Emissions Impact of Connected and Automated Vehicle Deployment in California

June 2021

Final Report from the UC Davis 3 Revolutions Future Mobility Program and the National Center for Sustainable Transportation

Giovanni Circella, University of California, Davis

Miguel Jaller, University of California, Davis

Ran Sun, University of California, Davis

Xiaodong Qian, University of California, Davis

Farzad Alemi, University of California, Davis

TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No.
NCST-UCD-RR-21-10

2. Government Accession No.
N/A

3. Recipient's Catalog No.
N/A

4. Title and Subtitle
Emissions Impact of Connected and Automated Vehicle Deployment in California

5. Report Date
June 2021

6. Performing Organization Code
N/A

7. Author(s)
Giovanni Circella, PhD, https://orcid.org/0000-0003-1832-396X; Miguel Jaller, PhD, https://orcid.org/0000-0003-4053-750X; Ran Sun, https://orcid.org/0000-0001-5380-3526; Xiaodong Qian, PhD, https://orcid.org/0000-0002-7245-3362; Farzad Alemi, PhD, https://orcid.org/0000-0003-4333-3393

8. Performing Organization Report No.
UCD-ITS-RR-21-17
UC-ITS-2019-43

9. Performing Organization Name and Address
University of California, Davis
Institute of Transportation Studies
1605 Tilia Street, Suite 100
Davis, CA 95616

10. Work Unit No.
N/A

11. Contract or Grant No.
USDOT Grant 69A3551747114
CARB Contract 17RD003

12. Sponsoring Agency Name and Address
U.S. Department of Transportation, Office of the Assistant Secretary for Research and Technology, 1200 New Jersey Avenue, SE, Washington, DC 20590

The University of California Institute of Transportation Studies, www.ucits.org

California Air Resources Board, Research Division, 1001 I Street, Sacramento, CA 95814

13. Type of Report and Period Covered
Final Report (May 2018 – June 2021)

14. Sponsoring Agency Code
USDOT OST-R
UC ITS

15. Supplementary Notes
DOI: https://doi.org/10.7922/G2DR2SS6
Dataset DOI: https://doi.org/10.25338/B86926

16. Abstract
This study helps understand how the anticipated emergence of autonomous vehicles will affect various aspects of society and transportation, including travel demand, vehicle miles traveled, energy consumption, and emissions of greenhouse gases and other pollutants. The study begins with a literature review on connected and automated vehicle (CAV) technology for light-duty vehicles, the factors likely to affect CAV adoption, expected impacts of CAVs, and approaches to modeling these impacts. The study then uses a set of modifications in the California Statewide Travel Demand Model (CSTDM) to simulate the following scenarios for the deployment of passenger light-duty CAVs in California by 2050: (0) Baseline (no automation); (1) Private CAV; (2) Private CAV + Pricing; (3) Private CAV + Zero emission vehicles (ZEV); (4) Shared CAV; (5) Shared CAV + Pricing; (6) Shared CAV + ZEV. The modified CSTDM is used to forecast travel demand and mode share for each scenario, and this output is used in combination with the emission factors from the EMission FACtor model (EMFAC) and Vision model to calculate energy consumption and criteria pollutant emissions. The modeling results indicate that the mode shares of public transit and in-state air travel will likely sharply decrease, while total vehicle miles traveled and emissions will likely increase, due to the relative convenience of CAVs. The study also reveals limitations in models like the CSTDM that primarily use sociodemographic factors and job/residence location as inputs for the simulation of activity participation and tour patterns, without accounting for some of the disruptive effects of CAVs. The study results also show that total vehicle miles traveled and vehicle hours traveled could be substantially impacted by a modification in future auto travel costs. This means that the eventual implementation of pricing strategies and congestion pricing policies, together with policies that support the deployment of shared and electric CAVs, could help curb tailpipe pollutant emissions in future scenarios, though they may not be able to completely offset the increases in travel demand and road congestion that might result from CAV deployment. Such policies should be considered to counteract and mitigate some of the undesirable impacts of CAVs on society and on the environment.

17. Key Words
Connected and Automated Vehicles, Travel Demand, Vehicle Miles Traveled, Emission Impacts, Mode Share, Future Scenarios, CSTDM

18. Distribution Statement
No restrictions.

19. Security Classif. (of this report)
Unclassified

20. Security Classif. (of this page)
Unclassified

21. No. of Pages
156

22. Price
N/A

Emissions Impact of Connected and Automated Vehicle Deployment in California

A Report from the 3 Revolutions Future Mobility Program and
the National Center for Sustainable Transportation

June 2021

Giovanni Circella, Miguel Jaller, Ran Sun, Xiaodong Qian and Farzad Alemi

Institute of Transportation Studies
University of California, Davis

Prepared for the California Air Resources Board and
the California Environmental Protection Agency

About the National Center for Sustainable Transportation

The National Center for Sustainable Transportation is a consortium of leading universities committed to advancing an environmentally sustainable transportation system through cutting-edge research, direct policy engagement, and education of our future leaders. Consortium members include: University of California, Davis; University of California, Riverside; University of Southern California; California State University, Long Beach; Georgia Institute of Technology; and University of Vermont. More information can be found at: ncst.ucdavis.edu.

About the UC Institute of Transportation Studies

The University of California Institute of Transportation Studies (UC ITS) is a network of faculty, research and administrative staff, and students dedicated to advancing the state of the art in transportation engineering, planning, and policy for the people of California. Established by the Legislature in 1947, ITS has branches at UC Berkeley, UC Davis, UC Irvine, and UCLA.

Disclaimer

NCST

Acknowledgments

This report was prepared for a project funded by the California Air Resources Board. This study was partially funded by a grant from the National Center for Sustainable Transportation (NCST), supported by the U.S. Department of Transportation (USDOT) through the University Transportation Centers program, and through funding received by the University of California Institute of Transportation Studies from the State of California through the Public Transportation Account and the Road Repair and Accountability Act of 2017 (Senate Bill 1). The authors would like to thank the California Air Resources Board, NCST, the USDOT, Caltrans and the State of California for their support of university-based research in transportation, and especially for the funding provided in support of this project. Additional funding for this project was provided by the 3 Revolutions Future Mobility Program of the University of California, Davis.

The study capitalizes on the work developed in several previous research projects carried out at the UC Davis Institute of Transportation Studies and the contributions from several modeling experts that participated in an expert workshop held at the University of California, Davis on April 29-30, 2019. The research team would like to thank Kailai Wang, Mollie D'Agostino Niloufar Yousefi, Rosa Dominguez-Faus and Tho Le for their contribution to the research. David Bunch and David Brownstone provided extremely useful ideas and contributions at various times during the development of the research.

The researchers would also like to acknowledge the contribution from the members of the advisory panel, including staff from the California Air Resources Board and other agencies, who greatly increased the quality of our work. The research team would like to thank Kalin Pacheco and Steven Vo from the California Department of Transportation for providing access to the California Statewide Travel Demand Model (CSTDM) and for allowing the research team to run the transportation scenarios on their remote workstation, as well as Ronald West and Mobashwir Khan from Cambridge Systematics, and Fatemeh Ranaiefar from Fehr & Peers for their assistance with the setup and troubleshooting of the CSTDM model runs.

This report was submitted in fulfillment of CARB contract 17RD003 by the University of California, Davis under the partial sponsorship of the California Air Resources Board. Work was completed as of June 25, 2021.

[page left intentionally blank]

TABLE OF CONTENTS

List of Tables

List of Figures

List of Acronyms Used

Acronym	Definition
ABM	Activity-Based Model
ACC	Adaptive Cruise Control
ADAS	Advanced Driver Assistance Systems
ADS	Automated Driving System
AV	Automated Vehicle
BAU	Business As Usual
CARB	California Air Resources Board
CA DMV	California Department of Motor Vehicle
CACC	Cooperative Adaptive Cruise Control
C-ADS	Cooperative-Automated Driving System
CAV	Connected and Automated Vehicle
CBD	Central Business District
CDA	Cooperative Driving Automation
CO_2	Carbon Dioxide
CPUC	California Public Utility Commission
CSTDM	California Statewide Travel Demand Model
CPUC	California Public Utilities Commission
CVR	ConVentional Rail
DDT	Dynamic Driving Task
DTA	Dynamic Traffic Assignment
DVI	Digital Visual Interface
EMFAC	EMission FACtor model
EV	Electric Vehicle
eVMT	Electric Vehicle Miles Traveled
FHWA	Federal Highway Administration
GAI	EMFAC (Emission) Sub-Area
GHG	Greenhouse Gas
GPS	Global Positioning System
HDV	Human-Drive Vehicle
HSR	High Speed Rail
ICE	Internal Combustion Engine
i-HEV	intelligent Hybrid Electric Vehicles
LB	Lower Bound

Acronym	Definition
LD	Long Distance
LCA	Lane Change Assistance
LIDAR	LIght Detection And Ranging
MPC	Model Predictive Control
MTC	Metropolitan Transportation Commission
NCSL	National Conference of State Legislatures
NOx	Nitrogen Oxides
NCHRP	National Cooperative Highway Research Program
OD	Origin Destination
PM2.5	Particulate Matter 2.5
p.p.	Percentage Point
PT	Public Transit
ROG	Reactive Organic Gases
ROW	Right of Ways
SACOG	Sacramento Area Council of Governments
SAV	Shared Automated Vehicle
SD	Short Distance
SIS	Signalized Intersection Scheme
SGC	Strategic Growth Council, California
TAZ	Transportation Analysis Zone
TMC	Traffic Management Center
UB	Upper Bound
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
VACS	Vehicle Automation and Communication Systems
VHT	Vehicle Hours Traveled
VMT	Vehicle Miles Traveled
VOT	Value of Time
VOTT	Value of Travel Time
VPHPL	Vehicles Per Hour Per Lane
WTP	Willingness to Pay
ZEV	Zero Emission Vehicle
ZOV	Zero Occupancy Vehicle

Abstract

This study helps understand how the anticipated emergence of autonomous vehicles will affect various aspects of society and transportation, including travel demand, vehicle miles traveled, energy consumption, and emissions of greenhouse gases and other pollutants. The study begins with a literature review on connected and automated vehicle (CAV) technology for light-duty vehicles, the factors likely to affect CAV adoption, expected impacts of CAVs, and approaches to modeling these impacts. The study then uses a set of modifications in the California Statewide Travel Demand Model (CSTDM) to simulate the following scenarios for the deployment of passenger light-duty CAVs in California by 2050: (0) Baseline (no automation); (1) Private CAV; (2) Private CAV + Pricing; (3) Private CAV + Zero emission vehicles (ZEV); (4) Shared CAV; (5) Shared CAV + Pricing; (6) Shared CAV + ZEV. The modified CSTDM is used to forecast travel demand and mode share for each scenario, and this output is used in combination with the emission factors from the EMission FACtor model (EMFAC) and Vision model to calculate energy consumption and criteria pollutant emissions. The modeling results indicate that the mode shares of public transit and in-state air travel will likely sharply decrease, while total vehicle miles traveled and emissions will likely increase, due to the relative convenience of CAVs. The study also reveals limitations in models like the CSTDM that primarily use sociodemographic factors and job/residence location as inputs for the simulation of activity participation and tour patterns, without accounting for some of the disruptive effects of CAVs. The study results also show that total vehicle miles traveled and vehicle hours traveled could be substantially impacted by a modification in future auto travel costs. This means that the eventual implementation of pricing strategies and congestion pricing policies, together with policies that support the deployment of shared and electric CAVs, could help curb tailpipe pollutant emissions in future scenarios, though they may not be able to completely offset the increases in travel demand and road congestion that might result from CAV deployment. Such policies should be considered to counteract and mitigate some of the undesirable impacts of CAVs on society and on the environment.

Executive Summary

As the autonomous vehicle revolution is on the horizon, questions on the changes that this revolution will bring to transportation and society remain. Researchers and transportation stakeholders are beginning to consider the potential effects of self-driving technology on passenger travel demand, vehicle miles traveled (VMT), energy consumption, and emissions of greenhouse gases (GHGs) and other pollutants. This report aims to support the efforts of the California Air Resources Board (CARB) in this area and to improve the understanding of the potential impacts of connected and automated vehicles (CAVs) on travel demand and on GHG and pollutant emissions in the State of California.

In this report, connected and automated vehicles refer to a combination of vehicle automation (i.e., vehicles can steer, accelerate, brake and navigate in traffic with little to no human intervention) and vehicle connectivity (i.e., vehicles can communicate with each other, connect with traffic signals, signs, and other road items, or obtain data from a cloud) technology, which will likely lead to large changes in the use of on-road vehicles and individuals' relationship with privately-owned and/or shared-fleet passenger vehicles. The study uses a travel demand modeling framework in combination with emission factors to calculate ranges of impacts of CAV deployment on travel demand, energy consumption and criteria pollutant emissions in a set of scenarios for the deployment of passenger light-duty CAVs in California by 2050. The modeling results highlight how the relative convenience of CAVs could cause a sharp reduction in the mode shares of public transit and in-state air travel, while total vehicle miles traveled and emissions will likely increase. The study also shows the important role of policies that could be implemented to counteract and mitigate some of the undesirable impacts of CAVs on society and on the environment, including pricing strategies and policies that support the deployment of shared and electric CAVs. Such policies could help curb tailpipe pollutant emissions in future scenarios, though they may not be able to completely offset the increases in travel demand and road congestion that might result from CAV deployment.

In the first part of this study, the research team reviewed a wide range of existing research projects. The literature offers ample evidence from projects that have focused on the following research questions:

- What are the different components of self-driving technologies and when will partially and fully automated vehicles become available to the different segments of the population?
- What are the factors that affect individuals' adoption and willingness to pay (WTP) for CAVs?
- What are the potential impacts of CAVs on transportation supply, travel behavior and demand, land use and urban form/design, pollutant emissions and energy consumption?
- How can modelers update travel demand forecasting models to forecast ranges of future impacts on travel demand deriving from the implementation of CAVs (under various deployment assumptions)?

New vehicle technologies make CAVs a more viable alternative for the future of transportation. Due to the variations in consumers' attitudes towards new technologies and uncertainties about regulatory approval for CAV deployment, there is no consensus on the timeline of CAV adoption. Generally, studies suggest the adoption of, intention to use, and WTP for CAVs will be primarily affected by socio-demographics, personal attitudes, current travel patterns, and built environment factors. There is a potential that early adopters will mainly include the segments of the population that are wealthier, younger, more highly educated, and living in cities, though adoption patterns will likely be affected by the business models and policies that are implemented to regulate CAV deployment.

The literature review in this report gives special attention to the impacts of CAVs based on the sequential spreading effects associated with CAV deployment, including:

(1) *first-order effects*, including the possible direct effects of CAVs on factors such as travel cost/time, road capacity, and the resulting travel choices;

(2) *second-order effects,* including the impacts of CAVs on private vehicle ownership vs. willingness to share vehicles that are part of fleets, residential location choices, urban form and land use;

(3) *third-order implications* of CAVs, including indirect impacts of CAV deployment in transportation, such the resulting impacts on energy consumption, GHG emissions, social equity, and economy.

The findings from existing studies have suggested that CAVs will affect both transportation demand and supply in various ways. On the transportation demand side, as a result of the introduction of CAVs, travel costs and parking costs may be reduced (or, alternatively, the space allocated to parking in denser urban areas may be reduced, opening opportunities for alternative development in cities). Further, the relationship of drivers (or, more accurately, "riders") with vehicles will change and on-board activities are expected to be rather different from the traditional non-CAV settings, as more activities could be conducted while traveling in a CAV. This might lead to a substantial modification in the evaluation of the value of travel time (VOTT) and the willingness to pay to shorten a trip, as time spent on board a CAV will be less tiring and unpleasant, and it will likely lead to higher productivity and/or individual satisfaction. Thus, the reduction in the marginal travel cost and the flexibility of CAV use (together with the increased comfort and reduced fatigue while traveling) will likely induce more trips and cause an increase in VMT, vehicle hours traveled (VHT), and the mode share for passenger light-duty vehicles.

On the side of transportation supply, CAV deployment will likely improve traffic flows assuming sufficient penetration rates and connectivity with other vehicles and infrastructure. In the interim, however, when mixed flows and interactions between CAVs and non-automated vehicles will be the norm, traffic flow may worsen. Thus, in the long run, highway capacity could substantially increase on the existing roadway network. However, the capacity of certain elements of the network—such as ramp sections, and local roads where pick-ups and drop-offs happen—may decrease because of more friction induced by merging and splitting vehicles.

Several sources of uncertainties associated with CAV deployment affect these outcomes. First, public opinion varies substantially across different cities and countries even though it is generally supportive of CAV technology. The public is largely in a wait-and-see position in terms of acceptance and use of self-driving vehicles, possibly due to a lack of knowledge and uncertainty about the characteristics of CAVs. Second, there are several factors affecting the adoption of CAVs, including socio-demographic attributes, personal attitudes, current travel behavior, and built-environment variables. Finally, we are uncertain of how people will use CAVs, and the resulting modifications in the purposes, frequency, and distance of trips by CAVs. All these uncertainties make it difficult to forecast the impacts of CAVs with existing modeling tools that have been developed using existing data that predate CAV deployment.

Decision-makers and transportation professionals are asked to address CAV deployment in long-range plans. The equity, environmental, and planning implications related to CAV deployment also warrant attention. We note that the difficulty in estimating the changes in both transportation supply and demand relates to the uncertainties that propagate through many different parts of the planning and modeling processes. Based on the review of the scientific literature and modeling practice, one effective way to account for the effect of CAVs on the future of transportation is to account for their impacts on the organization of various individuals' activity and travel choices that are included in an activity-based travel demand forecasting model and then to simulate a range of different scenarios that might include broadly diverse assumptions and contexts. This report attempts to tackle this process, even if more research might be needed to substantially expand the scope of the scenario assumptions and aspects to consider, as well as compare the application of different modeling approaches. Additional research would also be needed to overcome the limitations of specific modeling frameworks that might not be well suited to consider the impacts of a brand-new technology that is a potential game changer and might push existing travel demand forecasting models outside of their range of applicability.

In this study, we define several future transportation scenarios for the state of California in 2050, and model the range of potential impacts of CAV deployment under the framework of the California Statewide Travel Demand Model (CSTDM), the official statewide travel demand model commissioned and maintained by the California Department of Transportation (Caltrans). We test a set of scenarios that integrate CAV deployment into various travel demand assumptions. We directly target travel demand and network supply impacts of CAVs through modifying the CSTDM in the long-term decision, mode choice, travel costs, road network capacity, and other related components. Additional modifications include adjustments for the availability of (and need for) a driver's license to use a vehicle, value of time, parking cost and vehicle operating cost that could be associated with the availability of passenger light-duty CAVs. The resulting travel demand impacts are forecasted for various scenarios through the application of the modeling framework, including both its passenger and freight model components. Thus, the modifications in the model and scenario inputs result in updated trip tables by transportation mode and distance, VMT, VHT, as well as loaded network, traffic flows, and related congestion effects. We assume CAVs will use vehicle powertrain technology consistent with the forecasts for the future fleet mix available from the California Air Resources

Board at the time of this study, unless explicitly specified in the zero-emission vehicle (ZEV) scenarios, which assume a faster transition to ZEVs. Using the trip-related modeling results, we compute energy consumption and resulting GHG and other pollutant emissions using emission factors from the EMFAC and Vision models.

Based on the findings in the literature and the predicted combination of autonomous, electric, and shared vehicles in future years, this study compares six scenarios for the future year 2050, as shown in Table ES.1, where ZEV stand for zero emission vehicle and SAV for shared autonomous vehicle, respectively. Additional scenarios could be tested using the proposed modeling framework in future extensions of the research. The private CAV scenarios focus on privately-owned CAVs, where no specific assumptions are made about actions to promote carpool or shared use of CAVs. As a comparison, the SAV scenarios refer to the fleet-ownership model, where mobility service providers operate the SAV fleet and provide mobility services to travelers. All scenarios are modeled for year 2050 and compared to the baseline *Scenario 0* (business as usual, or BAU, in the same year 2050, as if there were no CAVs, based on the current official future scenario from Caltrans) in the discussion of the results and implications for the future of society.

Table ES.1. Scenario Design

Scenario	Private CAV	SAV	Pricing	ZEV
0				
1a & 1b	√			
2a & 2b	√		√	
3a & 3b	√			√
4a & 4b		√		
5a & 5b		√	√	
6a & 6b		√		√

Notes:
Scenario 0 – BAU (no vehicle automation, year 2050 from Caltrans);
Scenarios 1a & 1b – Private CAV, lower bound (LB) and upper bound (UB), respectively;
Scenarios 2a & 2b – Private CAV + Pricing, LB and UB;
Scenarios 3a & 3b – Private CAV + ZEV, LB and UB;
Scenarios 4a & 4b – Shared CAV, LB and UB;
Scenarios 5a & 5b – Shared CAV + Pricing, LB and UB; and
Scenarios 6a & 6b – Shared CAV + ZEV, LB and UB.
ZEV, zero emission vehicle; SAV, shared automated vehicle.

The comparison of the results from the alternative scenarios highlights the potential for increased travel demand that could be associated with CAV deployment, when compared to the baseline year 2050 scenario (Figure ES.1). In this report, each scenario is presented with a lower bound (LB) and upper bound (UB), with the upper bound accounting for additional impacts on vehicle miles traveled associated with induced demand associated with CAV availability and repositioning of vehicles, factors that are not directly accounted for in the modified CSTDM framework in the LB scenarios. The model results show increases in auto VMT for both private CAV and shared CAV scenarios, while a reduction in VMT could happen under certain circumstances, as shown in the lower-bound scenarios for both private CAV + pricing and shared CAV + pricing scenarios, though these LB scenarios do not consider any of the additional impacts on road travel from induced demand and repositioning of vehicles (and therefore might lead to an underestimation of VMT in these scenarios). The results from the implementation of the private CAV + pricing and shared CAV+ pricing scenarios show how the increase in auto VMT could be at least partially offset by the implementation of new road user and other pricing policies. Finally, the electrification of CAVs, while in this study is not expected to significantly affect the total amount of travel demand in the state, can significantly modify CAV environmental impacts and would lead to eliminating their tailpipe vehicle emissions. Under the assumption of a clean energy mix in California, that would lead to a substantial decarbonization of the road transportation sector. However, other externalities, such as traffic congestion, would persist.

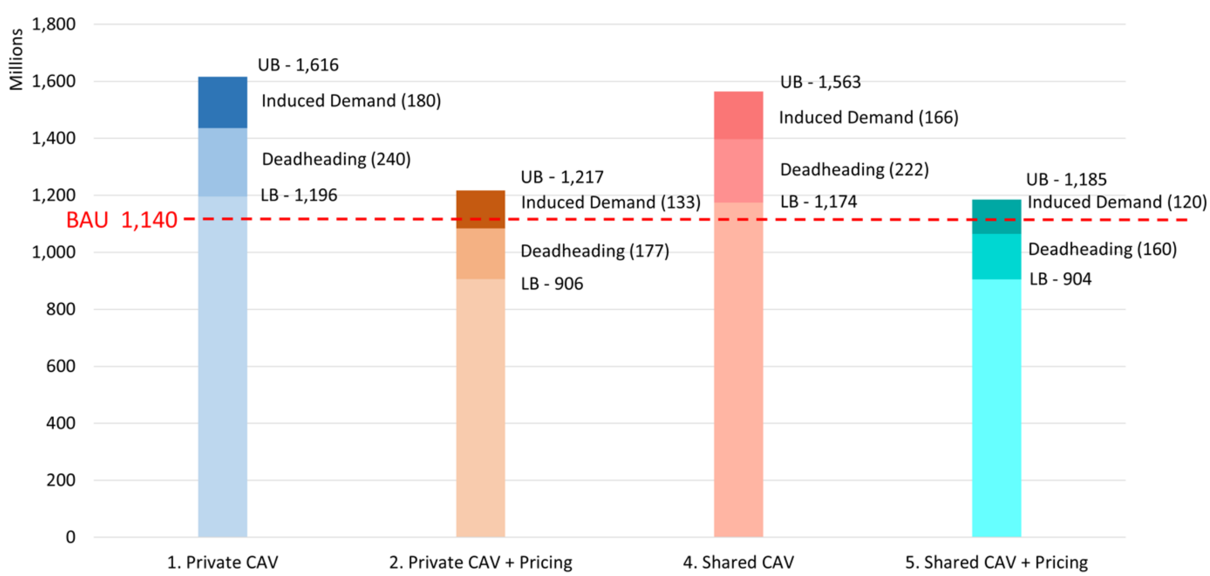

Figure ES.1. Range of VMT for Model Scenarios

It is important to note how the current CSTDM framework is not able to account for certain expected impacts of CAV deployment, such as individuals' modified activity patterns and additional trips that might be generated due to the increased travelling comfort, lower fatigue, and lower cost of traveling with CAVs, and the deadheading associated with repositioning passengers between trips. To accommodate for these factors, we present the results from all scenarios in terms of an expected range of outcomes that can be associated with the deployment of CAVs. However, additional long-term impacts of CAV deployment, such as eventual impacts on land use and residential location choices of individuals, are not accounted for in this range of travel demand results and might cause further increases in travel demand beyond these levels. This means that even the upper-bound scenarios in this project might underestimate the potential increases in the future demand for car travel in California in a CAV-dominated future.

The resulting pollutant emission patterns show an increase reflective of VMT increases in the private CAV and shared scenarios, while the private CAV + pricing, private CAV + ZEV, shared CAV + pricing and shared CAV + ZEV scenarios yield lower levels of pollutant emissions, thanks to the impacts of these strategies on travel demand and on tailpipe emissions. In particular, if CAV deployment is coupled with 91% electric vehicle miles traveled (eVMT) in 2050, based on Vision model forecast, a dramatic reduction in tailpipe emissions from the auto sector could be obtained. The geographic distribution pattern of the emissions is similar to that of travel demand, as pollutant emissions in this modeling framework are assumed to be proportional to VMT: higher VMT would generate higher criteria pollutants, and the CSTDM framework does not account for the impacts that the high penetration of zero-emission vehicles would have on travel demand (i.e., the vehicle powertrain is not considered a factor affecting travel costs and/or travel patterns).

The results from this study help inform CARB on the likely impacts that CAV deployment could have on transportation and emissions, and inform policy making, including the development of Sustainable Community Strategies, the Advanced Clean Cars II regulation, and other transportation and CAV planning efforts statewide. The results of this project have several policy implications. Specifically, there is a need to consider policy levers that can contain travel demand and emissions from transportation in future years. Uncertainty remains about how CAVs will be deployed and the details of their impacts on transportation and society. Nonetheless, this study implies that if adequate policies are not enacted to coordinate CAV deployment with other sustainability-inspired strategies, the deployment of this technology could largely derail the effects of many strategies that have been proposed in California to limit VMT and GHG emissions from transportation.

While this study provides an initial set of ranges of forecasts for the potential impacts of CAV deployment in California, important limitations might affect its results. In particular, the adjustments made to current travel demand forecasting tools may not account for the unknown impacts a new technology such as CAVs might have. In the case of the CSTDM, the current modeling framework is not well suited to simulate certain impacts of CAV deployment, and in particular the impacts of fleet-based CAVs and the potential for vehicle pooling. Further, some important questions relate to whether the model might be oversensitive to changes in travel costs and not enough sensitive to changes in travel time and other changes CAVs might cause on the comfort, fatigue and pleasure associated with travelling by car. Such sensitivity errors could lead to an underestimate of the impacts of CAV deployment on travel demand and VMT, and an overestimate of the impacts of pricing policies on reducing travel demand and VMT. In addition, the current modeling framework assumptions and the existing data available for its estimation and update limit the model's ability to predict changes in activity patterns and trip generation that will likely be associated with CAV deployment. Additional research on the expansion of the modeling framework, re-estimation of some of its components, and calibration of the relationship between travel behaviors and new technologies might be needed to better address these points.

Introduction

Advances in transportation technology are continuously reshaping our lives and cities. Progress in the field of self-driving vehicles has the potential to substantially affect travel demand, with eventual large impacts on vehicle miles traveled (VMT), energy consumption, and greenhouse gas (GHG) and criteria pollutant emissions. Further, connected and automated vehicles (CAVs) could substantially modify the existing transportation system by integrating with other on-demand mobility services and zero-emission fuels, leading to different outcomes depending on the way this technology is brought to the market and the policies that are enacted to regulate the field. Understanding the extent of these impacts is crucial and timely to policymakers and transportation professionals.

