution in California, accounting for approximately 50% of the state's greenhouse gas (GHG) emissions, nearly 80% of nitrogen oxide (NO_x) pollution, and 90% of diesel particulate matter (PM) pollution^{1,50}. Exposure to traffic-related air pollution (TRAP) has been consistently linked to increased risks of respiratory and cardiovascular diseases, preterm birth, cognitive function, and premature death, posing a significant health concern that necessitates the attention of policymakers and the public^{43,110,111}. Clean vehicles, particularly zero-emission vehicles (ZEVs), produce no tailpipe emissions compared to conventional gasoline and diesel vehicles^{112,113}. Thus, the transition towards clean vehicles presents an opportunity to improve air quality and yield health benefits^{105,114}.

Policymakers worldwide have committed to accelerating the transition to clean vehicles, leading to the implementation of various regional policies supporting these goals^{115,116}. For instance, the European Union has outlined a plan to strive towards achieving 100% sales of ZEVs by 2035, with the goal of achieving this target no later than 2040⁵. China has set ambitious targets for clean vehicle adoption, aiming for electric and plug-in hybrid vehicles to account for 25% of all new car sales by 2025¹¹⁷. The United States has a patchwork of clean vehicle transition policies, with some states offering more incentives for clean vehicles than others¹¹⁸. California, which is the largest market for new cars in the country, has set a goal including putting 5 million ZEVs on the road by 2030 and achieving 100% ZEVs sales for new passenger cars and light trucks by 2035 through Executive Orders B-48-18 and N-79-20, respectively². To promote the transition towards clean vehicles, governments often employ financial incentives, such as tax credits, rebates, and subsidies¹¹⁹. Such policy instruments are designed to alleviate the financial burden associated with

purchasing clean vehicles. Moreover, the development of charging infrastructure is an essential part of the clean vehicle transition, and governments frequently provide financial incentives to support its expansion^{120–122}.

In Los Angeles (LA), addressing air pollution has been an ongoing challenge for many decades, with a particular focus on emissions from motor vehicles^{123–125}. Disadvantaged communities (DACs) in the city are confronted with a wide range of socio-economic challenges, including high levels of poverty, unemployment, and limited access to essential healthcare services¹²⁶. Furthermore, DAC residents are more likely to live near-roadway, which exposes them to higher levels of TRAP, ultimately resulting in environmental inequities^{27,127–130}. Although previous studies have quantified the ambient air quality and health benefits linked to ZEVs adoption to some extent, there is a crucial knowledge gap in the literature on evaluating the distribution equity of air quality and health benefits during the transition to clean vehicles from an environmental justice perspective^{12,37,131}.

In this study, we build upon the previous LA100 study, which aimed for the transition to 100% renewable energy in LA City, and introduce a new focus on Equity Strategies. This new focus aims to ensure a just transition by investigating the potential environmental and public health benefits of replacing conventional vehicles with ZEVs in the city of LA, especially among DACs. We first utilize state-of-the-art methods to estimate future emission trends under different scenarios, with a focus on ZEVs disparity among DACs. A personal trip-level transportation model is used to generate precise spatial emission patterns for the on-road sector under different ZEVs distribution scenarios. We then simulate consequent changes in ambient particulate matter with an aerodynamic diameter less than or equal to 2.5 micrometers (PM_{2.5}) and ozone (O₃) concentrations using a high-resolution chemical transport model at about 1 km x 1 km. Finally, we assess the

related public health benefits and monetized economic benefits in the city of LA using racial and ethnic specific concentration-response data.

This new study emphasizes the importance of not only transitioning to cleaner energy sources but also ensuring that the benefits of this transition are equitably distributed among all communities, particularly those that have been historically underserved. By evaluating the potential health and economic impacts of increased ZEVs adoption, this study provides valuable insights for policymakers, stakeholders, and communities as they work together to create a more sustainable and equitable future for the city of LA.

3.3. METHODS

3.3.1. Emission Inventory Development

3.3.1.1. Scenario Development

To gain a deeper understanding of how the adoption of light-, medium-, and heavy-duty ZEVs by 2035 will impact various communities, particularly those that are disadvantaged, we developed three distinct future scenarios:

(1) **Disparity:** a 2035 ZEVs Disparity scenario that maps emission reductions based on varying ZEVs ownership adoption rates;

(2) **Equity:** a 2035 ZEVs Equity scenario where emission reductions in on-road transportation based on a uniform ZEVs ownership adoption rate at 50% for every census tract; and

(3) **Equity_MSS:** a 2035 ZEVs Equity scenario that emphasizes increased ZEVs usage in medium- and heavy-duty vehicles, with mobile source (both on-road and off-road) emission reductions aligned with the California Air Resources Board (CARB) 2020 Mobile Source Strategy (MSS)⁵⁰

To assess the changes in ambient air quality for these 2035 scenarios, we use a baseline scenario reflecting the 2017 emission levels (i.e., **Base**). Table A1 in the Appendix reports the technical details for each scenario.

The county-level mobile source emissions are calculated using methods described in Chapter 2.3.2 – 2.3.4. The county-level and source-specific emission data except the mobile sources are collected from California Emissions Projection Analysis Model (CEPAM2019 v1.03)¹³² with a base year of 2017. For mobile source (both on-road and off-road sectors), we used EMFAC2021 v1.0.2⁴⁹, which is an updated version as compared to the EMFAC2017 embedded in CEPAM2019. For the Base, Disparity, and Equity scenarios, we adjusted the emission for upstream and downstream energy use and production changes due to increased ZEVs population. For Equity_MSS scenario, we further adjusted the medium- and heavy-duty vehicle ZEVs penetration rate and off-road emission rates using EMFAC META model⁴⁹, which is created based on CARB 2020 MSS⁵⁰ document. We used CARB default settings for the META model.

3.3.1.2. Emission Inventory Development for Upstream and Downstream Production

As the future ZEVs population will increase the demand for electricity from the electricity generating sector while simultaneously reducing reliance on oil and gas production, it is essential to adjust the emissions from these two sectors accordingly. Therefore, we modify the emissions projections for both the electricity generating units and oil and gas production sectors based on the anticipated ZEVs population in 2035, ensuring a more accurate reflection of their environmental impact. We modified the stationary emissions from petroleum and gas industry for all 2035 scenarios. The overall Petroleum industry scaling down factor is calculated using the following equation:

$$\text{Scaling Down Factor} = \frac{\text{REAL Scenario EMFAC 2035 PC}}{\text{BAU Scenario EMFAC 2035 PC}} \times \text{Onroad \%} \quad (1)$$

where the PC stands for Petroleum Consumption (includes the gasoline, diesel, and gas energy consumption) from on-road vehicles in EMFAC 2035 database under different scenarios, Onroad% stands for the on-road transportation sector consumption percentage. Based on a report from the U.S. Energy Information Administration¹³³ in year 2019, 68% petroleum is used in the on-road transportation sector. The final scaling down factor for the petroleum and gas industry is 0.80 for Disparity and Equity scenarios and 0.78 for Equity_MSS scenario, assuming the emission factors and the on-road petroleum consumption percentage stay the same in 2035.

Similarly, we also modify the emissions from the electric generating units. We first obtain the 2017 California electricity net generation data from the Energy Information Administration¹³⁴. We then apply activity growth factor from CEPAM to project the electricity net generation data in 2035. The overall scaling up factor for electric generating units was calculated using the following equation:

$$\text{Scaling Up Factor} = \frac{E_{onroad} + E_{net}}{E_{net}} \quad (2)$$

Where the E_{onroad} stands for the electricity needed from the on-road transportation sector and E_{Net} stands for the projected net electricity generation in year 2035. The final scaling up factor is 1.20 for Disparity and Equity Scenarios, and 1.21 for Equity_MSS scenario. While our scaling-up calculation method for estimating emissions from electric generating units serves as a useful proxy, it is important to note that it remains a rough approximation due to the complexity involved in modeling the entire energy system. Given our study focuses on equity strategies, we have prioritized other aspects of the analysis, and we do not anticipate that uncertainties in energy system estimation will affect our main conclusions on equity analysis.

We utilized emission factors for power plants in LA City from the previous LA100 study¹³⁵, specifically adopting those from the Early & No Biofuels Scenario. In this scenario, emissions stem solely from NO_x and NH₃, as power plants have transitioned to using hydrogen as their fuel source, significantly altering their emission profiles.

3.3.2. Air Quality Modeling

We use WRF-Chem version 3.9.1, a fully coupled meteorology-chemistry model that considers highly nonlinear and complex meteorological and atmospheric chemistry processes. The simulations are conducted for January, April, July, and October, representing winter, spring, summer, and fall, respectively. We apply the model to three nested domains (Figure 3.1): Domain 1 covers the western United States and its surrounding areas at a 12×12 km² horizontal resolution; Domain 2 covers Southern California with a 4×4 km² resolution; and Domain 3 covers LA County with a high resolution of 1.33×1.33 km².

The vertical resolution of the WRF-Chem includes 24 layers from the surface to 100 hPa, with denser layers at lower altitudes to resolve the planetary boundary layer. We employ an extended Carbon Bond 2005 with chlorine chemistry coupled with the Modal for Aerosol Dynamics in Europe/Volatility Basis Set (MADE/VBS). MADE/VBS uses a modal aerosol size representation and an advanced secondary organic aerosol module based on the VBS approach. The aqueous-phase chemistry is based on the AQChem module used in the Community Multiscale Air Quality model¹³⁶. The National Centers for Environmental Prediction Final Analysis (NCEP-FNL) reanalysis data in year of 2017 was used to force the meteorology initial and boundary conditions for all simulations, which is able to isolate changes in air pollution resulting from future emissions changes, without additional confounding factors such as changing meteorology or climate.



Figure 3.1. Illustration of triple nested modeling domains used in this study

As described above, we obtain the county-level, source-specific anthropogenic emissions from the CARB CEPAM estimations and then convert the county-level emissions into 1.33×1.33 km² gridded data based on high-resolution spatial distribution information provided by the California Nexus project¹³⁷. The on-road transportation emission maps are based on the ZEVs ownership and the MATSim simulated trips in each year, as mentioned above. We then distribute the CEPAM on-road emission estimation in each county in the corresponding years to the grid level following the new emission map. The biogenic emissions are calculated online using the Model of Emissions of Gases and Aerosols from Nature¹³⁸. Dust emissions are calculated online, based on the Goddard Chemical Aerosol Radiation Transport dust emission scheme¹³⁹. Sea-salt emission calculation follows parameterization in a previous study¹⁴⁰.

We compared the simulated and observed monthly average PM_{2.5} concentrations and monthly average of daily MDA8 O₃ concentrations at each individual monitoring site over Southern California (shown in Figure A1). The observed O₃ concentrations were obtained from the U.S. EPA AQS, and the data were converted to MDA8 O₃ concentrations. Daily averaged PM_{2.5}

concentrations for the innermost domain were also gathered from AQS. We evaluated the model performance against these observations using various statistical measures, including normalized mean bias (NMB), normalized mean error (NME), mean fractional bias (MFB), and mean fractional error (MFE), which are listed in Table A2. The evaluation benchmarks suggested by the EPA and previous studies are also summarized in Table A2.

The model generally reproduces the magnitude and spatial distribution of PM_{2.5} concentrations, with an overall slight overestimation of 2% in January and underestimation in the other three seasons of 5%, 25%, and 9% in April, July, and October, respectively. The performance statistics for PM_{2.5} meet the model performance goal (MFB within $\pm 30\%$ and MFE $\leq 50\%$) in all months, indicating an overall good model-measurement agreement. For O₃, the model is able to capture the spatial variability but slightly overestimates the MDA8 O₃ concentrations in January by 4% on average and underestimates it in the other three seasons by 9%, 15%, and 10% in April, July, and October, respectively. The overall performance statistics for O₃ concentration meet the model performance criteria (i.e., NMB within $\pm 15\%$ and NME $< 25\%$), indicating a generally good agreement between the model and measurements.

3.3.3. Public Health Benefits Assessment

The Environmental Benefits Mapping and Analysis Program - Community Edition (BenMAP-CE) is a versatile and widely-used tool developed by the U.S. EPA¹⁴¹. BenMAP-CE is designed to estimate the health benefits and potential economic value associated with improvements in air quality, particularly those resulting from policy interventions or changes in emission sources. The program uses spatially-resolved air quality data, along with concentration-response functions and population data, to assess the health impacts of changes in air pollution levels. By quantifying the number of avoided premature deaths, respiratory illnesses,

hospitalizations, and other health outcomes, BenMAP-CE enables policymakers and researchers to better understand the implications of various air quality improvement strategies.

We used BenMAP-CE v1.5, the latest version published in March 2023 for our analysis. Drawing upon the changes in ambient concentrations of air pollutants simulated by the WRF-Chem model for the scenarios, we estimate the health impacts associated with PM_{2.5} and O₃, focusing on changes in mortality and morbidity. This analysis provides a clearer understanding of the potential consequences of different ZEVs adoption scenarios on public health. The following equations are used to calculate the health impact,

$$HR = e^{\beta\Delta Y} \quad (3)$$

$$AF = \frac{HR-1}{HR} = 1 - e^{-\beta\Delta X} \quad (4)$$

$$\Delta Impact = y_0(1 - e^{\beta\Delta X})Pop. \quad (5)$$

where ΔX is the pollution-specific concentration change based on scenarios, β is the exposure-response factor, HR is the hazard ratio found in relevant epidemiologic study which uses ΔY , a 10 ppb and 10 $\mu\text{g}/\text{m}^3$ value that links the change in cause-specific mortality rates to incremental O₃ and PM_{2.5} exposure, respectively, AF stands for the attributable fraction of the disease specific mortality attributable to a certain air pollutant, $\Delta Impact$ is the estimated changes in health impacts incidences, y_0 is the baseline incidences, and Pop. is the population studied.

We used the BenMAP-CE v1.5 default baseline incidences rates (y_0) for our analysis. For mortality, BenMAP-CE projected baseline incidences rate to 2035 for each racial and ethnic group. For morbidity, the available data are limited to 2014 for each racial and ethnic group, as BenMAP-CE v1.5 does not include projections for 2035. Consequently, our morbidity analysis is based on the 2014 data. For population (Pop.), we utilized the 2035 projected population data available within BenMAP-CE.

In order to select appropriate epidemiological studies for our analysis, we ensured that the selected studies are up-to-date with the most recent EPA guidelines on health impact assessment and comply with the EPA Standard Health Functions, which were updated in 2021. This ensures that our analysis adheres to the latest recommendations and best practices in the field.

Table 3.1 lists the exposure-response factors we used in this study.

Table 3.1. Exposure-response Factors Used

Pollutant	Category	Health Endpoint	Author	Metric	Beta type	Age Range
PM _{2.5}	Long-term mortality	All-cause mortality	Pope et al. (2019) ¹⁴²	D24HourMean	Uniform and racial/ethnic specific	18-99
	Morbidity	ER visit - Respiratory	Krall et al. (2016) ¹⁴³	D24HourMean	Uniform only	0-99
O ₃	Long-term mortality	All-cause mortality	Turner et al. (2016) ¹⁴⁴	D8HourMax	Uniform only	30-99
	Morbidity	ER visit - Respiratory	Barry et al. (2018) ¹⁴⁵	D8HourMax	Uniform only	0-99

3.3.4. Monetization of Public Health Benefits

To determine the worth of the health benefits, we employ a methodology that involves assigning monetary values to the estimated health outcomes derived from our previous steps. To achieve this, we use BenMAP-CE v1.5 which allows us to quantify the financial value of these health outcomes. First, we identify appropriate valuation functions from 2021 EPA Standard Health Functions database¹⁴¹, which are derived from relevant economic studies or guidelines. These valuation functions typically express the economic value of health outcomes in terms of dollars per unit (e.g., dollars per avoided premature death, hospitalization, or respiratory illness). Valuation functions used are listed in Table 3.2.

Table 3.2. Valuation Functions Selected from BenMAP-CE v1.5

Endpoint	Reference	Value (2015\$)
Mortality	VSL based on 26 studies, no discount rate applied	\$8,700,000
ER visit - Respiratory	Healthcare Cost and Utilization Project	\$875

We then apply the selected valuation functions to the estimated health outcome changes for each scenario. This involves multiplying the change in health outcomes (e.g., avoided premature deaths, hospitalizations) by the corresponding monetary values per unit, as provided by the valuation functions. Finally, we calculate the total monetized health benefits by summing the monetized health benefits across all health endpoints for each scenario comparison. This provides a comprehensive understanding of the economic impact associated with the changes in air quality due to different ZEVs adoption scenarios.

3.4. RESULTS

3.4.1. Changes in Emission Inventory

Figure 3.2 illustrates the total emission rates of all source categories for NO_x and PM_{2.5} in LA City in 2035, relative to the Base scenario. The figure highlights that intensive emissions, especially for NO_x, are predominantly transportation-related, as they are concentrated along the transportation networks within the city. The total emissions of NO_x and PM_{2.5} in the Disparity scenario are reduced by 55% and 11%, respectively, relative to the Base scenario. Since the Equity scenario is set with same total emissions as the Disparity scenario (see Table 3.3), both NO_x and PM_{2.5} emissions change only slightly (<1%) due to the offsetting changes in emissions at different locations. In the Equity_MSS scenario, the emissions are further reduced on the base of the Disparity scenario by 14% and 1% for NO_x and PM_{2.5}, respectively. This reduction is attributed to the increased electrification of medium- and heavy-duty vehicles.

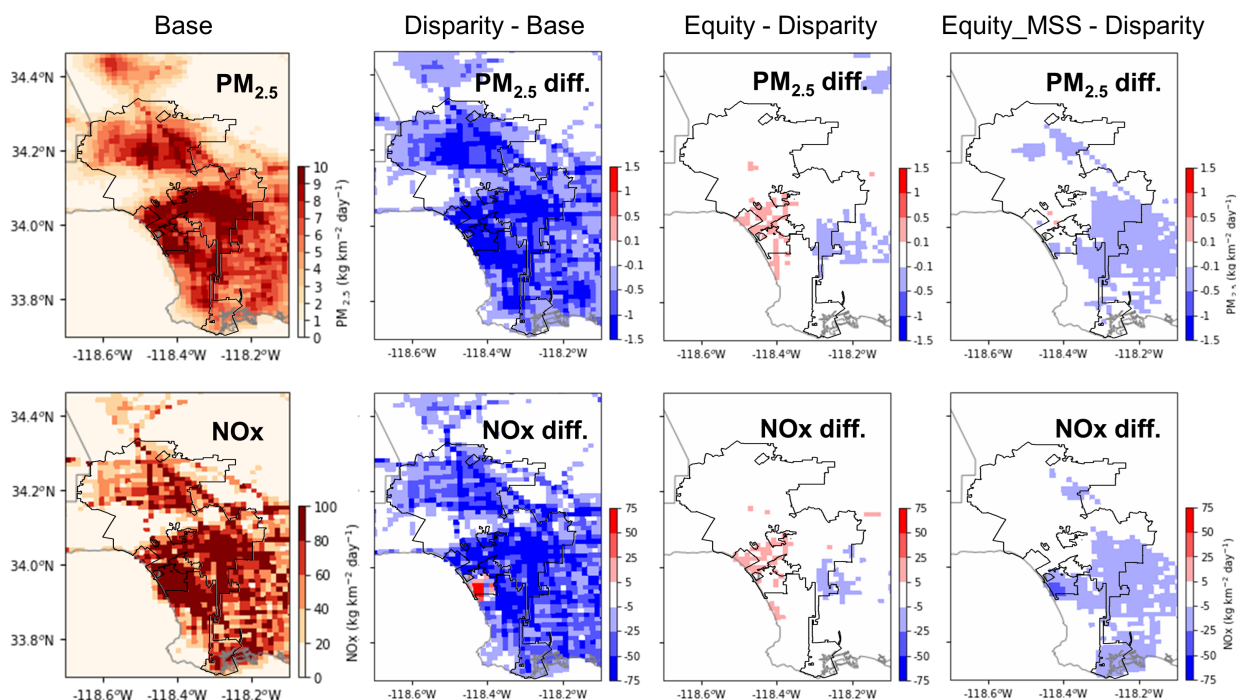


Figure 3.2. The total emission rates of all the source categories for PM_{2.5} and NO_x in LA City in 2035 relative to the 2017 Base. Black line marks LA City boundary.

Table 3.3. Pollutant-specific Emissions (tons per day) Under Base, Disparity, Equity, and Equity_MSS Scenarios and Their Relative Changes for Los Angeles County

Scenarios	CO	NH ₃	NO _x	PM ₁₀	PM _{2.5}	ROG	SO _x
<i>Base</i>	1032	46	252	96	32	303	13
<i>Disparity</i>	446	47	138	97	31	216	12
<i>Equity</i>	446	47	138	97	31	216	12
<i>Equity MSS</i>	425	46	97	97	30	215	12
<i>Disparity - Base</i>	-57%	2.2%	-45%	1.0%	-3.1%	-29%	-7.7%
<i>Equity_MSS - Disparity</i>	-4.7%	-2.1%	-30%	0.0%	-3.2%	-0.5%	0.0%

Note: Disparity and Equity are designed with same total emission amount but different spatial distributions.

Table 3.3 summarizes the total primary air pollutant emissions from all emissions sectors for the future. Compared to the Base scenario, the Los Angeles countywide total emissions of carbon monoxide (CO), NO_x, reactive organic gas (ROG) and sulfur oxides (SO_x) in the Disparity scenario are considerably reduced by 57%, 45%, 29%, and 7.7%, respectively, and the primary PM_{2.5} is slightly reduced (3.1%) in 2035 relative to 2017. In 2035, ammonia (NH₃) and particulate

matter with an aerodynamic diameter less than or equal to 10 micrometers (PM_{10}) emissions increased by 2.2% and 1.0%, respectively. These increases are likely associated with the economic development and population growth observed between 2017 and 2035. Compared to the Equity scenario, the Equity_MSS scenario shows slight decreases in emissions of most pollutants except for NO_x . The emission of NO_x in the Equity_MSS scenario is reduced by about 30% from the Equity (or Disparity) scenario. The primary $PM_{2.5}$ emission is further reduced by 3.2% in the Equity_MSS scenario.

3.4.2. Changes in Ambient Air Quality

For each emission scenario, four sets of one-month-long simulations are conducted, representing the winter, spring, summer, and fall seasons for January, April, July, and October, respectively. To evaluate the overall sensitivity of ambient air quality to emission scenarios, the simulated changes in concentrations of $PM_{2.5}$ and O_3 over LA City are examined.