To date, a wide range of possible effects of CAV deployment have been estimated based on a variety of datasets, modeling assumptions, and hypothetical scenarios. The California Department of Motor Vehicles (DMV) and the California Public Utility Commission (CPUC) have approved driverless vehicles and on-demand passenger testing and services in California.[1] Particularly, California sits at the epicenter of self-driving technology development. It is one of the most popular testbeds for many relevant companies (including Waymo, Cruise, Tesla, Lyft, and other automotive, technological, and ridesharing companies). However, limited attention has been given to evaluating the impacts that CAV deployment could have in the State of California on energy consumption, air quality, and regional or local criteria pollutant and GHG emissions. There is a pressing need to study the future transportation scenarios related to the adoption of CAVs in California.

This report helps bridge the above-mentioned gaps, supporting the efforts of the California Air Resources Board (CARB) to identify the range of potential impacts (in direction and magnitude) of the introduction and rapid adoption of CAVs on California's VMT, energy consumption, and GHG and criteria pollutant emissions. The aim of this research project is to address several research questions related to the adoption of CAVs in California. This report summarizes the state-of-the-art knowledge and the approaches and assumptions that were applied to model the impacts of CAV deployment in California as part of the research project, presents the range of impacts of CAV deployment on travel demand, GHG and other criteria pollutant emissions for a range of future travel scenarios for 2050 in California, and discusses policy implications of these findings.

In the first part of this report, we review the large and expanding literature on the potential effects of the widespread adoption of CAVs and look into possible strategies to incorporate them in a statewide travel demand modeling framework. The research team compiled the results of the related existing scientific papers and research projects as well as the outcomes from a two-day workshop with leading modeling experts affiliated with several academic institutions; national laboratories; federal, state, and regional planning agencies; and well-

[1] https://www.dmv.ca.gov/portal/vehicle-industry-services/autonomous-vehicles/autonomous-vehicle-testing-permit-holders/

established transportation consulting firms. The workshop was organized by the research team as part of this project and was held at the Institute of Transportation Studies of the University of California, Davis on April 29-30, 2019. Appendix A reports detailed information on the expert workshop, including the agenda and a list of the expert participants.

As part of the project, the research team focused on designing future scenarios associated with CAV deployment. A total of six scenarios, each one with a lower bound and upper bound in terms of travel demand and emission impacts, was created based on a combination of technological, behavioral, and policy assumptions. After developing the scenarios, the research team implemented these scenarios in a modeling framework, using modeling assumptions informed by the current literature. The research team evaluated a range of potential impacts of CAV deployment on travel demand, energy consumption and criteria pollutant emissions at the statewide level, through modifying the California Statewide Travel Demand Model (CSTDM), and integrating it with the EMFAC and Vision models to compute the related GHG and criteria pollutant emissions. Despite some limitations of the CSTDM modeling framework that are discussed in later sections of this report, the use of the official statewide travel demand forecasting model was found to be the most appropriate approach to produce travel estimates from future scenarios at the statewide scale in California.

The project leverages the insights from ongoing research carried out by our research team and many other colleagues at other institutions. The insights refer to the application of statewide and regional models to predict the impact of CAVs and the analysis of behavioral data collected by other studies. The literature review and a modeling expert workshop at UC Davis in April 2019[2] helped define the CAV deployment scenarios, the assumptions to be introduced in the modeling framework, and the likelihood of future scenarios. The end products of this project include a range of potential impacts associated with CAV deployment in 2050 and policy recommendations about ways to mitigate the outcomes of these impacts. We also discuss the limitations associated with the limited validity of certain modeling assumptions and how these might be addressed in future research.

[2] Additional information on the expert workshop is available at: https://3rev.ucdavis.edu/events/cav-model-workshop

Literature Review

Overview of CAV Technologies

Autonomous driving technologies have made great strides forward and might be commercially available in the near future. As of November 2017, Waymo's driverless cars had been driven more than 4 million miles on public roads. While it took about eight years to accrue 3 million miles in these tests, it took only another six months to hit the 4 million miles mark (Waymo Safety Report, 2020). The development of CAVs is contingent on the development of connectivity (e.g., 5G, GPS) and automation (e.g., Advanced Driver Assistance Systems [ADAS]), which will ultimately make vehicles capable of driving by themselves and communicating with each other. Connectivity refers to the real-time communication between vehicles and infrastructure, which will help improve the efficiency in using the transportation infrastructure and ultimately may lead to an increase in safety and fuel efficiency. Automation refers to self-driving and vehicle control technologies.

Vehicle communication and transportation-level control technologies provide more opportunities for CAV deployment by improving real-world performance and system-wide awareness, but it is the developments in ADAS that make automated driving possible. One of the examples of ADAS is the current progress in automated cruise-control ability. For an AV to drive smoothly and safely, two decoupled tasks need to be performed simultaneously: 1) controlling the speed to maintain safe headway; 2) steering to adjust lateral motions of the vehicle (Hatipoglu, Ozguner, and Redmill, 2003). The breakthroughs in vehicle-level control technologies, such as Adaptive Cruise Control (ACC) and Cooperative Adaptive Cruise Control (CACC), show the potential benefits of incorporating automation into the highway system. At the time of this writing, current low-level vehicle automation technologies, such as ACC and lane-keeping assistance, have proved the benefits associated with the deployment of such technologies. For example, ACC is an important enhancement over longitudinal vehicle cruise control that maintains a vehicle's speed while keeping a safe distance from the preceding vehicle, measuring the inter-vehicle gap and the preceding vehicle's speed via sensors. This vehicle control technology is expected to bring smoother driving maneuvers, as discussed several years ago (Zwaneveld and van Arem 1997).

A newer version of ACC is CACC, which extends the benefits of ACC with cooperative maneuvers. CACC vehicles are equipped with sensors that measure inter-vehicle gap, preceding vehicle speed, leading vehicle gap, and leading vehicle speed. For lateral control, such as lane change and merging, vehicles equipped with CACC and lane change assistance (LCA) would first assess lane-change risk by checking surrounding vehicles and then control the host vehicle to complete a lane change in the lateral direction if no risk exists. In addition, CACC allows vehicles to form platoons with controlled speed and headway (Wischhof, Ebner, and Rohling 2005).

Apart from vehicle control, there are many other breakthroughs, such as sensor technology, high-resolution GPS, vehicle to infrastructure communication, and software system development. Vehicle sensors such as Light Detection and Ranging (LIDAR), camera, and radar gather real-world physical information. This information is then processed in combination with

GPS geolocation information and information from other vehicles via vehicle communication systems for vehicle decision-making processes. All the new technologies make CAV a viable potential alternative for the future of transportation.

Levels of Automation

The Society of Automotive Engineers (SAE) On-Road Automated Vehicle Standards Committee (2020) defines five levels of driving automation and four classes of cooperation for on-road vehicles, based on a vehicle's minimum capabilities on each level. At level 1, the vehicle can perform basic tasks like steering and acceleration alone, but everything else needs intervention from the human driver. At level 2, vehicle control technology (e.g., ACC), can ensure driving safely in some specific scenarios but needs an alert human driver. At level 3, the automated driving system is capable of monitoring the driving environment. At level 4, the vehicle is able to safely navigate to the destination of the journey without the intervention of a human driver in most situations. Level 5 means the automated system can take control of the vehicle in all circumstances, and there is no need for any assistance from human drivers. Levels 4 and 5 are the only ones that require no human intervention. The relationship of SAE automation and Cooperative Driving Automation (CDA) classes is shown in Table 1. Five classes of CDA cooperation are defined as 1) no cooperative automation; 2) Class A: status-sharing; 3) Class B: Intent-Sharing; 4) Class C: Agreement-seeking; and 5) Class D prescriptive.

Table 1. SAE Levels of Vehicle Automation and Relationship with CDA Cooperation Classes (Source: adapted from SAE, 2020)

<table>
<tr><td colspan="2" rowspan="3"></td><td colspan="6">SAE Driving Automation Levels</td></tr>
<tr><td>No Automation</td><td colspan="2">Driving Automation System</td><td colspan="3">Automated Driving System (ADS)</td></tr>
<tr><td>Level 0
No Driving Automation</td><td>Level 1
Driver Assistance</td><td>Level 2
Partial Driving Automation</td><td>Level 3
Conditional Driving Automation</td><td>Level 4
High Driving Automation</td><td>Level 5
Full Driving Automation</td></tr>
<tr><td rowspan="3">CDA Cooperation Classes</td><td>No cooperative automation</td><td>(e.g., Signage</td><td colspan="2">Relies on driver to complete the Dynamic Driving Task (DDT) and to supervise feature performance in real-time</td><td colspan="3">Relies on Automated Driving System (ADS) to perform complete Dynamic Driving Task (DDT) under defined conditions (fallback condition performance varies between levels)</td></tr>
<tr><td>Class A: Status-sharing
Here I am and what I see</td><td>(e.g., Brake Lights, Traffic Signal)</td><td colspan="2">Limited cooperation: Human is driving and must supervise Cooperative Driving Automation (CDA) features (and may intervene at any time), and sensing capabilities may be limited compared to Cooperative-Automated Driving System (C-ADS)</td><td colspan="3">C-ADS has full authority to decide actions Improved C-ADS situational awareness beyond on-board sensing capabilities and increased awareness of C-ADS state by surrounding road users and road operators</td></tr>
<tr><td>Class B: Intent-sharing
This is what I plan to do</td><td>(e.g., Turn Signal, Merge)</td><td>Limited cooperation (only longitudinal OR lateral intent that may be overridden by human)</td><td>Limited cooperation (both longitudinal AND lateral intent that may be overridden by human)</td><td colspan="3">C-ADS has full authority to decide actions Improved C-ADS situational awareness through increased prediction reliability, and increased awareness of C-ADS plans by surrounding road users and road operators</td></tr>
</table>

	Class C: Agreement seeking *Let's do this together*	(e.g., Hand Signals, Merge)	N/A	N/A	C-ADS has full authority to decide actions Improved ability of C-ADS and transportation system to attain mutual goals by accepting or suggesting actions in coordination with surrounding road users and road operators
	Class D: Prescriptive *I will do as directed*	(e.g., Hand Signals, Lane Assignment by Officials)	N/A	N/A	C-ADS has full authority to decide actions, except for very specific circumstances in which it is designed to accept and adhere to a prescriptive communication

A Roadmap for Successful CAV Deployment

In 2014, the US DOT identified five major areas that needed further research in the period of 2015-2019 to facilitate CAV implementation, including enabling technologies, safety assurance, transportation system performance, testing and evaluation, and policy and planning (Barbaresso et al. 2014). Dokic et al. (2015) illustrated a roadmap for developing and deploying CAVs, which includes five entities, namely: technology, society, economics, human factors, and legal aspects. The linkages among those entities are (1) invention; (2) customer demand; (3) business model; (4) user needs; (5) product design; (6) norm; (7) regulation. Accelerators for the process of development and deployment of CAVs are (a) demonstration; (b) sandboxes; (c) co-creation; and (d) living labs. Technology has accelerator correlations with the other four entities. Whereas society is directly influenced by technology development, it has strong linkages with economics, human factors, and legal aspects. Remarkably, a linkage between legal and technological aspects is a critical path in this roadmap. This path closes the circle by translating requirements, needs, and expectations from society to technology creators through regulations.

Factors Affecting Adoption and Willingness to Pay for CAVs

This section briefly summarizes the key factors that will likely affect the success (or lack thereof) of light-duty passenger CAV deployment. It also discusses the prices that consumers are willing to pay for owning CAVs or using self-driving services.

Willingness to Pay and Adoption of Automated Vehicles

First, privacy sensitivity, time sensitivity, and interest in productive use of travel time contribute to the monetary value of travelling alone compared to riding with strangers. For example, Lavieri and Bhat (2019) found that 43% of surveyed participants found it not socially acceptable to switch to CAV technology, while 20% would consider reducing their household car ownership if they could access shared automated vehicles (SAVs), which might lead to an increase in empty vehicle travel for the pick-up and drop-off of passengers. Individuals are generally willing to travel longer distances when not in intense traffic congestion.

The number of studies that focus on understanding the factors affecting adoption and an individual’s willingness to pay for AV technologies has grown exponentially over the past few years. Each of these studies covers somewhat different objectives and targets different research questions focusing on either the general population or specific groups. As discussed by Gkartzonikas and Gkritza (2019), several common themes emerged from these studies, including the process and the likelihood of AV adoption, the perceptions of various aspect of AVs and individuals’ attitudes toward them, individual’s willingness to pay (WTP) for connectivity and various levels of automation (including the preferred modes of operation for AVs), and perceived benefits and major concerns regarding AV deployment. These studies can be differentiated by the type of research questions and pursued objectives, approach, methodologies, and target populations.

Becker and Axhausen (2017) and Gkartzonikas and Gkritza (2019) extensively reviewed AV-related studies and discussed their similarities and differences. Here, we summarize and update some of their findings. From a data collection perspective, most of the existing studies, and those discussed in this section, employed an online survey, while a handful of studies adopted different approaches. For example, Begg (2014) interviewed transportation experts in London, UK, to explore their opinions on how soon AVs would become a reality and found that about 30% of experts believe that AV Levels 4 and 5 will become operational in the UK by 2025 and 2040, respectively. Similarly, other studies conducted interviews to better understand the underlying reasons for the use of AVs, the factors limiting their use, and the functional forms for the utility and the parameters explaining the reported preferences and choices towards CAV adoption from stated preference studies (Daziano, Sarrias, and Leard 2017; Zmud, Sener, and Wagner 2016; Payre, Cestac, and Delhomme 2014). There are only a few studies conducted before-during-after a demonstration project or a field experiment (Piao et al. 2016; Xu et al. 2018).

Several studies investigate the frequency of use of various levels of connectivity and automation (Bansal, Kockelman, and Singh 2016; Bansal and Kockelman 2018; Nazari, Noruzoliaee, and Mohammadian 2018) or ask the respondents to rate the acceptance of AV technology (Payre, Cestac, and Delhomme 2014; Kyriakidis, Happee, and de Winter 2015; Zmud, Sener, and Wagner 2016). Other studies looked at future mode choice under various scenarios. These scenarios discussed the AV market penetration rate and business models for the diffusion of AVs with and without incentives (such as designated lanes for AVs) or pricing policies in place (Silberg et al. 2013; Krueger, Rashidi, and Rose 2016; Daziano, Sarrias, and Leard 2017; Haboucha, Ishaq, and Shiftan 2017; Shabanpour et al. 2018).

Overall, the results of these studies showed that the public is in general supportive of AV technology. However, public opinion varies substantially across different cities and countries. The public is in a wait-and-see position in terms of acceptance and use of self-driving vehicles, possibly due to a lack of knowledge and uncertainties about various characteristics of AVs. For example, Bansal, Kockelman, and Singh (2016) found that only 14% of Texans would buy or lease an AV as soon as it becomes available; that group is followed by 15% and 32% of Texans who reportedly would adopt AVs only after 10% and 50% of their friends/family adopt these technologies, respectively. Similarly, Zmud, Sener, and Wagner (2016) analyzed and classified early adopters as Enthusiasts or Pragmatists, with Laggards who were grouped as Rejecters or Traditionalists. The authors found that perceived safety benefits and data privacy can affect AV adoption. Wang and Akar (2019) analyzed the data from the 2015 and 2017 Puget Sound Regional Household Travel Studies and found that commuters surveyed in 2017 were less likely to be interested in shared AVs compared with their 2015 counterparts. Kelley, Lane, and DeCicco (2019) found, in their study in Michigan, about one-third of respondents were unwilling to make their non-commuting trips in the future by using personally-owned AVs or self-driving (shared) services (assuming privately-owned AVs or self-driving “robo-taxi” services were available). Kim, Circella, and Mokhtarian (2019) also found that some population segments are more favorable toward AV options. For example, the “AV over flight” group is more likely to replace some medium- and longer-distance trips that they would otherwise make by airplane with the use of AVs. In addition, they also point out that the way people prefer AVs over other modes is significantly influenced by the perception of the advantages and/or disadvantages of AVs technology.

How Adoption, Intention to Use and Willingness to Pay Vary?

Researchers have shown how the adoption and willingness to pay to own and/or use an AV vary significantly across different segments of the population. In this section, we summarize how various (1) socio-demographic attributes, (2) personal attitudes, (3) current travel behavior, and (4) built-environment variables can drive or hinder adoption and WTP for AVs. Some researchers have employed basic descriptive statistics to shows the association between AV acceptability and various exogenous factors, while others used more sophisticated statistical models to quantify this relationship while controlling for the impact of other exogenous factors. Table 2 presents a summary of findings from studies on AV adoption and WTP, using various methodologies and datasets.

Table 2. Research on Adoption and Willingness to Pay

Source	Methodology	Characteristics of the Sample	Findings
Silberg et al. 2013	*Type of study:* Focus group (of vehicle owners) *Type of analysis:* Descriptive analysis	N = 32, Context = US	Investigated factors affecting purchasing AVs; the median willingness to pay for the self-driving features of their vehicles can be as high as 4,500 USD.
Howard and Dai 2014	*Type of study:* Paper survey (after in-person meeting and watching a video clip) *Type of analyses:* Descriptive statistics, and logistic regression models	N = 107, Context = Berkeley Museum visitors, CA	75% of respondents found safety as the most attractive feature of AVs. Other important attributes are multi-tasking and convenience. Most concerning AV factors: Safety, liability, and lack of control
Payre, Cestac, and Delhomme 2014	*Type of study*: Semi-directive interview and online survey	N = 421, Context = France	The acceptance rate of AVs varies depending on the type of driving, such as usage of highway driving, presence of traffic congestion, and difficulty of finding parking.

Source	Methodology	Characteristics of the Sample	Findings
Kyriakidis, Happee, and de Winter 2015	*Type of study*: Online survey *Type of analysis*: Descriptive statistics	N = ~5,000. Context: 109 countries	22% participants did not want to pay for add-on AV driving technology while 5% of them would pay as much as $30,000, and 33% indicated fully automated driving feature would be highly enjoyable. Travel-related multitasking linearly increases by changes in the vehicle level of automation.
Krueger, Rashidi, and Rose 2016	*Type of survey*: Online survey	N = 435	Investigated the characteristics of the users of shared AV; 36% of respondents will shift their travel model to SAVs. Model results indicate that younger travelers and current carsharing users are more likely to prefer SAVs with ridesharing. If the respondent had used public transport for his/her recent trip, mode switching was less likely.
Piao et al. 2016	*Type of study*: Online survey/phone interviews During-after demonstration of automated bus project	N = 425, Context=La Rochelle, France	75% are interested in owning AVs and only 25% in using an SAV. Security found to be the most concerning factor during nighttime.
Zmud, Sener, and Wagner 2016	*Type of study*: Online survey and face-to-face interviews	N = 556 online survey, and 44 face-to-face interviews Context = Austin, TX	Discussed the impact of various factors on the adoption of AVs including personality and psychological measures, preventive driving factors, travel behaviors. Seven major factors were associated with likely adoption: safety; lower stress; mobility enabling for aging seniors; travel-related multi-tasking; trust of the technology; comparability to public transit experience; and attraction of new technology.

Source	Methodology	Characteristics of the Sample	Findings
Hohenberger, Spörrle, and Welpe 2016	*Type of study*: Online survey	N = 1,603 Context = Germany	Estimated the willingness to use AVs and identified potential differences among gender and age groups. This study finds that the differential effect of sex on anxiety toward CAVs becomes less significant as participants' ages increase.
Bansal, Kockelman, and Singh 2016	*Type of study*: Online survey *Type of analysis*: Bivariate ordered Probit model	N = 347 Context = Austin, TX	Looked at the factors affecting adoption, WTP, and adoption timing; at a cost of $5,000, 24% and 57% of respondents were willing to add partial and full automation, respectively, to their next vehicle purchase. Average WTP: can be as much as $3,300 for partial and $7,253 for full automation per vehicle.
Daziano, Sarrias, and Leard 2017	*Type of study*: Online survey (online opinion panel) *Type of analysis*: Semi-parametric discrete continuous mixture model	N = 1,260, Context = U.S.	WTP: On average, $3,500 and $4,900 for partial and full automation, respectively.
Haboucha, Ishaq, and Shiftan 2017	*Type of study*: Online survey (recruited via social media and LinkedIn) *Options*: No change, privately owned AV, and shared AV *Type of analysis*: Nested logit-kernel model	N = 721, Context = Israel and North American	Factors that increase adoption: - higher level of education - higher pro-AV and pro-technology attitudes - regular and less frequent trip pattern - high annual VMT

Source	Methodology	Characteristics of the Sample	Findings
Bansal and Kockelman 2018	*Type of study*: Online survey *Type of analyses*: Descriptive statistics of weighted sample. Interval regression and ordered Probit model of WTP and interest in connectivity and automation level 2-4	N = 1,088 Context = Texas, U.S.	WTP varies from \$127 for connectivity, \$2,910 for level 2 automation, \$4,607 for level 3, and \$7,589 for level 4.
Hulse, Xie, and Galea 2018	*Type of study*: Online survey *Type of analysis*: Descriptive statistics	N = 1,048 Context = UK residents	The perceived risks vary significantly across road users and types of cars; the factors affecting perceived safety are road-user type, gender, age, and tendency for risk-taking behavior.
Shabanpour et al. 2018	*Type of study*: Online survey SP survey (profile-case best-worst scaling) *Type of analysis*: an innovation diffusion model	N = 1,013 Context = Chicago metropolitan area	People are more sensitive to the purchase price of AVs, policy incentives (e.g., provision of exclusive lanes for AVs), and regulation (e.g., liability in case of accident), than to other cost components (e.g., fuel cost) or other limiting or encouraging factors (e.g., safety, energy efficiency),
Nazari, Noruzoliaee, and Mohammadian 2018	*Type of study*: Online survey *Type of analysis*: Multivariate ordered model	N = 2,726 (for daily travelers) and 1,755 (for commuters)	Jointly modeled the interest in private AVs vs. various SAVs; those who are more reliant on private car use are less likely to use SAVs. Those with limited ability to drive, including elderly people and people without driving licenses, are more likely to use shared AVs.

Source	Methodology	Characteristics of the Sample	Findings
Nordhoff et al. 2019	*Type of study*: Review paper *Type of analysis*: Descriptive statistics. A multi-level model of automated vehicle acceptance	N = 124 Context = worldwide studies	28 influencing factors are classified into seven categories: socio-demographics (28%), domain-specific system evaluation (22%), travel behavior (15%), personality (14%), moral-normative system evaluation (12%), exposure to AVs (6%), and symbolic-system evaluation (4%). The percentages represent the number of studies that investigated the factors.
Kelley, Lane, and DeCicco 2019	*Type of study*: Face-to-face interview *Type of analysis*: Descriptive statistics and logit model	N = 233 Context = Michigan, USA	36% of respondents were willing and 31% unwilling to use privately owned AVs or self-driving services for non-commuting trips.
Asgari and Jin 2019	*Type of study*: Online survey *Type of analysis*: Structural equation model	N = 1,198 Context = Florida and 10 US cities	WTP: \$652 for basic vehicles; \$1,192 for advanced features; \$1,542 for partial automation; and \$1,769 for fully automated alternatives.
Jing et al. 2019	*Type of study*: Literature review and online survey *Type of analysis*: Structural equation model	N = 906 Context = China	Top two influencing factors of choosing AV or SAVs are knowledge about AV technologies and perceived risk.
Zhang et al. 2019	*Type of study*: online survey *Type of analysis*: Structural equation model	N = 216 Context = China	Trust has a positive effect, while perceived risk has a negative effect on the acceptance of level 3 AVs.

Potential Impacts of CAV deployment

In this section, a comprehensive review of various studies on the potential effects of CAV deployment is discussed. We grouped CAV impacts into five large groups of effects, which each correspond to a subsection below: *transportation supply*, *transportation demand and travel behavior*, *vehicle miles traveled (VMT)*, *land use and urban design*, and *energy consumption and GHG emissions*.

In each subsection below, we summarize the findings of the expert workshop held at UC Davis in April 2019, and then we describe findings from the literature. Then, we expand the discussion on CAV impacts across different aspects, e.g., impacts on transportation supply, travel demand and behavioral choices.

Insights from the Expert Workshop

Changes in transportation capacity, travel times and corresponding activity patterns might be the results of a combination of factors. Travel time could increase, decrease, or remain unchanged depending on which factors prevail:

- Travel time could increase, if
  - formerly outside-the-trip activities are brought within-the-trip
  - free time is used for more travel
- Travel time could decrease, if
  - trips are efficiently chained
  - empty cars are given assigned tasks
  - the price of travel increases
  - new outside-the-trip activities are generated
- Travel time could remain constant, if
  - better/more/new within-the-trip activities are generated
  - formerly outside-the-trip activities are brought into within-the-trip and allow new outside-the-trip activities to be generated

CAVs, as a new transportation mode, share some features with ridehailing services and private vehicles. The shared features could lead to impacts similar to those that ridehailing has had on car ownership and transit use. If privately-owned CAVs prevail, the results are more likely to be similar to an increase in the use of current privately-owned vehicles.

Both short- and long-distance travel would be affected by CAV deployment in the following ways:

- Smaller airports might suffer the most and be shut down because of the higher attractiveness of longer trip distance by CAV
- Travel group size in long distance trips need to be reconsidered
- Dead-head trips might be worse due to empty-vehicle trips
- Scheduled intercity CAV services may be deployed
- Road congestion could increase market for air travel mode (counteracting some of the other AV impacts reducing demand for medium-distance air travel)

Willingness to share is another key point in understanding SAV adoption. Privacy sensitivity, time sensitivity, and interest in productive use of travel time contributes to the monetary value attributed to travelling alone versus with strangers. People are generally willing to travel longer distances when not exposed to traffic congestion.

Impacts on Transportation Supply

On the impacts of CAVs on transportation supply, as on the other groups of impacts addressed in the subsections below, the insights gained from the expert workshop are largely consistent with the findings from the reviewed literature. With sufficient penetration and connective ability, CAVs will likely improve traffic flow. Even automation alone, without connectivity, will likely improve traffic flow. From the system design perspective, safety and efficiency are two main concerns when designing an automated vehicle control system. The improved traffic flow and efficient traffic or vehicle control influence traffic capacity. However, this influence on road capacity by CAVs varies based on road types. With a certain penetration rate, increased highway capacity could be a direct benefit of vehicle automation (Shladover, Su, and Lu 2013). In addition, a more stable traffic flow can be achieved as fewer breakdowns would be expected. However, on connection roads (e.g., ramp) and local roads, where frequent pick-up and drop-off of passengers occur, the capacity may decrease because of more friction induced by merging and splitting of CAVs.

Impacts of CAV Deployment on Travel Demand and Behavioral Choices

This area of research has received a lot of attention from researchers who wanted to quantify the impacts of CAVs on the way people travel and engage in activities, and on the transportation system as a whole. Many hypothetical studies have been done. A noteworthy finding is that government (non-)intervention will play a significant role on the impact of CAVs on travel demand and choices, by influencing factors such as congestion and accessibility (Cohen and Cavoli 2019).

Travel Cost (Out-of-Pocket and Travel Time Cost)

Out-of-pocket travel cost is considered one of the most important variables in travel demand models. AVs can change both the fixed out-of-pocket costs of car ownership and the variable transportation costs, usually defined as a distance-based costs. In the short term, the initial purchase price for AVs is higher than that of a conventional vehicle, at least in the early stage of AV deployment. The additional equipment required for operation of CAVs (e.g., sensors, automated controls, wireless network, and navigation system) can increase the vehicle purchase prices and impose additional annual fees. Furthermore, AVs need to be checked on a regular basis to avoid any technological failures that could lead to serious crashes. Other additional costs may be imposed by additional in-vehicle security features, such as cameras and enforceable behavior equipment, as well as the cost of frequent interior cleaning and repair.