Figures 3.3 and 3.4 display the monthly mean spatial distributions of daily $PM_{2.5}$ and daily maximum 8-hour average (MDA8) O_3 concentrations in four representative months under various scenarios. Additionally, Figure 3.5 shows the citywide means of daily $PM_{2.5}$ and MDA8 O_3 concentration for each season. As shown in Figure 3.3, the $PM_{2.5}$ concentration hotspots (i.e., regions with high $PM_{2.5}$ concentration) over LA City are located over the city center areas and its southern part in both January and October, over the city center areas in April, and over the city center areas and its northern part in July. The LA citywide mean $PM_{2.5}$ concentrations exhibit similar seasonal variations across different scenarios, with summer being the least polluted season and winter and fall being the most polluted seasons (Figure 3.5A). The seasonal dependence of $PM_{2.5}$ concentration and spatial pattern reflects the seasonal variations in pollutant emissions and meteorological conditions in LA City. The sensitivity of $PM_{2.5}$ to emission scenarios exhibits little

seasonal variation, with Base having the highest concentration and Equity_MSS having the lowest concentration across all seasons. The spatial patterns of O_3 are consistent across different seasons (Figure 3.4), with two regions of low O_3 concentration in the domain: the central areas of LA City and the coastal region next to the San Pedro Bay. The domain mean O_3 concentration over the LA City region varies by season, with the lowest concentration in winter and the highest concentration in spring (Figure 3.5B).

It's worth noting that over a larger simulation domain, e.g., Southern California as shown in Figure A1 in the Appendix, both simulations and observations show that the month of July has the highest inland O_3 concentration, followed by April and October, while January shows the least O_3 pollution. The seasonal distribution of simulated O_3 over Southern California differs from that in LA City, which is also evident in the observed seasonality based on the Air Quality System (AQS) measurements from the U.S. Environmental Protection Agency (EPA) (Figure A2). The seasonality shift could be attributed to the following processes: Although the summer season is generally conducive to O_3 production, the prevailing westerly and southerly winds (Figure A3) from the ocean can dilute and blow O_3 pollution away from the coastal areas of the LA Basin towards its inland regions. The mountain ranges to the north and east could block the air flow, leading to a rapid accumulation of O_3 pollution in the mountain hill areas. Consequently, the western part of the LA Basin, where LA City is located, is cleaner than the eastern part of the Basin in July. In April and October, when there are no prevailing winds, pollution disperses more evenly in the LA Basin than in July, resulting in more O_3 pollution in LA City during these months. As for LA County and Southern California, they cover almost the entire LA Basin, including those mountain hill regions where severe pollution accumulates. Since summer produces more O_3 than other seasons, the domain-averaged O_3 concentration over LA County and Southern California is

higher in July than in April and October. In summary, the spatial heterogeneity of O₃ concentration over LA Basin caused by the prevailing winds in July leads to the distinctive seasonal patterns among LA City, LA County and/or Southern California. The sensitivity of O₃ concentration to emission scenarios is similar across different seasons, with Base having the highest O₃ concentrations and Equity_MSS having the lowest concentrations.

Table 3.4 summarizes the citywide average of annual mean daily PM_{2.5} concentrations and MDA8 O₃ in all scenarios. The annual mean values are obtained by averaging the four simulated months, as these months provide a representative view of the significant seasonal variations in emissions and meteorological conditions. The annual mean PM_{2.5} concentrations over LA City are 11.5, 10.6, 10.6, and 10.2 µg m⁻³ for the Base, Disparity, Equity and Equity_MSS scenarios, respectively. Reductions in emissions of precursors to secondary PM_{2.5} (e.g., NO_x and VOC) result in a decrease of 0.8 µg m⁻³ (7.4%) in annual mean PM_{2.5} in the Disparity relative to the Base scenario. The Equity scenario does not show any significant change in annual mean PM_{2.5} concentrations, maintaining the 10.6 µg m⁻³ level that was achieved in the Disparity scenario. The Equity_MSS scenario shows a further reduction, bringing the annual mean PM_{2.5} down to 10.2 µg m⁻³. This signifies a reduction of 1.3 µg m⁻³ (11%) compared to the Base scenario.

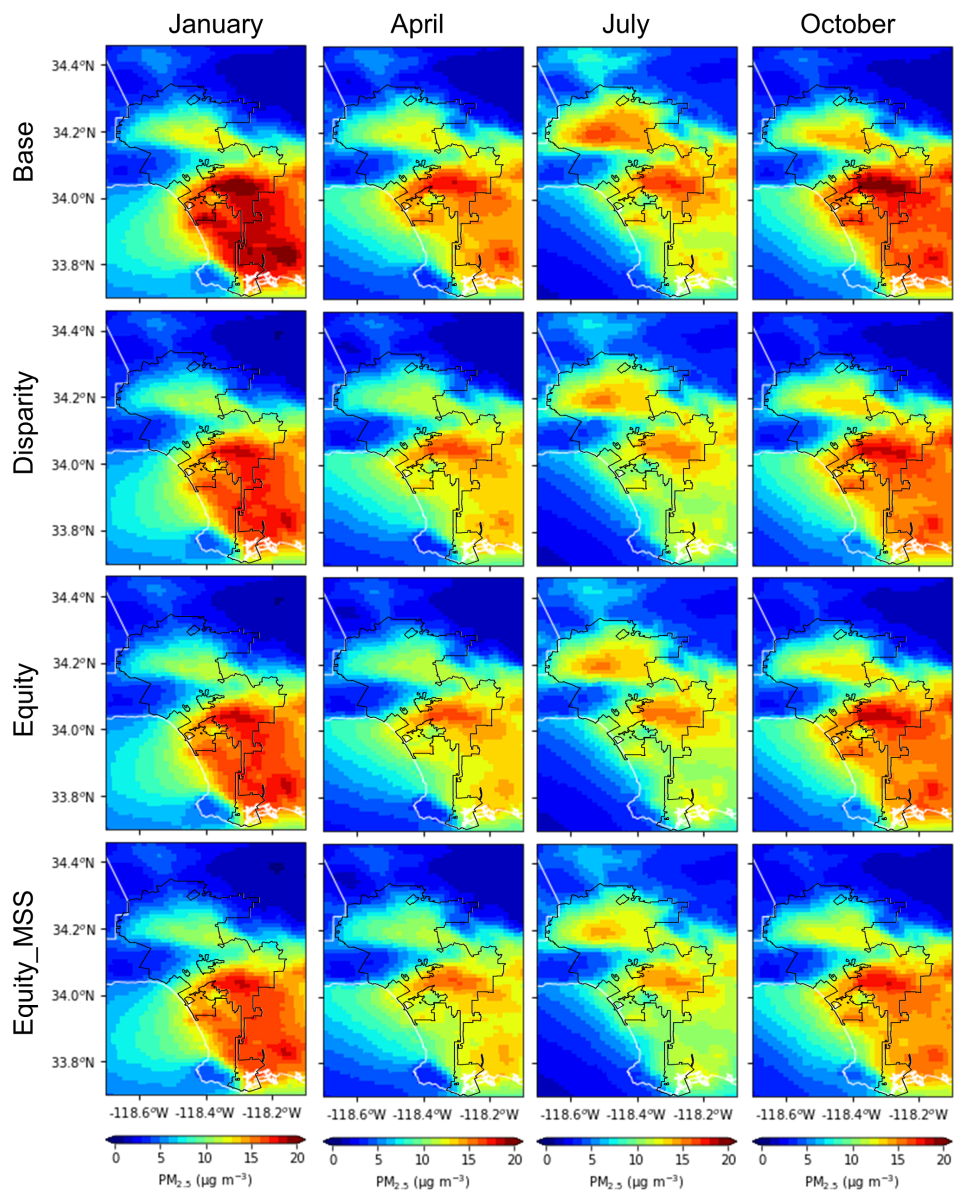


Figure 3.3. Monthly mean daily PM_{2.5} concentrations for four representative months in LA City for Base, Disparity, Equity, and Equity_MSS

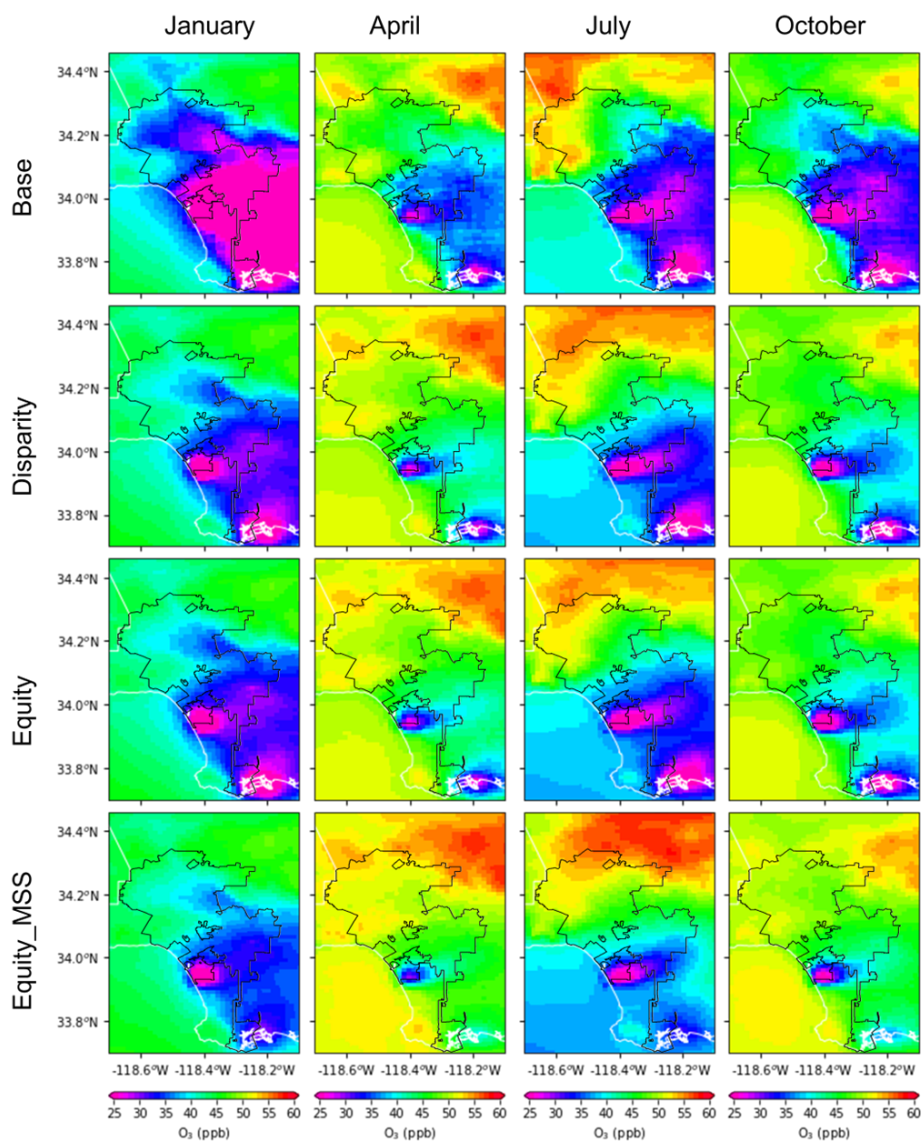


Figure 3.4 Monthly mean daily maximum 8-hour average O₃ concentration for four representative months in LA City for Base, Disparity, Equity, and Equity_MSS

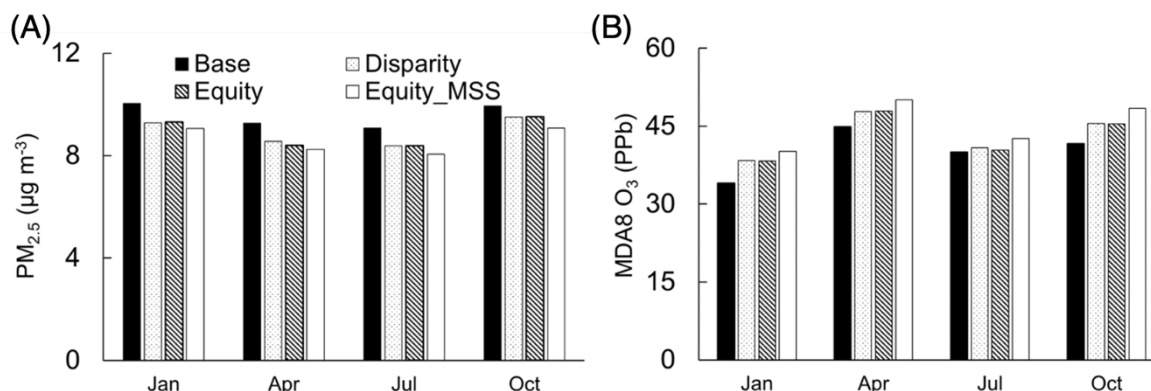


Figure 3.5. Monthly mean of LA City region daily PM_{2.5} concentrations (A) and daily maximum 8-hour average O₃ concentrations (B) for Base, Disparity, Equity, and Equity_MSS scenarios

Table 3.4. Simulated LA Citywide Annual Average of Daily Maximum 8-hour O₃ and Daily PM_{2.5} Concentrations for all Evaluated Scenarios

Pollutants	Base	Disparity	Equity	Equity_MSS
O ₃ (ppb)	38	42 (+12%)	42 (+12%)	45 (+18%)
PM _{2.5} (µg m ⁻³)	11.5	10.6 (-7.4%)	10.6 (-7.4%)	10.2 (-11%)

Note: Percentages in parentheses show relative changes between different scenarios and the Base.

In contrast, the annual mean MDA8 O₃ concentrations show an increase from the Base scenarios (i.e., in 2017) to future scenarios (i.e., in 2035), and the concentrations for the Base, Disparity, Equity, and Equity_MSS scenarios are 38, 42, 42, and 45 ppb, respectively. The O₃ concentration increases on average by 12% from Base to Disparity. The Equity scenario also has O₃ concentration of 42 ppb, maintaining the same level as the Disparity scenario. This represents the same increase of 12% in comparison to the Base scenario. The Equity_MSS scenario shows an increase to 45 ppb, which equates to an 18% rise in O₃ concentration relative to the Base scenario. The overall increase in O₃ concentrations occurs despite the reductions in NO_x emissions noted above, which is because O₃ production depends on the particular ratio of the two precursors: NO_x and volatile organic compounds (VOCs), and the nonlinearities of O₃ formation chemistry.

Currently, LA City is generally in a transition regime whereby VOC reductions can lead to reductions in O₃, yet NO_x reductions can lead to increases in O₃. It is important to note that the CARB 2020 MSS does not include a specific regulatory target for VOC reduction, which is why we did not model the VOC emission inventory change in our analysis. However, it is reasonable to assume that future VOC emissions would likely decrease in a real-world scenario, as the reduction in PM and NO_x emissions is expected to be achieved through the electrification of both on-road and off-road vehicles and devices. Consequently, the increase in O₃ levels found in our simulation results might be an overestimation, as it does not account for the potential reduction in VOC emissions that would accompany the transition to electric vehicles and equipment.

Figures 3.6 and 3.7 illustrate the spatial distributions of annual mean PM_{2.5} and MDA8 O₃ concentrations over LA City in the Base scenario and their changes in future scenarios. As shown in Figure 3.6, areas with high PM_{2.5} concentrations are located in the city center while the suburban and/or rural areas in the western and northern parts of the city typically have lower levels of PM_{2.5}. These high PM_{2.5} regions coincide with areas of larger emissions of primary PM_{2.5} and precursors to secondary PM_{2.5} as shown in Figure 3.2. From the Base to Disparity scenarios, the PM_{2.5} concentration decreases greatly over the entire LA City (Figure 3.6B). However, the adoption of the equal distribution of transportation emission reduction due to ZEVs implementation (i.e., the Equity scenario) results in relatively small changes in PM_{2.5} concentrations (Figure 3.6C), with slight increase over the city center and slight decrease over the southern part of the city, corresponding to the relatively small emission changes between the two scenarios observed over the two regions (Figure 3.2). In the Equity_MSS scenario, additional reduction in PM precursors contributes to a further decrease in PM_{2.5} concentrations from the Disparity scenario (Figure 3.6D).

Figure 3.7 shows that the O₃ concentration over the city center areas and its southern part is remarkably lower than that over its northern and western suburban and/or rural areas. This is mainly due to O₃ scavenging by nitric oxide (NO) which is emitted from traffic mainly over the urban source areas. In the Disparity scenario, O₃ levels are considerably elevated over almost all the areas in the city relative to the Base scenario, particularly over the urban centers of LA City (Figure 3.7B). This is consistent with the larger reduction in NO_x over the urban center areas, given that LA City is still in the VOC-limited regime and the reduction in NO_x results in more O₃ production. With the equal distribution of transportation emission reduction in the Equity scenario, the O₃ concentration shows slight decrease over the city center areas, consistent with the overall small positive changes in NO_x emissions over there from Disparity to Equity scenarios (Figure 3.7C). Further reductions in certain precursor emissions (e.g., NO_x in Table 3.3) in the Equity_MSS scenario yields even more O₃ production over the entire city (Figure 3.7D). Note that VOC is slightly reduced from the Disparity to Equity_MSS scenarios (see ROG emissions in Table 3.3), suggesting that the O₃ production over LA City is VOC-limited in the simulated future scenarios.

The DAC designation in LA City is obtained from the Senate Bill (SB) 535 DAC Designation¹⁸. Figures 3.6 and 3.7 also highlight the annual mean spatial distribution of PM_{2.5} and MDA8 O₃ concentrations over DACs in the city. In the Base scenario, higher PM_{2.5} concentrations are more frequently found over DACs than non-DACs (Figure 3.6), while O₃ concentrations are generally lower over DACs than non-DACs (Figure 3.7). The differences in PM_{2.5} and O₃ concentrations between DACs and non-DACs in the Base scenario are generally consistent with the emissions contrast between the urban center areas and suburban regions in LA City.

Figure 3.8 shows the LA citywide mean of daily PM_{2.5} and MDA8 O₃ concentrations over DACs and non-DACs under different emission scenarios. The PM_{2.5} concentrations over DACs are considerably higher than those over non-DACs, on average by 3.7-4.0 µg m⁻³ (~40%), depending on the scenario examined, while the O₃ concentrations are lower over DACs than over non-DACs, on average by 4.6-6.0 ppb (~13%).

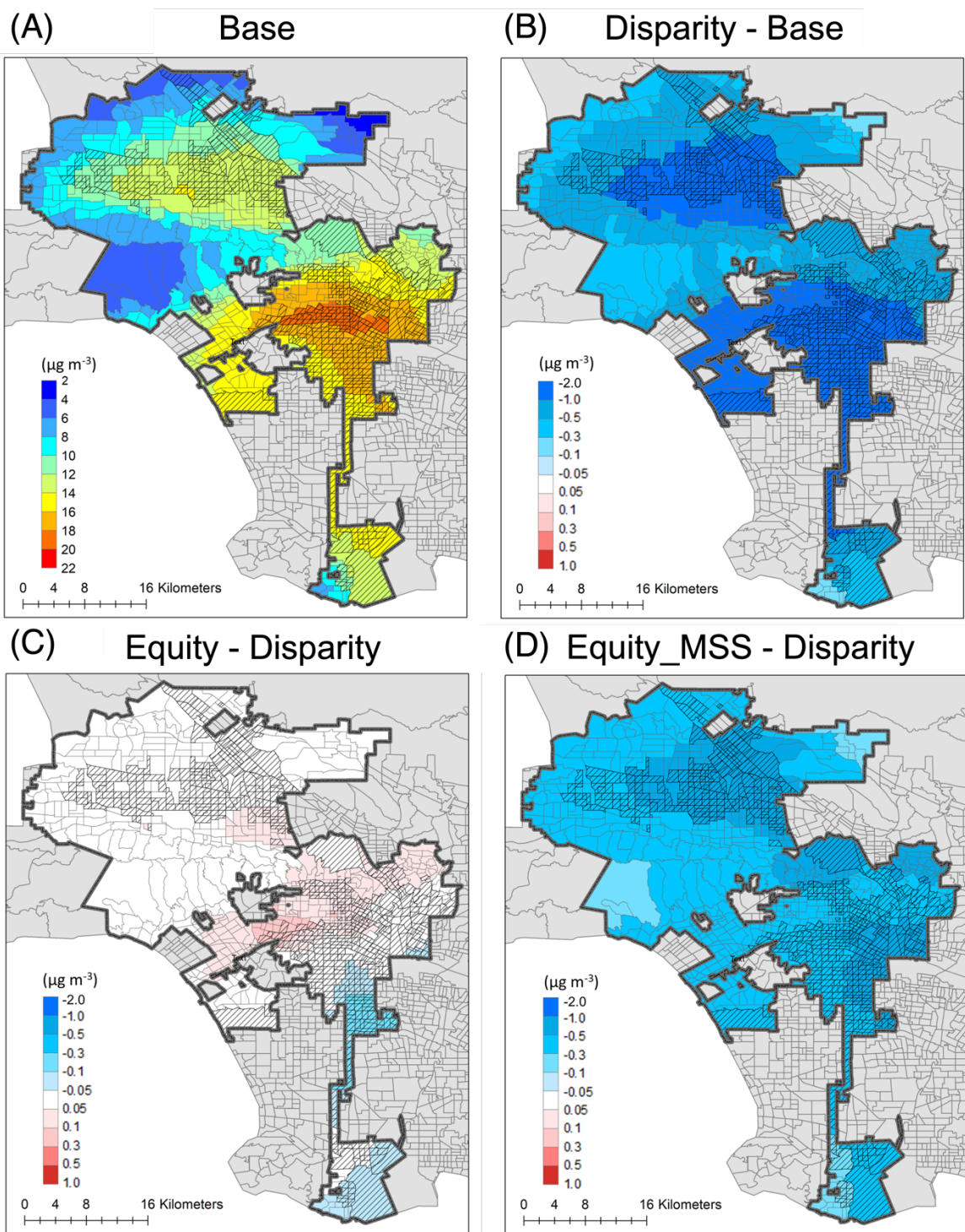


Figure 3.6. Annual mean daily PM_{2.5} concentrations in LA City for the Base scenario (A) and the differences between Disparity and Base (B), between Equity and Disparity (C), as well as between Equity_MSS and Disparity (D). Thick grey line marks the LA City boundary and hatch-filled areas denote disadvantaged communities in LA City.

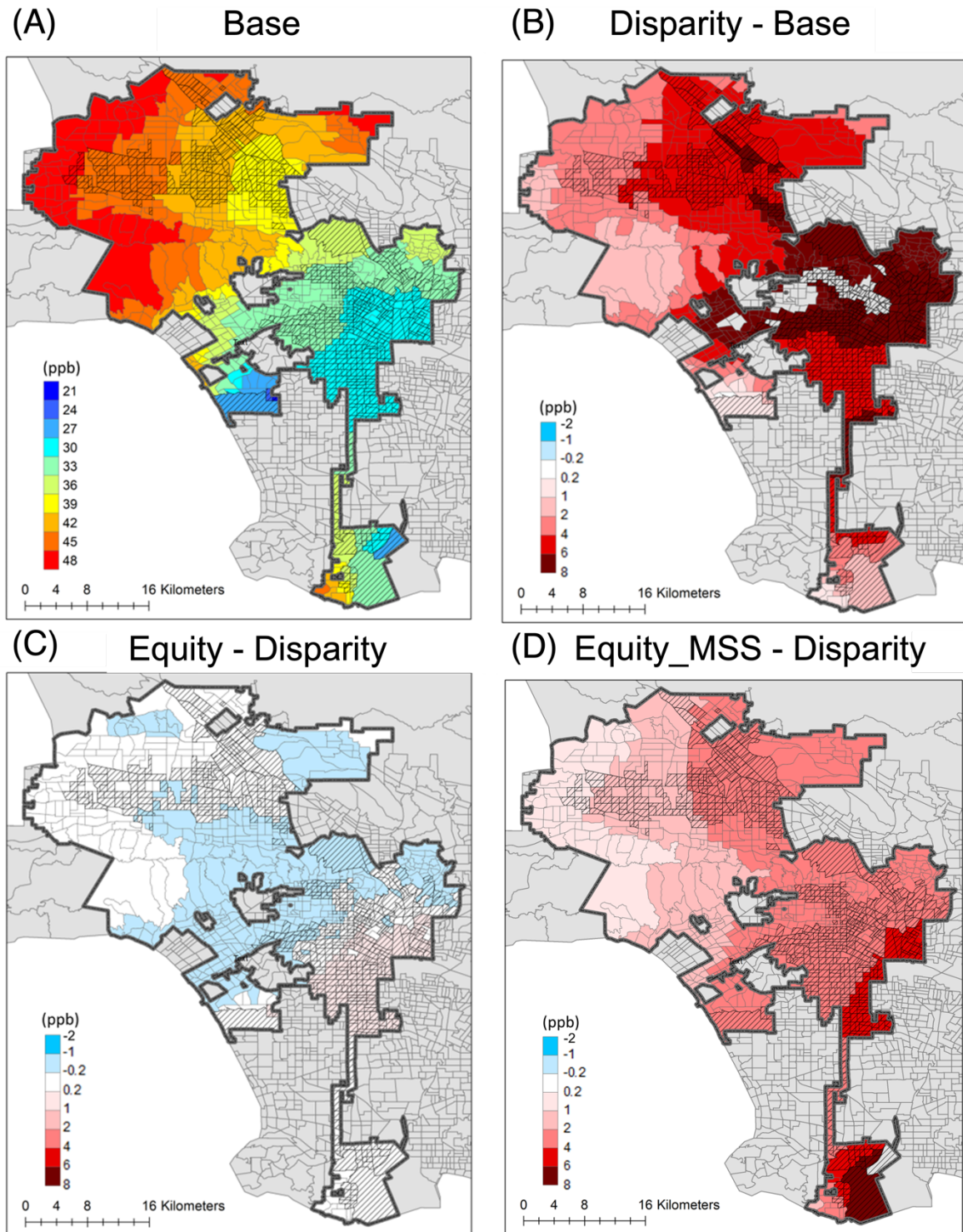


Figure 3.7. Annual mean daily maximum 8-hour average O_3 concentration in LA City for the Base scenario (A) and the differences between Disparity and Base (B), between Equity and Disparity (C), as well as between Equity_MSS and Disparity (D). Thick grey line marks the LA City boundary and hatch-filled areas denote the disadvantaged communities in LA City.

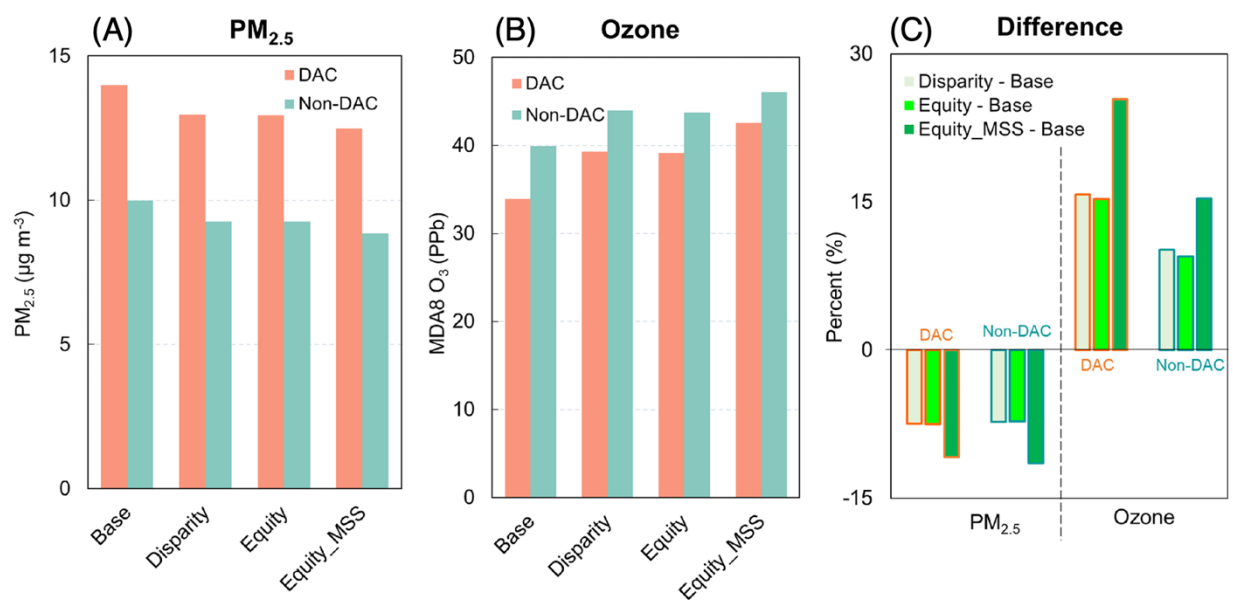
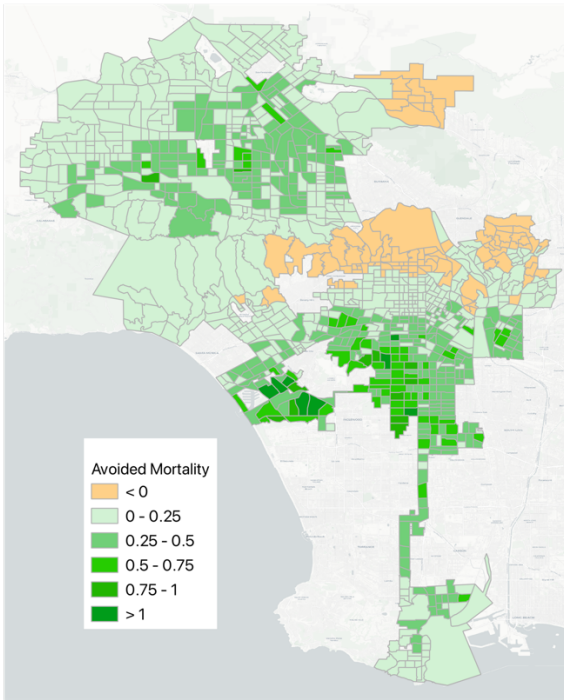


Figure 3.8. Community means of PM_{2.5} (A) and O₃ (B) concentrations averaged over DAC and non-DACs in LA City for Base, Disparity, Equity and Equity_MSS scenarios, as well as the relative differences between the Disparity, Equity, and Equity_MSS scenarios compared to the Base scenario (C)

3.4.3. Public Health Benefits

Figure 3.9 depicts the total avoided mortality in LA City, accounting for both PM_{2.5} and O₃ mortality changes. As observed in Figures 5 and 6, numerous census tracts experience health benefits due to the decrease in air pollution concentrations from 2017 to 2035. The public health benefits are more pronounced under the Equity_MSS scenario, which demonstrates the potential advantages of electrifying more medium- and heavy-duty vehicles. It is important to note that some areas exhibit disbenefits, primarily driven by the increase in O₃ concentrations in the future scenarios. Spatial distribution maps for both PM_{2.5} and O₃ related mortality changes between Equity_MSS and Base scenarios are presented separately in Figure A4. This highlights the need to consider both PM_{2.5} and O₃ levels when evaluating the overall impact of ZEVs adoption strategies on public health.

(A) Disparity - Base



(B) Equity_MSS - Base

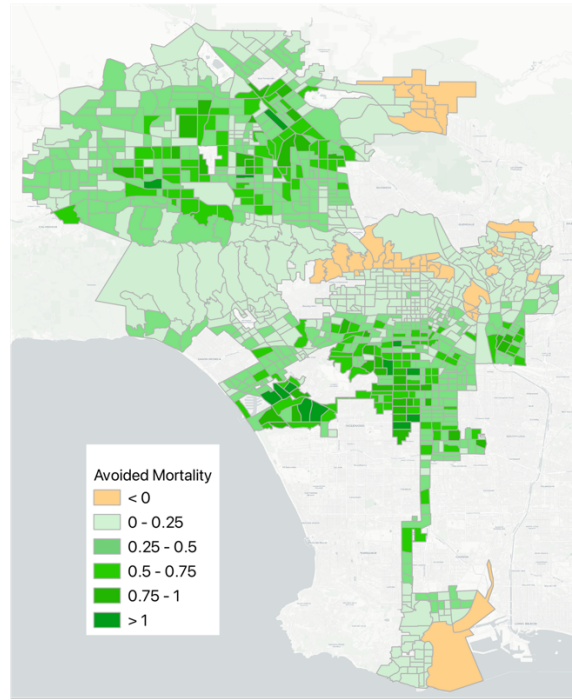


Figure 3.9. Total avoided mortality in LA City for the differences between Disparity and Base (A), and between Equity_MSS and Base (B)

Table 3.5 presents a detailed summary of the changes in both morbidity and mortality due to changes in $PM_{2.5}$ concentrations, in addition to the mortality changes highlighted in Figure 3.9. The changes are categorized by census tracts into DACs and non-DACs. As shown in Table 3.5, a total of 480 and 703 avoided mortalities attributed to $PM_{2.5}$ reduction using the uniform beta coefficient, were observed between the Disparity and Base scenarios, and between the Equity_MSS and Base scenarios, respectively. However, when the beta coefficient is adjusted based on race and ethnicity, the number of avoided mortalities related to $PM_{2.5}$ reduction increases to 567 and 831 between the same scenarios.

Figure 3.10 provides a more detailed analysis of the results, highlighting the underestimation of health benefits, particularly for the Hispanic population, when using a uniform exposure-response beta coefficient. When a racial and ethnic-specific beta coefficient was employed, the

estimated avoided mortality increased from 169 to 270 (a 60% increase) between the Disparity and Base scenarios, and from 250 to 400 (a 60% increase) between the Equity_MSS and Base scenarios. This is due to social health disparities, such as varying access to medical services, knowledge, and coping mechanisms among different racial and ethnic groups, resulting in distinct response rates to changes in air quality. Given the high proportion of people of color in LA City, using a uniform exposure-response beta coefficient would underestimate the health benefits for this population. These findings underscore the importance of considering racial and ethnic-specific factors in health impact assessments to more accurately capture the disparities in health outcomes and ensure a more equitable evaluation of air quality improvement strategies. Regarding morbidity, while positive health benefits are observed for PM_{2.5}-related respiratory emergency room (ER) visits, the overall morbidity exhibits a disbenefit due to the increase in O₃ levels. This highlights the need for a comprehensive approach to air quality management that considers the complex interplay between different air pollutants, ensuring that strategies aimed at reducing one pollutant do not inadvertently exacerbate the health impacts of another.

Table 3.5. Summary of Annual Health Changes Between Scenarios (Mortality and Morbidity)
Total mortality is the sum of O₃ mortality and PM_{2.5} mortality.

Health Endpoints	Disparity - Base			Equity_MSS - Base		
	Total	non-DAC	DA C	Total	non-DAC	DA C
Mortality						
PM _{2.5} Mortality (Uniform Beta)	480	214	266	703	321	383
PM _{2.5} Mortality (Racial/Ethnic Specific Beta)	567	231	336	831	347	484
O ₃ Mortality	-337	-155	-182	-499	-222	-277
Total Mortality	230	76	154	332	125	207
Morbidity						
PM _{2.5} ER Visits, Respiratory	239	88	151	349	132	217
O ₃ ER Visits, Respiratory	-677	-264	-413	-1017	-379	-638
Total Morbidity	-438	-176	-262	-668	-247	-421

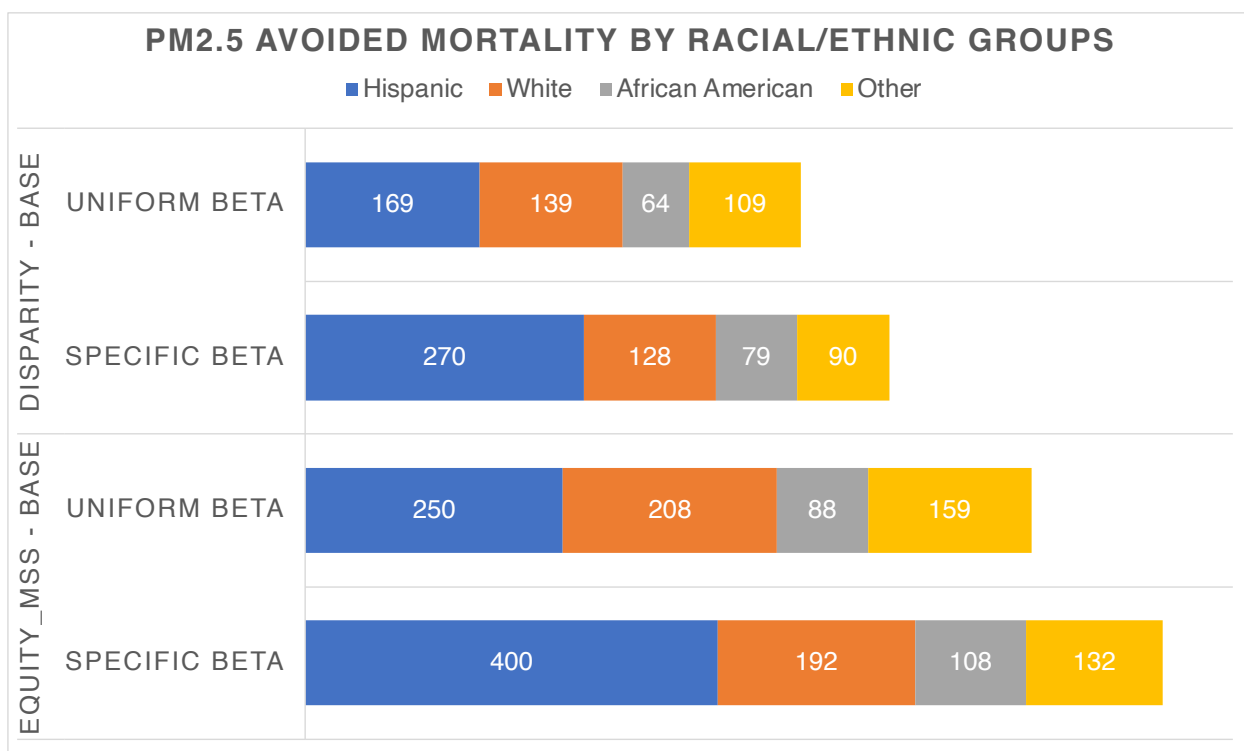


Figure 3.10. Differences in PM_{2.5}-related avoided mortality, comparing the use of uniform beta coefficients with racial/ethnic-specific beta coefficients. Upper panel represents the differences between Disparity and Base. Lower panel represents the differences between Equity_MSS and Base. This illustration highlights the disparities in health outcomes when accounting for race and ethnicity in the analysis. Other: Asian American, Pacific Islander and Native American.

3.4.4. Monetized Benefits

Table 3.6. Monetized Health Benefits Between Scenarios for Both Mortality and Morbidity

	Disparity – Base (in 2015 million U.S. dollars)			Equity_MSS – Base (in 2015 million U.S. dollars)		
	Mean	Low	High	Mean	Low	High
non-DAC	\$660	\$90	\$1,200	\$1,090	\$190	\$1,940
DAC	\$1,340	\$190	\$2,430	\$1,800	\$220	\$3,310
Total	\$2,000	\$280	\$3,630	\$2,890	\$411	\$5,250

Table 3.6 summarizes the health benefits, including their 95% confidence intervals for both lower and higher estimates, associated with PM_{2.5} and O₃ concentrations in LA City. The Disparity scenario, compared to the Base scenario, could result in \$2 billion in health benefits, with \$1.3 billion directed towards DACs. By implementing the Equity_MSS scenario, which

promotes electrification of medium- and heavy-duty truck fleets and off-road equipment, \$2.9 billion can be gained, with \$1.8 billion benefiting DACs as compared to the Base scenario. Although the uncertainties in the valuation and health impact functions lead to a wide range of estimates, significant benefits are observed. The findings highlight the potential for targeted air quality improvement strategies to result in substantial improvements in public health and economic gains, even when considering the uncertainties in the underlying models and assumptions.

3.5. DISCUSSION

In this study, we investigated the potential health impacts of various scenarios for ZEVs adoption in the city of LA. To do so, we developed three different scenarios: (1) a 2035 ZEVs Disparity scenario, (2) a 2035 ZEVs Equity scenario, and (3) a 2035 ZEVs Equity scenario with more ZEVs in medium- and heavy-duty vehicles following the 2020 Mobile Source Strategy (Equity_MSS). Our analysis focused on how these scenarios would affect DACs and other populations, taking into account the complex interplay between air pollutants such as PM_{2.5} and O₃.

Our findings suggest that implementing ZEVs policies can substantially reduce PM_{2.5} concentrations, leading to improved health outcomes for both DACs and non-DACs. Specifically, from the Base to Disparity scenarios, the citywide mean PM_{2.5} concentration decreases by 7.4% and 7.3% over both DACs and non-DACs, respectively. There is little change between Disparity and Equity scenarios over both types of communities. However, the enhancement in ZEVs portion of medium- and heavy-duty vehicles, i.e., from the Equity to Equity_MSS scenarios, leads to 3.6% and 4.6% more reductions in PM_{2.5} concentrations over DACs and non-DACs, respectively. In contrast, from the Base to Disparity scenarios, the increases in O₃ concentrations are about 16%

and 10% over DACs and non-DACs, respectively. From the Disparity to Equity scenarios, the O₃ concentrations over DACs and non-DACs both show a decrease, but the decrease is relatively small, less than 1%. The O₃ concentrations increase further from the Equity to Equity_MSS scenarios by 8.8% and 5.4% over DACs and non-DACs, respectively. In general, the implementation of ZEVs policy in the future will improve air quality in terms of the PM_{2.5} over both DACs and non-DACs, and the benefits are comparable between DACs and non-DACs.

While implementing ZEVs policy can improve air quality by reducing PM_{2.5}, our findings suggest that it may also lead to temporary increases in O₃ pollution, particularly over DACs. This phenomenon, referred to as temporary “growing pains” in the original LA100 report, occurs when O₃ concentration increases despite NO_x reduction. However, once NO_x emissions reach a certain level, further reductions can result in marked improvements in O₃ levels. To address this issue, decision-makers should prioritize reducing NO_x emissions further, while also working to reduce VOC emissions in conjunction with PM and NO_x emissions reductions.

Our study highlights several key points.

1. Vehicle electrification offers substantial reductions in PM_{2.5} that can lead to improved health outcomes for both disadvantaged and non-disadvantaged communities. This demonstrates the potential for significant improvements in public health and economic gains through targeted air quality improvement strategies.
2. Electrifying medium- and heavy-duty trucks will bring additional health benefits, particularly for DACs. Implementing the Equity_MSS scenario, which encourages the adoption of ZEVs in medium- and heavy-duty truck fleets and off-road equipment, would result in the highest health benefits in the city, with a substantial proportion of these benefits directed towards DACs.

3. The use of ethnic and racial-specific exposure-response functions can help reveal greater health benefits, particularly for the Hispanic population, than previously estimated. This underscores the importance of incorporating racial and ethnic-specific factors into health impact assessments to ensure a more equitable understanding of air quality improvement strategies.
4. To reduce O_3 , it is crucial to further reduce NO_x and reduce VOCs in parallel with PM and NO_x emissions reduction. Since our study does not account for the potential reduction in VOC emissions that would likely accompany the transition to electric off-road equipment, the increase in O_3 levels found in our simulation results might be an overestimation. By addressing VOC emissions alongside PM and NO_x , decision-makers can work towards a more comprehensive approach to air quality management.

In conclusion, our study highlights the necessity for holistic approaches to air quality control that account for the intricate interplay of various pollutants and prioritize equitable treatment for vulnerable communities. By understanding these complexities and targeting appropriate strategies, decision-makers can work towards improving public health and promoting greater equity in vehicle electrification.