Fagnant and Kockelman (2015) describe how the price of AVs might be several times higher than that of standard conventional vehicles at the earliest stage; however, the additional price would gradually decrease to $3,000 or even lower with mass production and other technological advances. In another study, IHS Automative (2014) predicted that these necessary technologies would increase vehicle prices by an average of 20%. However, this additional cost can be offset to some extent by insurance and fuel cost savings (Stephens et al. 2016). Further, not all costs are usually featured in the daily decisions about traveling, as the marginal costs of the additional trip has a stronger impact on everyday travel choices, while acquisition costs are more relevant in affecting long-term decisions such as vehicle purchase and the overall level of vehicle ownership in a household.

Further, equipping vehicles with additional features (such as office equipment or bedroom facilities) enables more productive time of traveling. Current studies have a great interest in evaluating the potential impacts of AVs based on the assumption that individuals are more likely to use their time more efficiently in the future. These studies are more likely to have lower valuation of their (in-vehicle) travel time. For example, Gucwa (2014) estimated the changes in travel demand could be induced by changes in the value of travel time, using a San Francisco Bay Area activity-based travel demand model.

On the other hand, we expect that out-of-vehicle time may change due to automation. For example, AVs may reduce walk access/egress time if AVs are allowed to park by themselves after dropping off the passenger. In case of SAVs, a range of wait times may add up to out-of-vehicle time. Individual perceptions of out-of-vehicle time may also change as a result of AV deployment. In current travel demand models, the value of out-of-vehicle time is usually considered to be a multiple (twice or three) times of the value for in-vehicle time (National Cooperative Highway Research Program (NCHRP) 2012), reflecting a higher weight that travelers put on out-of-vehicle travel time. Few studies looked at the impact of AVs on perceived out-of-vehicle time. For example, Krueger, Rashidi, and Rose (2016) found that value of waiting time is a critical service attribute of SAV operation and can vary across different service types. In another study, Kolarova et al. (2018) found that waiting time for AVs was perceived less negatively than waiting time for public transportation. Malokin, Circella, and Mokhtarian (2019) also found that the ability to integrate productive activities into commuting trips will affect the value of travel time and mode choice, leading to a potential AV future with much increased use of drive-alone modes, at the expense of public transportation and rail modes in particular. More studies are required to better understand the impact of AVs on the perceived cost of the out-of-vehicle travel time.

Changes in Activity Patterns and Time Use

The possibility of conducting new activities while traveling may lead to a re-arrangement of daily activity patterns. But what kind of activities can be conducted in AVs and how can this lead to re-arrangement of other activities? To answer these questions, Pudāne et al. (2018) conducted five focus group studies (N=27). The authors concluded that desired AV on-board activities can be divided based on their priority and novelty. The on-board activities can be classified into four main groups: (I) new high-priority activities: including work, business, sleep, food preparation, self-cleaning, childcare and administration; (II) current high-priority activities, including work, study, eat and apply make-up; (III) current optional activities, including read news, check phone/internet, relax, make phone call etc.; and (IV) new optional activities, including exercise, play games, watch movies, etc. People who experience time pressure more often are more likely to conduct activities in groups I and II. For those with a short travel time, current optional activities (type III) might be viable, as they can finish those activities when using CAVs. New optional activities (type IV) would be a suitable choice for those who seek leisure activities, possibly for those who do not have a suitable time or place in their schedule to conduct these activities. The time saved by transferring some activities to travel-time can substantially change individual schedules and activity patterns via a “saved time” effect. The freed time can be spent on new activities. Or activities or travel might be extended, swapped, or reshuffled. Further, in the future, individuals may be able to dispatch an empty AV to perform some activities (e.g., running errands), which ultimately leads to more freed time and increases the “save time” effect. Pudāne et al. also found that almost all participants agreed that AVs offer major gains for non-regular and long-distance trips, indicating the potential changes that AVs will have on long-distance trips.

The changes in the activity patterns and travel demand were explored in a naturalistic experiment mimicking private ownership of an AV by offering study participants 60 hours of free chauffeur service (Harb et al. 2018). Although the results are based on analyses of very small number of households (N=13) and may not be generalizable to the entire population, they have been largely confirmed by an extension of this study to a larger sample and in another area of California (Harb et al., *forthcoming*). The results show a significant shift in individuals and household activity and trip patterns. For example, people took more vehicle trips, in particular during evenings, and trips tended to be longer in distance.

Increase in Mobility of Individuals with Physical and/ or Age-related Driving Limitations

CAVs can increase mobility for many groups of people, including those with physical or age-related limitations that prohibit them from driving, including those without drivers licenses. Brown, Gonder, and Repac (2014) estimated that new demand from underserved populations could increase VMT by as much as 40%, using the 2009 NHTS and the 2003 ‘‘Freedom of Travel” study. This upper bound is estimated by assuming that each population segment from age 16–85 begins to travel as much as the top decile or travelers. Wadud, MacKenzie, and Leiby (2016) estimated that vehicle automation could increase VMT by 2% to 10% due to increased travel by new user groups and the rates of driving among existing users. This driving rate was derived from the differences between the actual age-driving curve and the linear extrapolation of the driving patterns for people between the ages of 44-62 years old. The naturalistic experiment from Harb et al. (*forthcoming*) also showed that seniors and individuals with disability are among those more likely to benefit from CAV deployment through the increased ability to travel and the participation in additional activities that would otherwise be avoided if CAVs were not available.

Travel-related Choices

Many changes can happen to individual travel-related choices, due to efficiency gains in the system (mainly due to higher network capacity, and fewer crashes), decrease of in-vehicle value of travel time and other travel-related out-of-pocket costs (e.g., parking), and increases in travel by non-drivers and other underserved populations. There is a consensus among all studies that AVs can increase the demand for traveling with a car and potentially reduce the share of other alternatives such as public transportation and active modes. Additionally, the possibility of dispatching an empty vehicle to conduct some activities (e.g., running errands) or to drive around the block to find parking or give a ride to another member of the households can lead to more VMT. People are also likely to choose more distant locations for living, working, leisure activities, among others, resulting in a significant growth in the amount of time spent in the car.

Thus, various changes could derive, including modifications in mode choice, vehicle ownership, and trip distance.

Vehicle Miles Traveled

Several published studies have estimated how VMT could change with the future emergence of CAVs. However, the results depend on the data and assumptions used for modeling VMT, as most of these studies are based on modeling simulations rather than on the analysis of travel behavior data and the causes of changes in travel choices. Below we summarize the findings of some of these studies, the majority of which are based on simulation and the use of a trip-based or an activity-based model (ABM). Gucwa (2014) used the Metropolitan Transportation Commission (MTC) activity-based model to evaluate the impact of changes in roadway capacity and travel time cost in a future dominated by AVs. The author found that an increase in road capacity (by 100%) can increase VMT by 2%, while a decrease in the value of time by half can increase VMT by 13%. Rodier et al. (2019) used the same model and showed that new drivers can increase VMT by 2% in the San Francisco Bay area. To model the impacts of new drivers, Rodier et al. relaxed the driving restriction for individuals between the ages of 13-16 years old.

In another study, Childress et al. (2015) found that increasing the road capacity by 30% can increase VMT by 3.6% and reduce VHT by 2.1%. Coupling road capacity increase with a 35% reduction of value-of-time (VOT) can lead to a 5% increase in VMT and 2.1% decrease in VHT. Correia, Homem, and van Arem (2016) showed that changes in parking policy (especially pricing) can affect the share of empty kilometers to great degree. The authors showed that, in a scenario with paid parking everywhere, the share of empty kilometers can reach its maximum (87.4% of vehicle kilometers traveled). Similarly, in the scenario where free parking was available only at peripheral nodes, the share of empty kilometers would be 64.8% of total vehicle kilometers traveled. In another study, Kröger, Kuhnimhof, and Trommer (2018) found that overall VMT can increase even at lower AV penetration rates. The authors found that context plays an important role in changes that will be brought by AVs. For example, even though a higher penetration rate is expected in Germany compared to the US, the increase in VMT induced by AVs will not be higher in Germany than in the US.

Auld, Sokolov, and Stephens (2017) provided a potential feasible bound for the effects of AVs, and investigated how increased VMT can vary by changes in VOT, roadway capacity, and AV penetration rate, using an activity-based model for the Chicago metro areas and random assignment of travelers to CAV technology. The authors showed that the elasticity of VMT with respect to road capacity is 0.05. Similarly, a decrease in the value of travel time (VOTT) can lead to more VMT: depending on AV market penetration rate (20% vs. 75%) VMT can increase by 18%–59% for a 75% reduction in the value of travel time. For an AV penetration rate of 100%, combined with a VOTT reduction of 25 or 75%, the increase in VMT was 21% or 79%. In another study, Van den Berg and Verhoef (2016) investigated the impact of AVs using a dynamic equilibrium model of congestion to study three main elements: the increase in road capacity, the decrease in the VOT, and the resulting changes in the heterogeneity of VOT. They showed that AVs could have both positive and negative externalities through increases in capacity and decreases in the value of time, although net positive externalities seem more likely, according to their analysis. One of the key changes that may affect VMT in the future is the ability of AVs to reposition themselves. For example, in a case where individuals face higher parking price they may send the car back to home and ask it to pick them up later when they need it. This situation may happen if the cost of fuel is lower than the cost of parking. Using a multi-class trip-based model, Levin and Boyles found that a significant increase in VMT (about 271%) is expected, about half of which can be attributed to vehicle repositioning. A household may decide to reduce its number of vehicles and instead use AVs more efficiently to maintain the current level of mobility. Zhang, Guhathakurta, and Khalil (2018) found that although only 18% of households could experience this mobility benefit from vehicle reduction, the system impact would not be desirable from an environmental lens because these households would lead to a negative externality of a system-wide increase in VMT by 29.8%, as empty vehicles relocate to fulfill the demand of various household members.

Studies also looked at the impacts of different AV operational models on VMT. Under the synthetic setting where 1,715 SAVs are used to serve 56,324 trips, Fagnant and Kockelman (2018) showed that VMT can increase by 8.7%, due to empty miles traveled for passenger pick-up and drop-off. This amount can be reduced by half if pooled SAVs are allowed. The International Transport Forum (2015) developed an agent-based model to examine the impact of various types of SAVs (regular vs. pooled ridehailing) in Lisbon, Portugal, and found that the impact of SAVs can be moderated in presence of high-capacity transit service: SAVs can increase vehicle kilometers traveled (VKT) by 6% in the presence of high-capacity transit services, while this rate can reach as high as 90% in the absence of these services. In another study, Fagnant, Kockelman and Bansal (2015) replaced only 1.3% of the regional trips in Austin, TX with 1,977 SAVs and found that one SAV could be used in place of about nine conventional vehicles just in exchange for an average waiting time of one minute, however this can lead to an 8% increase in VMT, mainly due to empty vehicle driving for passengers' pick-up and relocation. Chen, Kockelman, and Hanna (2016) showed that the empty vehicle miles would increase if the SAVs were electric, as they would need to travel frequently to and from charging stations in-between serving passengers. They also noted that electric SAVs can generate 7.1%–14% empty travel miles for relocation required for both charging and passenger pickups (almost twice the upper bounds found in their previous studies).

Land Use, Location Choice, and Urban Design

Insights from the Expert Workshop

- Location choice will likely be different in an AV era than it is now. Integrated land-use and travel demand forecasting models can help to envision the potential changes, though limitations in operational models still limit the applicability of this approach.
- Among the potential changes in land use and travel patterns, parking is one of the most important factors. The behavior of driving, idling, and parking can be determined by relative utilities, which could be affected by parking cost, parking availability, activity duration, ownership, operating costs, infraction risk, linear vs. non-linear cost behaviors, etc.
- The changes in the value of travel time, as well as in parking availability and use, might modify the demand and supply in urban and non-urban areas, eventually modifying real-estate prices and creating opportunities for redevelopment of certain areas in cities.
- Long-term choices about residential location can be significantly affected by the lower friction of travel, eventually leading to more sparse settlements in low-density areas and increased suburbanization, if individuals are less sensitive to the travel distance to their trip destinations, altering the space (and price) vs. accessibility balance that is behind location choices.

CAVs are very likely to alter the built environment, including roadway design, urban form, and building design in far-reaching ways (Chapin et al. 2016). However, these impacts—positive or negative—are not fully predictable. The impact of AVs may be similar to those that occurred during the rise of the private automobiles in the early 20th century (Crute et al., 2018).

The impact of AVs on land use can expand to both macro (regional) and micro (local) spatial scales. For example, AVs will affect accessibility at the macro level, and parking, road design, and building landscapes at micro level. People can overcome some of the spatial and temporal constraints that they have to deal on a daily basis, as they can use their time more productively while traveling and dispatch AVs to conduct some activities for them (e.g., running errands, picking up children). As a result, the burden of spending time for traveling may decrease, leading to increases in travel distances for different purposes. Below we summarize a few studies that investigate the impact of AVs on land use, location choice and urban design.

From the macro level perspective, most studies expect AV to produce increased urban sprawl (e.g., Fagnant, and Kockelman 2015; Meyer et al. 2017; and Crute et al. 2018), possibly due to a reduction in the disutility of longer distance traveling. Environmentally conscious people may justify their travel and residential choices because AVs will probably be electric in the future (Duarte and Ratti, 2018). The impact of AVs can also extend to the urban form. Zakharenko (2016) found that one of the advantages of AVs is the reduced need for parking in dense areas, relieving/freeing downtown areas for other uses.

Hawkins and Nurul Habib (2019) reviewed various integrated land use and transportation models and argued that the introduction of AVs would bring revolutionary changes and require significant modifications to modeling frameworks (e.g., in the trip generation steps) and toolboxes. AVs are expected to significantly affect regional accessibility: Meyer et al. (2017) used a Swiss national transport model to simulate the impact of AVs on accessibility (which is measured based on travel times) of the Swiss municipalities. The authors ran three different scenarios and evaluated the impacts of AVs if (1) AVs can only operate in extra-urban situations (i.e., transition scenario); (2) operate fully in every situation, but only private ownership is allowed; and (3) operate fully in every situation and SAVs are allowed. As expected, AVs were found to substantially change accessibility in Switzerland; however, the impacts varied by region types: the strongest positive impact on accessibility was observed for well-connected exurban and rural municipalities. (The accessibility in these areas has been degraded by congestion on arterial roads and highways during peak hours.) In contrast, accessibility remained unchanged (if not degraded) in larger cities, because the relative increase in demand often exceeds the relative increase in road capacity since the travel demand is increased.

The enhanced regional accessibility might encourage people to use the cost that they can save on transportation for other purposes, including working, shopping, or recreating further away from home. Enhanced accessibility can also lead to shifts in individuals' residential location choices: Zhang, Guhathakurta (2018) and Kim et al. (2019) discussed how the massive deployment of SAVs might lead to more distance between residence and workplace, possibly due to the low cost and high convenience of SAVs. The authors discussed that some households would move to neighborhoods with more appealing property attributes and better schools. At the same time, compact development may become more appealing as the waiting time would be lowest in dense neighborhoods. Their simulation results showed that older population would relocate closer to central business district (CBD), while younger people are likely to move away from downtown areas (within 25 miles of CBD) (Zhang & Guhathakurta, 2018 and Kim et al., 2019).

As discussed by Milakis, van Arem, and van Wee (2017), enhanced accessibility may also affect the development of new centers. For example, suburban employment centers may change to a pole for peripheral growth, to serve demand for employment and parking structures. Further studies are required to understand the impact of AVs at macro/regional levels.

At the local scale, AVs can lead to changes in the number of required parking spots and the location of off- and on-street parking, streetscape, building landscape, and urban design. For example, the International Transport Forum (2015) showed that SAVs can completely remove the need for on-street parking and can lead to the removal of 80% of off-street parking spaces. In another study, Zhang et al. (2015) used an agent-based model to simulate the impacts of SAVs on urban parking demand, varying SAV fleet size, an individual's level of use of SAVs, waiting time, and empty vehicle cruising strategies in a hypothetical gridded-like city, ignoring the differences in networks attributes. The authors showed that 90% of parking demand can be eliminated even at a low market penetration rate (2%). To address these problems with the results of previous studies, Zhang and Guhathakurta (2017) simulated the operation of SAVs in

Atlanta, Georgia by using Atlanta's real parking inventory, the estimated origin-destination demand table from an Atlanta region activity-based model, and the detailed transportation networks with the corresponding link travel speed. The authors found that parking can be reduced by about 4.5% if 5% of trips within Atlanta are served by SAVs, indicating that each SAV can reduce the need for approximately 20 parking spaces.

Bahrami et al. (2021) studied the parking choices of private AVs in the downtown area. An equilibrium-based formulation was used to model the parking behavior based on the individual parking cost. They found that AVs are very likely to cause more congestion due to extensive cruising. However, an extra time-based congestion pricing can help mitigate the congestion in the area. Moreover, AVs along with other emerging transportation services provide unique opportunities for thinking about how streets are used—by whom, by what modes, and for access to what locations (Schlossberg et al, 2018). AVs offer the possibility of freeing up a significant amount of space for other public uses (e.g., sidewalk space) by reducing the number of travel lanes, reducing the amount of on-street parking, reducing the widths of some travel lanes and through deploying bi-directional lanes (Snyder, 2018).

Crute et al. (2018) discussed how the potential impacts of AVs on street and urban design can be extended (but not limited) to:

- Right-of-ways
- Access management
- The form and function of traffic signage and signalization
- Pedestrian and bicycle networks
- Design and location of parking
- Redevelopment opportunities in urban and suburban locales.

Table 21 in the appendix summarizes the findings from previous studies. This table provides a big picture of how CAV technologies will likely transform cities in several aspects including urban form, road capacity, lane design, parking demand, and infrastructure. In addition, most studies showed that lanes (both number and space) might be reduced, as AVs are able to operate in a narrower lane and potentially share opposite-direction lanes when available. The degree to which lane widths could be reduced will depend on the design of AVs. In another study, Ambühl, Ciari, and Menendez (2016) simulated the impacts of AVs on-road space and found that road space can be reduced by 11–12%. However, this required creating actual bottlenecks that reduce the efficiency gained in highway capacity. For more details about the discussion in street design under CAVs scenarios, please refer to Table 24 in the appendix.

Emission, Energy Consumption, and Environment

Insights from the Expert Workshop

To represent the potential changes in energy consumption and emissions of GHGs and criteria pollutants in a travel demand forecasting model, modelers need to identify and fully understand all the changes from these three main streams:

- Technological change
  - Level of automation
  - Market penetration
  - Fuel type and fuel economy
- Behavioral change
  - Mode choice
  - Activity pattern
  - Value of time
- Policy change
  - Business model
  - Private AV vs. shared AV
  - Carpooling

Depending on penetration rates, CAVs can reduce pollutant emissions and fuel consumption because automation and connectivity will lead to more efficient traffic flows, assuming the travel demand remains at the same level. Changes in emission and energy consumption are believed to be results from mixed aspects.

Pollution or emission mainly comes from three sources:

- Travel demand factors
- Vehicle factors
- Driving behavior factors

Wadud, MacKenzie and Leiby (2016) estimated emissions using the ASIF framework, i.e., **A**ctivity Level & Modal **S**hare & Energy **I**ntensity & **F**uel Carbon Content), which is a common method for measuring the impact of automation on emissions. The factors considered are activity level, modal share, energy intensity, and fuel carbon content. The authors classified all potential effects into three categories: energy intensity effects, travel demand effects, and fuel mix changes, as shown in Table 3.

Table 3. Categories of Changes in Emission and Energy Consumption

Categories	Effects
Energy intensity effects	Congestion mitigation
	Automated eco-driving
	Platooning
	Changing highway speeds
	Reduced emphasis on aspects of vehicle performance, e.g., acceleration
	Improved crash avoidance
	Right-sizing of vehicles
	Increased feature content (in-vehicle activity)
Travel demand effects	Increased travel from reduced cost of driver's time
	Increased travel due to new user groups
	Changes in mobility service models
Fuel mix changes	Unattended refueling at alternative fuel stations
	Vehicles refueling/recharging themselves frequently to bypass low volumetric energy density and high storage costs
	Good candidates for high-capital-cost advanced vehicles (especially for car-sharing)

Several studies proposed vehicle control strategies based on fuel-economy optimization. Eco-driving, one of the common vehicle control objectives, has also been developed to increase vehicle fuel efficiency and improve transportation system sustainability. In essence, eco-driving aims at finding optimal decisions for energy efficiency and emission intensity (Sivak and Schoettle, 2012). Barkenbus (2010) summarized three approaches to promote eco-driving: 1) accelerating moderately and avoiding sharp starts and stops; 2) maintaining a smooth driving pace; and 3) eliminating excessive idling. Ma et al. (2019) showed that a proposed eco-driving system could save more than 20% of fuel consumption.

In some studies, fuel-consumption based optimization was carried out to deal with vehicle control and driving tasks. For example, Wu, Zhao, and Ou (2011) designed a fuel-economy optimization system (FEOS). The authors found that the drivers with FEOS consumed significantly less fuel than those without FEOS in all acceleration conditions (22–31% overall gas savings) and the majority of deceleration conditions (12–26% overall gas savings). In another study, Wang et al. (2015) proposed a nonlinear model predictive control (MPC) approach for emission mitigation via longitudinal control of intelligent vehicles in a congested platoon. This study showed that an instantaneous emission optimization software application significantly reduces emissions without increasing travel time. In addition, emission mitigation and traffic stabilization increase with the penetration rate of intelligent vehicles, as this higher penetration allows for larger vehicle platoons. Also, note that when the market penetration rate reached 70%, the emission reduction effect is almost as good as that achieved under 100% penetration rate. Kamalanathsharma and Rakha (2016) proposed a trajectory optimization to minimize the vehicle's fuel consumption level in the vicinity of signalized intersections. Modeling of the trajectory optimization in 30 top-sold vehicles in the United States demonstrated fuel savings within the vicinity of signalized intersections in the range of 5 to 30%. Ala, Yang, and Rakha (2016) developed an eco-CACC system and proved that energy and environmental benefits increase with penetration rate of CACC vehicles and overall fuel consumption savings can be as high as 19% with a 100% penetration rate. However, the algorithm may produce higher fuel consumption levels with penetration rates less than 30%. Choi and Bae (2013) believed that the use of connected vehicles can reduce CO2 emissions. Simulation results showed that for lane changing from a faster to a slower lane, the reduction in CO2 emissions of the connected vehicle was in the range 4770–54,291 g/km in comparison to the manual vehicle. For lane changing from a slower to a faster lane, the CO2 reductions were in the range 40,788–91,884 g/km. Similarly, Elham et al. (2020) and Jaller et. al. (2020) found that CAV-enabled mechanisms such as eco-driving can lead to positive environmental impacts, e.g., over 30% reduction in CO2 emission reduction.

Several other studies discussed the potential impact of CAVs on GHG emissions and fuel consumption based on macroscopic methods. For example, Fagnant and Kockelman (2014) evaluated the energy use and emission outcomes from the deployment of SAVs, assuming the same trip patterns and demand. The authors found that volatile organic compounds (VOC) and carbon monoxide (CO) emissions would significantly decrease if SAVs were constantly in operation and had fewer vehicle starts. Similarly, PM10 would decrease but by less. Liu et al. (2017) estimated the energy consumption and emission of SAVs for different fare points, including both macroscopic (e.g., life cycle, parking, vehicle starts, traffic control) and microscopic estimates (i.e., those related to driving cycle). The results showed that the total energy savings for SAVs from conventional cars is 22.4% (Table 4). Similarly, emissions would decrease by 16.8% to 42.7% (Liu et al. 2017). In addition, Chester and Horvath's (2009) life-cycle inventory estimates were used to evaluate the SAV system's emissions and energy consumptions. An investigation of life-cycle inventories and emission inventories showed that the overall emission saving is promising.

Table 4. Fuel Consumption and GHG Emissions if Average SAVs Replaced Conventional Cars (Source: Liu et al. 2017)

Sustainability Elements	Fuel consumption (%)	GHG (%)	PM (%)	CO (%)	NOx (%)	SO2 (%)
Macroscopic estimates (life cycle based)	-12	-5.6	-6.5	-34	-18	-19
Microscopic estimates (driving cycle based)	-11.8	-11.9	-19.1	-13.2	-15.5	-6.6
Total saving (distance based)	-22.4	-16.8	-24.3	-42.7	-30.7	-24.3

Note: Greenhouse gas (GHG), Particulate Matter (PM), Carbon Monoxide (CO), Oxides of Nitrogen (NOx), Sulfur Dioxide (SO2)

Further, to more precisely estimate of effects of SAVs on energy consumption and emissions, other factors directly affected by SAVs should be considered, including: VMT, parking search activities, reduction of delays associated with crashes, eco-driving/eco-routing, and platooning. Of note, all of the discussed potential changes in energy consumption and GHG emissions depend on model assumptions and the scale and type of each model. For example, the changes in emissions and energy indicators were significantly higher in a that used a network-based model (e.g., Fagnant, Kockelman, and Bansal (2015)) rather than a grid-based model (Fagnant and Kockelman (2014)).

Apart from the first-order effects directly associated with energy consumption (e.g., energy intensity and travel demand), life-cycle effects also play important roles in predicting environmental implications. For example, Wadud, MacKenzie and Leiby (2016) found that AVs could operate with significantly lower embodied energy. AVs can operate on narrower lanes with more advanced vehicle control technology, i.e., a lane width from 2.7 m (9') to 3.6 m (12') can be reduced to 2.7 m (9') for AV operation. This can reduce the footprint of the U.S. road system by 16%. Besides, with higher lane capacity, the number of lanes required can be decreased. Thus, 5% of the footprint can be saved by reducing lane-kilometers. Combining the road construction and vehicle operation energy use, the life-cycle energy use of the road system can be reduced by 2-4%.

Equity Impacts of CAV Deployment

AVs are believed to have the great potential to improve mobility and accessibility for children, elderly people, and individuals with physical disabilities or other impairments to driving (Adnan et al., 2018; Harb et al., 2018, *forthcoming*). Many studies have explored equity issues associated with emerging innovative technologies, such as AVs. This field of research also examines how disadvantaged and underserved populations fit into the big picture of future transportation planning, and in particular new transportation systems and infrastructure that are dedicated to automatic, electric vehicles and shared mobility. The studies in this area emphasize the importance of equitable planning in transportation infrastructure development, including during this new era of transportation.

Lin (2016) raised an important consideration on how CAVs benefit society as a whole instead of specific population subgroups. Among other aspects, in his book, he discussed how the potential reduction or shifting of parking-space caused by CAVs may lead to negative effects on fresh suburbanization. Cohen et al. (2017) urged that local governments should not only deploy CAV technologies quickly but also should put more weight on those who really need this new technology, in order to harvest the benefits that this technology could bring to the individuals that are currently more limited in their access to mobility. Bills (2020) compared current methodologies to access potential impacts of CAVs on disadvantaged communities. In this report, he argued that current studies assessing equity implications associated with travel behavior applied traditional four-step travel demand models, which cannot handle individual-level measures of equity. Noah (2014) focused on the ethical challenge in decision making when facing possible crashes. Equity implications of CAV deployment are clearly important. Accordingly, Alexander et al., 2021 discussed how incentive programs for shared CAV projects targeted at elderly and/or physically-impaired individuals can reduce the barriers of CAV deployment and efficiently allocate technology recourses.

Modeling CAV Deployment

We open this section with a brief summary of findings that emerged from the discussion in the expert workshop that was organized as part of this project. The experts' suggestions on how to incorporate CAV deployment into models helps us identify assumptions and parameters for the modeling part of the project.

Insights from the Expert Workshop

Metropolitan planning organizations (MPOs) and planning consultants have begun to add components to models to account for recent changes in transportation, including new modes such as ridesharing/ridehailing and those that will emerge with CAVs. For example, the Sacramento Area Council of Governments (SACOG) modified the DaySim model under the SACSIM framework to deal with AV/ridehailing options, as follows:

- Auto ownership model
  - Different adoption rates for different households—higher for younger, higher-income households with longer commute distances
  - Households with AVs are less likely to own multiple vehicles
  - Generally, less private vehicle ownership because of shared vehicles
- Mode choice model
  - Higher usage rate for trips originating from denser areas
  - Higher usage for younger households
  - Mode choice is affected by the availability of shared vehicles

SACOG found fewer vehicles will be on the road and lower emissions will be generated if electrification, automation, and sharing become a reality in the future. Private car ownership and the number of privately-owned cars per household could decrease, assuming CAVs are deployed as SAVs. Paid ridesharing mobility, with an up to 70% person trip mode share, could become a dominant choice. Also, with carsharing and ridesharing/ridehailing, people would be less likely to drive alone (10% in person trip mode share), while transit trips would likely account for a mode share as low as 0.2%.

In the Atlanta Regional Commission (ARC) modeling framework, various combinations of capacity increase (50%), decrease in travel time disutility (50%), reduction in vehicle operating cost (70%), and changes in parking cost have been considered. They project daily vehicle trips could increase by up to 2.6% and average trip length would slightly increase (from 10 miles in the base case to 12 miles). In addition, daily VHT would change by -8.7% to +12.2%. Most importantly, ARC envisions an increase in daily VMT up to 23.9%.

Fehr and Peers tested the range of potential changes, assuming private AV ownership and 50% shared AVs assumptions. They used various models, including trip-based models, activity-based models, and limited sensitivity models. Their work showed how results could vary based on the modeling framework. Their forecasts show that the increases in VMT could range from about 5% to 65% with private AVs and from about 0% to 43% with 50% shared AVs. Also, the average vehicle trip length could either increase or decrease, with the majority of model applications pointing to an overall increase. Transit trips in total, bus transit trips, and rail transit trips in most models are expected to decrease under both assumptions.

As discussed in the previous sections, CAV deployment can affect both transportation demand and supply in different ways. Thus, it is important to account for the effect of CAVs on the future of transportation in demand forecasting and planning tools. Cottam (2018) reported that in 2017 more than 60% of the long-range transportation plans in large urban areas included discussion of CAVs; however, the report concluded that the many uncertainties associated with CAV deployment were not explicitly discussed or accounted for in long-range plans. Furthermore, potential policy and planning implications to shape a future dominated by CAVs were absent. On the other hand, the difficulty in estimating the changes in both supply and demand propagate through different parts of the planning process. The author further discussed that the CAV pilot program is crucial to reducing uncertainties about future transportation supply and demand and to calibrating and validating the model parameters. For additional details on the uncertainties specific to CAVs and how they propagate in different parts of the planning process, please refer to Table 23 in the Appendix.

The potential factors affecting travel demand and behavior are variable and uncertain. As discussed in the National Cooperative Highway Research Program (NCHRP) Report 896 (Zmud et al. 2018), several approaches can be used to reduce these uncertainties, such as scenario planning that provides information on how near-term policies might shape and be shaped by those futures, and assumption-based planning that makes assumptions about the future due to the presence of uncertainties. The former approach is limited, as it only considers a few scenarios. Kuhr et al. (2017) selected the key factors that are expected to have the most influence on CAV planning and discussed how these factors should be either modeled explicitly or clearly captured by simplified modeling assumptions. Table 21 (in Appendix A) summarizes the behavioral and technological factors to be considered in the modeling of CAVs impacts.

Zmud et al. (2018) classified the potential impacts of CAVs into five major areas, including the impacts associated with the changes in the cost of technology and future transportation services, safety, operation/business models, electrification, and personal mobility and convenience. Given the limitations of existing modeling tools, particularly those appropriate for regional-level analysis, significant simplifications have been employed to represent desired assumptions in the early stages of modeling CAVs. Soteropoulos, Berger, and Ciari (2019) provided a comprehensive review of several research projects and papers on modeling the impact of AVs on travel behavior and land use between 2013 and 2018. The authors confirmed that there are several simplifications and modeling assumptions made to assess the potential impact of AVs, including:

- The share of trips, particularly in modeling SAVs (e.g., splitting trips by modes using a rule-based approach, or incorporating assumptions on SAVs such as pricing structure in the mode choice model)

- How SAVs are assigned and relocated to serve the demand (e.g., based on first-come-first-served or demand-supply balancing) and the acceptable waiting time thresholds
- Use of simplified network such as gridded-like city
- Reduction of value of travel time
- Increase in road capacity
- The operation and parking cost of AVs (e.g., empty miles)
- Changes in the mobility of people with age or physically related limitations that prohibit them from driving

Table 22 (in Appendix) summarizes several current modeling studies, the assumptions used in scenario developments, and the result of each scenario. As shown in this table, the results are largely dependent on model assumptions and framework (i.e., types of models). The changes are assumed by analysts and may not be applicable in the future when compared to actual CAV use and related behavioral changes. Soteropoulos, Berger, and Ciari (2019) concluded that the impacts assessed by the models appear to be particularly sensitive to a reduction in the value of time as compared to increases in road capacity or operating costs. Moreover, many of the model simplifications could lead to overestimations in the reduction of the number of vehicles or parking spaces due to the emergence of SAVs. The authors showed that the context in which these services are provided also matters. For example, trip durations and distances vary significantly in different cities and neighborhood types.

Behavioral data also indicates that the changes in the following would be limited: trip/tour frequency, length, mode, route, time of day, and other CAV characteristics. Moreover, the results from stated preference surveys may involve a large number of uncertainties in the estimates due to the hypothetical bias. This is true for the conditions affecting market penetration and consumer adoption rate, which are expected to depend on the cost of technology, the business/operation model, actual experience and comfort, roadway and parking infrastructure, and policy regulations (Zmud et al. 2018). NCHRP Report 896 provides a high-level guideline on the methods to account for CAVs in both 4-step (trip-based) models and activity-based models.

Table 24 and Table 25 (in the Appendix) summarize the changes required in the 4-step and activity-based models, respectively. To forecast a future dominated by CAVs, the authors further discussed current knowledge on the impacts that CAVs have on aggregate speed–flow relationships. The use of a simulations that can represent detailed differences in the ways that human drivers and AVs will navigate the road networks may be the most promising approach for learning how CAVs will influence traffic capacity and congestion levels. The NCHRP report shows the benefit of an integration of an activity-based model with dynamic traffic assignment (in place of more traditional static equilibrium assignment methods) for the evaluation of CAV impacts.

Methodology

As the literature presented in the previous section discusses, CAVs are expected to bring many changes to current transportation systems, including in transportation supply, travel demand, and land use. Given the multiple sources of uncertainties and possibilities, we aimed to quantify the impacts using travel demand forecasting tools.

In the second part of this report, we present the methodology that we apply to forecast the potential ranges of impacts of CAV deployment using the CSTDM framework for the State of California. We then present a list of scenarios of future travel demand considering factors and parameters rooted in the literature. Using the travel demand and trip related results from the modified CSTDM model, we calculated the criteria pollutants and greenhouse gas emissions using the emission factors from the EMFAC and Vision models.

We compare the scenarios with the baseline scenario for 2050 created by the California Department of Transportation (Caltrans) and draw some final conclusions on the potential impacts of CAVs on mode share, VMT, emission, and other aspects of future society, and the implications that these will have for planning processes and future policy making.

Overview of the CSTDM

In this section, we describe the activity-based model framework and the EMFAC and Vision models that we used to forecast the impacts of CAV deployment. We used the California Statewide Travel Demand Model Version 3.0 (CSTDM V3.0). The CSTDM V3.0, a scenario- and activity-based travel demand model that forecasts all personal travel made by every California resident and all commercial vehicle travel for a typical weekday in fall/spring in a certain target year. Each forecasting year is coded as one specific scenario, and the required model input includes the scenario-specific files for the corresponding future target year.

In the CSTDM framework, the entire state of California is divided into 5,454 transportation analysis zones (TAZs) for internal travel and 53 external zones to represent entry/exit points on the state boundary. The model considers four time periods:

1) AM peak from 6 am to 10 am;
2) Midday from 10 am to 3 pm;
3) PM peak from 3 pm to 7 pm; and
4) Off-peak from 7 pm to midnight and from 12 am to 6 am of the following day.

The CSTDM V3.0 is an update based on the CSTDM V2.0, where the majority of model components for passenger travel remain unchanged. The CSTDM V2.0 has five major demand models:

1. A Short Distance Personal Travel Model (for intra-California trips) (SDPTM);
2. A Long Distance Personal Travel Model (for intra-California trips) (LDPTM);
3. A Short Distance Commercial Vehicle Model (for intra-California trips) (SDCVM);
4. A Long Distance Commercial Vehicle Model (for intra-California trips) (LDCVM); and

5. An External Vehicle Trip Model (ETM) (for trips with an origin and/or destination outside California).

The freight demand models, SDCVM and LDCVM, from version 2.0 have been replaced by the newer California Statewide Freight Forecasting Model (CSFFM) in version 3.0. The structure of passenger models and external trip model are kept from version 2.0. Personal trips with a distance shorter than 100 miles are forecasted by SDPTM, and trips longer than 100 miles are forecasted by LDPTM. The SDPTM and LDPTM are calibrated to match the observed travel patterns from 2010-2012 California Household Travel Survey (2012 CHTS). The forecasting years conducted by Caltrans range from 2015 towards 2050.

The CSTDM V3.0 model uses input from the zone system, networks, population, employment, and zonal properties. Then the major model components—SDPTM, LDPTM, CSFFM, and ETM—compute lists of trip tables by mode at the zonal level, which are then processed by the assignment and skims modules. The outputs of the CSTDM V3.0 include a trip table, loaded network, travel cost, and several summary statistics. The framework is shown in Figure 1 below.

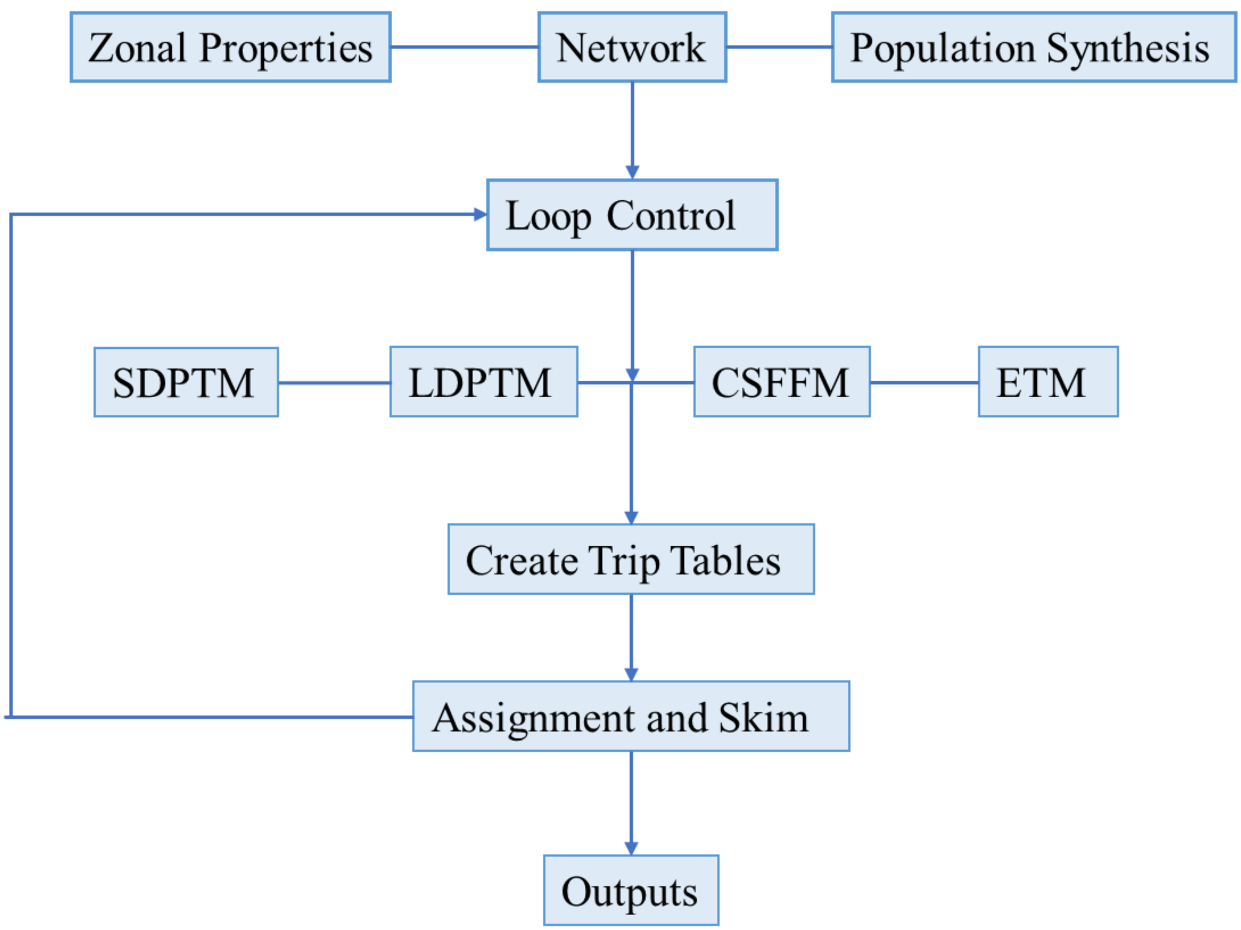

Figure 1. The CSTDM V3.0 Modeling Framework

The SDPTM component considers eight travel modes:

1. SOV (single-occupant auto)
2. HOV2 (high-occupant auto with two persons in the vehicle)
3. HOV3+ (high-occupant auto with three or more persons in the vehicle)
4. Walk access local transit
5. Drive access local transit
6. Walk
7. Bicycle
8. School Bus

SDPTM is designed to follow the procedure as:

1. Long term decision (Driver's license, Household car ownership, Work/School location)
2. Day patterns (including number, purpose, time of tours, and stops on tours conditioned by household)
3. Primary destination choice
4. Tour mode choice (logit models)
5. Secondary destination (the destination of all secondary stops on tour)
6. Trip mode (logit models)

The LDPTM component considers five travel modes:

1. SOV
2. HOV2
3. HOV 3+
4. Rail (conventional rail and optional high-speed rail)
5. Air

LDPTM is designed to follow the procedure as:

1. Travel choice model (multinomial logit model)
2. Party formation model (including base party size, primary traveler model, solo traveler model, and group size model)
3. Tour property model (including tour duration model, travel day status model, and time of travel model)
4. Destination choice model (5 logit models for different purposes)
5. Mode choice model, including main mode choice models and access/egress mode choice models (based on California High-Speed Rail Authority high-speed rail model)

As passenger travel is the focus of this project, we emphasized the related model components from the description above. However, the commercial vehicle models in the CSTDM also need to be included and run, since commercial trips contribute to roadway congestion, and realistic modeling of future travel scenarios should consider both passenger and freight contribution to road flows.

We ran all final scenario analyses using the CSTDM Version 3.0, which became available halfway through the development of this project. The research team initially had access to the CSTDM Version 2.0, which was installed on a local machine in a UC Davis research lab, as part of the activities for this project. Installing the local copy of the model required finetuning the model and computer settings, a process that can be rather tedious and time consuming. This process was performed with the support from Caltrans and its transportation modeling consultants. At the time the research activities were carried out, the CSTDM Version 2.0 did not include a complete scenario for future transportation in California until 2050. Accordingly, the research team performed analysis for the scenario year 2040 in the initial stages of the research. Following the release of the CSTDM Version 3.0, Caltrans and its consultants were no longer able to provide assistance and support for the use of Version 2.0, and a decision to transition to the CSTDM Version 3.0 was made. The CSTDM V3.0 includes several upgrades, including an updated freight component in the statewide travel demand model, which replaced the corresponding component in Version 2.0 (that was actually inherited from the original Version 1.0). The CSTDM Version 3.0 includes future scenarios until year 2050.

Access to the CSTDM V3.0 was initially made somewhat difficult by the social distancing restrictions during the COVID-19 pandemic in the first quarters of 2020. However, also as an effect of the new regulations from Caltrans that do not allow for third-party researchers to obtain a local copy of the model now that remote access has been made available, a work-around solution was designed through gaining access to the Version 3.0 of the model through a remote desktop connection to a workstation owned and operated by Caltrans. All final scenario runs in this project were performed remotely with the CSTDM Version 3.0 on the Caltrans workstation. As documentation to the newer CSTDM Version 3.0 is still rather limited, the research team worked in collaboration with the Caltrans modeling staff, and their consultants at Cambridge Systematics, to adjust the required settings and parameters in the model (in particular for components that were modified in the newer Version 3.0 of the model), and to troubleshoot several error messages and discrepancies in the scenario results that were obtained. The research team also received assistance from a modeler (now at Fehr & Peers) that previously worked on the development of the freight component of the CSTDM Version 3.0. These consultants helped compare results and troubleshoot some discrepancies in the model output that were obtained in some of the model runs. This entire process proved to be much more labor-intensive and time-consuming than initially forecasted. In fact, not all inconsistencies in some of the scenario model outputs (in particular on the freight side) could be worked out and reconciled by the time of writing this report.

The scenarios were developed prior to the COVID-19 pandemic, and the model coefficients were calibrated and validated based on a regular year before the interruption of COVID-19. Thus, the results of the application of CSTDM in this project do not take into consideration the short- or long-term impacts of the pandemic.

Expected Impacts and Corresponding Model Components

CAVs are very likely to affect trip generation, including people's long-term decisions (such as vehicle ownership, residential locations, etc.) and short-term decisions (such as destination choice, mode choice, etc.). In this section, we present the modifications to the CSTDM V3.0 activity-based model framework that were introduced to incorporate the impacts of CAVs.

Before we dig into the implementation details, it is worth mentioning some factors that are held constant in the modeling framework for this study. For example, the vehicle ownership component remains unchanged in our implementation. This is simply because there is only one vehicle type for automobiles within the CSTDM, and we cannot differentiate human-driven vehicles and CAVs under this setup. Similarly, we do not implicitly add a shared-use SAV component. Because vehicle sharing and ride sharing often require a central controller and agent-based simulation, our activity-based approach cannot handle the direct modeling of SAVs within the CSTDM. Accordingly, we treat the SAV component as a part of post-processing work.

Other examples of the factors held constant in our modification in the CSTDM are residential location and land use, carried out in the population synthesizer and zonal property inputs in the model. These factors largely rely on urban planning strategy and policy shift for CAVs for the future. Currently, evidence in the literature and practices in the real world can hardly serve as strong evidence for us to project future land use impacts of CAVs. In the sections below, we list the expected impacts of privately owned and shared use CAVs and our implementation with corresponding model components using the CSTDM V3.0.

Driver's License

CAVs are expected to provide better mobility and reduce travel inconveniences for the general population, and these would bring changes in their long-term decision making. The population segment that is not well served by human-driven vehicles should have more opportunities to travel, especially for the young, elderly, and those with physical limitations.

It is difficult to directly modify the household vehicle ownership module of the CSTDM, since determining the cost of buying an AV is still a challenge for both the industry and public sectors. Thus, we choose to change the driver's license module, which is an immediate upstream to the vehicle ownership. An individual must obtain a driver's license to be qualified to own a vehicle.

We relax the age limitation of obtaining a driver's license to greater or equal to 12 years old. Instead of using a binary logit model to determine whether an individual has a driver's license, we allow anyone 12 years-old or older to have a driver's license. This would lead to more driver's licenses and higher vehicle ownership in general even though people from 12 to the current driver license age typically do not have an income and may not be direct purchasers of vehicles. This is used to approximate that CAV would enable more accessibility to vehicles for teenagers, senior population, and people with physical constraints to drive a human-driven vehicle. We assume that in the future all individuals age 12+ are allowed to ride in a CAV, even when traveling alone.

Value of Time (VOT)

The availability of CAVs would bring more convenience for traveling and enable various in-vehicle activities. More in-vehicle activities can be conducted in CAVs than in human-driven vehicles, such as working, sleeping, and consuming entertainment. The convenience of in-vehicle activities within CAVs would lower people hesitancy to travel or make people less resistant to traveling by car. Also, CAVs would then probably make people more tolerant of longer in-vehicle travel time. The original coefficients of VOT in the CSTDM are estimated for human-driven vehicles, which is not suitable for AVs. Thus, we modified the value of travel time to model the change in generalizing cost for mode choice and destination choice. The change in the utility function can be passed down to long-term decisions in the next model, since the travel cost and disutility would differ due a modified cost structure.

Parking Cost

In the CSTDM, parking costs are included in the zonal property database i.e., zonal properties associated with each transportation analysis zone in California. Parking cost consists of base cost, time-based cost, and additional cost. Base parking cost represents 1/20 of parking purchased monthly, where this parameter is used in the STPTM for work and school purposes, since parking is typically purchased on a long-term basis. A regression model is developed in the CSTDM to calculate daily and hourly costs based on the base price, which is used in the SDPTM for other tour purposes. The daily parking cost is also used in the LDPTM. The additional cost is used to represent the paid parking for visitors.

Parking cost would be very different with the availability of CAVs, in terms of both cost structure and magnitude. For example, a CAV can wander around on its own after dropping off the passenger and then come back to pick up the passenger in the same or different location. This behavior would lead to no parking demand generated at the destination. Or the traveler can let the vehicle self-park at a farther location at a potentially lower parking cost. Apart from parking choice, the land use and curbside management would also be different in the CAV era. Local policymakers would likely consider the disruption caused by frequent pick-ups and drop-offs and make corresponding regulations and policy changes.

Vehicle Operating Cost

Operating costs of CAVs would be different due to automated driving technologies, electrification, and other cost components that are difficult to measure directly. In the CSTDM, the operating cost ($/mile) consists of fuel and non-fuel operating components. The fuel component cost is largely based on the motor gasoline price and fuel economy (mpg) forecast by the U.S. Energy Information Administration (EIA). The non-fuel component is adapted from the California High-Speed Rail Ridership and Revenue model (calibrated in 2006-2007), and it is assumed to be 67% of the fuel component operating cost. The non-fuel component is kept as a fixed constant ($0.09/mile) throughout the projected years, based on the assumption that non-fuel operating costs are less volatile than fuel prices.

To account for the impacts of CAVs, we change the projected auto operating cost provided by Caltrans. This consideration includes the assumptions of changes in electrification, vehicle type, and road user charges. Electrification would likely decrease the operating cost since an increasing number of vehicles (including CAVs) would be electrified, and thus fuel components would be directly reduced. Also, operating cost is a good surrogate for congestion pricing and road user charges, meaning extra cost might be imposed when traveling. Thus, in this project, we implement pricing strategies by adjusting the operating cost component in the CSTDM.

Highway Network

One of the most direct impacts of automation and vehicle technology will be the changes in traffic flow in terms of throughput, stability, safety, and so on. However, these advances cannot be directly implemented under the activity-based framework since the travel decision-making process is not directly affected by vehicle technologies. However, vehicle technology and traffic influence travel choices in a higher-order manner, mainly through the change of generalized cost and traffic network operations.

With the automation and connectivity features, traffic flow on the highway would be more stable and yield higher throughput. If incidents and congestion are reduced, vehicle travel can be faster, safer, and more reliable. This all leads to the increased level of service of transportation networks. We choose to model changes in vehicle technology and traffic supply by modifying the capacity of the highway network.

Different changes are implemented based on the corresponding facility type, to quantify impacts for different driving environments. There are seven facility types in the CSTDM for highway networks, including freeway, expressway, major arterial, minor arterial, collector, ramp, and centroid connector (dummy link). We assume the capacity would decrease on ramps due to frequent vehicle-to-vehicle interaction. And capacity is assumed to increase everywhere else except on dummy links.

Emissions

The GHG and criteria pollutants emissions are calculated based on EMFAC and Vision emission factors. The emission factors depend on region, fuel type and vehicle categories, consistent with EMFAC 2017 fuel types and vehicle categories. We target four criteria pollutants in this study: Carbon dioxide (CO_2), Nitrogen Oxides (NOx), Particulate Matter 2.5 (PM2.5) and Reactive Organic Gases (ROG). The processing method is summarized in Figure 2. Following the recommendations from CARB, emission factors from the Vision scenario model are used for passenger vehicles. The Vision scenario model is a scenario planning tool that incorporates EMFAC 2017 emission rates and scenario-specific forecasted vehicle activities to assess emission and energy impact of future technologies and policies. The emission factors used in the non-ZEV scenarios and in the ZEV scenario in this study are consistent with the Vision inventories supporting CARB's 2020 Mobile Source Strategy (MSS), respectively, for the business-as-usual (BAU) scenario and the MSS main scenario[3]. The MSS main scenario reflects achieving 100% new sales of passenger vehicles being ZEV or PHEV by 2035. In MSS BAU case, eVMT contributes 11% to the total VMT in year 2050. In MSS main case, eVMT contributes 91%

---

[3] Vision Data and Results for LDV WTW emissions (November 2020) https://ww2.arb.ca.gov/sites/default/files/2020-11/LDV_MSS_supporting_materials_ISAS_Nov2020.xlsx

to the total VMT in year 2050. The emission factors are provided at county level. EMFAC emission factors for trucks are retrieved from the EMFAC 2017 Web Database (v1.0.2).[4]

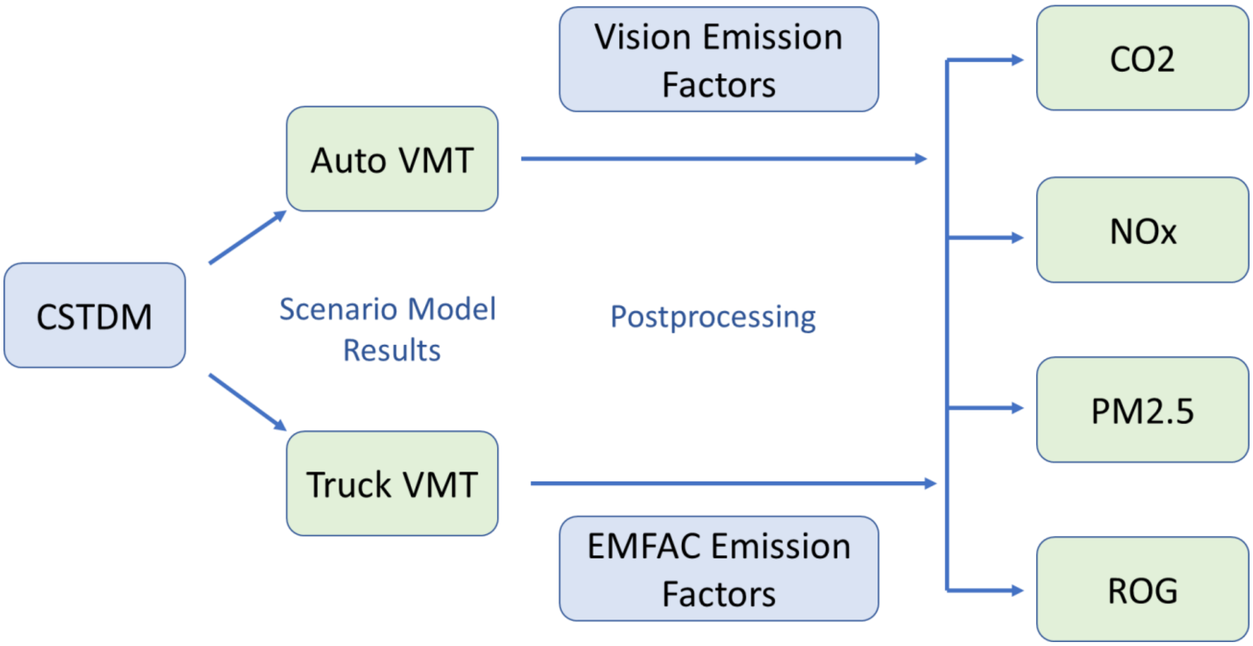

Figure 2. Emission Processing Method

Road transportation emissions are calculated separately for passenger vehicles and freight trucks. This could help to segregate the impacts for passenger and freight travel, since the main target is on the passenger side for this project. We follow the procedure below to calculate the emissions for passenger vehicles (auto):

1. The Vision emission factors originally at GAI level are aggregated into county level by taking the countywide averages. (Note that there are 69 GAI areas and 58 counties in the state of California.)
2. The county level VMT results are retrieved from the scenario results from the CSTDM.
3. Statewide emissions are calculated as the sum of the products of county-level VMT and emission factors for CO_2, NOx, PM2.5 and ROG.

The EMFAC 2017 model is used for truck emission calculations. The emission factors from EMFAC are separated for different vehicle categories, while the results from the CSTDM have only one truck type. Therefore, we derive the weighted average of emission factors, weighted by VMT for three different vehicle categories: light, medium, and heavy duty trucks. The EMFAC 2011 vehicle categories are used to match the categories for the emission factor calculation. We use the weighted average of the "one" truck vehicle type to represent truck emissions for all of California. As a result, we obtain the statewide average of the emission factors for CO_2, NOx, PM2.5 and ROG. Similarly, the VMT at the county level is used to as input to calculate

[4] https://arb.ca.gov/emfac/2017/

pollutants based on corresponding county-level emission factors from Vision and EMFAC in year 2050. These results are aggregated at the statewide level.