CHAPTER 3 APPENDIX

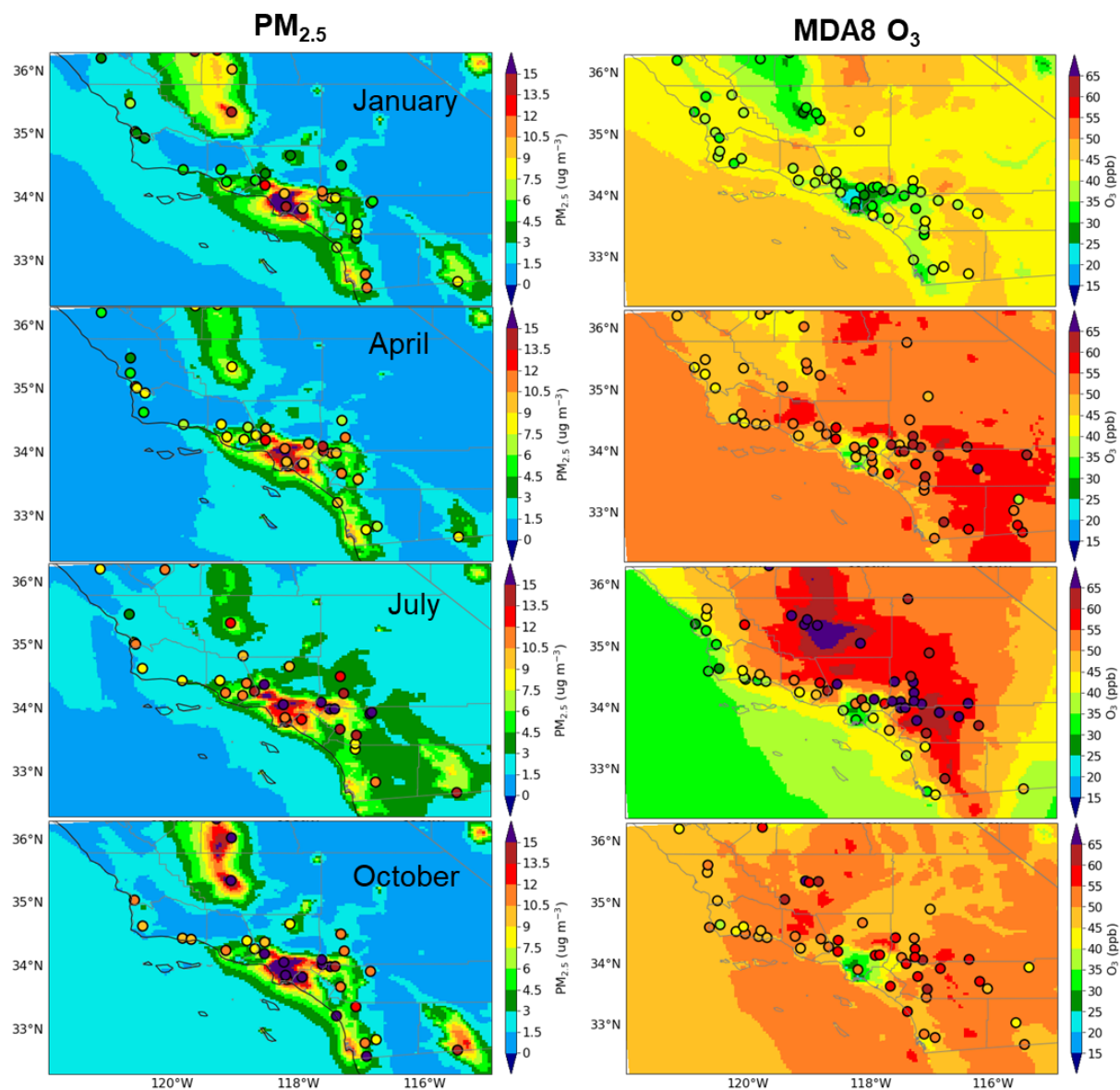


Figure A1. Observed (dots) and simulated (contours) monthly mean $PM_{2.5}$ concentrations (left), and monthly mean daily maximum 8-h O_3 concentrations (MDA8 O_3 , right) over south California in January, April, July, and October 2017. The observations are from US EPA Air Quality System (AQS).

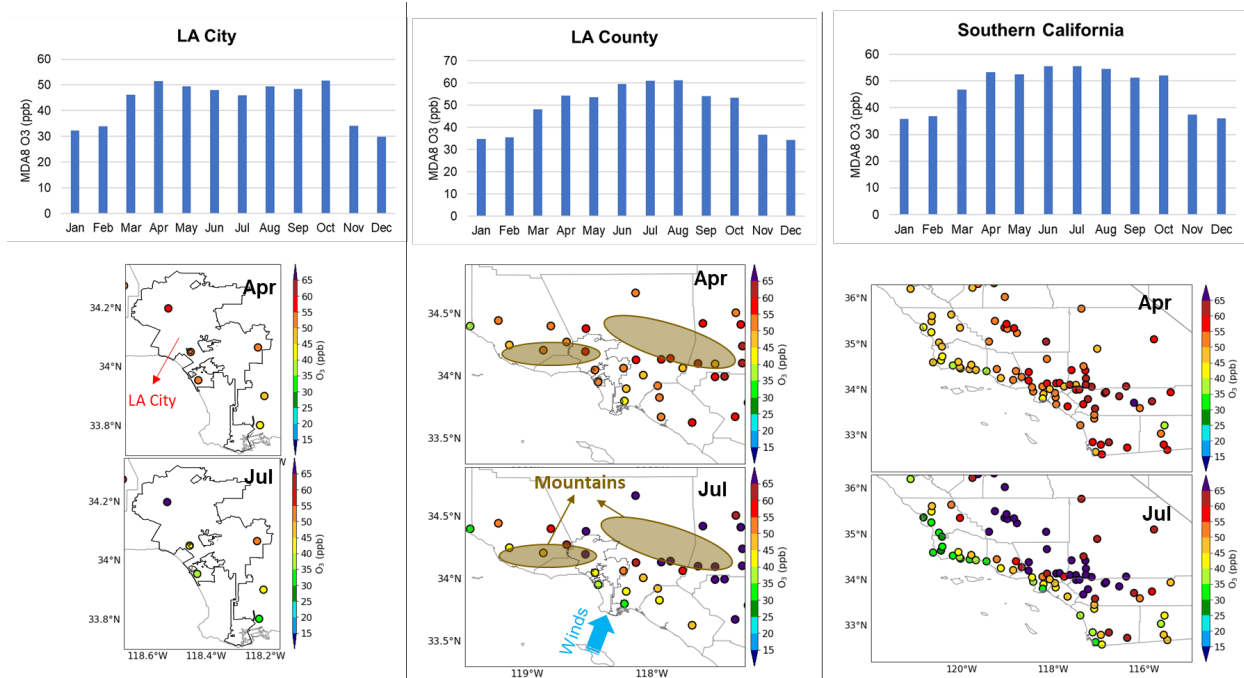


Figure A2. First row shows the seasonal variations of MDA8 O₃ concentrations over LA City, LA County, and Southern California based on EPA AQS observations (<https://www.epa.gov/aqs>). Second row shows the corresponding spatial distribution of AQS observed O₃ concentrations in April and July.

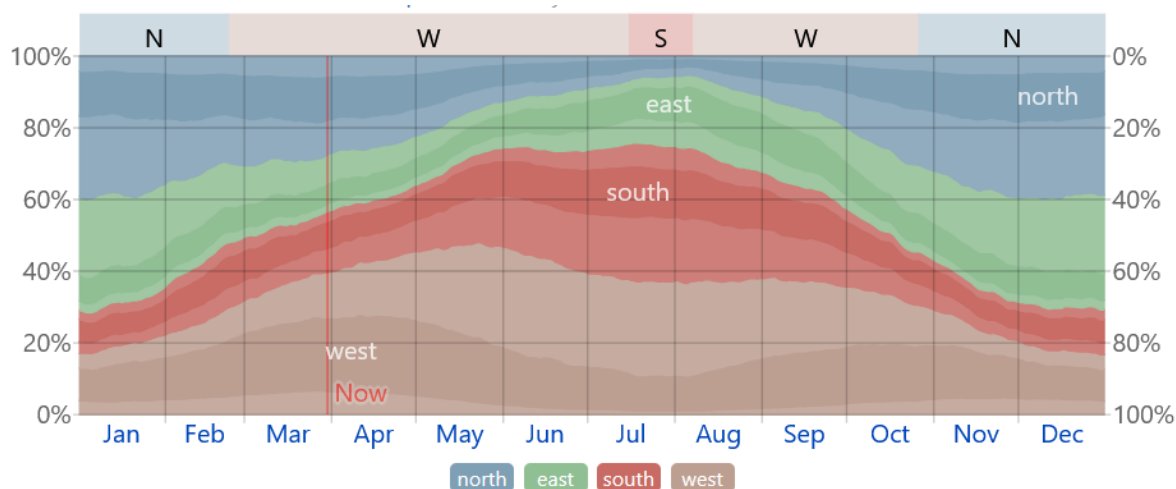


Figure A3. Wind direction climatology in Los Angeles (adapted from <https://weatherspark.com/y/1705/Average-Weather-in-Los-Angeles-California-United-States-Year-Round#Figures-WindDirection>)

Note that westerly and southerly are prevailing in summer months.

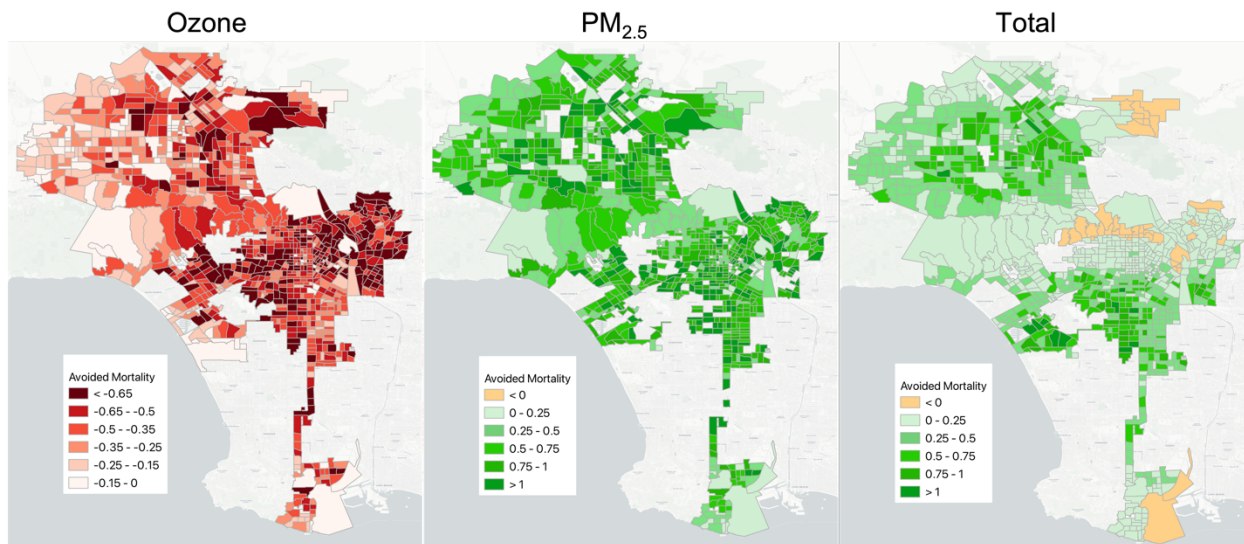


Figure A4. Avoided mortality between Equity_MSS and Base scenarios. From left to right: Ozone-related, PM_{2.5}-related, and total avoided mortality. Ozone-related avoided mortality values are negative, indicating disbenefits due to increased ozone concentrations.

Table A1. Technical Specifications of Scenarios Analyzed in This Study

	LA 100 Early & No Biofuels - High	LA 100 ES UCLA ¹		
Time	2035	2035 ZEV Disparity	2035 ZEV Equity 100% clean ²	2035 ZEV Equity (more MD-HD) (MSS)
Energy Profile	100% clean ² energy	100% clean ² energy	100% clean ² energy	100% clean ² energy
	On-road Transportation Electrification Profile			
Light-duty	50%	50%	50%	50%
Medium-duty	0%	15.6% ³	15.6% ³	22%
Heavy-duty	0%	19.6% ³	19.6% ³	39%
School and urban buses	100%	EMFAC	EMFAC	100%
	On-road Transportation Emission Spatial Distribution			
Passenger Vehicle	Equally distributed	Emission reduction map based on (1) ZEV ownership and (2) the MATSim simulated trips		
Medium-duty		Equally distributed	Equally distributed	
Heavy-duty				
School and urban buses				
	ZEV Fleet Profile (LDV / MDV / HDV) ⁴			
PHEV	50%	25% / 0% / 0%		
BEV	50%	67% / 100% / 100%		
FCEV	0%	8% / 100% / 100%		
	Off-road Transportation ⁵			
Heavy-duty in ports	100%	No data in EMFAC	No data in EMFAC	No data in EMFAC
Ocean-going Vessels	90%	EMFAC 2035 Original	EMFAC 2035 Original	EMFAC META Off-road (https://arb.ca.gov/emfac/meta/off-road, check "?" for detailed supporting regulations) MSS
Cargo Handling Equipment	100%			
Commercial Harbor Craft	N/A			
Construction, Mining, Industrial Forklift	N/A			
Airport GSE	N/A			
Locomotive	N/A			
Recreational Marine Vessel	N/A			
Small Off-road Engine	N/A			
Transport Refrigerator Unit	N/A			
	Buildings Electrification			
Commercial	Scaling factor ~3-5%	N/A	N/A	N/A
Residential	Scaling factor ~12-15%	N/A	N/A	N/A
	Oil & Gas Industry			
Demand Reduction	N/A	Scale down based on ZEV population		

1. Electrification %s for LA 100 ES (if not specified) are in line with CARB most recent MSS (2020), and a recent CEC report (2021, <https://efiling.energy.ca.gov/getdocument.aspx?tn=238853>)

2. "clean energy" defined as no natural gas generation or biofuels. Natural gas electricity generation are replaced with gas electricity generation with wind, solar and battery storage. LA city has approved LA100 Early & No Biofuels (<https://www.utilitydive.com/news/la-approves-100-clean-energy-by-2035-target-a-decade-ahead-of-prior-goal/605980/>)

3. Based on EMFAC V2021.

4. For MDV and HDV, we assume 100% BEV and FCEV. During emission calculation, BEV and FCEV will both generate zero tailpipe emissions.
5. Will be equally distributed into "Area" source in WRF-Chem, "Aircraft" has specific spatial emission inventory

Table A2. Statistics of Model Performance for Chemical Predictions

	Month	Site number	Mean Sim ^a	Mean Obs ^b	NMB ^c (%)	NME ^d (%)	MFB ^e (%)	MFE ^f (%)
PM _{2.5} ($\mu\text{g m}^{-3}$)	Jan	34	8.2	8.1	2	53	4	39
	Apr	36	8.5	9.0	-5	60	-13	41
	Jul	35	8.1	10.8	-25	47	-21	36
	Oct	31	10.8	13.4	-19	47	-23	36
	Recommended performance benchmarks*				< ± 30	<50	< ± 30	< ± 50
MDA8 O ₃ (ppb)	Jan	53	37	35	4	18	2	13
	Apr	58	48	53	-9	16	-5	11
	Jul	59	48	57	-15	23	-8	16
	Oct	49	47	53	-10	19	-6	13
	Recommended performance benchmarks**				< ± 15	<25	-	-

^aMean Sim stands for the spatially and temporally averaged simulated concentrations at those observation sites; ^bMean Obs is the spatially and temporally averaged observed concentrations across all observation sites;

^cNMB is normalized mean bias;

^dNME is normalized mean error;

^eMFB is mean fractional bias;

^fMFE is mean fractional error.

*Based on Boylan and Russell (2006);

**Based on U.S. Environmental Protection Agency (EPA),
https://www3.epa.gov/ttn/scram/guidance/guide/O3-PM-RH-Modeling_Guidance-2018.pdf.

4. EQUITY AND RELIABILITY OF PUBLIC ELECTRIC VEHICLE CHARGING STATIONS IN THE UNITED STATES

4.1. ABSTRACT

Equitable and reliable access to electric vehicle charging stations (EVCSs) is crucial for achieving a just transition to a carbon-free energy future. Yet, a comprehensive national analysis of the equity of distribution and reliability of public EVCSs across different communities is lacking. Here, we utilized data from a user-generated content platform combined with real-world user reviews ($n = 470\,142$) to analyze public EVCSs in the United States at the census tract level. Our findings indicate that disadvantaged communities (DACs) in the United States have 26% fewer per capita public EVCSs than non-DAC areas do. The disparity spikes to 60% when considering renters living in multi-dwelling units. Additionally, EVCS users in DACs and urban areas face significantly worse reliability issues compared to those in non-DACs and rural areas. The most common problems involve hardware and technical issues, accounting for 47% of negative user experiences. As residents of DACs encounter challenges with at-home charging and inequitable access to public EVCS, this study highlights the pressing equity issues related to EV charging and advocates for more infrastructure investments, particularly in DACs. Future policies should also prioritize enhancing the reliability of EVCS.

4.2. INTRODUCTION

Electric vehicles (EVs) can substantially reduce greenhouse gas emissions and contribute to improved air quality and health co-benefits^{11,83,146,147}. The International Energy Agency (IEA) projects that by 2030, the global EV fleet will reach 236 million vehicles¹⁴⁸. The development of a reliable and widespread electric vehicle charging station (EVCS) network is essential to meet the growing demand for EVs and achieve carbon neutrality in the transportation sector. The IEA

projects that the global number of public electric vehicle supply equipment (EVSE) ports will exceed 15 million by 2030 and reach nearly 25 million by 2035. In the United States, approximately 900 000 public EVCSs will be needed by 2030 and 1.7 million by 2035¹⁴⁹ to support ambitious goals for EV adoption. The U.S. National Electric Vehicle Infrastructure Program¹⁵⁰ and the Charging and Fueling Infrastructure Grant Program¹⁵¹, both stemming from the Infrastructure and Investment and Jobs Act¹⁵² (also known as the Bipartisan Infrastructure Law) will provide \$7.5 billion in funding. The Inflation Reduction Act¹⁵³ also provides considerable incentives to promote clean energy initiatives, including support for EV charging infrastructure for disadvantaged communities (DACs).

DACs in the United States are designated through a comprehensive assessment of various factors^{154,155}. These factors, including energy burden, environmental justice burden, public health burden and climate change hazards¹⁵⁵, often disproportionately affect low-income and minoritized racial and ethnic groups. DACs have a greater demand for public EVCSs, due to the higher prevalence of multi-dwelling units (MDUs) and renters within these communities. DAC residents and minoritized racial and ethnic groups are more likely to rent their home and reside in MDUs^{156–158}. Although more than 80% of charging needs are predicted to be met through at-home or residential charging¹⁵⁹, the reliance on public charging stations varies significantly on the basis of the housing type. While only 4–16% of U.S. EV drivers with detached houses use public charging, this percentage increases dramatically to 31–81% for drivers who do not have access to private or semi-private parking facilities¹⁶⁰. In addition, renters frequently lack both the financial means and property rights necessary to install private charging stations. A recent study¹⁶¹ reported that over half of EV buyers will come from the low-to-middle income population by 2035, many of whom do not have access to home charging. Research also indicates that EV can reduce energy and

maintenance costs, particularly benefiting low-income and minoritized racial and ethnic groups who face high fuel expenses^{162,163}. Without access to public charging infrastructure, the opportunity to address the transportation cost burden might be lost, further exacerbating existing disparities.

Despite the critical need for equitable charging infrastructure, equity analysis of EV charging accessibility has been limited, and even fewer studies have been conducted at the national scale. A recent study analyzed EV adoption and EVCS distribution in California and reported that the number of public EVCSs per 1 000 households is 0.92 and 0.67 for non-DACs and DACs, respectively⁸⁹. Another recent study analyzed access disparities for public EVCSs in California across different race and income groups and found that, neighborhoods with a majority of Black and Hispanic populations had the lowest likelihood of accessing public EVCSs⁹⁶. Their likelihood of access was half that of White majority neighborhoods. A similar pattern was found for low-income neighborhoods, especially those with more MDUs. Similarly, a recent study investigated access to public EVCSs in New York City at the zip code level¹⁶⁴ and reported that that low-income, Black-identifying, and underserved communities had less access to public EVCSs compared to higher-income, white, and non-disadvantaged communities.

These studies often sourced public EVCSs data from the U.S. Department of Energy's (DOE) Alternative Fuels Data Center (AFDC)¹⁶⁵. The DOE defines an EVCS as a location that houses one or more EVSEs, such as a parking garage or a mall parking lot. An EVSE, which is sometimes referred to as an EV charging port, is designed to deliver power to a single vehicle at a time. However, the DOE collects the public EVCS data directly from different charging point operators (CPOs) who use different criteria for reporting. As a result, some EVCSs classified as “public” might, for example, actually be workplace charging locations that are not accessible to the public.

Owing to the potential misclassification of EVCSs with access restrictions, the actual gap in public charging stations could be more substantial than reported. The true potential for increased EV use in DACs also hinges on whether residents can freely access these public EVCSs without additional parking fees, highlighting the need for more validated real-world usage data to assess accessibility accurately. To address this, the California Energy Commission has enhanced its public EVCS location data by integrating input from a user-generated content platform in California¹⁶⁶. However, nationwide data of this type are not available.

Moreover, charging reliability significantly influences the user experience and is a critical factor in the adoption and sustained use of EVs. A poor charging experience can even deter current EV users, potentially causing them to revert to gasoline vehicles¹⁶⁷. Despite its importance, EVCS operation data are often treated as proprietary business secrets, which restricts access for researchers. This limitation poses a unique challenge in evaluating the reliability, operation, and maintenance status of charging stations across the nation. Despite public concerns¹⁶⁸ and industry reports^{169,170} on the reliability of public EVCS, there is a notable gap in research focusing on charging station reliability and user experiences, especially in DACs.

This study aims to address the gap in our understanding of national-level public EVCS accessibility and reliability assessment, examining the distribution of EVCSs and analyzing user experiences across various communities, with a special emphasis on DACs. We begin by using a EVCS data platform with user reviews to analyze distributive equity in EVCSs across all census tracts in the United States. We then employ large language models (LLMs) to conduct a sentiment analysis of real-world user review data from the platform on public EVCS experience. We subsequently apply grounded theory to conduct qualitative analysis and identify issues encountered by EVCS users. The results of these analyses demonstrate that those who have limited

at-home charging opportunities have less access to reliable public charging infrastructure, highlighting significant equity issues.

4.3. Methods

4.3.1. EV Charging Station Location and Review Data

We gathered publicly available data on EVCS from the DOE Alternative Fuel Data Center's Alternative Fueling Station Locator¹⁶⁵. We obtained data for EVCS by selecting "electric" as the fuel option in October 2022. At the time of collection, the DOE data were sourced from EVCS network providers or charging point operators (CPOs) through their APIs. The data included information on whether the stations were public or private, as provided directly by the network providers rather than the DOE.

To obtain more comprehensive and real-world information regarding station usage, user experience, and restriction information, we acquired EV charging station location and equipment data, as well as user review data, from a popular user-generated content (UGC) platform. The data were also obtained in October 2022. This platform is widely used by EV owners to share their experiences, providing valuable insights into the practical challenges and satisfaction levels associated with various charging stations.