Scenario Design and Implementation

Based on the literature review and experts' insights from the workshop in April 2019, a set of scenarios simulating potential future changes for transportation in California were identified in this project and modeled, in addition to the baseline scenario in 2050 provided by the CSTDM V3.0, which serves in all cases as the business-as-usual (BAU) comparison for the scenario results. The following sections provide the details on how we simulate each scenario in the CSTDM V3.0. The scenario design is summarized in Table 5. All scenarios are modeled for year 2050 and compared to the baseline Scenario 0 in the discussion of the results and implications for the future of society.

We compute lower bound (LB) and upper bound (UB) cases for each scenario to provide the ranges of impacts of potential changes due to CAV. Any results within the range are likely to happen for the forecasted year. The summary table of scenario design is shown in Table 6. The factor inputs include the adjustments introduced in certain model components and factors directly coded in the CSTDM V3.0. The off-model post-processing adjustments (*b* series) are based on modifications of the corresponding model outputs for the LB scenarios (*a* series).

Table 5. Scenario Design

Scenario	Private CAV	SAV	Pricing	ZEV
0				
1a & 1b	√			
2a & 2b	√		√	
3a & 3b	√			√
4a & 4b		√		
5a & 5b		√	√	
6a & 6b		√		√

Notes:
Scenario 0 – BAU (no vehicle automation, year 2050 from Caltrans);
Scenarios 1a & 1b – Private CAV, lower bound (LB) and upper bound (UB), respectively;
Scenarios 2a & 2b – Private CAV + Pricing, LB and UB;
Scenarios 3a & 3b – Private CAV + ZEV, LB and UB;
Scenarios 4a & 4b – Shared CAV, LB and UB;
Scenarios 5a & 5b – Shared CAV + Pricing, LB and UB; and
Scenarios 6a & 6b – Shared CAV + ZEV, LB and UB.
ZEV, zero emission vehicle; SAV, shared automated vehicle.

Table 6. Scenario Overview

No	Scenario	Factor input (change compared with Scenario 0 BAU 2050)	Off-model processing adjustment
0	BAU 2050	*	*
1a	Private CAV (LB)	1. Operating cost -25%; 2. Capacity +50% (-20%); 3. Parking cost - 25%; 4. Driver's license relax to age 12; 5. Auto (SOV,HOV2,HOV3+) VOT -50%.	*
1b	Private CAV (UB)	1. Operating cost -25%; 2. Capacity +50% (-20%); 3. Parking cost - 25%; 4. Driver's license relax to age 12; 5. Auto (SOV,HOV2,HOV3+) VOT -50%.	1. TAZ level OD trips +15% induced demand for all modes for SD and LD; 2. SD deadheading trips +20% SOV, +15% HOV2, +15% HOV3+.
2a	Private CAV + Pricing (LB)	1. Operating cost +50%; 2. Capacity +50% (-20%); 3. Parking cost - 25%; 4. Driver's license relax to age 12; 5. Auto (SOV,HOV2,HOV3+) VOT -50%.	*
2b	Private CAV + Pricing (UB)	1. Operating cost +50%; 2. Capacity +50% (-20%); 3. Parking cost - 25%; 4. Driver's license relax to age 12; 5. Auto (SOV,HOV2,HOV3+) VOT -50%.	1. TAZ level OD trips +15% induced demand for all modes for SD and LD; 2. SD deadheading trips +20% SOV, +15% HOV2, +15% HOV3+.

No	Scenario	Factor input (change compared with Scenario 0 BAU 2050)	Off-model processing adjustment
3a	Private CAV + ZEV (LB)	1. Operating cost -25%; 2. Capacity +50% (-20%); 3. Parking cost -25%; 4. Driver's license relax to age 12; 5. Auto (SOV, HOV2, HOV3+) VOT -50%.	1. Post-processing on ZEV emission
3b	Private CAV + ZEV (UB)	1. Operating cost -25%; 2. Capacity +50% (-20%); 3. Parking cost -25%; 4. Driver's license relax to age 12; 5. Auto (SOV, HOV2, HOV3+) VOT -50%.	1. TAZ level OD trips +15% induced demand for all modes for SD and LD; 2. SD deadheading trips +20% SOV, +15% HOV2, +15% HOV3+; 3. Post-processing on ZEV emission.
4a	Shared CAV (LB)	1. Operating cost -25%; 2. Capacity +50% (-20%); 3. Parking cost -25%; 4. Driver's license relax to age 12; 5. Auto (SOV, HOV2, HOV3+) VOT -50%.	1. For SD TAZ level OD, move 10% of SOV trips to HOV2 (get 60%), and HOV3+(get 40%); move 40% of PT trips to HOV2 (get 70%) and HOV3+ (get 30%); 2. SD deadheading +10% HOV2, +10% HOV3+.
4b	Shared CAV (UB)	1. Operating cost -25%; 2. Capacity +50% (-20%); 3. Parking cost -25%; 4. Driver's license relax to age 12; 5. Auto (SOV, HOV2, HOV3+) VOT -50%.	1. TAZ level OD trips +15% induced demand for all modes for SD and LD; 2. For SD TAZ level OD, move 10% of SOV trips to HOV2 (get 60%), and HOV3+ (get 40%); move 40% of PT trips to HOV2 (get 70%) and HOV3+ (get 30%); 3. SD deadheading +20% SOV, +20% HOV2, +20% HOV3.

No	Scenario	Factor input (change compared with Scenario 0 BAU 2050)	Off-model processing adjustment
5a	Shared CAV + Pricing (LB)	1. Operating cost +50%; 2. Capacity +50% (-20%); 3. Parking cost -25%; 4. Driver's license relax to age 12; 5. Auto (SOV, HOV2, HOV3+) VOT -50%.	1. For SD TAZ level OD, move 10% of SOV trips to HOV2 (get 60%), and HOV3+ (get 40%); move 40% of PT trips to HOV2 (get 70%) and HOV3+ (get 30%); 2. SD deadheading +10% HOV2, +10% HOV3+.
5b	Shared CAV + Pricing (UB)	1. Operating cost +50%; 2. Capacity +50% (-20%); 3. Parking cost -25%; 4. Driver's license relax to age 12; 5. Auto (SOV, HOV2, HOV3+) VOT -50%.	1. TAZ level OD trips +15% induced demand for all modes for SD and LD; 2. For SD TAZ level OD, move 10% of SOV trips to HOV2(get 60%), and HOV3+(get 40%); move 40% of PT trips to HOV2 (get 70%), HOV3+ (get 30%); 3. SD deadheading +20% SOV, +20% HOV2, +20% HOV3.

No	Scenario	Factor input (change compared with Scenario 0 BAU 2050)	Off-model processing adjustment
6a	Shared CAV + ZEV (LB)	1. Operating cost -25%; 2. Capacity +50% (-20%); 3. Parking cost -25%; 4. Driver's license relax to age 12; 5. Auto (SOV, HOV2, HOV3+) VOT -50%	1. For SD TAZ level OD, move 10% of SOV trips to HOV2 (get 60%), and HOV3+ (get 40%); move 40% of PT trips to HOV2 (get 70%) and HOV3+ (get 30%); 2. SD deadheading +10% HOV2, +10% HOV3+; 3. Post-processing on ZEV emission.
6b	Shared CAV + ZEV (UB)	1. Operating cost -25%; 2. Capacity +50% (-20%); 3. Parking cost -25%; 4. Driver's license relax to age 12; 5. Auto (SOV, HOV2, HOV3+) VOT -50%.	1. TAZ level OD trips +15% induced demand for all modes for SD and LD; 2. For SD TAZ level OD, move 10% of SOV trips to HOV2 (get 60%), and HOV3+ (get 40%); move 40% of PT trips to HOV2 (get 70%), HOV3+ (get 30%); 3. SD deadheading +20% SOV, +20% HOV2, +20% HOV3; 4. Post-processing on ZEV emission.

Note: * stands for no change based on the reference scenario setup.

Scenario 0 – Baseline (BAU)

We take the 2050 Caltrans scenario as a baseline for comparison with the other scenarios. The 2050 baseline scenario takes in the projected zonal properties, networks, and lists of socio-economic data as input. The daily activity pattern is computed from a predetermined day pattern pool. Average auto occupancy for HOV3+ vehicles is set as 3.6. In the forecasting year 2050, the baseline operating cost is $0.20. A high-speed rail option is available in the long-distance travel model. CAVs are not included in the baseline scenario.

The outputs include trips by modes by time period at the TAZ level, and this can be further aggregated into the MPO, county, and super-region levels. VMT and VHT are also generated for separate modes. The following scenarios are built on top of the baseline scenario.

Scenario 1 – Private CAV

Assumptions on the model components:

1a LB:

1. Highway capacity change: increase by up to 50% (or decrease by 20%) based on facility types;
2. Value of time: decrease by up to 50%;
3. Vehicle operating cost: decrease by up to 25%;
4. Parking cost: decrease by up to 25%;
5. Access to AVs: driver's license available for individuals starting at 12 years old.

1b UB:

Same as 1a LB 1-5

\+ Off-model processing:

1. TAZ level OD trips (induced demand): increase 15% for all modes in SD and LD;
2. SD deadheading trips: SOV increase 20%, HOV2 increase 15%, HOV3+ increase 15%.

In this scenario, we model the highest penetration of personally owned AVs in the year 2050 (scenario 1a Private CAV LB). CAVs are assumed to be only available as private options with a 75% to 100% penetration rate based on the literature specified in previous section. The range of CAV penetration rate is dependent on various beliefs about how CAV technology would be developed in the future. Such high penetration rates would ensure that most of the benefits from the CAV deployment are available to travelers (and minimizing some of the mixed-flows disutilities that might be present for lower penetration rates).

The VOT of using the private car mode is assumed to decrease by 50%. This is generally because of the convenience of traveling with a privately-owned CAV, as the "driver" could conduct other activities while in the vehicle. Here we assume the VOT is decreased for single occupancy vehicles (SOVs), high occupancy vehicles with 2 travelers (HOV2s), and high occupancy vehicles with 3 or more travelers (HOV3+). Note that the VOT is kept unchanged for transit users and freight vehicles, based on the assumption that most uncertainties come from passenger vehicles and that the benefits from automated trucks would need to be accounted for in different settings (e.g., truck platooning) rather than with changes in the VOT. Scenarios involving these modifications in the freight sector are considered outside the scope of this project.

The overall vehicle operating cost per mile in 2010 dollars is set at $0.15; this is the same for all passenger vehicles. The network capacity is treated separately for different facility types of the highway network. The capacity is assumed to increase by 50% for the majority of the highway, including freeways, expressways, major arterials, minor arterials, and collectors. The capacity of the ramp section is assumed to decrease by 20%, because of more friction induced by merging and splitting of CAV vehicles. The dummy links, acting as centroid connectors, are kept with original free-flow speed and infinite capacity. The parking cost, based on the zonal properties corresponding to each TAZ, is assumed to decrease by 25%. This treatment is due to two assumptions: 1) a lower parking cost would lead to a higher probability of parking, to mimic the possibilities that CAVs could park on their own and maybe at a different place (usually farther from the CBD area) with a lower cost; 2) a lower parking cost would induce a low total travel cost, thus causing more potential travels that would not be made without the availability of CAV. The availability of a driver's license, originally developed as a binary logit model for each individual, is now relaxed into a simpler *if* condition. Anyone with an age greater than or equal to 12 years would have access to a driver's license. Note that having a driver's license is the precondition of owning a vehicle, so we anticipate seeing higher vehicle ownership within the model results because of this adjustment.

Next, based on the model outputs, we study the range of demand expansion and deadheading for the upper bound case (scenario 1b Private CAV UB). As shown in Table 22 in Appendix A, various studies reported range of potential impacts on extra VMT due to deadheading and induced demand that the CSTDM fail to capture. Thus, we create an upper bound case to account for the extra VMT and mode share penalty based on the setup for scenario 1a.

As in the first part of this report, the literature indicates that trip generation will likely differ in the CAV era, especially since CAVs will be a brand-new advanced transportation mode. With much lower travel costs for CAVs compared to human-driven vehicles on current infrastructure, more trip generation is anticipated systemwide. However, the trip generation process in the CSTDM mainly depends on sociodemographics and home/work locations. As these factors would not change dramatically simply because of the availability of CAV, the total trip generation in the CSTDM would also remain constant, which is not realistic and/or consistent with the expectations from the literature on a CAV future, which might lead to substantial induced demand. In other terms, even with a much lower travel cost due to the availability of CAVs, the CSTDM V3.0 is not likely to capture the induced demand associated with CAVs. Thus, we apply a 15% increase in demand for all travel modes (including auto modes, transit, rail and air) to account for the induced demand. This can be considered an even conservative estimate when compared to the findings from recent studies (Harb et al., *forthcoming*). Further, the availability of CAVs would also generate extra deadheading that is not captured in the original CSTDM framework. Based on the literature shown in Table 22 in Appendix A, we assume that the impacts of deadheading would translate in increasing SOV trips by 20%, HOV2 trips by 15% and HOV3+ trips by 15%. Therefore, based on the assumptions in scenario 1a for the lower bound and the assumptions on demand expansion that have just been discussed, we model scenario 1b (upper bound), including two main additional assumptions:

1. TAZ level OD trips (induced demand): increase 15% for all modes in short distance model (SD) and long distance model (LD);
2. SD deadheading trips: SOV increase 20%, HOV2 increase 15%, HOV3+ increase 15%.

These two adjustments are used as a proxy for the induced demand and extra travel generated for zero-occupancy vehicle pickup and return trips.

Scenario 2 – Private CAV + Pricing

Assumptions on the model components:

2a LB:

1. Highway capacity change: increase by up to 50% (or decrease by 20%) based on facility type;
2. Value of time: decrease by up to 50%;
3. Vehicle operating cost: increase by 50% based on policy assumptions;
4. Parking cost: decrease by up to 25%;
5. Access to CAVs: driver's license available for individuals starting at 12 years old.

2b UB:

Same as 2a LB 1-5
+ Off-model processing:

1. TAZ level OD trips (induced demand): increase 15% for all modes in SD and LD;
2. SD deadheading trips: SOV increase 20%, HOV2 increase 15%, HOV3+ increase 15%.

In this scenario, we model a policy with road user charges, based on the Private CAV scenario (scenario 1). We assume that only privately owned CAVs are available, with a penetration rate of 75% to 100%. Adding road user charges would increase travel costs for travelers by automobile. Since there are multiple types of user charge and congestion pricing, and also it is still unclear how to determine the geographical boundary of such change, we assume the changes are applied to all trips made by passenger vehicles so that the overall vehicle operating cost can reflect the system-wide adjustment. The operating cost parameter is assumed to increase by 50% over the BAU cost and set as $0.30/mile). Since the operating cost component is not directly dependent on the highway network, it is safe to assume that network capacity changes by the same amount as in the Private CAV scenario. Similarly, VOT, parking cost, and driver's license are kept the same as in the Private CAV scenario. Similar as in the scenario 1b, we make demand expansion and deadheading adjustments for the upper bound case.

Scenario 3 – Private CAV + ZEV

Assumptions on the model components:

3a LB

1. Highway capacity change: increase by up to 50% (or decrease by 20%) based on facility type;
2. Value of time: decrease by up to 50%;
3. Vehicle operating cost: decrease by 25%;
4. Parking cost: decrease by up to 25%;
5. Access to CAVs: driver's license available for individuals starting at 12 years old.

\+ Off-model processing:

1. Post-processing on ZEV emission.

3b UB:

Same as 3a LB 1-5

1. Highway capacity change: increase by up to 50% (or decrease by 20%) based on facility type;
2. Value of time: decrease by up to 50%;
3. Vehicle operating cost: decrease by 25%;
4. Parking cost: decrease by up to 25%;
5. Access to CAVs: driver's license available for individuals starting at 12 years old.

\+ Off-model processing:

1. TAZ level OD trips (induced demand): increase 15% for all modes in SD and LD;
2. SD deadheading trips: SOV increase 20%, HOV2 increase 15%, HOV3+ increase 15%;
3. Post-processing on ZEV emission.

Due to the limitation that only one passenger vehicle type is available in the CSTDM, we choose to use postprocessing on emission factors to estimate the potential impacts of electrified CAVs. This treatment would ignore the potential changes in travel patterns and travel impedance caused by electrification, but it still provides some insights on how emissions would be affected in a scenario with wide ZEV adoption.

We assume total 91% VMT are zero-emission, based on Vision MSS main scenario assumption. This scenario is computed by post-processing using various emission factors from the Vision and EMFAC emission model in combinations with the model assumptions and results for scenario 1a and 1b.

Scenario 4 – Shared CAV

Assumptions on the model components:

4a LB:

1. Highway capacity change: increase by up to 50% (or decrease by 20%) based on facility types;
2. Value of time: decrease by up to 50%
3. Vehicle operating cost: decrease by up to 25%
4. Parking cost: decrease by up to 25%
5. Access to AVs: driver's license available for individuals starting at 12 years old

+ Off-model processing:

1. For SD TAZ level OD,
   move 10% of SOV trips to HOV2 (get 60%), and HOV3+ (get 40%);
   move 40% of public transit trips to HOV2 (get 70%) and HOV3+ (get 30%);
2. SD deadheading: increase HOV2 trips by 10%, increase HOV3+ trips by 10%.

4b UB:

Same as 4a LB 1-5

+ Off-model processing:

1. TAZ level OD trips (induced demand): increase 15% for all modes in SD and LD;
2. For SD TAZ level OD,
   move 10% of SOV trips to HOV2 (get 60%), and HOV3+ (get 40%);
   move 40% of public transit trips to HOV2 (get 70%) and HOV3+ (get 30%);
3. SD deadheading: increase SOV trips by 20%, increase HOV2 trips by 20%, increase HOV3+ trips by 20%.

The CSTDM V3.0 cannot properly incorporate the shared use of CAVs (i.e., SAVs), especially for complicated vehicular behavior for pick-up and repositioning. We assume the SAV fleet provide a TNC-like mobility service in this scenario. Everyone could request SAV trips given the availability of the service. We divide the potential impacts of SAVs into three categories:

1. Trip generation: more trips are generated because of lower travel costs and the convenience (e.g., no need to park vehicles, and easier access to a vehicle from the fleet independent from the mode used for the previous trip) of SAVs.
2. Mode share: a portion of single-occupancy vehicle trips would shift to shared trips; and some of the public transit trips would also shift to auto trips.
3. Deadheading and repositioning: extra VMT would be generated for zero-occupancy vehicle travel.

For the same reasons that have been previously discussed, additional induced demand would be generated with the availability of shared AVs. One thing to note is that the amount of deadheading is closely related to the demand density and fleet service provided in the region. With more service provided, the VMT caused by deadheading for repositioning would be proportionally smaller. Based on the Clean Miles Standard analysis from CARB[5], the statewide average deadheading of TNC VMT is 38.5%. In this scenario, we assume the deadheading contributed to 40% of the total VMT for the entire state. If each trip contributes the same amount of VMT on average, we have 40% of trips to be the repositioning trips. If we assume 50% of the SOV trips would be conducted via SAV mode, provided enough SAV fleet supply, the extra trips for deadheading would be 20% of the total auto trips. Accordingly, our assumption is consistent with CARB's Clean Miles Standard analysis. Thus, we make the following adjustments for upper bound scenario 4b:

1. TAZ level OD trips (induced demand): increase 15% for all modes in SD and LD;
2. For SD TAZ level OD,
   move 10% of SOV trips to HOV2(get 60%), and HOV3+ (get 40%);
   move 40% of public transit trips to HOV2 (get 70%) and HOV3+ (get 30%);
3. SD deadheading: increase SOV trips by 20%, increase HOV2 trips by 20%, increase HOV3+ trips by 20%.

[5] https://www.dof.ca.gov/Forecasting/Economics/Major_Regulations/Major_Regulations_Table/documents/Clean_Miles_Standard_SRIA.pdf

Scenario 5 – Shared CAV + Pricing

Assumptions on the model components:

5a LB:

1. Highway capacity change: increase by up to 50% (or decrease by 20%) based on facility types;
2. Value of time: decrease by up to 50%
3. Vehicle operating cost: increase by up to 50%
4. Parking cost: decrease by up to 25%
5. Access to AVs: driver's license available for individuals starting at 12 years old

\+ Off-model processing:

1. For SD TAZ level OD,
   move 10% of SOV trips to HOV2 (get 60%), and HOV3+ (get 40%);
   move 40% of public transit trips to HOV2 (get 70%) and HOV3+ (get 30%);
2. SD deadheading: increase HOV2 trips by 10%, increase HOV3+ trips by 10%.

5b UB:

Same as 5a LB 1-5

\+ Off-model processing:

1. TAZ level OD trips (induced demand): increase 15% for all modes in SD and LD;
2. For SD TAZ level OD,
   move 10% of SOV trips to HOV2 (get 60%), and HOV3+ (get 40%);
   move 40% of public transit trips to HOV2 (get 70%) and HOV3+ (get 30%);
3. SD deadheading: increase SOV trips by 20%, increase HOV2 trips by 20%, increase HOV3+ trips by 20%.

In this scenario, we want to evaluate the combination of pricing (scenario 2) and sharing (scenario 4) strategies. The assumptions are based on the setup used in the corresponding two scenarios.

Scenario 6 – Shared CAV + ZEV

Assumptions on the model components:

5a LB:

1. Highway capacity change: increase by up to 50% (or decrease by 20%) based on facility types;
2. Value of time: decrease by up to 50%
3. Vehicle operating cost: decrease by up to 25%
4. Parking cost: decrease by up to 25%
5. Access to AVs: driver's license available for individuals starting at 12 years old

+ Off-model processing**:**

1. For SD TAZ level OD,
   move 10% of SOV trips to HOV2 (get 60%), and HOV3+ (get 40%);
   move 40% of public transit trips to HOV2 (get 70%) and HOV3+ (get 30%);
2. SD deadheading: increase HOV2 trips by 10%, increase HOV3+ trips by 10%;
3. Post-processing on ZEV emission.

5b UB:

Same as 5a LB 1-5

+ Off-model processing:

1. TAZ level OD trips (induced demand): increase 15% for all modes in SD and LD;
2. For SD TAZ level OD,
   move 10% of SOV trips to HOV2 (get 60%), and HOV3+ (get 40%);
   move 40% of public transit trips to HOV2 (get 70%) and HOV3+ (get 30%);
3. SD deadheading: increase SOV trips by 20%, increase HOV2 trips by 20%, increase HOV3+ trips by 20%;
4. Post-processing on ZEV emission.

As in the electrification scenario for private CAV + ZEV, we use a post-processing approach to account for the reduced GHG and criteria pollutant emissions for shared CAV + ZEV. Based on the MSS main scenario in Vision model, we assume 91% of VMT from scenario 4 (Sharing) are zero-emission VMT.

Results

Trips, VMT, and VHT

We here report the travel demand model results for a regular weekday for the entire state of California. The units of VMT are in miles, and units of VHT are in hours, unless otherwise specified. As previously discussed, our modeling approach assumes there are no travel behavior differences between the zero-emission vehicle scenarios and non–zero-emission vehicle scenarios. Accordingly, the travel-related metrics for the ZEV scenarios (3a, 3b, 6a and 6b) are not duplicated here (as they are identical to those from the scenarios 1a, 1b, 4a and 4b, respectively). We show the total number of trips and number of trips by mode, including auto, short distance transit, conventional rail (CVR), high-speed rail (HSR), in-state air and walk/bike. We also include the VMT and VHT for autos (passenger travel) and trucks (freight), as well as the trips per person and trips per household across all modes. Finally, trip mode share comparisons are provided. For each metric, we compute the percentage change compared to BAU, and the percentage point (p.p.) change in the mode share results, also compared to BAU. The results and the percentage changes compared to BAU are shown in Table 7 to Table 18.

Table 7. Daily Trips for Scenarios 1a and 1b

Scenario	BAU 2050	1a. Private CAV LB	1a % change vs. BAU	1b. Private CAV UB	1b % change vs. BAU
Population	53,407,484	53,407,484	0.0%	53,407,484	0.0%
Households	19,900,074	19,900,074	0.0%	19,900,074	0.0%
Total Person Trips	208,484,087	211,988,016	1.7%	283,140,473	35.8%
Auto Person Trips	181,925,683	190,009,673	4.4%	257,865,378	41.7%
SOV Person Trips	100,949,045	116,155,011	15.1%	160,252,157	58.7%
HOV2 Person Trips	47,352,231	43,472,590	-8.2%	57,461,388	21.3%
HOV3+ Person Trips	33,624,407	30,382,072	-9.6%	40,151,833	19.4%
Short Distance Transit Trips	7,322,712	4,953,980	-32.3%	5,697,077	-22.2%
Long Distance Rail Trips (CVR + HSR)	82,079	34,397	-58.1%	39,557	-51.8%
In-state Air Trips	21,127	6,432	-69.6%	7,397	-65.0%
Walk/Bike Trips	17,627,299	16,255,805	-7.8%	18,694,176	6.1%
School Bus Trips	1,505,187	727,729	-51.7%	836,888	-44.4%
Trips per Person	3.9	4.0	1.7%	5.3	35.8%
Trips per Household	10.5	10.7	1.7%	14.2	35.8%
Truck Trips	1,513,800	1,513,800	0.0%	1,513,800	0.0%

Table 8. Daily Trips for Scenarios 2a and 2b

Scenario	BAU 2050	2a. Private CAV + Pricing LB	2a % change vs. BAU	2b. Private CAV + Pricing UB	2b % change vs. BAU
Population	53,407,484	53,407,484	0.00 %	53,407,484	0.0%
Households	19,900,074	19,900,074	0.0%	19,900,074	0.0%
Total Person Trips	208,484,087	211,921,665	1.6%	282,031,638	35.3%
Auto Person Trips	181,925,683	185,507,411	2.0%	251,655,246	38.3%
SOV Person Trips	100,949,045	111,543,157	10.5%	153,893,408	52.4%
HOV2 Person Trips	47,352,231	43,817,426	-7.5%	57,919,405	22.3%
HOV3+ Person Trips	33,624,407	30,146,828	-10.3%	39,842,433	18.5%
Short Distance Transit Trips	7,322,712	6,005,806	-18.0%	6,906,677	-5.7%
Long Distance Rail Trips (CVR + HSR)	82,079	48,231	-41.2%	55,466	-32.4%
In-state Air Trips	21,127	10,056	-52.4%	11,564	-45.3%
Walk/Bike Trips	17,627,299	19,590,124	11.1%	22,528,643	27.8%
School Bus Trips	1,505,187	760,037	-49.5%	874,043	-41.9%
Trips per Person	3.9	4.0	1.6%	5.3	35.3%
Trips per Household	10.5	10.6	1.6%	14.2	35.3%
Truck Trips	1,513,800	1,513,800	0.0%	1,513,800	0.0%

Table 9. Daily Trips for Scenarios 4a and 4b

Scenario	BAU 2050	4a. Shared CAV LB	4a % change vs. BAU	4b. Shared CAV UB	4b % change vs. BAU
Population	53,407,484	53,407,484	0.0%	53,407,484	0.0%
Households	19,900,074	19,900,074	0.0%	19,900,074	0.0%
Total Person Trips	208,484,087	220,696,172	5.9%	287,824,869	38.1%
Auto Person Trips	181,925,683	200,699,421	10.3%	264,828,606	45.6%
SOV Person Trips	100,949,045	104,557,666	3.6%	144,244,565	42.9%
HOV2 Person Trips	47,352,231	56,985,320	20.3%	71,465,683	50.9%
HOV3+ Person Trips	33,624,407	39,156,436	16.5%	49,118,358	46.1%
Short Distance Transit Trips	7,322,712	2,972,388	-59.4%	3,418,246	-53.3%
Long Distance Rail Trips (CVR + HSR)	82,079	34,397	-58.1%	39,557	-51.8%
In-state Air Trips	21,127	6,432	-69.6%	7,397	-65.0%
Walk/Bike Trips	17,627,299	16,255,805	-7.8%	18,694,176	6.1%
School Bus Trips	1,505,187	727,729	-51.7%	836,888	-44.4%
Trips per Person	3.9	4.1	5.9%	5.4	38.1%
Trips per Household	10.5	11.1	5.9%	14.5	38.1%
Truck Trips	1,513,800	1,513,800	0.0%	1,513,800	0.0%