We validated the total number of EVCS locations and EVSE data between the DOE database and the UGC platform and found them to be consistent with each other (Fig. 1). This validation confirmed the reliability of our data sources. All subsequent analyses are based on the detailed user experience and feedback data obtained from the UGC platform, which provides a real-world perspective on EV charging station usage and issues.

4.3.2. Environmental Justice Data

For this chapter, in order to perform environmental justice analysis on a national scale, we obtained environmental justice and DAC designation data from the DOE Justice40 initiative via the DOE Disadvantaged Community Reporter¹⁷¹. This dataset includes a set of indicators to identify and characterize DACs. Specifically, the DOE dataset encompasses multiple environmental, economic, and social indicators that reflect the cumulative burdens experienced by different census tracts. Examples of these indicators include air quality, energy burden, and socioeconomic factors¹⁵⁴.

It is important to note that the White House Council on Environmental Quality (CEQ) also provides the Climate and Economic Justice Screening Tool (CEJST)¹⁷², a new tool that aims to help federal agencies identify DACs. However, the CEJST provides a binary indication of whether a community is disadvantaged or not, without offering a detailed score. In contrast, the DOE's data include a DAC score and national and state percentile rankings, which provides a more nuanced understanding of the burdens experienced by different census tracts. The CEJST and DOE DAC data overlap substantially, which ensures consistency in identifying DACs. Using data from the DOE Disadvantaged Community Reporter helps us better understand the challenges faced by DACs and how these challenges correlate with user experiences and sentiments regarding EV charging stations.

In addition to the EJ data, we also gathered additional data from the U.S. Census American Community Survey (ACS)¹⁷³ 2010 to match the ACS version year with the DOE data. We obtained information on whether a census tract is categorized as “Urbanized Areas” to determine whether a census tract is urban or rural via the Census Geocoder¹⁷⁴. Furthermore, we downloaded data on available vehicles, renters, and housing characteristics from the 2010 ACS Table B08013 and

subject Table S2504. This supplementary dataset provides a broader context for our analysis, allowing us to account for urbanization levels and housing characteristics in our analysis of EV charging station accessibility for different populations in need.

4.3.3. LLM Sentiment Analysis

To determine the sentiment of online reviews, previous studies^{175–177} typically use natural language processing (NLP) techniques, employing models such as convolutional neural networks (CNN). The process usually involves several steps: data preprocessing, feature extraction, model training, and evaluation. On the other hand, large language models (LLMs) leverage transformer architectures, which include both encoder and decoder mechanisms. The encoder processes the input text to create a rich, context-aware representation, whereas the decoder generates human-like text or performs classification tasks based on this representation. These models can reduce the expensive and time-consuming processes associated with traditional NLP methods because they are pre-trained on vast amounts of text data and can be fine-tuned to address specific tasks.

To validate the performance of the LLM model on EVCS review sentiment analysis, we first randomly selected a subset of user reviews from the entire dataset. Unlike traditional methods, which require extensive time and a large dataset to train a CNN model, LLMs can achieve high performance with pre-trained models. Previous studies have suggested that validating sentiment analysis results requires a sample size of at least 100, ideally 300, with studies ranging from 250 to 3 000 reviews, representing 0.13% to 1.46% of the total dataset^{178,179}. We randomly selected a sample size of 3 000 reviews, which provides a balance between robustness and practical constraints.

Table A1 shows the model performance on sentiment analysis using different models. The CNN model on similar EVCS review dataset sentiment classification, as reported by Asensio et al., achieved an accuracy of 84.7% with a precision, recall, and F1 score of 0.86. In comparison, for the LLMs used in this study, GPT-3.5 achieved an accuracy of 86.2% with a precision of 0.95, a recall of 0.81, and an F1 score of 0.88; and GPT-4 further improved the performance, achieving an accuracy of 87.1%, with a precision of 0.96, recall of 0.82, and an F1 score of 0.88. Considering that the interrater reliability (measured by Cohen's kappa in Table A2) is 0.81, the prediction results from the LLM underscore the effectiveness of LLMs in handling sentiment analysis in EVCS reviews, providing a more efficient and accurate alternative to traditional methods.

Figure 4.1 shows a schematic of the data curation and model validation process. Two research assistants, acting as human experts, annotated the sentiment of review samples as either positive or negative. Similar to a previous study on EVCS sentiment analysis¹⁷⁵, we trained our researchers to understand the typical terminologies used in the EV charging user community and reached a consensus on what constitutes a positive or negative sentiment. The Cohen's kappa coefficient for interrater reliability was 0.81, indicating substantial agreement between the two researchers. This high interrater reliability demonstrates the robustness of our annotation process.

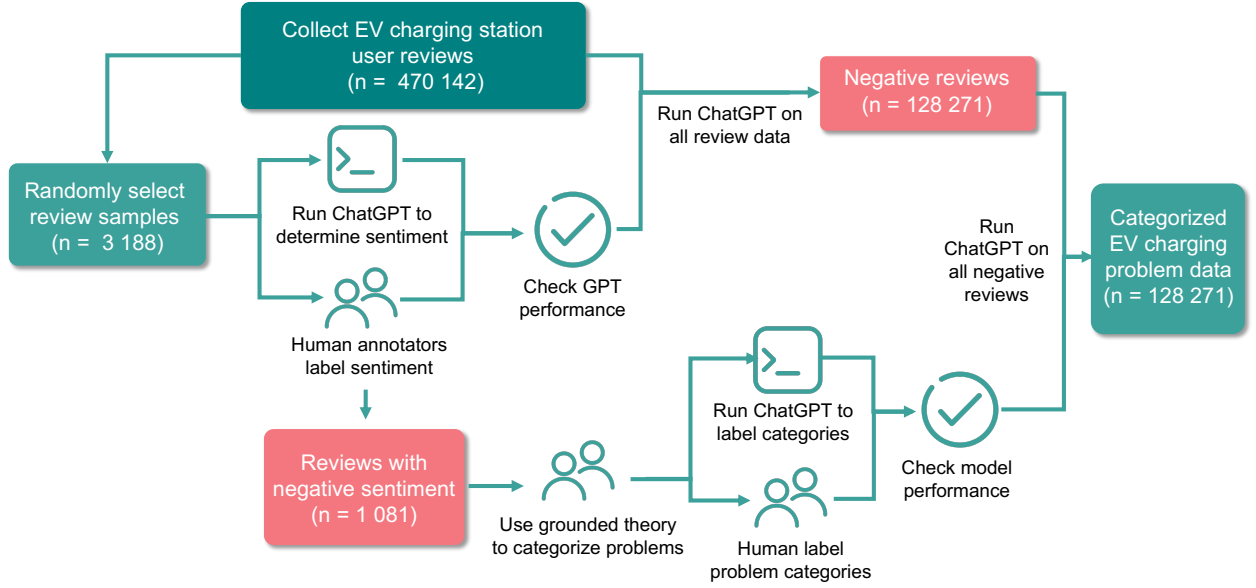


Figure 4.1. Schematic of Data Curation, LLM Model Validation and Application

Next, we created a prompt for ChatGPT. Prompt engineering is crucial as it defines the scope and context for the LLM, helping it leverage its vast training data more effectively to increase accuracy^{180,181}. We used the following prompt:

"You are an assistant analyzing the sentiment of Electric Vehicle Charging Station reviews. For each review provided, determine its overall sentiment and return a number indicating this sentiment: 1 for positive and 0 for negative. Please keep your response short, formatted as a single digit integer number."

Using this prompt, we employed ChatGPT to batch process the reviews. We also set the "temperature," a parameter that controls the variability of responses generated by the LLMs, to 0 to ensure consistency in the output. The results are presented in Table S2. We found that while ChatGPT-4 performed better, the GPT-3.5 model, which is 20 times cheaper, also exhibited strong NLP capabilities in determining the sentiment of EVCS reviews. This demonstrates the

effectiveness of LLMs in performing sentiment analysis. After validating the model on the subset, we applied it to the entire dataset ($n = 470\ 142$) to identify negative reviews.

After determining the sentiment of each review, we synthesized a sentiment score for each census tract, accounting for the varying number of reviews per station. This process addresses the common challenge in online review analysis, whereas a single positive review can result in a misleadingly high score for a station, while a station with numerous positive reviews might receive a comparatively lower score because of the higher volume of reviews.

To mitigate this issue, we employed the lower bound of the Wilson score confidence interval for a Bernoulli parameter, a method frequently used in similar research contexts^{182,183}. The Wilson score confidence interval is calculated using the Eq. 1:

$$Wilson\ score = \hat{p} + \frac{z^2}{2n} \pm z \sqrt{\frac{\hat{p}(1-\hat{p}) + \frac{z^2}{4n}}{n}} / \left(1 + \frac{z^2}{n}\right) \quad (1)$$

where $\hat{p}$ is the observed proportion of positive reviews, n is the total number of reviews, and z is the z-value corresponding to the desired confidence level.

We applied a 95% confidence level to generate a more reliable sentiment score for each census tract with EV charging stations and reviews. These scores were then ranked and converted into percentile rankings on a national scale to facilitate subsequent analysis.

4.3.4. Problem Categorization of Negative Reviews

We used grounded theory^{184,185}, a systematic methodology in social science research that involves constructing theories through methodical gathering and analysis of data, to analyze the negative sentiment in the reviews ($n = 1\ 081$) and categorize them into distinct themes. In the initial

phase, two researchers independently reviewed the dataset to perform open coding. Each review was scrutinized line-by-line to identify key phrases and concepts, with the primary goal of breaking down the data into discrete parts and generating initial codes that represent the various issues and experiences described in the reviews. This process resulted in a diverse set of initial codes reflecting the wide range of user feedback.

Example quotes and initial codes:

- Quote: "The charger stopped working after a few minutes."
 - Annotator 1 Code: Interrupted Charging Sessions
 - Annotator 2 Code: Charging Stops Unexpectedly
- Quote: "Had trouble connecting my car to the charger. Adapter didn't fit."
 - Annotator 1 Code: Adapter Compatibility
 - Annotator 2 Code: Adapter Issues
- Quote: "The app kept crashing, and it took forever to find an available station."
 - Annotator 1 Code: App Crashes
 - Annotator 2 Code: App Functionality
- Quote: "There was no shelter or lighting at the station."
 - Annotator 1 Code: Lack of shelter
 - Annotator 2 Code: Inadequate lighting

Development of Subcategories. Following the initial coding, the researchers created subcategories from the generated codes. Each subcategory represented a more specific aspect of the broader themes identified during open coding. This step involved grouping related codes together to form meaningful subcategories that encapsulate distinct dimensions of the user feedback.

Example Subcategories:

- Hardware and Technical Issues:
 - Charger Functionality (e.g., "The charger stopped working after a few minutes")
 - Adapter Compatibility (e.g., "The adapter didn't fit properly")
 - General Failures
 - Interrupted Charging Sessions (e.g., "The charging stopped unexpectedly")
- Software and Digital Infrastructure:
 - App Functionality (e.g., "The app kept crashing")
 - Connectivity Problems
- User Experience:
 - Slow Charging
 - Capacity
 - Customer Support
 - Physical Infrastructure and Amenity Gap (e.g., "No shelter or lighting")

Collaborative Discussion and Refinement. After independently generating subcategories, the two researchers engaged in a series of collaborative discussions to refine and consolidate the subcategories. This involved critically evaluating each subcategory and discussing overlaps, redundancies, and unique aspects. Through this iterative process, we added, deleted, and merged subcategories as necessary to ensure that the resulting categories accurately reflected the data and were comprehensive and distinct.

Example Refinements:

- Merged Code:
 - "App Crashes" and "App Problems" were merged into "App Functionality"

- "Charging Stops Unexpectedly" and "Interrupted Charging Sessions" were merged
- Added Subcategories:
 - Network Dependency
 - Signage and Policy Enforcement

Axial Coding. In the axial coding phase, we focused on reassembling the data by identifying relationships between the subcategories. This process involved exploring connections, patterns, and hierarchies among the subcategories to understand how they interact and influence each other. The goal was to integrate the data in a way that provided a deeper understanding of the underlying issues and themes within the EVCS reviews.

Example Relationships:

- Hardware and Technical Issues and User Experience:
 - Issues with charger functionality directly impact user satisfaction and perceived convenience.
- Software and Digital Infrastructure and User Experience:
 - App functionality and connectivity issues affect the overall user experience and accessibility of charging stations.

Selective Coding. The final phase of our analysis was selective coding, where we identified the core category that encapsulated the central phenomenon emerging from the data. Through careful consideration and synthesis of the subcategories and their relationships, we determined the core category that represented the most impactful aspect of the user experiences with EVCSs. This core category served as the central theme around which all other categories were organized.

4.3.5. LLM for Problem Category Labeling

After defining the problem categories, we employed a validation method similar to our sentiment analysis to assess the model's performance in problem categorization. We first reached agreements on the problem labeling criteria, such as selecting the major problem or the first problem mentioned if multiple issues were described in a negative review. Subsequently, we independently labeled the reviews and validated the LLM's performance in categorizing these problems. Given that multiple classifications can reduce inter-rater consistency compared with binary classifications, our inter-rater reliability ($\kappa = 0.71$) decreased but still remained within an acceptable range for reliability. The LLM exhibited commendable accuracy, with values ranging from 0.77 to 0.82, indicating robust performance despite the complexity of the task (Tables A3 and A4).

We used the following prompt to run LLM on all negative reviews ($n = 128\ 271$):

"You are an assistant analyzing the problem mentioned in Electric Vehicle Charging Station reviews. For each review provided, determine the problem category and return only a number indicating this. If multiple problems detected in the review, choose the major problem or the first problem. Please keep your response short, formatted as a single digit integer number." Human-categorized categories was also provided to the LLM along with the prompt.

4.4. RESULTS

4.4.1. Public EVCSs in the United States

We collected data on EVCS and EVSE from both the Department of Energy (DOE) Alternative Fuels Data Center database and a popular online user-generated content (UGC) platform that hosts EVCS user reviews (similar to Yelp or Google Maps) in October 2022 (see Methods). As shown in Fig. 4.2a, the total numbers of EVCSs from both data sources are similar. The DOE database contains a total of 59 826 EVCS data points, with 93% (55 792) of which are labeled as public.

With more detailed user inputs and information gathered from the UGC platform, we filtered out 2% (1 106) of the stations that were under repair, 27% (16 290) of the stations that had access restrictions (such as employees only or hotel patrons only), and 10% (6 202) of the stations that required additional parking fees. This filtering process left 61% (37 536) of the stations that were fully public, without any restrictions or additional payments needed, ensuring that the UGC data accurately reflects EVCS that are genuinely accessible to the public.

We further analyzed the public EVSE data from the DOE (93% of the records) and the UGC platform (61% of the records) as shown in Fig. 4.2b. The UGC data show a similar distribution of Level 1 (up to 1.9 kW power), Level 2 (2.9 to 19.2 kW power), and direct current (DC) fast chargers (25 – 350 kW power) as compared to the DOE data, while providing more detailed site information and user reviews. We found that currently, most of the EVSEs are Level 2 (78–80%), with 18–21% having DC fast charging capability.

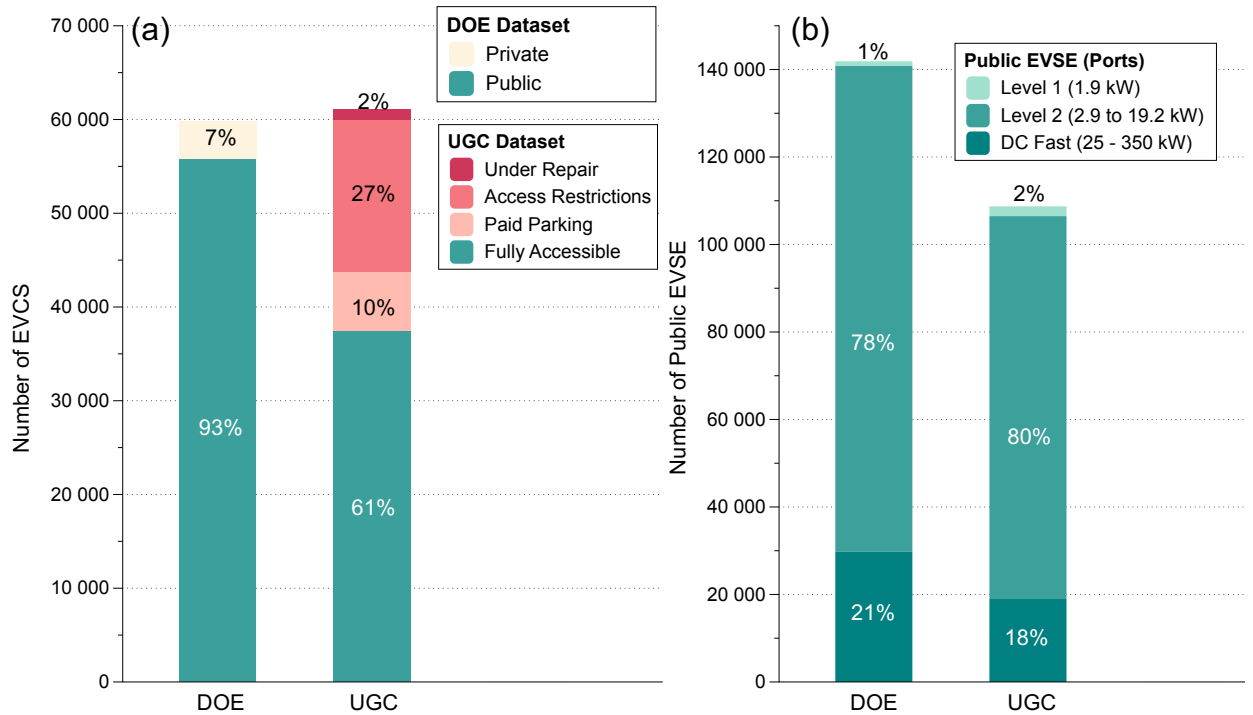


Figure 4.2. Data comparison between the Department of Energy (DOE) database and the user-generated content (UGC) platform. (a) Electric vehicle charging stations (EVCSs), and (b) public electric vehicle supply equipment (EVSEs).

4.4.2. EVCS Access Disparity

Utilizing data from the UGC platform, we compared the distribution of EVCS per 1 000 population in the contiguous United States and found significant disparities in accessibility between DAC and non-DAC areas (Fig. 4.3a). Out of the 48 states and the District of Columbia, 27 states did not show statistically significant results between DACs and non-DACs, primarily due to the small number of EVCSs available for analysis. For the other 22 states with statistically significant results, 19 showed disparities. Overall, on average, DACs have 26% fewer per capita public EVCS available in the contiguous United States. While California and New York have the highest number of public EVCS (Fig. A1) among the 22 states with statistically significant results, they also exhibit the highest disparity issues, with DACs having 69% and 87% fewer public EVCS,

respectively. Conversely, in states such as Washington, Utah, and Ohio, the existing EVCS infrastructure is more equitably distributed, providing better access to DACs and supporting broader EV adoption.

The national disparity is further compounded when considering the MDUs and renters, who require greater access to public EV charging. Table 4.1 provides further analysis, revealing three key findings: First, only 29% of non-DAC and 21% of DAC census tracts in the United States have public EVCS. Second, the disparity is similar for both EVCS and EVSE. Third, the disparity is consistent when comparing renters and MDUs, with figures of 52% vs. 57% for EVCS and 52% vs. 56% for EVSE. The disparity is most pronounced when both renters and MDUs are considered in a single metric (100 renters living in MDUs) as shown in Fig. 4.3b. Among the states with statistically significant results ($n = 21$), all now show disparities, with the mean national disparity between DACs and non-DACs spiking from 26% to 60%.

Figure 4.3.: Mean public electric vehicle charging stations (EVCS) density in 2022, comparing disadvantaged and non-disadvantaged communities: (a) per 1 000 population and (b) per 100 renters living in multi-dwelling units.

The red columns represent disadvantaged communities, while green columns represent non-disadvantaged communities. The light red state cells indicate states with statistically significant disparities, the light green state cells indicate significant but without disparity, and the white cells represent non-statistically significant states. Disparity percentage is calculated by dividing the difference between disadvantaged and non-disadvantaged communities by the value in non-disadvantaged communities. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Table 4.1. Inequitable access to public electric vehicle charging stations (EVCS) and supply equipment (EVSE) between DACs and non-DACs in the United States.

Metric description	non-DAC	DAC	Difference between non-DAC and DAC
% of Census tracts with public EVCS	29%	21%	8%
Mean Statistics of EV Charging Stations			
EVCS per 1 000 people	0.115	0.0854	26%
EVCS per 100 multi-dwelling units	0.160	0.0771	52%
EVCS per 1 000 renters	0.487	0.211	57%
EVCS per 100 renters living in multi-dwelling units	0.244	0.0976	60%
Mean Statistics of EV Supply Equipment			
EVSE per 1 000 people	0.336	0.240	28%
EVSE per 100 multi-dwelling units	0.454	0.216	52%
EVSE per 1 000 renters	1.36	0.602	56%
EVSE per 100 renters living in multi-dwelling units	0.672	0.276	59%

4.4.3. EVCS Reliability

In addition to inequitable access to the public EVCSs, we also found statistically significant differences in mean sentiment scores (e.g. whether the experience with an EVCS is positive) between DAC and non-DAC, as well as between urban and rural areas, as shown in Fig. 4.4a. The average sentiment score, ranked in percentiles among all communities, is significantly lower in the DAC than in the non-DAC. In other words, users in the DAC are more likely to have a negative experience with public EVCSs. On the right side of Fig. 4.4a, similar to another study¹⁷⁵, we find that the sentiment percentile ranking is significantly lower in urban areas than in rural areas.

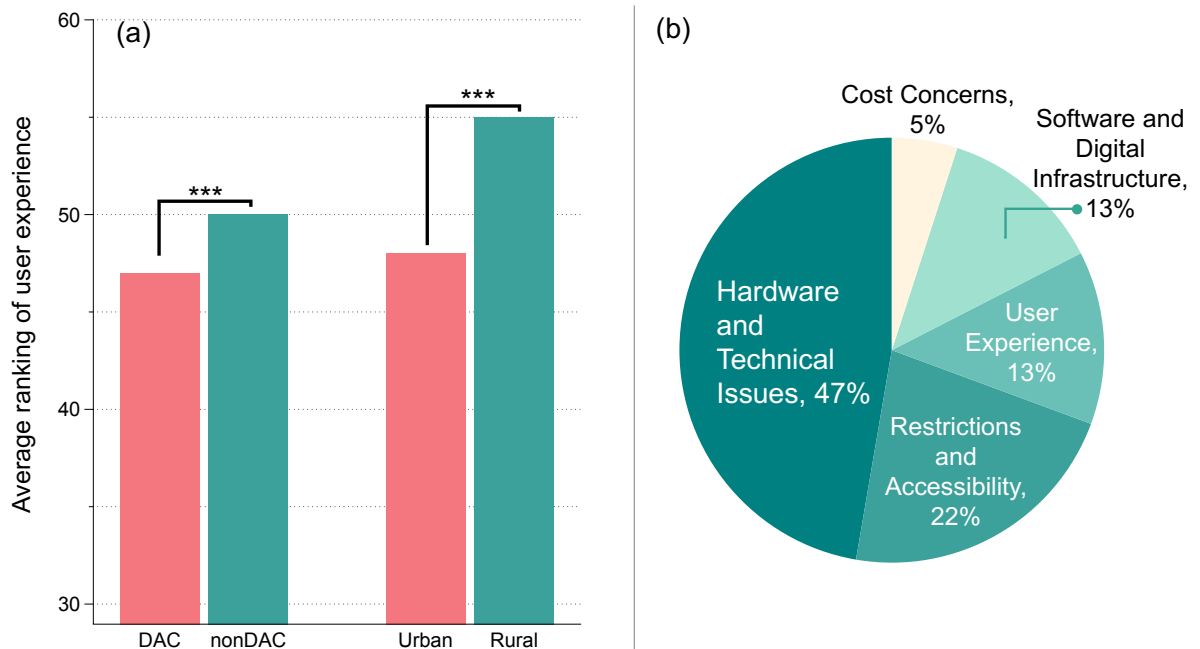


Figure 4.4. User experience rankings and problem categorization results for public EV charging stations. (a) Non-disadvantaged communities (non-DAC) and rural areas exhibit significantly higher average rankings of positive user experience, as compared to disadvantaged communities (DAC) and urban areas (***) $p < 0.001$). User experience is ranked by sentiment scores, which are derived from each user review. **(b)** Distribution of different categories of problems encountered by public EVCS users. The developed procedural equity framework ultimately guided our analysis of interview data.

Using grounded theory, we analyzed a comprehensive set of negative EVCS user reviews to identify and categorize the main issues (see Table 4.2) for all communities. These categories were then used to generate prompts for an LLM, which classified all the negative reviews ($n = 128\,271$). Fig. 4.4b illustrates the distribution of public EVCS issues, broken down by category percentage. Among the most prominent issues, hardware and technical issues were reported by 47% of the users, who frequently mentioned malfunctions with chargers, screens, card readers, and plugs, as well as issues related to adapter compatibility and general failures impacting the charging process. Software and digital infrastructure problems were also substantial, as noted by 13% of the users, particularly issues with app functionality, such as crashes and incorrect charging availability information, along with connectivity problems at charging stations that further exacerbated user frustration. In terms of user experience, 13% of the users cited common issues, including slow charging speeds, long wait times, and the availability and quality of customer support. The users also noted discomfort from unsheltered setups, inadequate lighting, and a lack of nearby amenities. Restrictions and accessibility posed major challenges for 22% of the users, with reports of parking and access limitations, blocked charging spots by internal combustion vehicles or noncharging EVs, and limited parking for larger EVs. This category also highlighted the need for clear signage and policy enforcement. Finally, cost concerns were raised by 5% of the users, who perceived charging services as too expensive and expressed confusion over pricing transparency. These findings underscore the multifaceted challenges that EVCSs face, highlighting areas for improvement to enhance the overall user experience and support the broader adoption of EVs.

Table 4.2. Summary of current issues for electric vehicle charging stations (EVCSs) based on negative user reviews

Category	Issue	Description
1. Hardware and Technical Issues	Charger Functionality	Malfunctions with chargers, screens, card readers, and plugs.
	Adapter Compatibility	Issues related to the physical connection between the EV and the charging station, including the availability and compatibility of adapters.
	General Failures	Broken parts, power failure and physical damage impacting the charging process.
	Interrupted Charging Sessions	Charging stops unexpectedly.
2. Software and Digital Infrastructure	App Functionality	Technical problems within apps, such as crashes and bugs affecting user interaction and charging station operation, or App showing incorrect charging availability information.
	Connectivity Problems	Challenges with internet connection at charging stations, affecting functionality and access to services.
3. User Experience	Slow Charging	Issues related to lower-than-expected charging speeds.
	Capacity	Long wait times for charging or requests for more charging stations
	Customer Support	Availability and quality of support for troubleshooting, guidance, and resolving charging issues.
	Physical Infrastructure and Amenity Gap	Discomfort from unsheltered setups in inclement weather, inadequate lighting, or the lack of nearby amenities like restrooms and food services.
	Network Dependency	Challenges due to the need for network-specific apps or payment cards for charging access, restricting ease of use.
4. Restrictions and Accessibility	Parking and Access Limitations	Customer-only or employee-only restrictions, no entry, parking permit requirements, time restrictions, high-cost paid parking and difficulty locating chargers.
	Blocked Charging Spots	Issues with ICE vehicles or EVs not charging occupying spots.
	Limited parking for different EVs	Parking spaces that are too small for vans and larger EVs, limiting accessibility for diverse EV users.
	Signage and Policy Enforcement	The need for clear signage indicating spots are designated exclusively for EV charging, guide signs to direct users to EV chargers, and enforcement measures to prevent ICE (Internal Combustion Engine) vehicles from blocking these spots.
5. Cost Concerns	High Pricing	Perceived as too expensive, especially in comparison to previous free services or when compared to the cost of gasoline.
	Pricing Transparency	Confusions raised from discrepancies between displayed and billed charging costs.

4.5. DISCUSSION

We present the first national analysis of equity in access to public EV charging using user-generated data that more accurately reflects real-world conditions and charger reliability. We applied LLMs to streamline the sentiment analysis of a substantial volume ($n = 470\,142$) of review data. With input from real-world EVCS users, we have found that despite several policies targeting the development of public EVCS in DACs, significant disparities still exist nationwide. Previous studies^{89,164,186} relying solely on DOE data were either unable to detect these disparities or identified them only at the local and state levels.

The issue of charging infrastructure in the DAC is complex and multifaceted. At-home charging, often considered the predominant solution for EV charging, presents many challenges for DAC residents. This is particularly problematic as a study¹⁸⁷ found that more than 46% of households in DACs may require updates to their electrical service panels for higher amperage to accommodate at-home EV charging and other electrification needs, but such upgrades often are not prioritized. Additionally, while single-family homes typically have less demand for public charging due to their potential to support overnight charging¹⁸⁸, the prevalence of accessory dwelling units (ADUs) in the DAC — often implemented to support affordable housing — makes at-home charging complicated. It is common for multiple families in DACs to share a single-family home, often utilizing ADUs with the same property^{189,190}. This living arrangement could increase the need for public charging infrastructure. Despite having greater needs for public charging than non-DAC residents, significant disparities in public EVCS access persist across nearly all DACs with sufficient sample sizes for analysis as illustrated in Fig. 4.3.

One viable solution to mitigate the limited availability of overnight charging in DACs is the strategic deployment of more DC fast chargers. Currently, as illustrated in Fig 4.2, these chargers constitute only 18% of the total charging infrastructure. Increasing the proportion of DC fast chargers could enhance charging accessibility and efficiency, compensating for the lack of private charging options in these areas. However, implementing DC fast chargers will require a reliable power infrastructure. Residents of DACs experience more frequent and longer power outages than others do, especially during extreme weather events^{191–193}. Such frequent outages could hinder DAC residents' willingness to adopt EVs or clean energy in general¹⁹⁴. Prolonged power outages can impede the effective charging of EVs, which are essential for mobility and accessing vital services. The increased frequency and duration of power outages in these areas underscore the vulnerability of existing infrastructure, which is often outdated and underfunded for necessary upgrades and maintenance. This perpetuates inequality, leaving these communities less resilient against both routine and extreme weather events that are increasingly common due to climate change^{195,196}. To address these issues, it is essential to prioritize infrastructure improvements in DACs, ensuring that they receive the necessary upgrades to withstand power disruptions. Additionally, integrating renewable energy sources and storage solutions could provide these communities with more stable and independent power supplies, reducing their dependency on the traditional grid and increasing their resilience to outages^{197–199}.

Reliability, or the performance of public EVCS, is another crucial aspect of infrastructure effectiveness. Instead of sending out surveys to collect user reviews on EVCS experience, we explored how LLMs can substantially streamline the analysis of the public EVCS user experience by directly analyzing existing online reviews. In addition, the traditional approach to sentiment analysis on user reviews can be labor-intensive and costly; for example, manually labeling

sentiment in 3 000 user reviews takes approximately 25 hours, and problem categorization tasks, being more complex, require even more time. In contrast, using LLMs to process the same batch of 3 000 sentiments takes only a few minutes and costs between \$0.50 and \$2.5, depending on the chosen LLMs and the length of the reviews. LLMs have demonstrated utility across various fields such as education²⁰⁰, medicine²⁰¹, and clinical research²⁰². This study shows their effectiveness in analyzing secondary qualitative data to assess public EVCS reliability. By leveraging the LLMs, we find that the public EVCS user experience is significantly lower in the DAC and urban areas.

Our sentiment analysis aligns with a previous study¹⁷⁵ regarding differences in user experiences with urban and rural public EVCSs, indicating that urban areas often report lower user satisfaction. One reason for this could be that individuals in rural settings, such as those near camping sites or national parks, typically have lower expectations. For example, users commented: "Very pleased to see an EV charging station here in the park. Thanks for making this possible!!!" or "Loved discovering a charging station during our camping trip! Will come back for more adventures!" This difference in expectations could partially explain why urban users report more negative experiences, as they frequently face access restrictions, longer charging times, and hardware issues. Similarly, since DAC areas are often located in densely populated urban areas, this could also explain why public EVCS in these regions tend to have lower sentiment scores. However, this does not negate the need for improvements in charging infrastructure in rural areas. Study²⁰³ has shown that many rural areas still lack public charging stations, and the average travel time to charge in these regions are higher.

Our research identified that hardware and technical issues are the most frequently mentioned problems encountered by users of public EVCSs. This finding highlights the urgent need to increase maintenance funding, as exemplified in small part by programs such as the recent Electric

Vehicle Charger Reliability and Accessibility Accelerator²⁰⁴. This program allocates \$100 million specifically for the repair and upkeep of public EVCSs, addressing a critical gap in the current infrastructure and ensuring that these essential services remain functional and accessible. Additionally, access restrictions present substantial barriers, as many stations are not available to the general public. Funding stipulations should enforce public accessibility. Another critical aspect is the network dependency of charging stations. Both the National Electric Vehicle Infrastructure¹⁵⁰ and California Electric Vehicle Infrastructure Project²⁰⁵ have recognized this by requiring charging point operators (CPOs) do not limit user access to specific charging network subscriptions, which is a step in the right direction. Charging speed has also emerged as a key concern, particularly in DACs where residents often spend more time commuting and working across various locations^{92,206,207}. The existing infrastructure may not adequately support the rapid charging necessary for efficient use in these communities.

While cost concerns may not seem paramount, it is important to recognize that early adopters of EVs are typically wealthier individuals^{89,159,208}. Households without access to residential charging face higher overall costs of EV ownership, as non-residential charging options tend to be more expensive²⁰⁹. Research indicates that EVs can address future transportation needs and reduce energy and maintenance costs, particularly benefiting low-income and minoritized racial and ethnic groups who face high fuel expenses^{162,163}. Yet, higher charging prices might exacerbate existing energy insecurity, especially for Black and Hispanic households²¹⁰. Thus, policies such as providing subsidized charging programs to DAC residents could provide a great opportunity to address historical burdens and advance equity in these communities. This approach could further lower barriers to EV adoption and ensure that all community members can benefit from the transition to EVs.

A recent study²¹¹ demonstrated a strong correlation between the availability of EVCSs and the adoption of EVs in DACs. The study revealed that increasing the number of public charging stations in DACs could have a nearly threefold greater impact on EV adoption than non-DAC areas. This finding aligns with our analysis of the physical characteristics of housing, which indicates that individuals in non-DAC areas have less reliance on public charging due to the availability of private residential charging options. Another study²¹² reported that charging \$100 for a designated overnight parking space with charging capabilities could reduce people's willingness to adopt EVs by approximately 65%, highlighting the dilemma faced by DAC residents who often lack access to designated parking spaces. Our study, along with previous literature, underscores the critical need for public EVCSs in DACs and the importance of addressing these disparities.

In the discussion concerning infrastructure development, a well-known chicken-and-egg dilemma frequently arises: the notion that without adequate infrastructure, there is little incentive to adopt EVs, yet without substantial EV adoption, the expansion of infrastructure may seem unjustified. Challenging this perspective, particularly in the context of DACs, we argue the importance of prioritizing the establishment of publicly accessible EVCSs—the "chicken"—to stimulate EV adoption—the "eggs." By emphasizing infrastructure development initially, we can prevent DAC residents from being marginalized in the clean energy transition, thereby addressing and mitigating existing disparities. By initially emphasizing infrastructure development and coupling it with equitable incentive policies for EVs^{88,91,213,214}, we can make EVCSs more accessible, reliable, easy to use, and affordable. This comprehensive approach will prevent DAC residents from being marginalized in the clean energy transition and pave the way for a cleaner energy future.

CHAPTER 4 APPENDIX

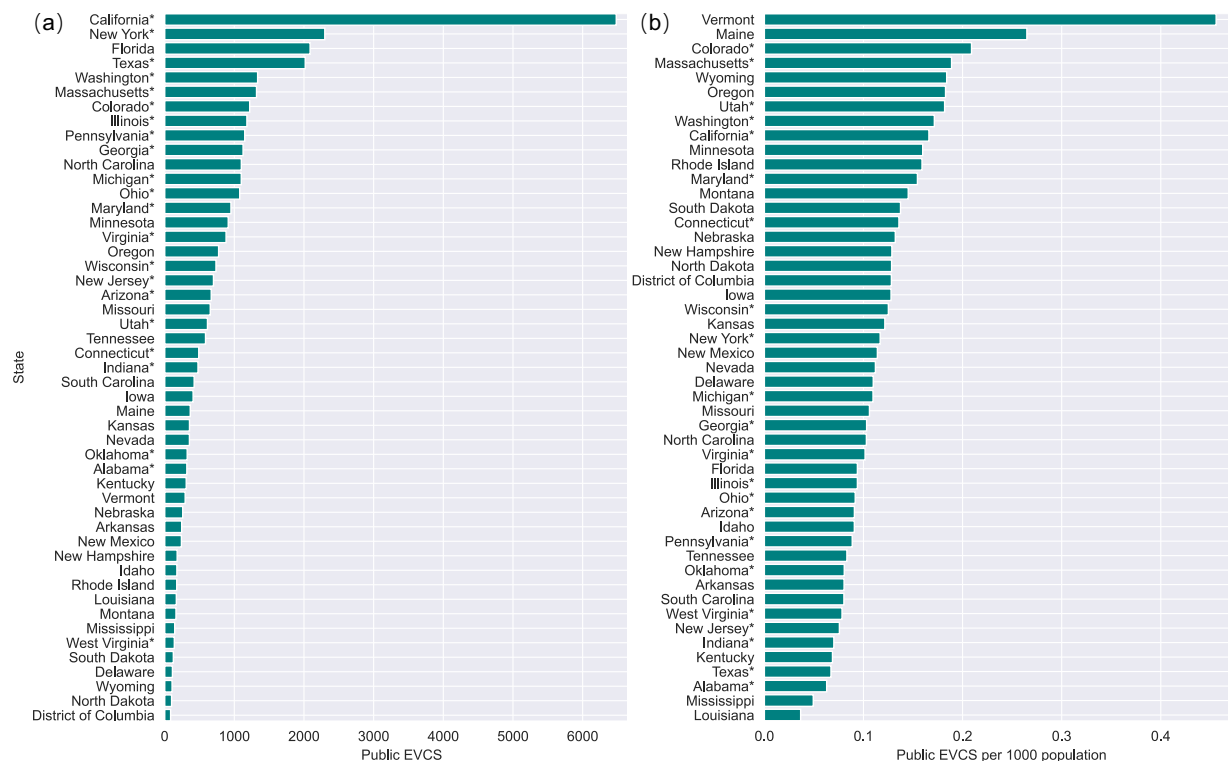


Figure A1. (a) Count of fully public EVCSs by state in the contiguous United States in 2022; (b) fully public EVCS per 1 000 population. States marked with an asterisk (*) indicate a statistically significant difference in the distribution between DAC (Disadvantaged Communities) and non-DAC areas within those states ($p < 0.05$). The state population data are obtained from the U.S. Census for the year of 2022.

Table A1: Model performance on sentiment analysis using different models.

Model	Accuracy (%) (s.d.)	Precision	Recall	F1 score
CNN (Asensio et al., 2020)	84.7 (0.8)	0.86	0.86	0.86
GPT 3.5	86.2 (0.02)	0.95	0.81	0.88
GPT 4	87.1 (0.01)	0.96	0.82	0.88

GPT 3.5 model: gpt-3.5-turbo-0125

GPT 4 model: gpt-4-0125-preview

Table A2: Comparison of sentiment annotations conducted by the two researchers (Interrater reliability: $\kappa = 0.81$)

	Researcher 1	Researcher 2
Positive Annotation	1 885 (59.1%)	2 034 (63.8%)
Negative Annotation	1 303 (40.9%)	1 154 (36.2%)
Total	3 188 (100.0%)	3 188 (100.0%)

Table A3: Model performance on problem categorization using different models.

Model	Accuracy (%) (s.d.)	Precision	Recall	F1 score
GPT 3.5	76.5 (0.19)	0.83	0.76	0.79
GPT 4	82.4 (0.08)	0.87	0.82	0.84

GPT 3.5 model: gpt-3.5-turbo-0125

GPT 4 model: gpt-4-0125-preview

Table A4: Comparison of problem categorization labels conducted by two researchers (Interrater reliability: $\kappa = 0.71$)

Problem Category	Researcher 1	Researcher 2
Hardware and Technical Issues	571 (52.8%)	556 (51.4%)
Software and Digital Infrastructure	34 (3.1%)	44 (4.1%)
User Experience	137 (12.7%)	143 (13.2%)
Restrictions and Accessibility	265 (24.5%)	286 (26.5%)
Cost Concerns	28 (2.6%)	20 (1.9%)
Incomprehensible comments	46 (4.3%)	32 (3.0%)
Total	1 081 (100.0%)	1 081 (100.0%)

5. CONCLUSIONS AND FUTURE DIRECTIONS

In this dissertation, we characterize public health and equity outcomes associated with zero-emission vehicle (ZEV) adoption and electric vehicle charging station (EVCS) accessibility, focusing on three main topics: (1) the environmental justice implications of ZEV adoption, (2) the regional air quality and health benefits of ZEVs in Los Angeles, and (3) the equity and reliability of public EVCS infrastructure across the United States. Using a range of methods, including geospatial analysis, transportation and air quality modeling, and qualitative analysis of user-generated data, we provide a comprehensive assessment of the clean transportation transition, with a focus on vulnerable populations such as disadvantaged communities (DACs) and racially and ethnically minoritized populations. This research is particularly relevant in the context of California's ambitious climate change targets, as the state aims for 100% ZEV sales by 2035, alongside efforts to reduce greenhouse gas emissions and improve air quality. The work presented in this dissertation offers evidence-based insights that can guide policy development and help address the persistent environmental inequities faced by DACs. As California moves forward with its climate action plans, including expanding ZEV adoption and EVCS infrastructure, it is critical that these policies are designed and implemented in a way that ensures equitable access to the benefits of clean transportation technologies. This dissertation highlights the need for targeted interventions that address disparities in ZEV ownership, pollutant exposure, and EVCS accessibility, with the ultimate goal of reducing pollution burdens and improving public health outcomes for all communities. Additionally, this research is timely given the increasing vulnerability of DACs to climate impacts, including extreme weather events, air pollution from wildfires, and prolonged exposure to traffic-related air pollution (TRAP). As the climate continues to change, these communities face heightened risks, and equitable policies are essential to

protecting them from the adverse health effects of environmental exposures. By focusing on ZEV adoption and EVCS accessibility, this dissertation contributes to a broader understanding of how clean transportation policies can be leveraged to promote environmental justice and safeguard public health in the face of climate change. The findings in this dissertation have significant implications for policymakers, environmental justice advocates, and other stakeholders. They provide actionable recommendations for designing more equitable ZEV incentive programs, improving the distribution and reliability of public EVCSs, and addressing the complex interplay between air pollutants such as fine particulate matter and ozone. The insights gained from this research can be used to inform future interventions aimed at reducing pollution burdens in DACs, ensuring that all communities benefit from the transition to a cleaner and more sustainable transportation system.

In **Chapter 2**, we projected the future ZEV fleet population in California using logistic models based on current and forthcoming policies, such as the state's mandate for 100% ZEV sales by 2035. Our analysis focused on the Greater Los Angeles area and explored disparities in ZEV ownership between disadvantaged communities (DACs) and non-DACs, highlighting how ZEV adoption could reduce traffic-related air pollution (TRAP) disparities while still leaving room for improvement. By integrating ZEV ownership data with household travel demand and transportation supply models, we predicted electric vehicle miles traveled (eVMT) and the associated emission changes at the census tract level. The results provided key insights into how ZEV adoption can contribute to cleaner air and address environmental justice issues, while also identifying persistent gaps in ownership and exposure.

For **Chapter 2 future research**, it will be important to investigate the potential spillover effects of California's ZEV adoption on other regions, both within and beyond the United States.

As California accelerates the transition to ZEVs, older internal combustion engine vehicles (ICEVs) are likely to be retired at a faster pace. This raises important questions about where these vehicles will go. In states without progressive ZEV policies, could this lead to an influx of older, more polluting vehicles, thus exacerbating air quality issues in those regions? Additionally, the global implications of California's ZEV policies are worth exploring, particularly in low-income countries where the demand for affordable used vehicles is high. There is a concern that while California may reduce emissions locally, it could unintentionally increase pollution in other parts of the world by exporting retired ICEVs. This issue has been discussed with the Global Director of Transport Global Practice at the World Bank, who has expressed interest in providing data and support for further investigation. Collaborative research with the World Bank could offer valuable insights into the cross-border effects of clean vehicle policies, ensuring that California's progress in reducing emissions does not inadvertently exacerbate environmental challenges in other regions, particularly in low-income countries.