Table 10. Daily Trips for Scenarios 5a and 5b

Scenario	BAU 2050	5a Shared CAV + Pricing LB	5a % change vs. BAU	5b Shared CAV + Pricing UB	5b % change vs. BAU
Population	53,407,484	53,407,484	0.0%	53,407,484	0.0%
Households	19,900,074	19,900,074	0.0%	19,900,074	0.0%
Total Person Trips	208,484,087	220,720,887	5.9%	286,820,613	37.6%
Auto Person Trips	181,925,683	196,700,212	8.1%	259,206,892	42.5%
SOV Person Trips	100,949,045	100,428,134	-0.5%	138,519,460	37.2%
HOV2 Person Trips	47,352,231	57,412,096	21.2%	71,971,480	52.0%
HOV3+ Person Trips	33,624,407	38,859,983	15.6%	48,715,952	44.9%
Short Distance Transit Trips	7,322,712	3,603,484	-50.8%	4,144,006	-43.4%
Long Distance Rail Trips (CVR + HSR)	82,079	55,466	-32.4%	55,466	-32.4%
In-state Air Trips	21,127	11,564	-45.3%	11,564	-45.3%
Walk/Bike Trips	17,627,299	19,590,124	11.1%	22,528,643	27.8%
School Bus Trips	1,505,187	760,037	-49.5%	874,043	-41.9%
Trips per Person	3.9	4.1	5.9%	5.4	37.6%
Trips per Household	10.5	11.1	5.9%	14.4	37.6%
Truck Trips	1,513,800	1,513,800	0.0%	1,513,800	0.0%

Table 11. Daily VMT/VHT for Scenarios 1a and 1b

Scenario	BAU 2050	1a. Private CAV LB	1a % change vs. BAU	1b. Private CAV UB	1b % change vs. BAU
VMT Total (Autos + Trucks)	1,242,083,300	1,297,255,300	4.4%	1,717,247,500	38.3%
VMT Autos	1,140,235,200	1,196,268,400	4.9%	1,616,268,400	41.7%
VMT Trucks	101,848,000	100,986,900	-0.9%	100,979,100	-0.9%
Auto VMT per Person	21	22	5.2%	30	42.3%
Auto VMT per Household	57	60	4.9%	81	41.7%
VHT Total (Autos + Trucks)	30,743,800	30,390,600	-1.2%	43,895,500	42.8%
VHT Autos	28,840,400	28,623,600	-0.8%	42,061,300	45.8%
VHT Trucks	1,903,400	1,767,000	-7.2%	1,834,200	-3.6%
Auto VHT per Person (Min)	32	32	0.0%	47	46.9%
Auto VHT per Household (Min)	87	86	-1.2%	127	46.0%

Table 12. Daily VMT/VHT for Scenarios 2a and 2b

Scenario	BAU 2050	2a. Private CAV + Pricing LB	2a % change vs. BAU	2b. Private CAV + Pricing UB	2b % change vs. BAU
VMT Total (Autos + Trucks)	1,242,083,300	1,007,122,600	-18.9%	1,317,964,300	6.1%
VMT Autos	1,140,235,200	906,346,100	-20.5%	1,217,167,900	6.7%
VMT Trucks	101,848,000	100,776,500	-1.1%	100,796,300	-1.0%
Auto VMT per Person	21	17	-20.2%	23	7.0%
Auto VMT per Household	57	46	-20.6%	61	6.8%
VHT Total (Autos + Trucks)	30,743,800	23,867,700	-22.4%	32,783,200	6.6%
VHT Autos	28,840,400	22,130,400	-23.3%	31,022,000	7.6%
VHT Trucks	1,903,400	1,737,400	-8.7%	1,761,300	-7.5%
Auto VHT per Person (Min)	32	25	-21.9%	35	9.4%
Auto VHT per Household (Min)	87	67	-23.0%	94	8.0%

Table 13. Daily VMT/VHT for Scenarios 4a and 4b

Scenario	BAU 2050	4a. Shared CAV LB	4a % change vs. BAU	4b. Shared CAV UB	4b % change vs. BAU
VMT Total (Autos + Trucks)	1,242,083,300	1,275,265,400	2.7%	1,664,822,400	34.0%
VMT Autos	1,140,235,200	1,174,326,900	3.0%	1,563,847,600	37.2%
VMT Trucks	101,848,000	100,938,400	-0.9%	100,974,800	-0.9%
Auto VMT per Person	21	22	3.3%	29	37.6%
Auto VMT per Household	57	59	3.0%	79	37.2%
VHT Total (Autos + Trucks)	30,743,800	29,816,100	-3.0%	42,004,800	36.6%
VHT Autos	28,840,400	28,051,900	-2.7%	40,182,900	39.3%
VHT Trucks	1,903,400	1,764,200	-7.3%	1,821,900	-4.3%
Auto VHT per Person (Min)	32	32	0.0%	45	40.6%
Auto VHT per Household (Min)	87	85	-2.3%	121	39.1%

Table 14. Daily VMT/VHT for Scenarios 5a and 5b

Scenario	BAU 2050	5a Shared CAV + Pricing LB	5a % change vs. BAU	5b Shared CAV + Pricing UB	5b % change vs. BAU
VMT Total (Autos + Trucks)	1,242,083,300	1,005,663,900	-19.0%	1,286,110,200	3.5%
VMT Autos	1,140,235,200	904,886,900	-20.6%	1,185,310,300	4.0%
VMT Trucks	101,848,000	100,777,100	-1.1%	100,799,900	-1.0%
Auto VMT per Person	21	17	-20.7%	22	4.2%
Auto VMT per Household	57	46	-20.6%	60	4.0%
VHT Total (Autos + Trucks)	30,743,800	23,751,900	-22.7%	31,830,800	3.5%
VHT Autos	28,840,400	22,013,500	-23.7%	30,072,100	4.3%
VHT Trucks	1,903,400	1,738,400	-8.7%	1,758,800	-7.6%
Auto VHT per Person (Min)	32	25	-21.9%	34	6.3%
Auto VHT per Household (Min)	87	66	-24.1%	91	4.6%

Table 15. Trip Mode Share for Scenarios 1a and 1b

Scenario	BAU 2050	1a. Private CAV LB	1a vs BAU Absolute Difference	1a % change vs. BAU	1b. Private CAV UB	1b vs BAU Absolute Difference	1b % change vs. BAU
SOV	48.42%	54.79%	6.37 p.p.	13.16%	56.60%	8.18 p.p.	16.89%
HOV2	22.71%	20.51%	-2.21 p.p.	-9.71%	20.29%	-2.42 p.p.	-10.65%
HOV3+	16.13%	14.33%	-1.80 p.p.	-11.14%	14.18%	-1.95 p.p.	-12.07%
Short Distance Transit	3.51%	2.34%	-1.18 p.p.	-33.47%	2.01%	-1.50 p.p.	-42.71%
Long Distance Rail	0.04%	0.02%	-0.02 p.p.	-58.79%	0.01%	-0.03 p.p.	-64.51%
In-state Air	0.01%	0.00%	-0.01 p.p.	-70.06%	0.00%	-0.01 p.p.	-74.22%
Walk/Bike	8.45%	7.67%	-0.79 p.p.	-9.30%	6.60%	-1.85 p.p.	-21.91%
School Bus	0.72%	0.34%	-0.38 p.p.	-52.45%	0.30%	-0.43 p.p.	-59.06%

Table 16. Trip Mode Share for Scenarios 2a and 2b

Scenario	BAU 2050	2a. Private CAV + Pricing LB	2a vs BAU Absolute Difference	2a % change vs. BAU	2b. Private CAV + Pricing UB	2b vs BAU Absolute Difference	2b % change vs. BAU
SOV	48.42%	52.63%	4.21 p.p.	8.70%	54.57%	6.15 p.p.	12.69%
HOV2	22.71%	20.68%	-2.04 p.p.	-8.97%	20.54%	-2.18 p.p.	-9.58%
HOV3+	16.13%	14.23%	-1.90 p.p.	-11.80%	14.13%	-2.00 p.p.	-12.41%
Short Distance Transit	3.51%	2.83%	-0.68 p.p.	-19.31%	2.45%	-1.06 p.p.	-30.28%
Long Distance Rail	0.04%	0.02%	-0.02 p.p.	-42.19%	0.02%	-0.02 p.p.	-50.05%
In-state Air	0.01%	0.00%	-0.01 p.p.	-53.17%	0.00%	-0.01 p.p.	-59.54%
Walk/Bike	8.45%	9.24%	0.79 p.p.	9.33%	7.99%	-0.47 p.p.	-5.52%
School Bus	0.72%	0.36%	-0.36 p.p.	-50.32%	0.31%	-0.41 p.p.	-57.07%

Table 17. Trip Mode Share for Scenarios 4a and 4b

Scenario	BAU 2050	4a. Shared CAV LB	4a vs BAU Absolute Difference	4a % change vs. BAU	4b. Shared CAV UB	4b vs BAU Absolute Difference	4b % change vs. BAU
SOV	48.42%	47.38%	-1.04 p.p.	-2.16%	50.12%	1.69 p.p.	3.50%
HOV2	22.71%	25.82%	3.11 p.p.	13.68%	24.83%	2.12 p.p.	9.32%
HOV3+	16.13%	17.74%	1.61 p.p.	10.01%	17.07%	0.94 p.p.	5.81%
Short Distance Transit	3.51%	1.35%	-2.17 p.p.	-61.65%	1.19%	-2.32 p.p.	-66.19%
Long Distance Rail	0.04%	0.02%	-0.02 p.p.	-60.41%	0.01%	-0.03 p.p.	-65.09%
In-state Air	0.01%	0.00%	-0.01 p.p.	-71.24%	0.00%	-0.01 p.p.	-74.64%
Walk/Bike	8.45%	7.37%	-1.09 p.p.	-12.88%	6.49%	-1.96 p.p.	-23.18%
School Bus	0.72%	0.33%	-0.39 p.p.	-54.33%	0.29%	-0.43 p.p.	-59.73%

Table 18. Trip Mode Share for Scenarios 5a and 5b

Scenario	BAU 2050	5a Shared CAV + Pricing LB	5a vs BAU Absolute Difference	5a % change vs. BAU	5b Shared CAV + Pricing UB	5b vs BAU Absolute Difference	5b % change vs. BAU
SOV	48.42%	45.50%	-2.92 p.p.	-6.0%	48.29%	-0.13 p.p.	-0.3%
HOV2	22.71%	26.01%	3.30 p.p.	14.5%	25.09%	2.38 p.p.	10.5%
HOV3+	16.13%	17.61%	1.48 p.p.	9.2%	16.98%	0.85 p.p.	5.3%
Short Distance Transit	3.51%	1.63%	-1.88 p.p.	-53.5%	1.44%	-2.07 p.p.	-58.9%
Long Distance Rail	0.04%	0.03%	-0.01 p.p.	-36.2%	0.02%	-0.02 p.p.	-50.9%
In-state Air	0.01%	0.01%	-0.00 p.p.	-48.3%	0.00%	-0.00 p.p.	-60.2%
Walk/Bike	8.45%	8.88%	0.43 p.p.	5.0%	7.85%	-0.60 p.p.	-7.1%
School Bus	0.72%	0.34%	-0.38 p.p.	-52.3%	0.30%	-0.42 p.p.	-57.8%

Figure 3 and Figure 4 summarize the range of auto VMT in the various scenarios. The results of auto VMT range from 1,196 million vehicle miles to 1,616 million vehicle miles for scenario 1a and 1b, where the induced demand contributes to 15% and deadheading contributes to 20% of the differences. For 2a and 2b, the results of auto VMT ranges from 906 million vehicle miles to 1,217 million vehicle miles. Note that the lower bound VMT for this scenario is lower than the baseline 2050 scenario, which shows how, according to the CSTDM outputs, the pricing strategy could be effective in calming total auto VMT. For scenarios 4a and 4b, auto VMT range from 1,174 to 1,652 million vehicle miles. The auto VMT of 5a and 5b range from 904 to 1,185 million miles.

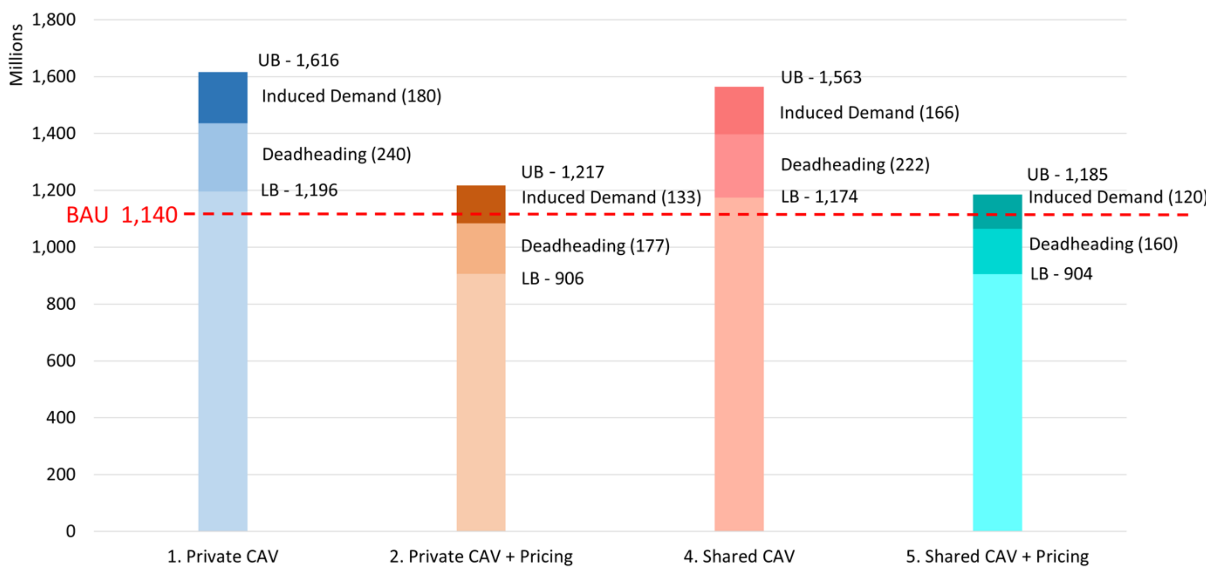

Figure 3. Range of Auto VMT in the Modeling Scenarios

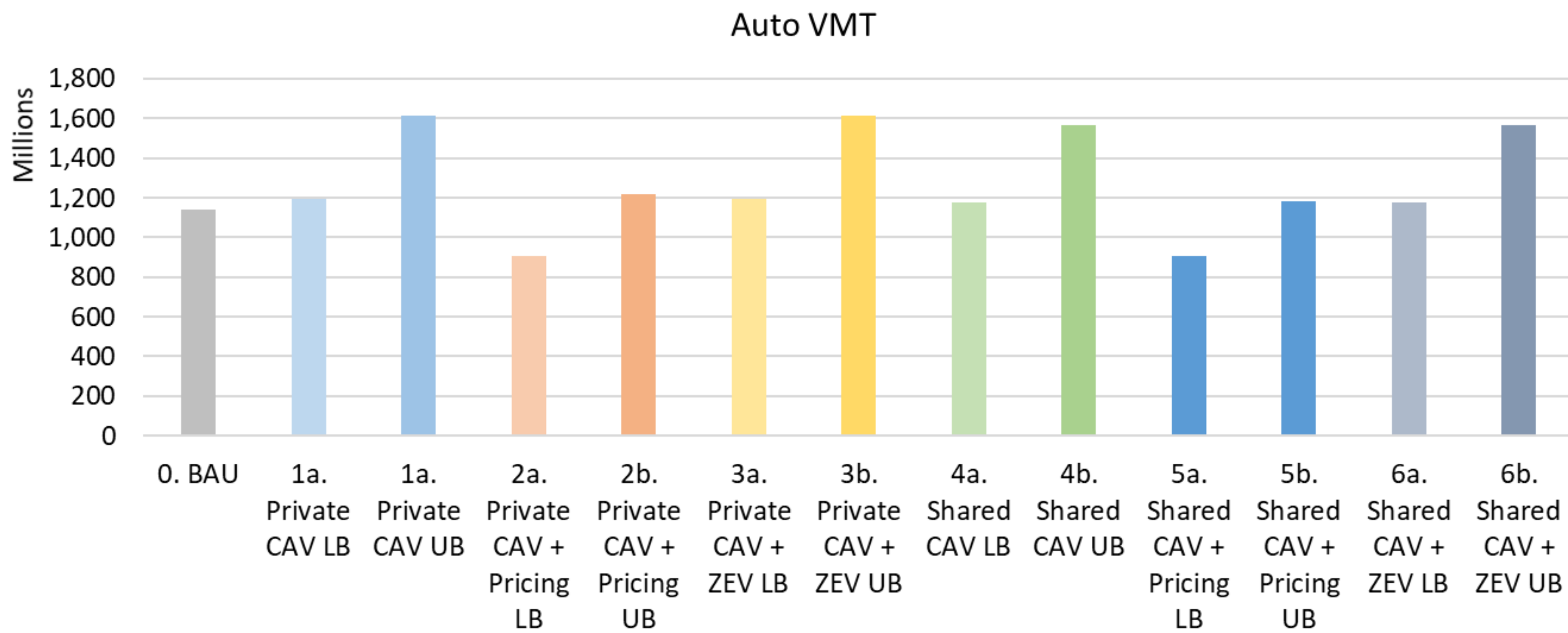

Figure 4. Auto Vehicle Miles Traveled

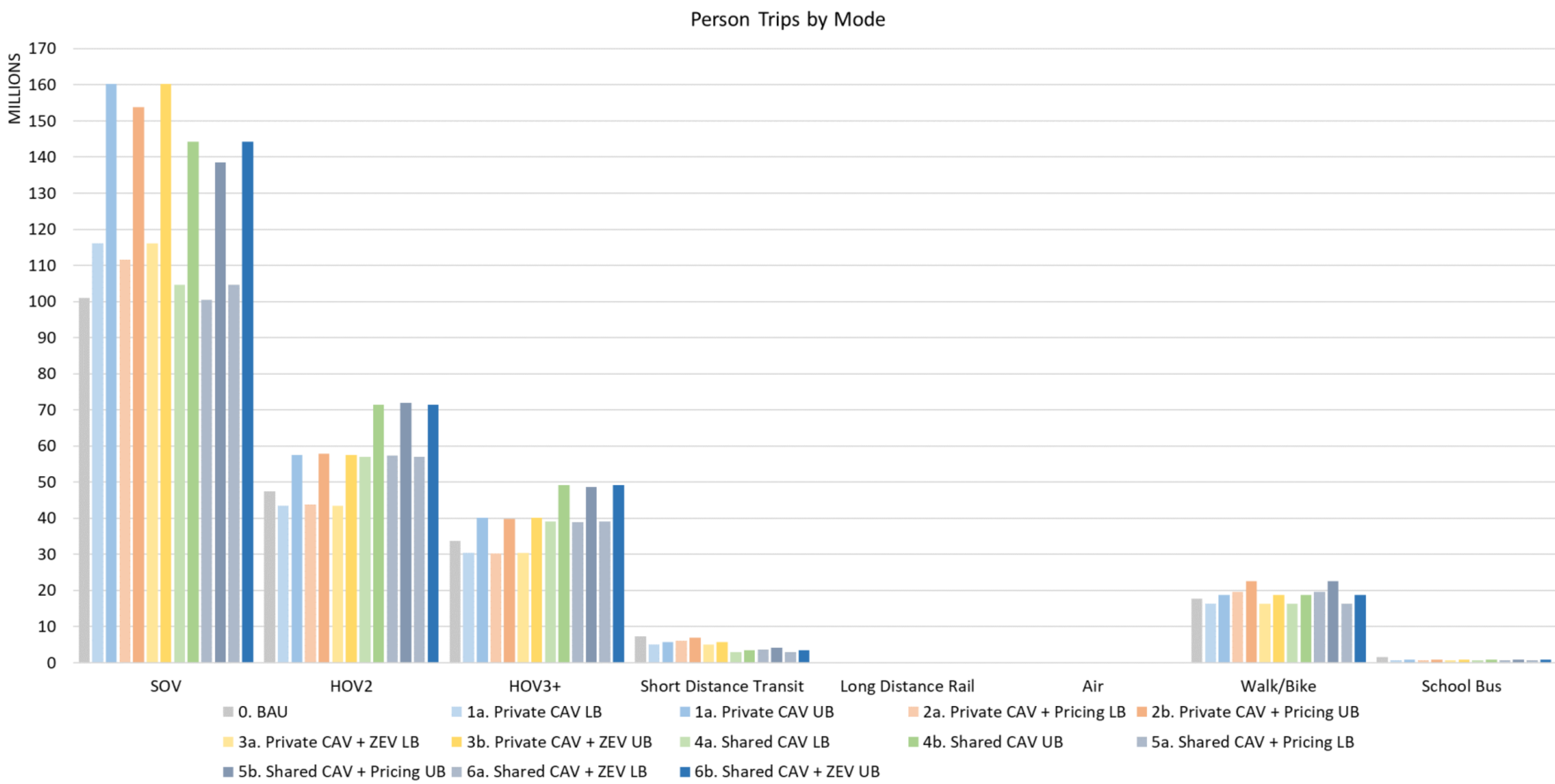

Figure 5. Person Trips by Mode

The sociodemographic profiles remain constant in all CAV scenarios compared with the BAU scenario for 2050. For both the private CAV scenario and shared CAV scenario, there are slight increases in the number of passenger vehicle (auto) trips in LB scenarios. There is a decrease in total trips and VMT in scenario 2a private CAV + pricing LB, meaning that, according to the CSTDM model forecasts, the increased operating cost would somewhat hinder people from traveling, through both a reduction in the number of trips and a reduction of the average trip distances.

We also observe a substantial mode shift towards automobiles from transit for both short- and long-distance trips. The number of rail and in-state air trips is largely reduced with the availability of CAVs. For the private CAV scenario, the number of trips and VMT of autos slight increases compared to the baseline. However, the VMT of auto decreases in the pricing strategies scenario, due to the penalty of higher vehicle operating costs. Similar effects on VMT are observed in the shared CAV + pricing scenario, in particular in the LB case in which VMT decreases to a level that is lower than BAU. This shows the effectiveness of scenarios that involve pricing strategies and policies to promote the deployment of SAVs. In particular, the scenario results show how person trips in such a situation increase without a sizable in total VMT, thanks to a reduction in the average trip distances and an increase in vehicle occupancy.

The numbers of truck trips are relatively stable, based on the assumption that the truck trip generation would not be affected by the popularity of CAVs for passenger travel. The VMT and VHT of trucks differ slightly compared to the BAU, mostly due to the changes in network capacity and the interactions with passenger vehicles on the road.

Total trip numbers remain relatively stable across all lower bound scenarios, partially due to the design of the CSTDM. The trip generation step largely depends on household and employment locations and socioeconomic factors, such as population, age, income, occupation, etc. These factors are held constant in all CAV scenarios. The adjusted travel cost functions in our scenarios do not have much impact on the upstream trip generation. Rather, they mainly appear to have an impact on the mode choice component. However, a difference of approximately 50 million person trips separates the lower bound and upper bound cases, highlighting the important role that induced demand and extra deadheading will likely cause on future travel in a CAV-dominated era.

Next, we show the spatial pattern of auto VMT differences in terms of absolute value and percentage change compared to the baseline 2050 scenario. Figure 6 shows the distribution of auto VMT in the BAU scenario, while Figure 7 to Figure 14 show the absolute differences in auto VMT and relative differences compared to BAU for all modeled scenarios.

In the BAU baseline case for the year 2050, most of the auto VMT are generated in the Sacramento, the San Francisco Bay Area, the Greater Los Angeles and San Diego regions. Relatively small amounts of VMT are forecasted in the remaining lower-population regions.

Uneven spatial distributions of changes are observed in the private CAV, private CAV + pricing, shared CAV and shared CAV + pricing scenarios. For the private CAV and shared CAV scenarios, the majority of the absolute changes in auto VMT compared to the BAU scenario are in areas with already high amount of auto VMTs, i.e., Sacramento, the San Francisco Bay Area, the Greater Los Angeles and San Diego regions. However, it is the San Joaquin Valley region that reports a rather high relative change. This is possibly due to the fact that the networks in high auto VMT areas are already running at capacity, and higher demand for CAV would not largely impact the already congested network. Instead, the San Joaquin region has more capacity to allow more CAV trips and higher VMT, and is also crossed by thru long-distance travel to/from other regions in the state.