In Chapter 3, we evaluated the health benefits of ZEV adoption in Los Angeles by modeling the reduction in air pollutants such as fine particulate matter and ozone and applying racially and ethnically specific dose-response curves. This approach allowed us to more accurately assess how different communities, particularly disadvantaged and minoritized populations, benefit from reduced air pollution exposure. Our findings suggest that applying racial and ethnic-specific dose-response curves reveals a larger health benefit for these populations, who are more susceptible to air pollution. As a result, previous assessments that used generalized dose-response data may have underestimated the potential public health gains from air quality improvements, particularly among vulnerable groups. Furthermore, we scaled down air pollution concentration maps to a

high-resolution grid (1 km x 1 km), providing more localized estimates of air quality improvements.

However, despite the advancements in our analysis, data limitations prevented us from conducting the assessment at an even finer scale. Specifically, the absence of racially, ethnically, and age-stratified baseline mortality rates at the census tract level posed a challenge. Addressing this data gap is essential for producing more accurate estimates of health outcomes related to air pollution and for ensuring that environmental justice (EJ) considerations are fully integrated into health assessments.

For Chapter 3 future research, we are developing a comprehensive health assessment model that incorporates EJ perspectives by integrating fine-scale, stratified baseline mortality rates with air pollution exposure data. This model will improve the estimation of health outcomes across different racial, ethnic, and socioeconomic groups. As part of this effort, we are working on a project that utilizes Bayesian statistics to estimate census tract-level baseline mortality rates in California. This approach will allow for more precise assessments and provide policymakers with the data needed to design equitable interventions that address the disproportionate pollution burdens faced by vulnerable communities, thereby maximizing the public health benefits of ZEV adoption and other environmental policies.

In Chapter 4, we conducted a national analysis of the equity and reliability of EVCSs by utilizing user-generated data and reviews. Our analysis highlighted significant disparities in public EVCS availability and reliability, particularly in DACs and among populations without access to at-home charging. While public EVCS infrastructure is critical to supporting electric vehicle adoption, particularly for residents of multi-dwelling units (MDUs) and renters, it is also important to recognize that the majority of charging will occur at home. However, data on at-home charging

is challenging to obtain, as there are no public reviews or centralized records similar to those available for public charging stations.

For Chapter 4 future research, we aim to assess the ability of households to install and utilize at-home charging infrastructure. Given the scarcity of available data, we plan to obtain public building permits and use artificial intelligence to streamline the process of identifying EVCS-related applications. This approach will allow us to analyze the characteristics of early adopters of at-home charging and assess the potential for charging infrastructure in different regions. Additionally, we aim to investigate potential racial and ethnic disparities in access to at-home charging infrastructure, which could have significant implications for the equitable adoption of electric vehicles. By filling this gap in the data, we hope to provide a more comprehensive understanding of the barriers to electric vehicle adoption and identify policy interventions that promote equity in the clean energy transition.

6. REFERENCES

1. California Air Resources Board. *2016 Mobile Source Strategy*.
<https://ww2.arb.ca.gov/resources/documents/2016-mobile-source-strategy> (2016).
2. Office of Governor Gavin Newsom. Executive Order N-79-20. *Executive Department, State of California* at <https://www.gov.ca.gov/wp-content/uploads/2020/09/9.23.20-EO-N-79-20-Climate.pdf> (2020).
3. California Air Resources Board. California moves to accelerate to 100% new zero-emission vehicle sales by 2035. *California Air Resources Board Website*
<https://ww2.arb.ca.gov/news/california-moves-accelerate-100-new-zero-emission-vehicle-sales-2035> (2022).
4. Office of Governor Kathy Hochul. Governor Hochul Drives Forward New York's Transition to Clean Transportation. *State of New York*
<https://www.governor.ny.gov/news/governor-hochul-drives-forward-new-yorks-transition-clean-transportation> (2022).
5. Department for Transport U.K. Transitioning to zero emission cars and vans: 2035 delivery plan. *Gov.UK* 57 <https://www.gov.uk/government/publications/transitioning-to-zero-emission-cars-and-vans-2035-delivery-plan> (2021).
6. Council of the European Union. First 'Fit for 55' proposal agreed: the EU strengthens targets for CO2 emissions for new cars and vans.
<https://www.consilium.europa.eu/en/press/press-releases/2022/10/27/first-fit-for-55-proposal-agreed-the-eu-strengthens-targets-for-co2-emissions-for-new-cars-and-vans/> (2022).
7. California Office of Environmental Health Hazard Assessment. CalEnviroScreen 4.0.

- <https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-40> (2022).
8. Boehmer, T. K. *Residential Proximity to Major Highways — United States, 2010*.
<https://www.cdc.gov/mmwr/preview/mmwrhtml/su6203a8.htm#Fig> (2013).
 9. Lu, T. *et al.* Leveraging Citizen Science and Low-Cost Sensors to Characterize Air Pollution Exposure of Disadvantaged Communities in Southern California. *Int. J. Environ. Res. Public Health* **19**, 8777 (2022).
 10. Yuan, Q. Environmental Justice in Warehousing Location: State of the Art. *J. Plan. Lit.* **33**, 287–298 (2018).
 11. Wang, T. *et al.* Health co-benefits of achieving sustainable net-zero greenhouse gas emissions in California. *Nat. Sustain.* **3**, 597–605 (2020).
 12. Liang, X. *et al.* Air quality and health benefits from fleet electrification in China. *Nat. Sustain.* **2**, 962–971 (2019).
 13. Pan, S. *et al.* Potential impacts of electric vehicles on air quality and health endpoints in the Greater Houston Area in 2040. *Atmos. Environ.* **207**, 38–51 (2019).
 14. Li, N. *et al.* Potential impacts of electric vehicles on air quality in Taiwan. *Sci Total Env.* **566–567**, 919–928 (2016).
 15. Peters, D. R., Schnell, J. L., Kinney, P. L., Naik, V. & Horton, D. E. Public Health and Climate Benefits and Trade-Offs of U.S. Vehicle Electrification. *GeoHealth* **4**, e2020GH000275 (2020).
 16. International Energy Agency (IEA). Global EV Outlook 2022 – Analysis - IEA. *IEA* <https://www.iea.org/reports/global-ev-outlook-2022> (2022).
 17. California Energy Commission. California Energy Commission Zero Emission Vehicle and Infrastructure Statistics. *Council of the EU* <https://www.energy.ca.gov/data->

- reports/energy-insights/zero-emission-vehicle-and-charger-statistics (2022).
18. OEHHA. SB 535 Disadvantaged Communities | OEHHA. *OEHHA*
<https://oehha.ca.gov/calenviroscreen/sb535> (2017).
 19. Morello-Frosch, R., Zuk, M., Jerrett, M., Shamasunder, B. & Kyle, A. D. Understanding the cumulative impacts of inequalities in environmental health: Implications for policy. *Health Aff.* **30**, 879–887 (2011).
 20. Conching, A. K. S. & Thayer, Z. Biological pathways for historical trauma to affect health: A conceptual model focusing on epigenetic modifications. *Soc. Sci. Med.* **230**, 74–82 (2019).
 21. Mitchell, U. A., Nishida, A., Fletcher, F. E. & Molina, Y. The Long Arm of Oppression: How Structural Stigma Against Marginalized Communities Perpetuates Within-Group Health Disparities. *Heal. Educ. Behav.* **48**, 342–351 (2021).
 22. Gee, G. C. & Payne-Sturges, D. C. Environmental health disparities: A framework integrating psychosocial and environmental concepts. *Environ. Health Perspect.* **112**, 1645–1653 (2004).
 23. National Institutes of Health (NIH). *National Institute on Minority Health and Health Disparities*. <https://www.nimhd.nih.gov/about/overview/> (2023).
 24. National Institutes of Health (NIH). NOT-OD-15-089: Racial and Ethnic Categories and Definitions for NIH Diversity Programs and for Other Reporting Purposes. <https://grants.nih.gov/grants/guide/notice-files/NOT-OD-15-089.html> (2015).
 25. Milner, A. & Jumbe, S. Comment Using the right words to address racial disparities in COVID-19. *Lancet Public Heal.* **5**, e419–e420 (2020).
 26. Black, C., Cerdeña, J. P. & Spearman-McCarthy, E. V. I am not your minority. *Lancet*

- Reg. Heal. - Am.* **19**, 100464 (2023).
27. Boeing, G., Lu, Y. & Pilgram, C. Local inequities in the relative production of and exposure to vehicular air pollution in Los Angeles. *Urban Stud.* (2023)
doi:10.1177/00420980221145403.
 28. Union of Concerned Scientists. Inequitable Exposure to Air Pollution from Vehicles in California. 4 <https://www.ucsusa.org/resources/inequitable-exposure-air-pollution-vehicles-california-2019> (2019).
 29. Frey, W. H. Central city white flight: racial and nonracial causes. *Am. Sociol. Rev.* **44**, 415–448 (1979).
 30. Frey, W. H. Black in-migration, white flight, and the changing economic base of the central city. *Am. J. Sociol.* **85**, 1396–1417 (1980).
 31. Galster, G. C. White Flight from Racially Integrated Neighbourhoods in the 1970s: The Cleveland Experience. *Urban Stud.* **27**, 385–399 (1990).
 32. Cushing, L. J., Vavra-Musser, K., Chau, K., Franklin, M. & Johnston, J. E. Flaring from Unconventional Oil and Gas Development and Birth Outcomes in the Eagle Ford Shale in South Texas. *Environ. Health Perspect.* **128**, 077003-1-077003–9 (2020).
 33. Bae, C. H. C., Sandlin, G., Bassok, A. & Kim, S. The Exposure of Disadvantaged Populations in Freeway Air-Pollution Sheds: A Case Study of the Seattle and Portland Regions. <https://doi.org/10.1068/b32124> **34**, 154–170 (2016).
 34. Reibel, M., Glickfeld, M. & Roquemore, P. Disadvantaged communities and drinking water: a case study of Los Angeles County. *Geoj. 2019 863* **86**, 1337–1354 (2020).
 35. Daniels, G. & Friedman, S. Spatial Inequality and the Distribution of Industrial Toxic Releases: Evidence from the 1990 TRI. *Soc. Sci. Q.* **80**, 244–262 (1999).

36. Vieira, V. M., Villanueva, C., Chang, J., Ziogas, A. & Bristow, R. E. Impact of community disadvantage and air pollution burden on geographic disparities of ovarian cancer survival in California. *Environ. Res.* **156**, 388–393 (2017).
37. Skipper, T. N., Lawal, A. S., Hu, Y. & Russell, A. G. Air quality impacts of electric vehicle adoption in California. *Atmos. Environ.* **294**, 119492 (2023).
38. Chang, S. Y. *et al.* Electric vehicle fleet penetration helps address inequalities in air quality and improves environmental justice. *Commun. Earth Environ.* **4**, 1–15 (2023).
39. Jerrett, M. *et al.* Spatial analysis of air pollution and mortality in California. *Am. J. Respir. Crit. Care Med.* **188**, 593–599 (2013).
40. Hoek, G. *et al.* Land use regression model for ultrafine particles in Amsterdam. *Environ. Sci. Technol.* **45**, 622–628 (2011).
41. Fuzzi, S. *et al.* Particulate matter, air quality and climate: Lessons learned and future needs. *Atmos. Chem. Phys.* **15**, 8217–8299 (2015).
42. HEI Panel on the Health Effects of Long-Term Exposure to Traffic-Related Air Pollution. Special Report 23: Systematic Review and Meta-analysis of Selected Health Effects of Long-Term Exposure to Traffic-Related Air Pollution. 628 at https://www.healtheffects.org/system/files/hei-special-report-23_4.pdf (2022).
43. Beelen, R. *et al.* Natural-cause mortality and long-term exposure to particle components: an analysis of 19 European cohorts within the multi-center ESCAPE project. *Environ. Health Perspect.* **123**, 525–533 (2015).
44. Roswall, N. *et al.* Long-term residential road traffic noise and NO₂ exposure in relation to risk of incident myocardial infarction - A Danish cohort study. *Environ. Res.* **156**, 80–86 (2017).

45. Alexeeff, S. E. *et al.* High-resolution mapping of traffic related air pollution with Google street view cars and incidence of cardiovascular events within neighborhoods in Oakland, CA. *Environ. Heal. A Glob. Access Sci. Source* **17**, 1–13 (2018).
46. Bowatte, G. *et al.* Traffic related air pollution and development and persistence of asthma and low lung function. *Environ. Int.* **113**, 170–176 (2018).
47. Li, L., Laurent, O. & Wu, J. Spatial variability of the effect of air pollution on term birth weight: Evaluating influential factors using Bayesian hierarchical models. *Environ. Heal. A Glob. Access Sci. Source* **15**, 1–12 (2016).
48. California Air Resources Board. Fleet Database. <https://arb.ca.gov/emfac/fleet-db> (2022).
49. California Air Resources Board. Emission FACtor (EMFAC) 2021. <https://arb.ca.gov/emfac/> (2021).
50. California Air Resources Board. 2020 Mobile Source Strategy. <https://ww2.arb.ca.gov/resources/documents/2020-mobile-source-strategy> (2021).
51. California Air Resources Board. Vision Model - LDV Raw Data and Results. https://ww2.arb.ca.gov/sites/default/files/2020-11/LDV_MSS_supporting_materials_ISAS_Nov2020.xlsx (2020).
52. California Air Resources Board. META Online Tool. <https://arb.ca.gov/emfac/meta/> (2021).
53. Bowman, J. L. & Ben-Akiva, M. E. Activity-based disaggregate travel demand model system with activity schedules. *Transp. Res. Part A Policy Pract.* **35**, 1–28 (2001).
54. Southern California Association of Governments. *2016 Regional Travel Demand Model and Model Validation*. https://scag.ca.gov/sites/main/files/file-attachments/validationsummaryreport_20rtp_final_2020_05.pdf?1659028273 (2020).

55. Yueshuai He, B., Jiang, Q. & Ma, J. Connected automated vehicle impacts in Southern California part-I: Travel behavior and demand analysis. *Transp. Res. Part D Transp. Environ.* **109**, 103329 (2022).
56. Horni, A., Nagel, K. & Axhausen, K. W. *The Multi-Agent Transport Simulation MATSim*. *The Multi-Agent Transport Simulation MATSim* (Ubiquity Press, 2016). doi:10.5334/baw.
57. Federal Highway Administration. Comprehensive Truck Size and Weight Study, Vol III Scenario Analysis, Chapter 9. (2000).
58. OpenStreetMap contributors. OpenStreetMap. <https://www.openstreetmap.org/> (2015).
59. OpenMobilityData. General Transit Feed Specification. at <https://transitfeeds.com/l/154-los-angeles-ca-usa> (2022).
60. He, B. Y. *et al.* A validated multi-agent simulation test bed to evaluate congestion pricing policies on population segments by time-of-day in New York City. *Transp. Policy* **101**, 145–161 (2021).
61. Ravina, M., Esfandabadi, Z. S., Panepinto, D. & Zanetti, M. Traffic-induced atmospheric pollution during the COVID-19 lockdown: Dispersion modeling based on traffic flow monitoring in Turin, Italy. *J. Clean. Prod.* **317**, 128425 (2021).
62. Wu, J., Wilhelm, M., Chung, J. & Ritz, B. Comparing exposure assessment methods for traffic-related air pollution in an adverse pregnancy outcome study. *Environ. Res.* **111**, 685–692 (2011).
63. Milando, C. W. & Batterman, S. A. Operational evaluation of the RLINE dispersion model for studies of traffic-related air pollutants. *Atmos. Environ.* **182**, 213–224 (2018).
64. Snyder, M. G. *et al.* RLINE: A line source dispersion model for near-surface releases. *Atmos. Environ.* **77**, 748–756 (2013).

65. WHO Regional Office for Europe. Proximity to roads, NO₂, other air pollutants and their mixtures. in *Review of evidence on health aspects of air pollution – REVIHAAP Project: Technical Report* (WHO Regional Office for Europe, 2013).
66. Ginzburg, H. *et al.* Monitoring study of the near-road PM_{2.5} concentrations in Maryland. *J. Air Waste Manag. Assoc.* **65**, 1062–1071 (2015).
67. USEPA. Near Roadway Air Pollution and Health: Frequently Asked Questions. 1–9 (2014).
68. National Centers for Environmental Information. Surface Meteorological Data. <https://www.ncei.noaa.gov/data/global-hourly/archive/isd/> (2020).
69. National Oceanic and Atmospheric Administration. NOAA/ESRL Radiosonde Database. <https://rucsoundings.noaa.gov/> (2020).
70. US EPA. AERMET v22112. <https://www.epa.gov/scram/meteorological-processors-and-accessory-programs> (2022).
71. Python Software Foundation. Python 3.9.13. at <https://www.python.org/downloads/release/python-3913/> (2022).
72. The Pandas Development Team. Pandas 1.5.2. at <https://pandas.pydata.org/pandas-docs/version/1.5.2/> (2022).
73. The NumPy Developers. NumPy 1.23.5. at <https://numpy.org/doc/1.23/release/1.23.5-notes.html> (2022).
74. Schreiner, H. *et al.* SciPy 1.8.1. at <https://docs.scipy.org/doc/scipy/reference/release.1.8.1.html> (2022).
75. The GeoPandas Development Team. GeoPandas 0.13.2. at <https://geopandas.org/en/stable/changelog.html> (2022).

76. QGIS Development Team. QGIS 3.26.2 ‘Buenos Aires’. at <https://qgis.org/en/site/forusers/visualchangelog326/index.html> (2022).
77. Burlig, F., Bushnell, J., Rapson, D. & Wolfram, C. Low Energy: Estimating Electric Vehicle Electricity Use. *AEA Pap. Proc.* **111**, 430–435 (2021).
78. Davis, L. W. Electric vehicles in multi-vehicle households. *Appl. Econ. Lett.* (2022) doi:10.1080/13504851.2022.2083563.
79. Saltelli, A., Andres, T. H. & Homma, T. Sensitivity analysis of model output: An investigation of new techniques. *Comput. Stat. Data Anal.* **15**, 211–238 (1993).
80. Tal, G. *et al.* Advanced Plug-in Electric Vehicle Travel and Charging Behavior Final Report (CARB Contract 12-319-Funding from CARB and CEC). (2020).
81. Holland, S. P., Mansur, E. T., Muller, N. Z. & Yates, A. J. Distributional effects of air pollution from electric vehicle adoption. *J. Assoc. Environ. Resour. Econ.* **6**, S65–S94 (2019).
82. Nopmongcol, U. *et al.* Air Quality Impacts of Electrifying Vehicles and Equipment Across the United States. *Environ. Sci. Technol.* **51**, 2830–2837 (2017).
83. Schnell, J. L. *et al.* Air quality impacts from the electrification of light-duty passenger vehicles in the United States. *Atmos. Environ.* **208**, 95–102 (2019).
84. Hettinger, D. *et al.* Chapter 10. Environmental Justice FINAL REPORT: LA100-The Los Angeles 100% Renewable Energy Study. <https://www.nrel.gov/docs/fy21osti/79444-10.pdf>. (2021).
85. Gastwirth, J. L. A General Definition of the Lorenz Curve. *Econometrica* **39**, 1037 (1971).
86. Zhu, Y., Hinds, W. C., Kim, S. & Sioutas, C. Concentration and size distribution of ultrafine particles near a major highway. *J. Air Waste Manag. Assoc.* **52**, 1032–1042

- (2002).
87. Zhu, Y., Hinds, W. C., Kim, S., Shen, S. & Sioutas, C. Study of ultrafine particles near a major highway with heavy-duty diesel traffic. *Atmos. Environ.* **36**, 4323–4335 (2002).
 88. Guo, S. & Kontou, E. Disparities and equity issues in electric vehicles rebate allocation. *Energy Policy* **154**, 112291 (2021).
 89. Canepa, K., Hardman, S. & Tal, G. An early look at plug-in electric vehicle adoption in disadvantaged communities in California. *Transp. Policy* **78**, 19–30 (2019).
 90. Hennessy, E. M. & Syal, S. M. Assessing justice in California’s transition to electric vehicles. *iScience* **26**, 106856 (2023).
 91. DeShazo, J. R., Sheldon, T. L. & Carson, R. T. Designing policy incentives for cleaner technologies: Lessons from California’s plug-in electric vehicle rebate program. *J. Environ. Econ. Manage.* **84**, 18–43 (2017).
 92. Pierce, G., Deshazo, J. R., Sheldon, T. & Blumenberg, E. Designing Light-Duty Vehicle Incentives for Low- and Moderate-Income Households. (2019).
 93. Muehlegger, E., Rapson, D. & Org, E. Understanding the Distributional Impacts of Vehicle Policy: Who Buys New and Used Electric Vehicles? Publication Date. (2019) doi:10.7922/G21Z42N.
 94. Pierce, G., McOmber, B. & DeShazo, J. R. Supporting Lower-Income Households’ Purchase of Clean Vehicles: Implications From California-Wide Survey Results. (2020).
 95. Muehlegger, E. & Rapson, D. S. Subsidizing low- and middle-income adoption of electric vehicles: Quasi-experimental evidence from California. *J. Public Econ.* **216**, 104752 (2022).
 96. Hsu, C. W. & Fingerman, K. Public electric vehicle charger access disparities across race

- and income in California. *Transp. Policy* **100**, 59–67 (2021).
97. Finlayson-Pitts, B. J. & Pitts, J. N. Atmospheric chemistry of tropospheric ozone formation: Scientific and regulatory implications. *Air Waste* **43**, 1091–1100 (1993).
 98. Heath, G., Ban-Weiss, G., Li, Y., Zhang, J. & Ravi, V. *Chapter 9. Air Quality and Public Health FINAL REPORT: LA100-The Los Angeles 100% Renewable Energy Study*. <https://www.nrel.gov/docs/fy21osti/79444-9.pdf>. (2021).
 99. Miranda, M. L., Edwards, S. E., Keating, M. H. & Paul, C. J. Making the Environmental Justice Grade: The Relative Burden of Air Pollution Exposure in the United States. *Int. J. Environ. Res. Public Heal.* **2011**, Vol. 8, Pages 1755-1771 **8**, 1755–1771 (2011).
 100. Thomas, J. M. Planning History and the Black Urban Experience: Linkages and Contemporary Implications. *J. Plan. Educ. Res.* **14**, 1–11 (1994).
 101. Domingue, S. J. & Emrich, C. T. Social Vulnerability and Procedural Equity: Exploring the Distribution of Disaster Aid Across Counties in the United States. <https://doi.org/10.1177/0275074019856122> **49**, 897–913 (2019).
 102. Schweitzer, L. & Valenzuela, A. Environmental Injustice and Transportation: The Claims and the Evidence. <http://dx.doi.org/10.1177/0885412204262958> **18**, 383–398 (2016).
 103. Zhu, S., Mac Kinnon, M., Carlos-Carlos, A., Davis, S. J. & Samuelsen, S. Decarbonization will lead to more equitable air quality in California. *Nat. Commun.* **13**, 1–10 (2022).
 104. Qiu, M., Zigler, C. M. & Selin, N. E. Impacts of wind power on air quality, premature mortality, and exposure disparities in the United States. *Sci. Adv.* **8**, 8762 (2022).
 105. Garcia, E., Johnston, J., McConnell, R., Palinkas, L. & Eckel, S. P. California’s early transition to electric vehicles: Observed health and air quality co-benefits. *Sci. Total*