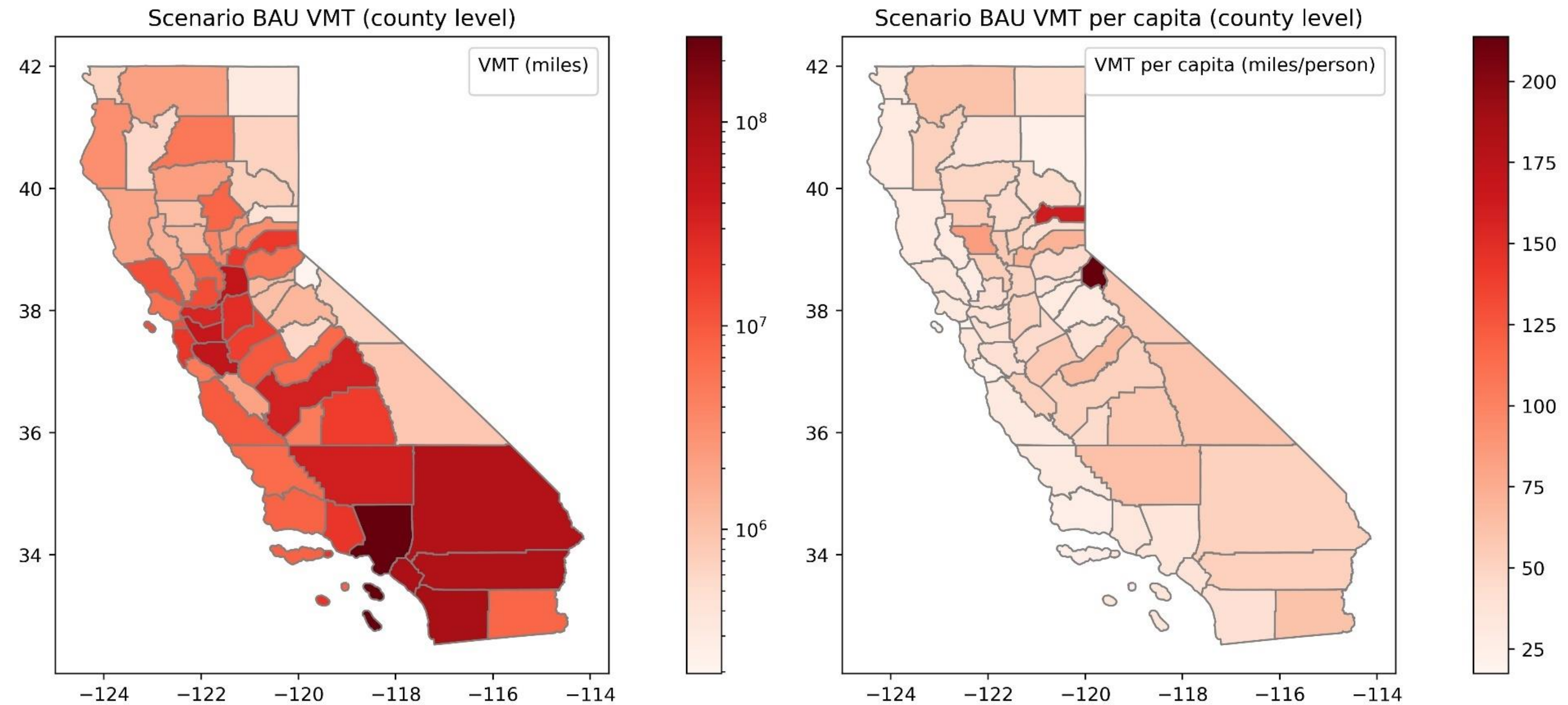

Figure 6. Daily Auto VMT for Scenario 0 (BAU)

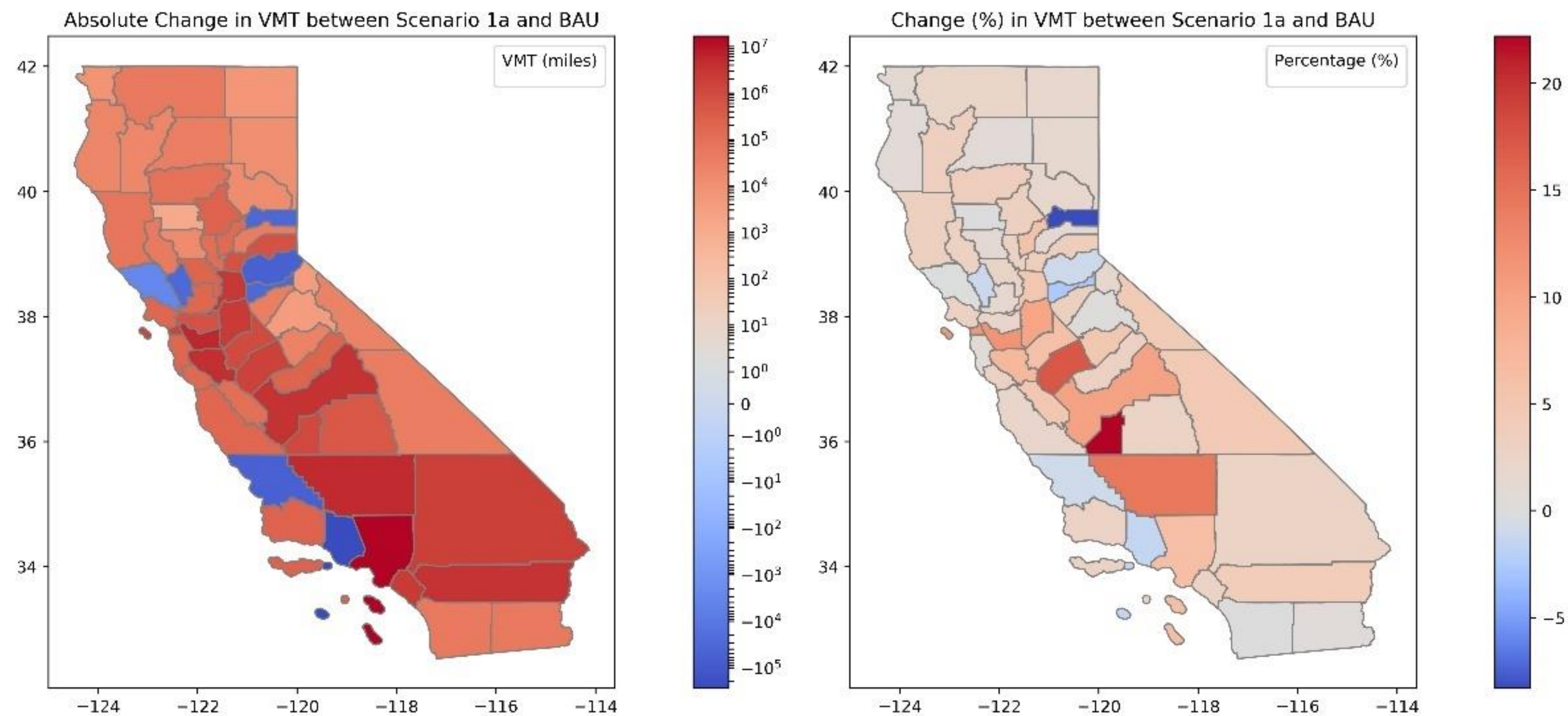

Figure 7. Changes in Daily Auto VMT for Scenario 1a vs. BAU

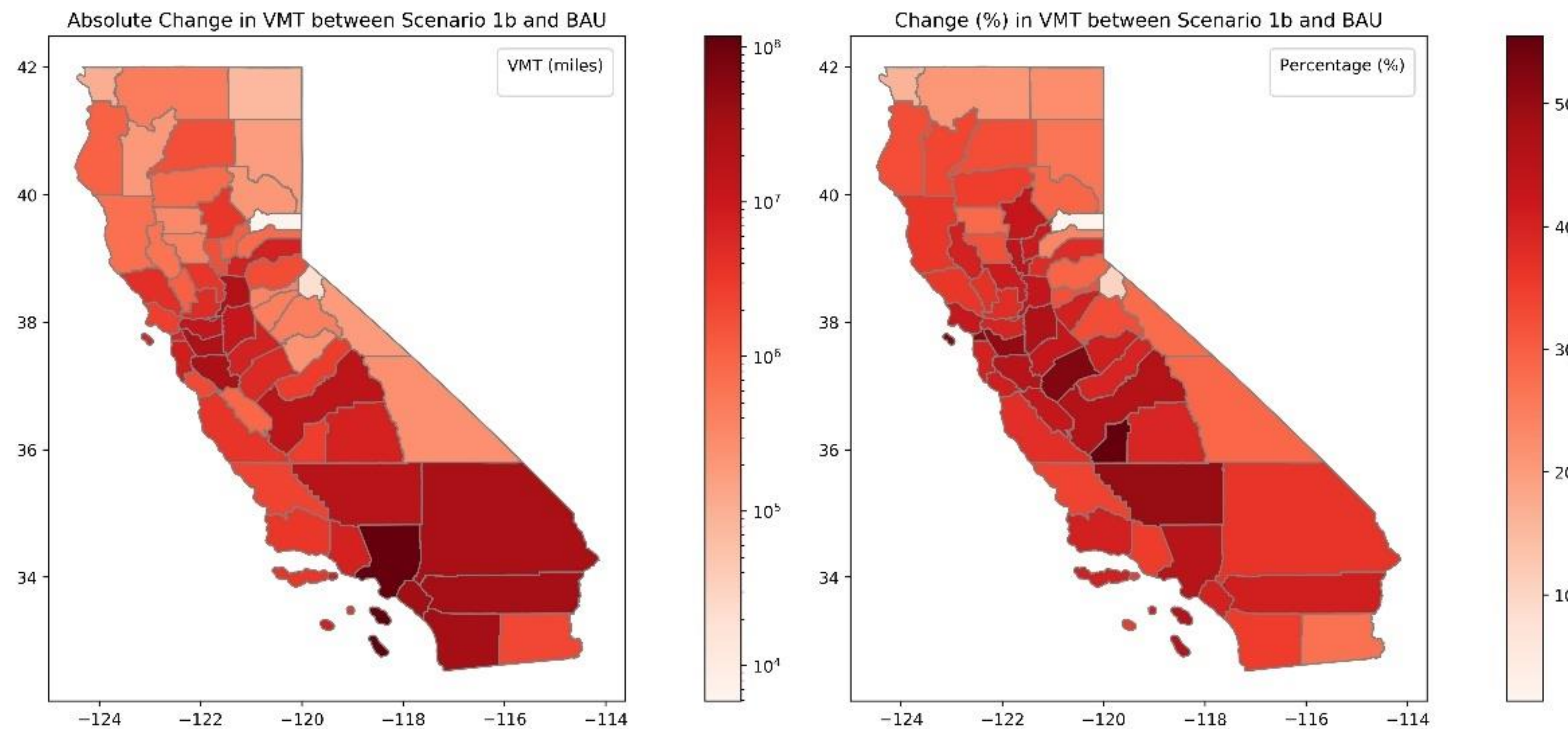

Figure 8. Changes in Daily Auto VMT for Scenario 1b vs. BAU

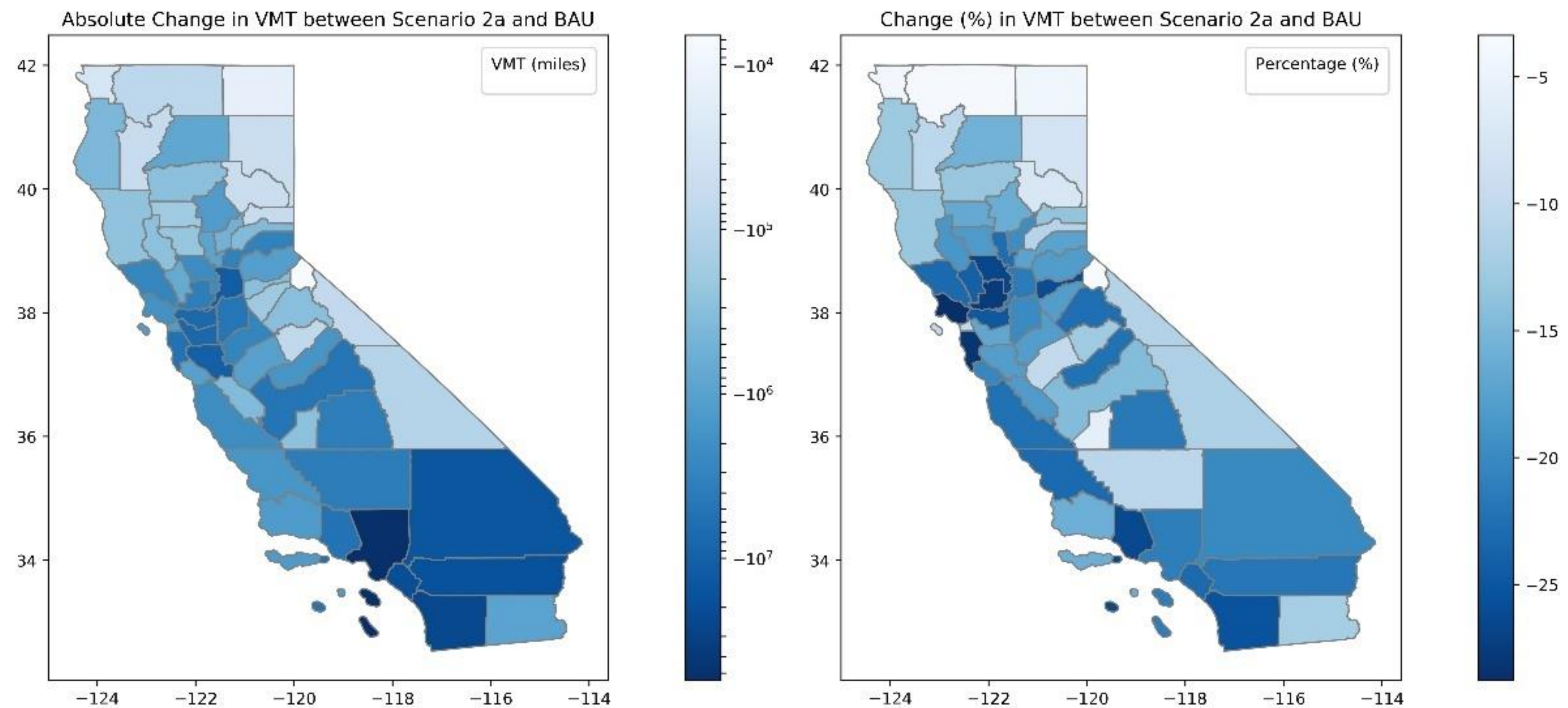

Figure 9. Changes in Daily Auto VMT for Scenario 2a vs. BAU

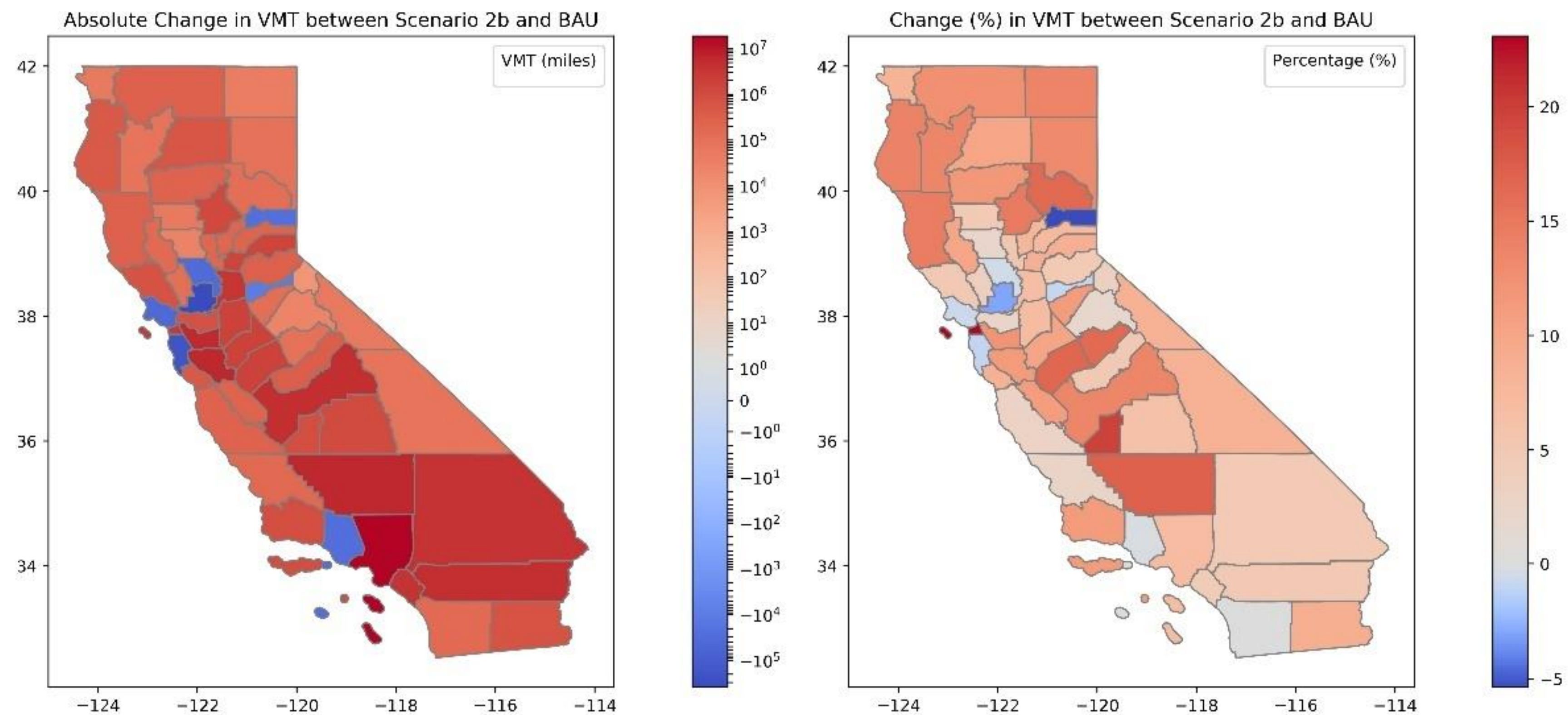

Figure 10. Changes in Daily Auto VMT for Scenario 2b vs. BAU

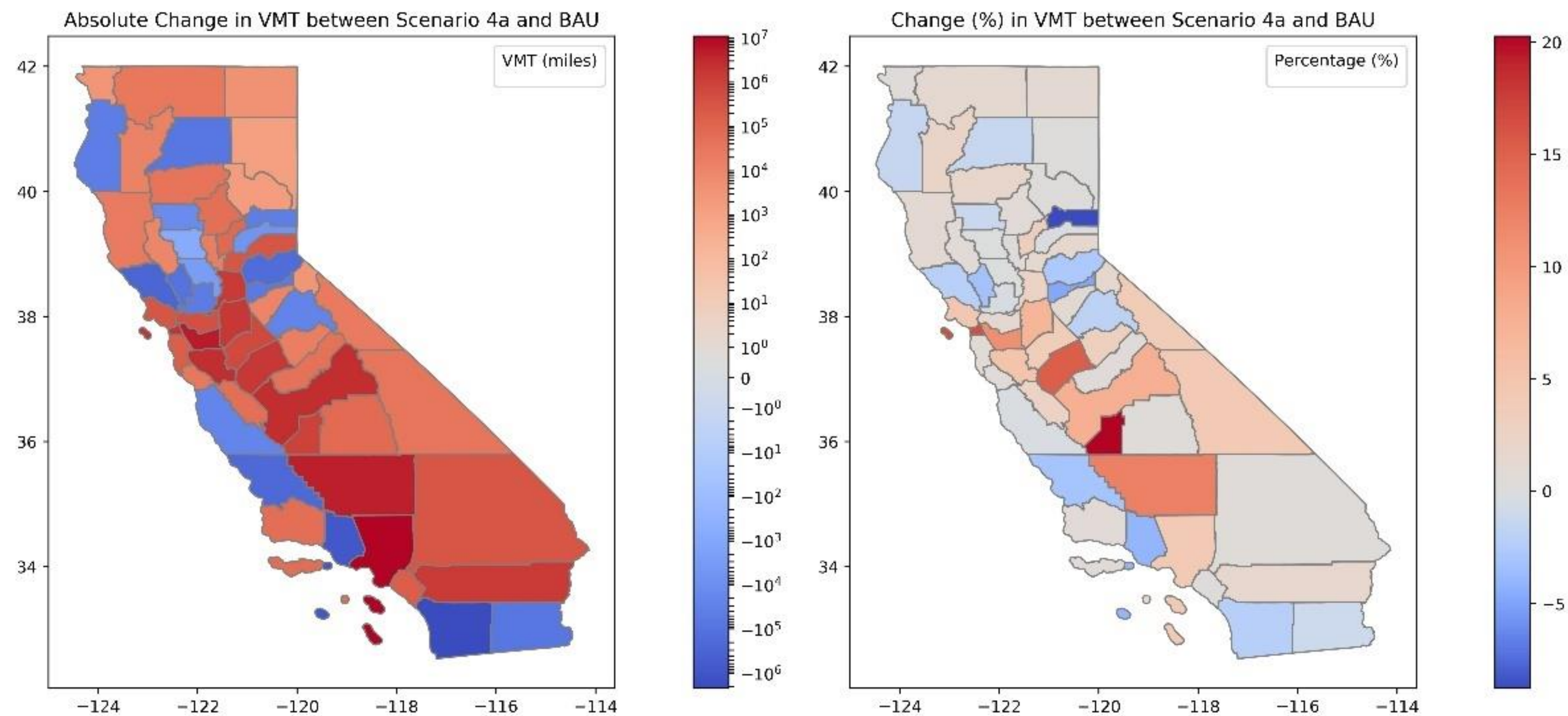

Figure 11. Changes in Daily Auto VMT for Scenario 4a vs. BAU

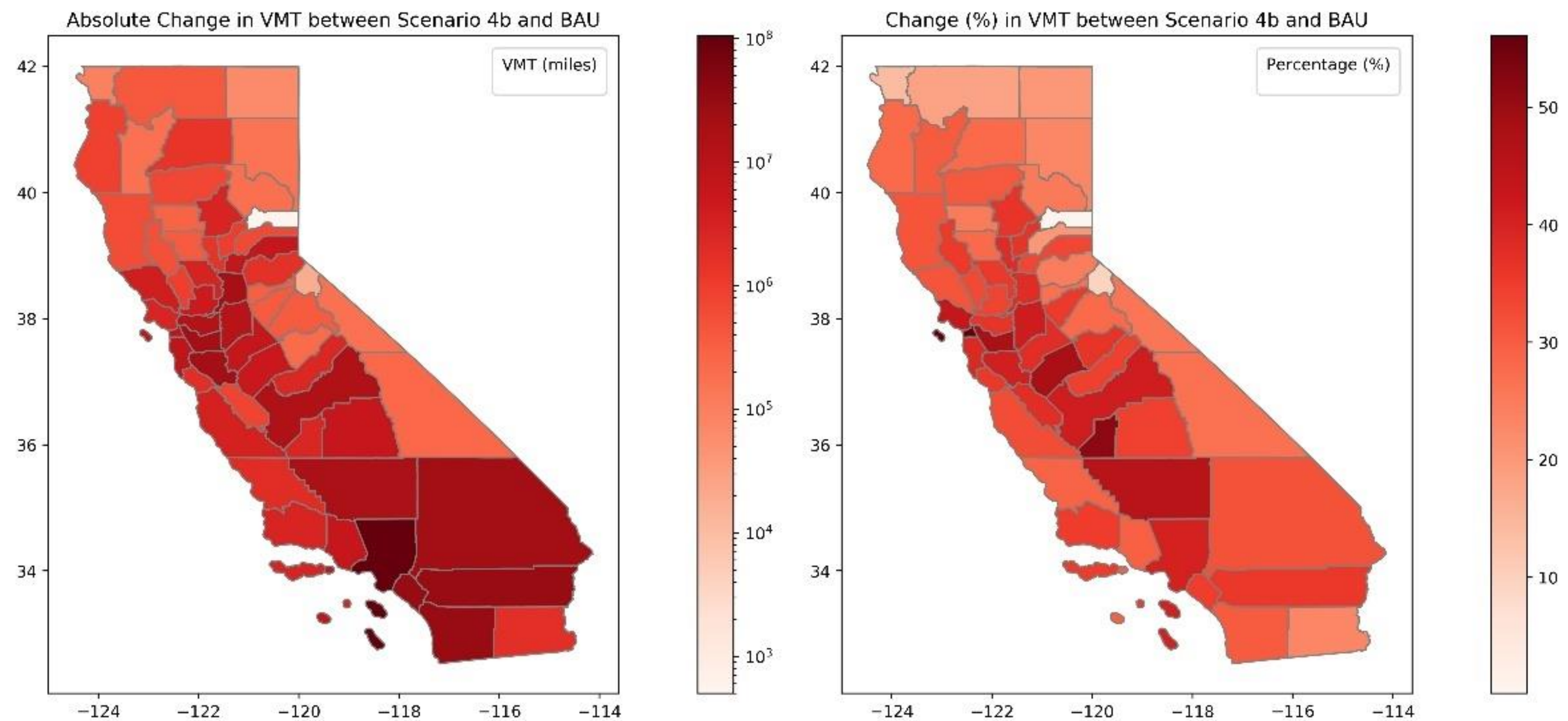

Figure 12. Changes in Daily Auto VMT for Scenario 4b vs. BAU

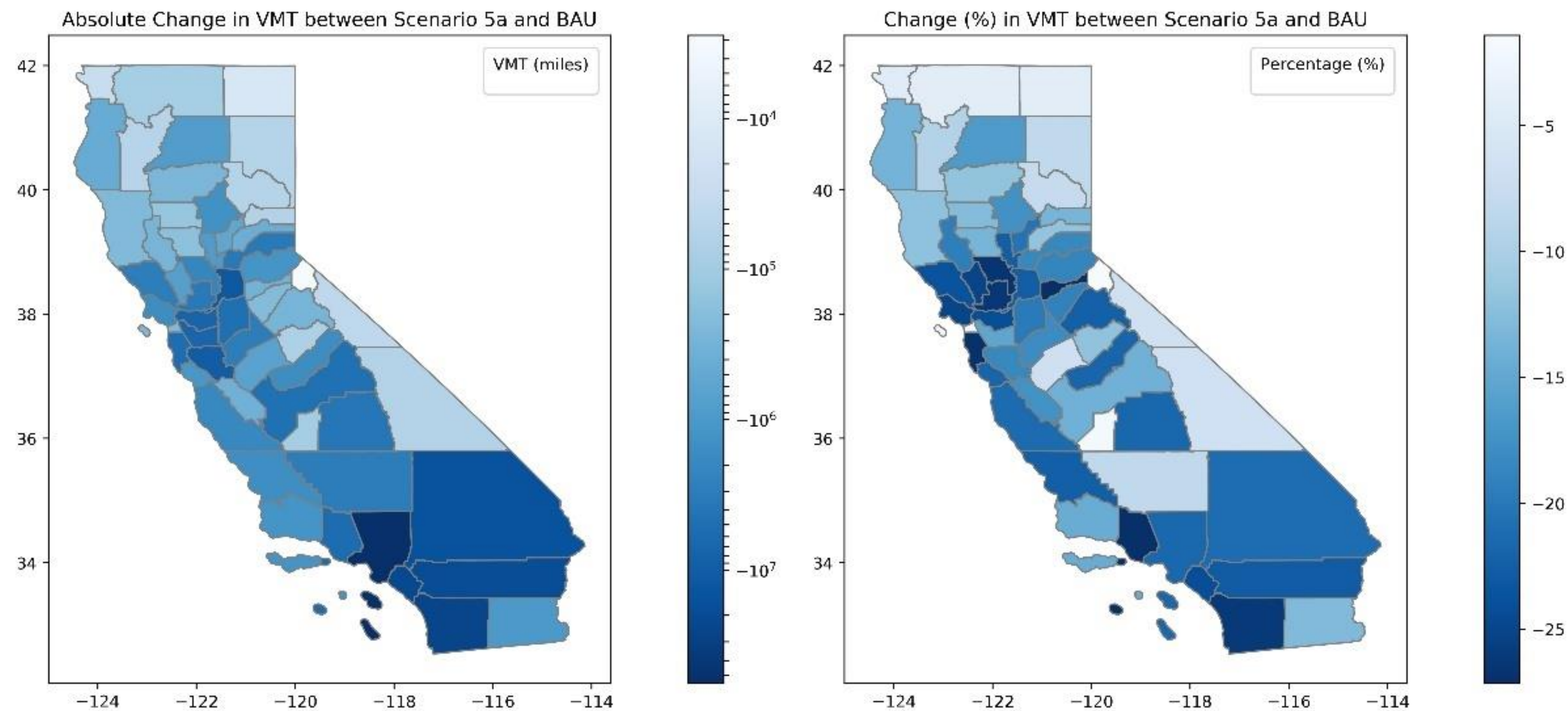

Figure 13. Changes in Daily Auto VMT for Scenario 5a vs. BAU

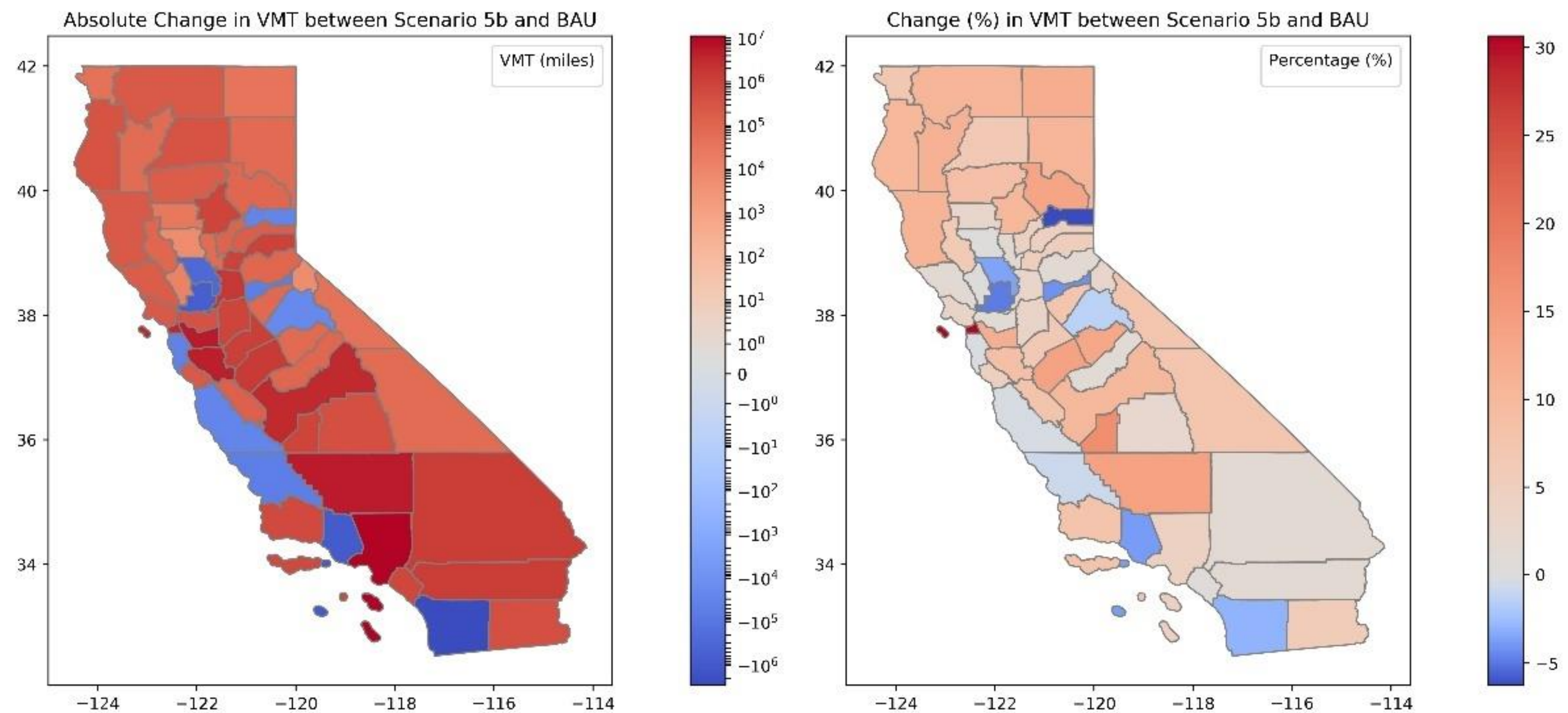

Figure 14. Changes in Daily Auto VMT for Scenario 5b vs. BAU

GHG and Criteria Pollutant Emissions

Based on the results of the travel demand forecasting model, we evaluated the environmental impacts of CAV deployment in the State of California. The calculation is based on a combination of the Vision and EMFAC model emission factors. Criteria pollutant emission results are shown in Table 19 and Table 20. Total statewide results are shown in Figure 15 to Figure 18. The absolute differences and percentage changes are shown in Figure 19 to Figure 30. Note that only auto pollutants are plotted in the maps. The values used in these plots are point estimates. The potential values should lie in the range between the *a* series of lower-bound cases and the *b* series of upper-bound cases for these scenarios. For the emission visualization, we only show the results for CO_2 emissions since the other emission factors (e.g., PM2.5, NOx) have a similar spatial distribution pattern as CO_2. The units of CO_2 emissions are megatons per year (MT/yr), and the units for NOx, PM2.5, and ROG are tons per day (T/d). We use 347 as the conversion factor from daily to yearly measurement.