- Environ.* **867**, (2023).
106. Carley, S. & Konisky, D. M. The justice and equity implications of the clean energy transition. *Nat. Energy* 2020 58 **5**, 569–577 (2020).
 107. Karner, A., London, J., Rowangould, D. & Manaugh, K. From Transportation Equity to Transportation Justice: Within, Through, and Beyond the State. <https://doi.org/10.1177/0885412220927691> **35**, 440–459 (2020).
 108. Ramirez-Ibarra, M. & Saphores, J. D. M. Health and equity impacts from electrifying drayage trucks. *Transp. Res. Part D Transp. Environ.* **116**, 103616 (2023).
 109. Pan, S., Roy, A., Choi, Y., Sun, S. Q. & Gao, H. O. The air quality and health impacts of projected long-haul truck and rail freight transportation in the United States in 2050. *Environ. Int.* **130**, 104922 (2019).
 110. Khreis, H. *et al.* Exposure to traffic-related air pollution and risk of development of childhood asthma: A systematic review and meta-analysis. *Environ. Int.* **100**, 1–31 (2017).
 111. Boogaard, H. *et al.* Long-term exposure to traffic-related air pollution and selected health outcomes: A systematic review and meta-analysis. *Environ. Int.* **164**, (2022).
 112. Raju, A. S. K., Wallerstein, B. R. & Johnson, K. C. Achieving NO_x and Greenhouse gas emissions goals in California’s Heavy-Duty transportation sector. *Transp. Res. Part D-Transport Environ.* **97**, (2021).
 113. Forrest, K., Lane, B., Tarroja, B., Mac Kinnon, M. & Samuelsen, S. Emissions and Air Quality Implications of Enabling On-Road Vehicles as Flexible Load Through Widescale Zero Emission Vehicle Deployment in California. *Transp. Res. Rec.* (2022)
doi:10.1177/03611981221121259.
 114. Pan, S. *et al.* Impacts of the large-scale use of passenger electric vehicles on public health

- in 30 US. metropolitan areas. *Renew. Sustain. Energy Rev.* **173**, (2023).
115. Lieven, T. Policy measures to promote electric mobility - A global perspective. *Transp. Res. Part a-Policy Pract.* **82**, 78–93 (2015).
 116. Axsen, J., Hardman, S. & Jenn, A. What Do We Know about Zero-Emission Vehicle Mandates? *Environ. Sci. Technol.* **56**, 7553–7563 (2022).
 117. Ou, S. Q. *et al.* The dual-credit policy: Quantifying the policy impact on plug-in electric vehicle sales and industry profits in China. *Energy Policy* **121**, 597–610 (2018).
 118. Greene, D. L., Park, S. & Liu, C. Z. Public policy and the transition to electric drive vehicles in the U.S.: The role of the zero emission vehicles mandates. *Energy Strateg. Rev.* **5**, 66–77 (2014).
 119. McConnell, V. & Leard, B. Pushing New Technology into the Market: California’s Zero Emissions Vehicle Mandate. *Rev. Environ. Econ. Policy* **15**, 169–179 (2021).
 120. Lane, B., Shaffer, B. & Samuelsen, S. A comparison of alternative vehicle fueling infrastructure scenarios. *Appl. Energy* **259**, (2020).
 121. Davis, A. W. & Tal, G. Investigating the Sensitivity of Electric Vehicle Out-of-Home Charging Demand to Changes in Light-Duty Vehicle Fleet Makeup and Usage: A Case Study for California 2030. *Transp. Res. Rec.* **2675**, 1384–1395 (2021).
 122. Ledna, C., Muratori, M., Brooker, A., Wood, E. & Greene, D. How to support EV adoption: Tradeoffs between charging infrastructure investments and vehicle subsidies in California. *Energy Policy* **165**, (2022).
 123. Kawamura, K. & Kaplan, I. R. Motor Exhaust Emissions as a Primary Source for Dicarboxylic-Acids in Los-Angeles Ambient Air. *Environ. Sci. Technol.* **21**, 105–110 (1987).

124. Zhu, Y. F., Fung, D. C., Kennedy, N., Hinds, W. C. & Eiguren-Fernandez, A. Measurements of ultrafine particles and other vehicular pollutants inside a mobile exposure system on Los Angeles freeways. *J. Air Waste Manage. Assoc.* **58**, 424–434 (2008).
125. Sowlat, M. H., Hasheminassab, S. & Sioutas, C. Source apportionment of ambient particle number concentrations in central Los Angeles using positive matrix factorization (PMF). *Atmos. Chem. Phys.* **16**, 4849–4866 (2016).
126. Evans, M. C., Bazargan, M., Cobb, S. & Assari, S. Pain Intensity among Community-Dwelling African American Older Adults in an Economically Disadvantaged Area of Los Angeles: Social, Behavioral, and Health Determinants. *Int. J. Environ. Res. Public Health* **16**, (2019).
127. Wilhelm, M. & Ritz, B. Residential proximity to traffic and adverse birth outcomes in Los Angeles County, California, 1994-1996. *Environ. Health Perspect.* **111**, 207–216 (2003).
128. Westerdahl, D., Fruin, S., Sax, T., Fine, P. M. & Sioutas, C. Mobile platform measurements of ultrafine particles and associated pollutant concentrations on freeways and residential streets in Los Angeles. *Atmos. Environ.* **39**, 3597–3610 (2005).
129. Fruin, S., Westerdahl, D., Sax, T., Sioutas, C. & Fine, P. M. Measurements and predictors of on-road ultrafine particle concentrations and associated pollutants in Los Angeles. *Atmos. Environ.* **42**, 207–219 (2008).
130. Winter, P. L., Padgett, P. E., Milburn, L. A. S. & Li, W. M. Neighborhood Parks and Recreationists' Exposure to Ozone: A Comparison of Disadvantaged and Affluent Communities in Los Angeles, California (vol 63, pg 379, 2019). *Environ. Manage.* **63**, 836 (2019).

131. Peters, D. R., Schnell, J. L., Kinney, P. L., Naik, V. & Horton, D. E. Public Health and Climate Benefits and Trade-Offs of US Vehicle Electrification. *Geohealth* **4**, (2020).
132. California Air Resources Board. CEPAM2019v1.03 - Standard Emission Tool. <https://ww2.arb.ca.gov/applications/cepam2019v103-standard-emission-tool> (2021).
133. U.S. EIA. California - State Energy Profile Overview - U.S. Energy Information Administration (EIA). <https://www.eia.gov/state/?sid=CA> (2021).
134. U.S. EIA. State Electricity Profiles - 2017. (2019).
135. Heath, G., Ban-Weiss, G., Li, Y., Zhang, J. & Ravi, V. *LA 100 Study Chapter 9*. (2021).
136. Wang, K., Zhang, Y., Yahya, K., Wu, S. Y. & Grell, G. Implementation and initial application of new chemistry-aerosol options in WRF/Chem for simulating secondary organic aerosols and aerosol indirect effects for regional air quality. *Atmos. Environ.* **115**, 716–732 (2015).
137. US Department of Commerce, N. E. S. R. L. C. S. L. NOAA ESRL CSD Projects: CalNex 2010.
138. Guenther, A. *et al.* Estimates of global terrestrial isoprene emissions using MEGAN (Model of Emissions of Gases and Aerosols from Nature). *Atmos. Chem. Phys.* **6**, 3181–3210 (2006).
139. Ginoux, P. *et al.* Sources and distributions of dust aerosols simulated with the GOCART model. *J. Geophys. Res. Atmos.* **106**, 20255–20273 (2001).
140. Gong, S. L. A parameterization of sea-salt aerosol source function for sub- and super-micron particles. *Global Biogeochem. Cycles* **17**, 1097 (2003).
141. US EPA. Environmental Benefits Mapping and Analysis Program - Community Edition (BenMAP-CE). *US Environmental Protection Agency* Last updated on May 18

- <https://www.epa.gov/benmap> (2023).
142. Pope, C. A. *et al.* Mortality risk and fine particulate air pollution in a large, representative cohort of U.S. adults. *Environ. Health Perspect.* **127**, (2019).
 143. Krall, J. R. *et al.* Associations between Source-Specific Fine Particulate Matter and Emergency Department Visits for Respiratory Disease in Four U.S. Cities. *Environ. Health Perspect.* **125**, 97–103 (2017).
 144. Turner, M. C. *et al.* Long-Term Ozone Exposure and Mortality in a Large Prospective Study. *Am. J. Respir. Crit. Care Med.* **193**, 1134–1142 (2016).
 145. Barry, V. *et al.* Characterization of the concentration-response curve for ambient ozone and acute respiratory morbidity in 5 U.S. cities. *J. Expo. Sci. Environ. Epidemiol.* **29**, 267 (2019).
 146. American Lung Association. Boosting Health for Children: Benefits of Zero-Emission Transportation and Electricity.
 147. Jenn, A. Emissions of electric vehicles in California’s transition to carbon neutrality. *Appl. Energy* **339**, 120974 (2023).
 148. International Energy Agency (IEA). *Global EV Outlook 2024*.
<https://www.iea.org/reports/global-ev-outlook-2024> (2024).
 149. International Energy Agency (IEA). Outlook for electric vehicle charging infrastructure.
<https://www.iea.org/reports/global-ev-outlook-2024/outlook-for-electric-vehicle-charging-infrastructure> (2024).
 150. Federal Highway Administration. National Electric Vehicle Infrastructure (NEVI) Program. <https://www.fhwa.dot.gov/environment/nevi/> (2022).
 151. Federal Highway Administration. Charging and Fueling Infrastructure Discretionary

- Grant Program. <https://www.fhwa.dot.gov/environment/cfi/> (2022).
152. US Congress. H.R.3684 - 117th Congress (2021-2022): Infrastructure Investment and Jobs Act. *Congress.gov* <https://www.congress.gov/bill/117th-congress/house-bill/3684> (2021).
 153. US Congress. H.R.5376 - Inflation Reduction Act of 2022. *US 117th Congr.* 1–11 (2022).
 154. Office of Energy Justice and Equity. Justice40 Initiative | Department of Energy. <https://www.energy.gov/justice/justice40-initiative> (2023).
 155. The White House. Justice40 Initiative | Environmental Justice | The White House. *The White House* <https://www.whitehouse.gov/environmentaljustice/justice40/> (2022).
 156. Manturuk, K., Lindblad, M. R. & Quercia, R. G. Homeownership and Local Voting in Disadvantaged Urban Neighborhoods. *SSRN Electron. J.* (2009) doi:10.2139/SSRN.2066796.
 157. Grimes, A. & Aitken, A. House Prices and Rents: Socio-Economic Impacts and Prospects. *SSRN Electron. J.* (2007) doi:10.2139/SSRN.975413.
 158. Habib, R. R., Mahfoud, Z., Fawaz, M., Basma, S. H. & Yeretizian, J. S. Housing quality and ill health in a disadvantaged urban community. *Public Health* **123**, 174–181 (2009).
 159. Wood, E., Rames, C., Muratori, M., Raghavan, S. & Melaina, M. *National Plug-In Electric Vehicle Infrastructure Analysis. National Renewable Energy Laboratory* https://www.energy.gov/eere/vehicles/downloads/national-plug-electric-vehicle-infrastructure-analysis%0Ahttps://www.afdc.energy.gov/uploads/publication/national_pev_infrastructur e.pdf (2017).
 160. Nicholas, M., Dale, H. & Lutsey, N. *Quantifying the electric vehicle charging*

- infrastructure gap across U.S. markets*. <https://theicct.org/publications/charging-gap-US> (2019).
161. Lee, D.-Y. *et al.* LA100 Equity Strategies. Chapter 10: Household Transportation Electrification. (2023) doi:10.2172/2221842.
 162. Vega-Perkins, J., Newell, J. P. & Keoleian, G. Mapping electric vehicle impacts: greenhouse gas emissions, fuel costs, and energy justice in the United States. *Environ. Res. Lett.* **18**, 014027 (2023).
 163. Markel, T. & Simpson, A. Cost-Benefit Analysis of Plug-In Hybrid Electric Vehicle Technology. *World Electr. Veh. J.* 2007, Vol. 1, Pages 294-301 **1**, 294–301 (2007).
 164. Khan, H. A. U., Price, S., Avraam, C. & Dvorkin, Y. Inequitable access to EV charging infrastructure. *Electr. J.* **35**, 107096 (2022).
 165. U.S. Department of Energy. Alternative Fuels Data Center: Alternative Fueling Station Locator. <https://afdc.energy.gov/stations#/analyze> (2022).
 166. California Energy Commission. Electric Vehicle Chargers in California. <https://www.energy.ca.gov/data-reports/energy-almanac/zero-emission-vehicle-and-infrastructure-statistics-collection/electric> (2024).
 167. Hardman, S. & Tal, G. Understanding discontinuance among California’s electric vehicle owners. *Nat. Energy* 2021 65 **6**, 538–545 (2021).
 168. Schulz, B. How reliable are public EV charging stations? Report shows many EV drivers have issues. *USA TODAY* (2023).
 169. McKinsey & Company. *Mobility Consumer Pulse 2024*. (2024).
 170. J.D. Power. EV Leasing Volumes Poised to Surge as Tax Rule Makes It Cheaper to Lease than Buy. (2023).

171. U.S. Department of Energy. Energy Justice Mapping Tool - Disadvantaged Communities Reporter. <https://energyjustice.egs.anl.gov/> (2024).
172. White House Council on Environmental Quality. Climate & Economic Justice Screening Tool. <https://screeningtool.geoplatform.gov/en/#3/33.47/-97.5> (2022).
173. U.S. Census Bureau. 2008-2012 American Community Survey 5-Year Estimates. <https://data.census.gov/cedsci/> (2015).
174. United States Census Bureau. Geocoder. <https://geocoding.geo.census.gov/> (2021).
175. Asensio, O. I. *et al.* Real-time data from mobile platforms to evaluate sustainable transportation infrastructure. *Nat. Sustain.* 2020 36 **3**, 463–471 (2020).
176. Sun, S., Luo, C. & Chen, J. A review of natural language processing techniques for opinion mining systems. *Inf. Fusion* **36**, 10–25 (2017).
177. Yi, J., Nasukawa, T., Bunescu, R. & Niblack, W. Sentiment analyzer: Extracting sentiments about a given topic using natural language processing techniques. *Proc. - IEEE Int. Conf. Data Mining, ICDM* 427–434 (2003) doi:10.1109/ICDM.2003.1250949.
178. van Attevelde, W., van der Velden, M. A. C. G. & Boukes, M. The Validity of Sentiment Analysis: Comparing Manual Annotation, Crowd-Coding, Dictionary Approaches, and Machine Learning Algorithms. *Commun. Methods Meas.* **15**, 121–140 (2021).
179. Gohil, S., Vuik, S. & Darzi, A. Sentiment Analysis of Health Care Tweets: Review of the Methods Used. doi:10.2196/publichealth.5789.
180. Lo, L. S. The CLEAR path: A framework for enhancing information literacy through prompt engineering. *J. Acad. Librariansh.* **49**, 102720 (2023).
181. Heston, T. F. & Khun, C. Prompt Engineering in Medical Education. *Int. Med. Educ.* 2023, Vol. 2, Pages 198-205 **2**, 198–205 (2023).

182. Dai, W. (Daisy), Jin, G., Lee, J. & Luca, M. Aggregation of consumer ratings: an application to Yelp.com. *Quant. Mark. Econ.* **16**, 289–339 (2018).
183. Jiang, Y. & Porter, M. Discovering Influence of Yelp Reviews Using Hawkes Point Processes. *Lect. Notes Networks Syst.* **296**, 84–104 (2022).
184. Charmaz, K. *Constructing grounded theory: A practical guide through qualitative analysis*. (sage, 2006).
185. Foley, G. & Timonen, V. Using Grounded Theory Method to Capture and Analyze Health Care Experiences. *Health Serv. Res.* **50**, 1195–1210 (2015).
186. Roy, A. & Law, M. Examining spatial disparities in electric vehicle charging station placements using machine learning. *Sustain. Cities Soc.* **83**, 103978 (2022).
187. Fournier, E. D. & Pincetl, S. UCLA LADWP LA100 Equity Strategies Title Chapter 17. Service Panel Upgrade Needs for Future Residential Electrification. at <https://escholarship.org/uc/item/2pm0x8vt> (2023).
188. California Energy Commission. Home Charging Access in California. (2022).
189. Chapple, K., Wegmann, J., Nemirow, A. & Dentel-Post, C. Yes in My Backyard: Mobilizing the Market for Secondary Units. *Center for Community Innovation at the Institute of Urban and Regional Development* vol. 147 1–17 at <https://doi.org/10.13140/RG.2.2.20618.62407> (2012).
190. Gellen, M. *Accessory apartments in single-family housing. Accessory Apartments in Single-family Housing* (2017). doi:10.4324/9781315083117.
191. Do, V. *et al.* Spatiotemporal distribution of power outages with climate events and social vulnerability in the USA. *Nat. Commun.* **2023 141 14**, 1–13 (2023).
192. Dugan, J., Byles, D. & Mohagheghi, S. Social vulnerability to long-duration power

- outages. *Int. J. Disaster Risk Reduct.* **85**, 103501 (2023).
193. Liévanos, R. S. & Horne, C. Unequal resilience: The duration of electricity outages. *Energy Policy* **108**, 201–211 (2017).
 194. Qiu, Y. *et al.* Power supply disruptions deter electric vehicle adoption in cities in China. *Nat. Commun.* 2024 151 **15**, 1–14 (2024).
 195. National Academies of Sciences. *Attribution of Extreme Weather Events in the Context of Climate Change. Attribution of Extreme Weather Events in the Context of Climate Change* (National Academies Press, 2016). doi:10.17226/21852.
 196. Ummenhofer, C. C. & Meehl, G. A. Extreme weather and climate events with ecological relevance: a review. *Philos. Trans. R. Soc. B Biol. Sci.* **372**, (2017).
 197. Ross, E., Day, M., Ivanova, C., McLeod, A. & Lockshin, J. Intersections of disadvantaged communities and renewable energy potential: Data set and analysis to inform equitable investment prioritization in the United States. *Renew. Energy Focus* **41**, 1–14 (2022).
 198. Hanke, F., Guyet, R. & Feenstra, M. Do renewable energy communities deliver energy justice? Exploring insights from 71 European cases. *Energy Res. Soc. Sci.* **80**, 102244 (2021).
 199. Cowell, R., Bristow, G. & Munday, M. Wind energy and justice for disadvantaged communities. *Joseph ...* 1–44 at http://www.communityenergyscotland.org.uk/assets/0000/6655/JRF_Paper.pdf (2012).
 200. Kasneci, E. *et al.* ChatGPT for good? On opportunities and challenges of large language models for education. *Learn. Individ. Differ.* **103**, 102274 (2023).
 201. Thirunavukarasu, A. J. *et al.* Large language models in medicine. *Nat. Med.* 2023 298 **29**, 1930–1940 (2023).

202. Tayebi Arasteh, S. *et al.* Large language models streamline automated machine learning for clinical studies. *Nat. Commun.* 2024 151 **15**, 1–12 (2024).
203. Carlton, G. J. & Sultana, S. Electric vehicle charging equity and accessibility: A comprehensive United States policy analysis. *Transp. Res. Part D Transp. Environ.* **129**, 104123 (2024).
204. Federal Highway Administration. Electric Vehicle Charger Reliability and Accessibility Accelerator. https://www.fhwa.dot.gov/environment/nevi/evc_raa/ (2023).
205. California Electric Vehicle Infrastructure Project (CALeVIP). Guide to California Regulations for Electric Vehicle Charging Stations. https://calevip.org/sites/default/files/docs/calevip/California_EVCS_Regulations_Guide.pdf (2023).
206. Besser, L. M., Marcus, M. & Frumkin, H. Commute Time and Social Capital in the U.S. *Am. J. Prev. Med.* **34**, 207–211 (2008).
207. Sultana, S. Job/housing imbalance and commuting time in the atlanta metropolitan area: Exploration of causes of longer commuting time. *Urban Geogr.* **23**, 728–749 (2002).
208. Priessner, A., Sposato, R. & Hampl, N. Predictors of electric vehicle adoption: An analysis of potential electric vehicle drivers in Austria. *Energy Policy* **122**, 701–714 (2018).
209. Ge, Y., Simeone, C., Duvall, A. & Wood, E. *There's No Place Like Home: Residential Parking, Electrical Access, and Implications for the Future of Electric Vehicle Charging Infrastructure*. <https://research-hub.nrel.gov/en/publications/thereaposs-no-place-like-home-residential-parking-electrical-acce> (2021) doi:10.2172/1825510.
210. Graff, M., Konisky, D. M., Carley, S. & Memmott, T. Climate Change and Energy

- Insecurity: A Growing Need for Policy Intervention. *https://home.liebertpub.com/env* **15**, 76–82 (2022).
211. Patwary, A. L. & Khattak, A. J. Explainable artificial intelligence for decarbonization: Alternative fuel vehicle adoption in disadvantaged communities. *Int. J. Sustain. Transp.* **18**, 393–407 (2024).
212. Guerra, E. & Daziano, R. A. Electric vehicles and residential parking in an urban environment: Results from a stated preference experiment. *Transp. Res. Part D Transp. Environ.* **79**, 102222 (2020).
213. Hennessy, E. M. & Syal, S. M. Assessing justice in California’s transition to electric vehicles. *iScience* **26**, 106856 (2023).
214. DeShazo, J. R. & Di Fillippo, J. *An Agenda for Equity-Centered Clean Transportation*. (2021).