Table 19. Criteria Pollutants for Year 2050

Scenario	0	1a	1b	2a	2b	3a	3b	4a	4b	5a	5b	6a	6b
CO2 Auto (MT/yr)	73.7	77.4	104.5	58.6	78.7	6.7	9.1	75.9	101.1	58.5	76.7	6.6	8.8
NOX Auto (T/d)	18.7	19.6	26.5	14.9	20.0	2.4	3.2	19.3	25.7	14.9	19.5	2.3	3.1
PM2.5 Auto (T/d)	0.5	0.5	0.7	0.4	0.5	0.1	0.1	0.5	0.7	0.4	0.5	0.1	0.1
ROG Auto (T/d)	2.1	2.2	3.0	1.7	2.2	0.3	0.4	2.2	2.9	1.7	2.2	0.3	0.4
CO2 Total (MT/yr)	123.2	126.4	153.6	107.6	127.7	55.7	58.1	125.0	150.2	107.5	125.6	55.6	57.8
NOX Total (T/d)	47.9	48.5	55.4	43.7	48.8	31.3	32.1	48.2	54.6	43.7	48.3	31.2	32.0
PM2.5 Total (T/d)	0.9	0.9	1.0	0.7	0.9	0.4	0.4	0.9	1.0	0.7	0.9	0.4	0.4
ROG Total (T/d)	8.3	8.4	9.2	7.8	8.4	6.5	6.6	8.4	9.1	7.8	8.4	6.5	6.5

Table 20. Percentage Change of Criteria Pollutants for Year 2050 Compared with BAU

Scenario	1a	1b	2a	2b	3a	3b	4a	4b	5a	5b	6a	6b
CO2 Auto (MT/yr)	5.0%	41.7%	-20.5%	6.7%	-90.9%	-87.7%	3.0%	37.1%	-20.6%	3.9%	-91.1%	-88.1%
NOX Auto (T/d)	5.0%	41.7%	-20.5%	6.8%	-87.2%	-82.8%	3.0%	37.1%	-20.6%	4.0%	-87.5%	-83.3%
PM2.5 Auto (T/d)	4.9%	41.7%	-20.6%	6.7%	-86.9%	-82.3%	2.9%	37.1%	-20.7%	3.9%	-87.1%	-82.8%
ROG Auto (T/d)	4.9%	41.7%	-20.6%	6.7%	-87.0%	-82.5%	2.9%	37.1%	-20.7%	3.9%	-87.3%	-83.1%
CO2 Total (MT/yr)	2.6%	24.6%	-12.7%	3.6%	-54.8%	-52.8%	1.4%	21.9%	-1.1%	-1.0%	-54.9%	-53.1%
NOX Total (T/d)	1.4%	15.8%	-8.6%	2.0%	-34.6%	-32.9%	0.6%	14.0%	-1.1%	-1.0%	-34.7%	-33.1%
PM2.5 Total (T/d)	2.4%	23.4%	-12.2%	3.3%	-49.8%	-47.2%	1.3%	20.7%	-1.1%	-1.0%	-50.0%	-47.5%
ROG Total (T/d)	0.6%	9.9%	-6.0%	0.9%	-22.6%	-21.4%	0.1%	8.7%	-1.1%	-1.0%	-22.7%	-21.6%

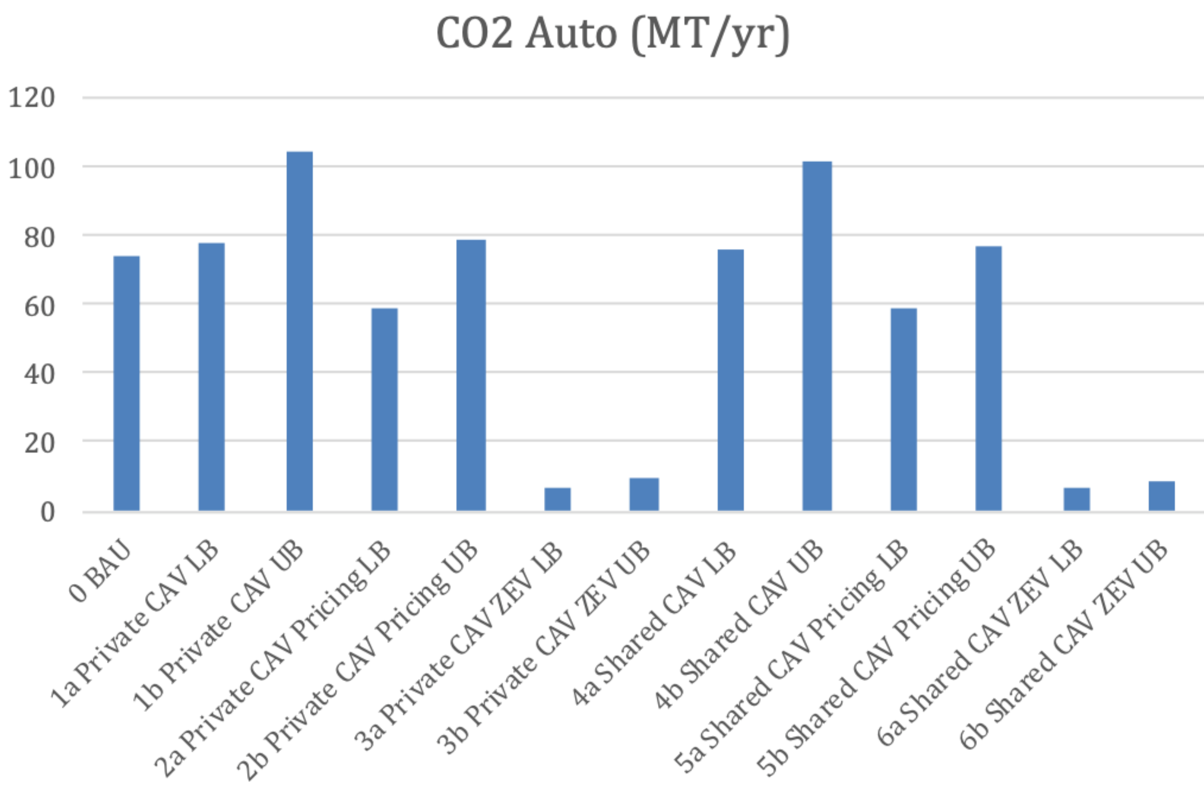

Figure 15. Statewide CO2 Comparison

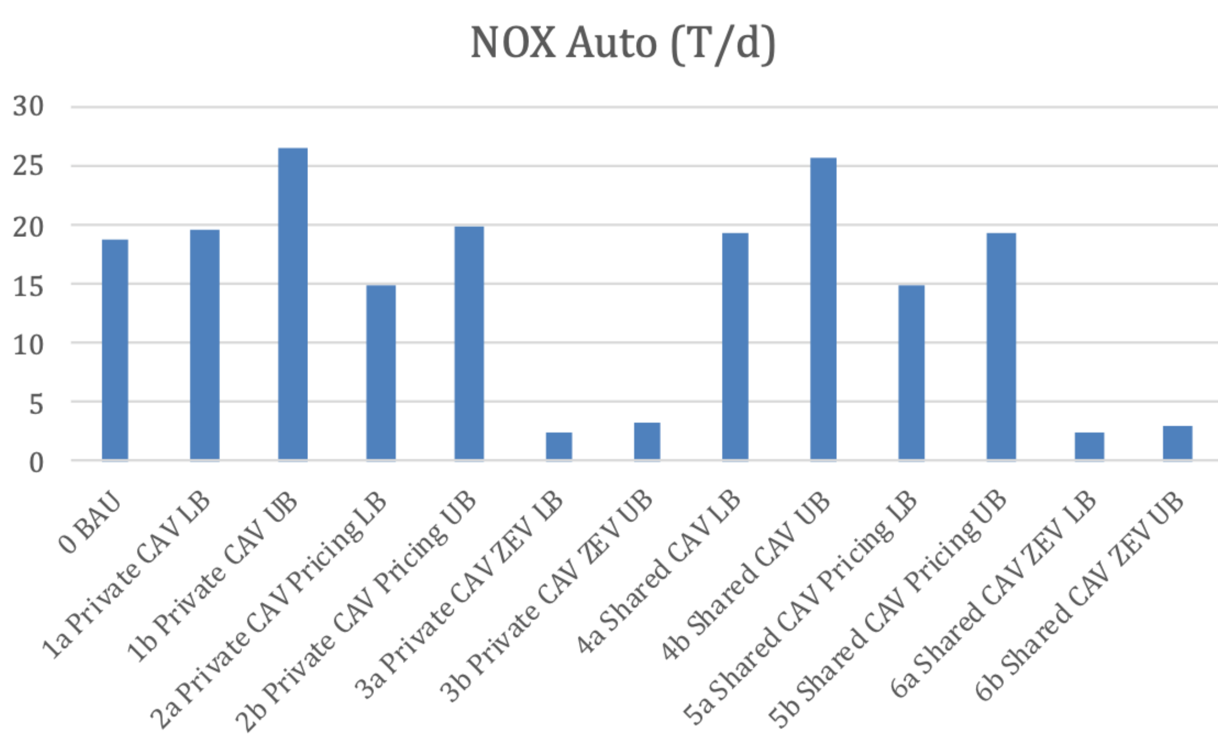

Figure 16. Statewide NOX Comparison

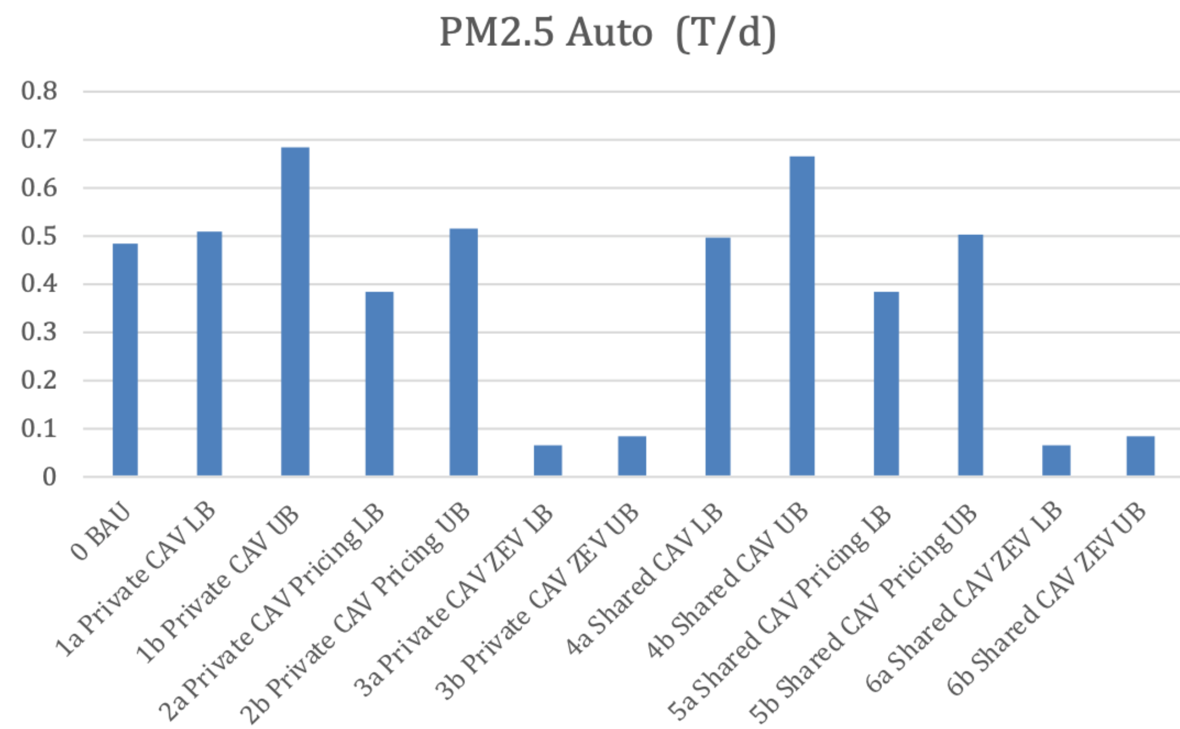

Figure 17. Statewide PM2.5 Comparison

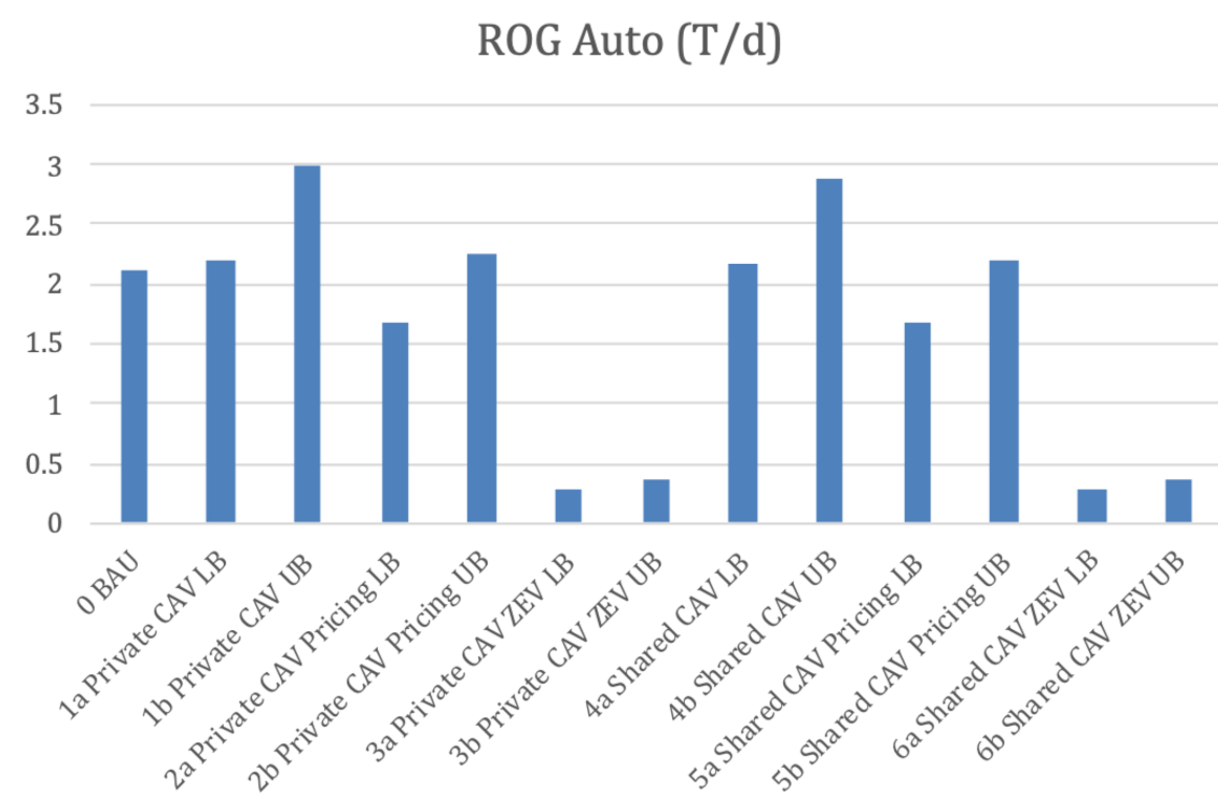

Figure 18. Statewide ROG Comparison

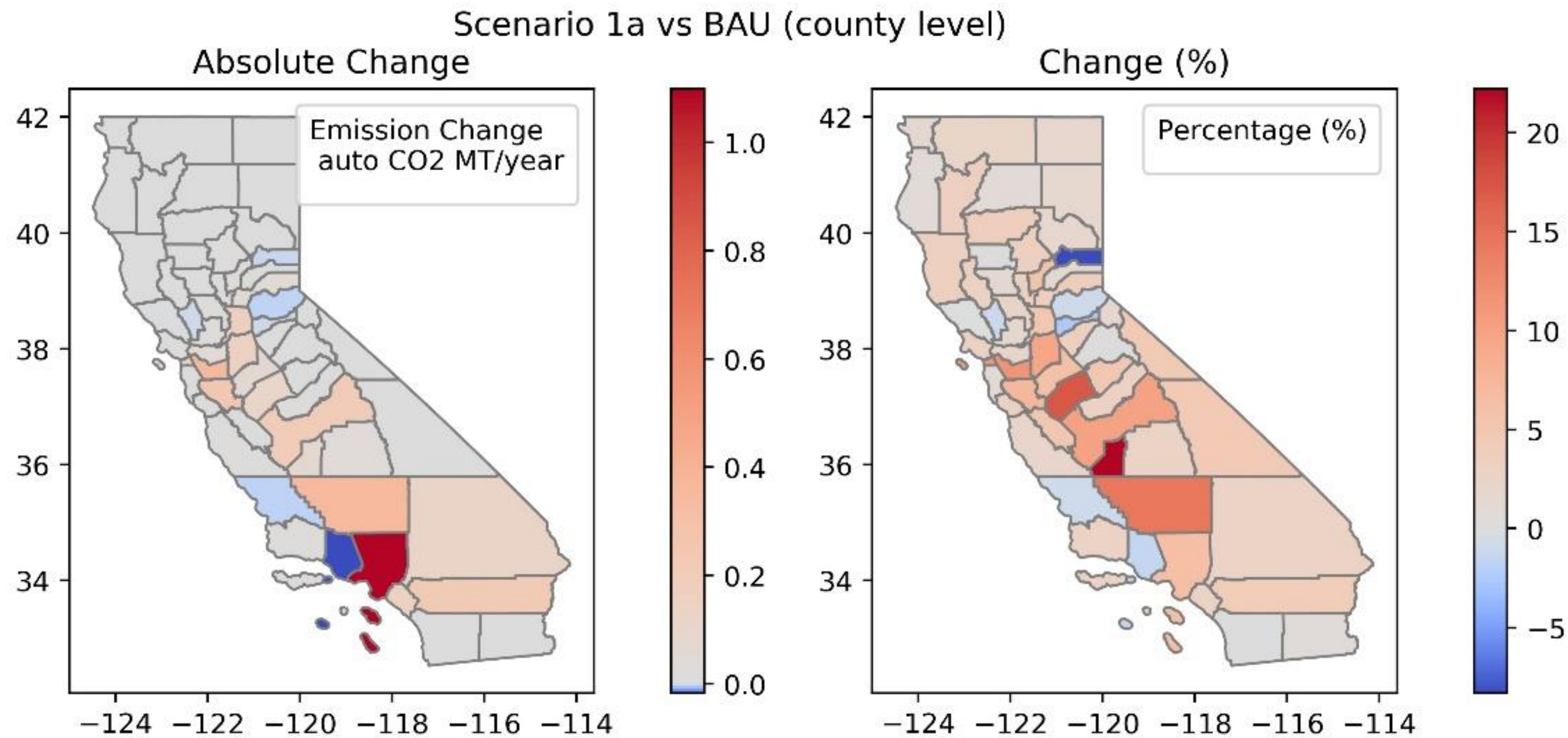

Figure 19. Comparison of Auto CO2 Emissions in Scenario 1a vs. BAU

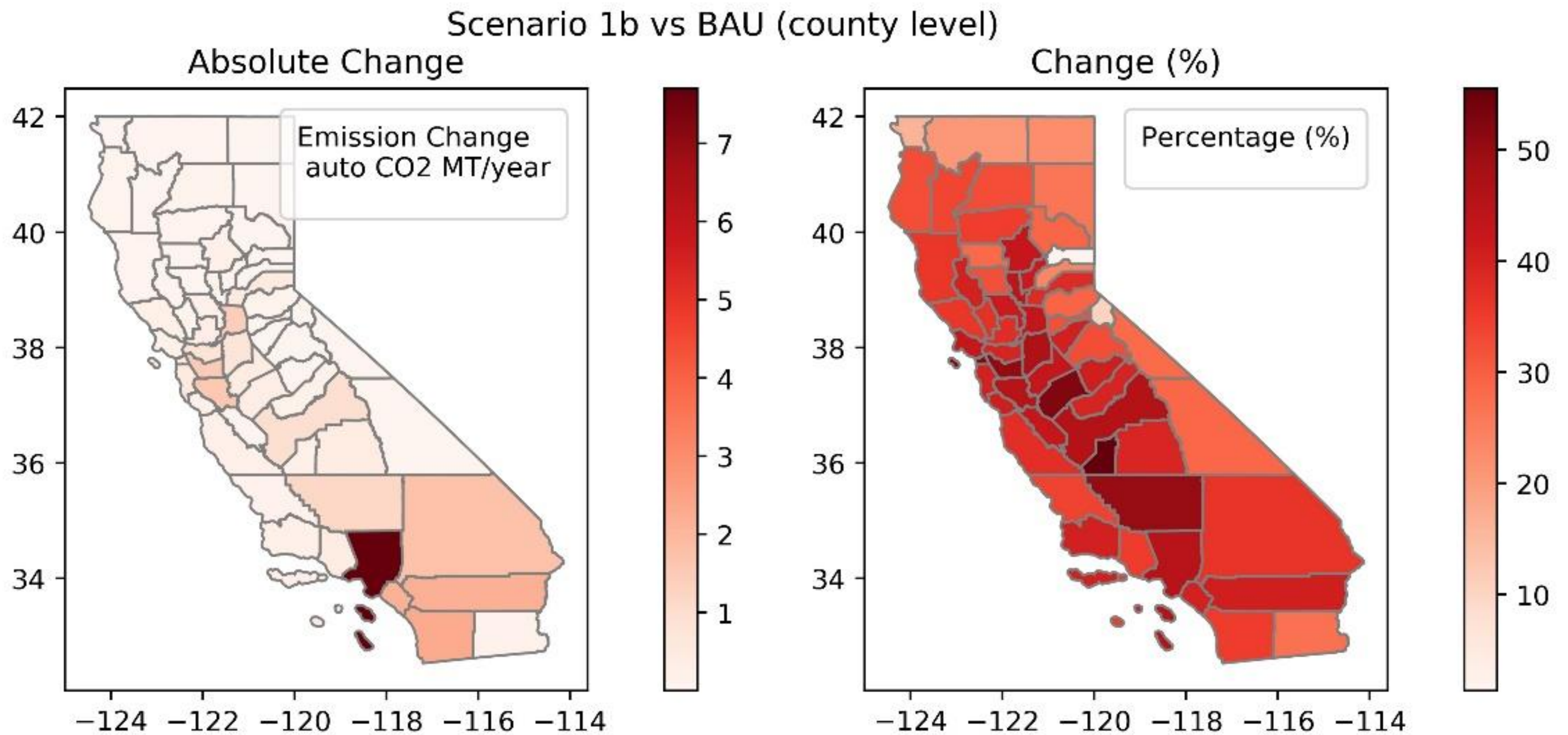

Figure 20. Comparison of Auto CO2 Emissions in Scenario 1b vs. BAU

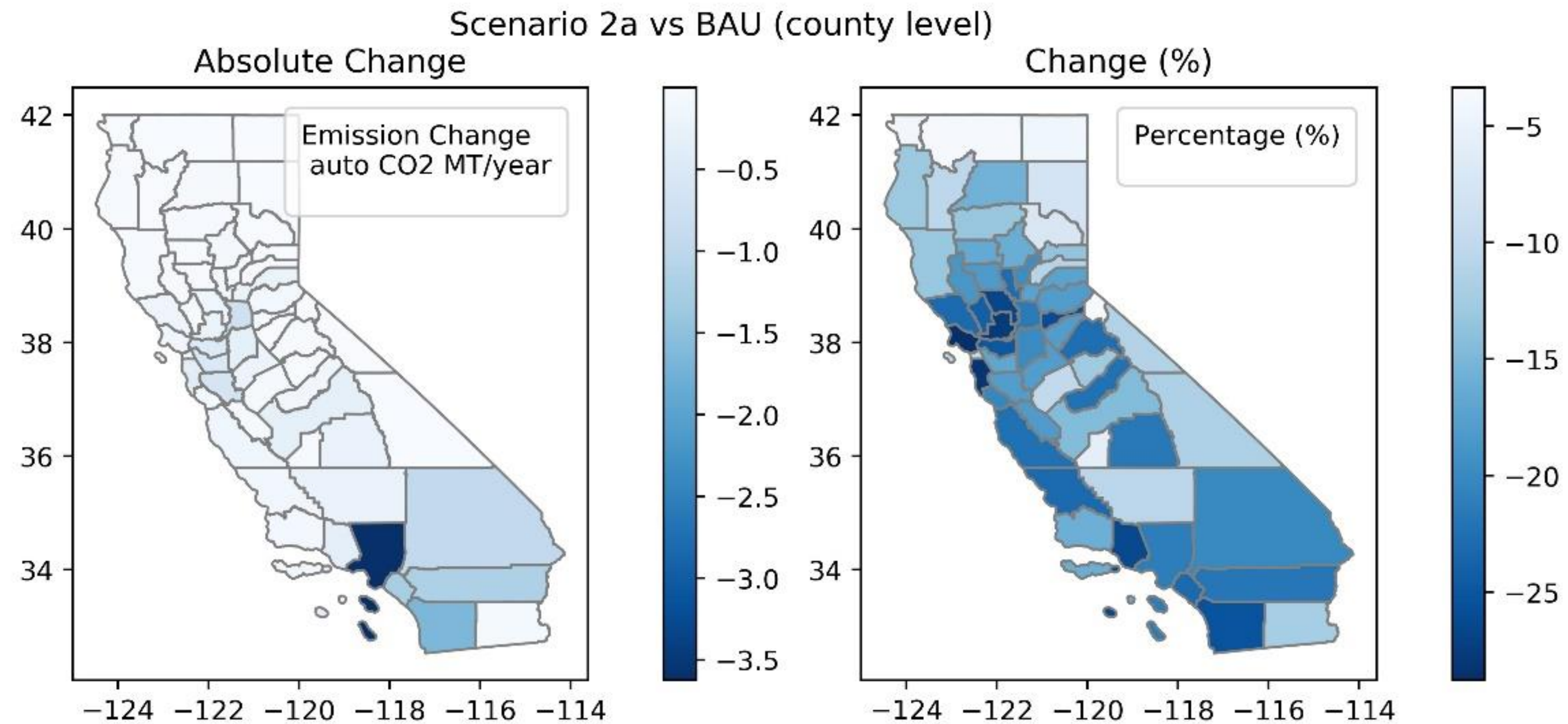

Figure 21. Comparison of Auto CO2 Emissions in Scenario 2a vs. BAU

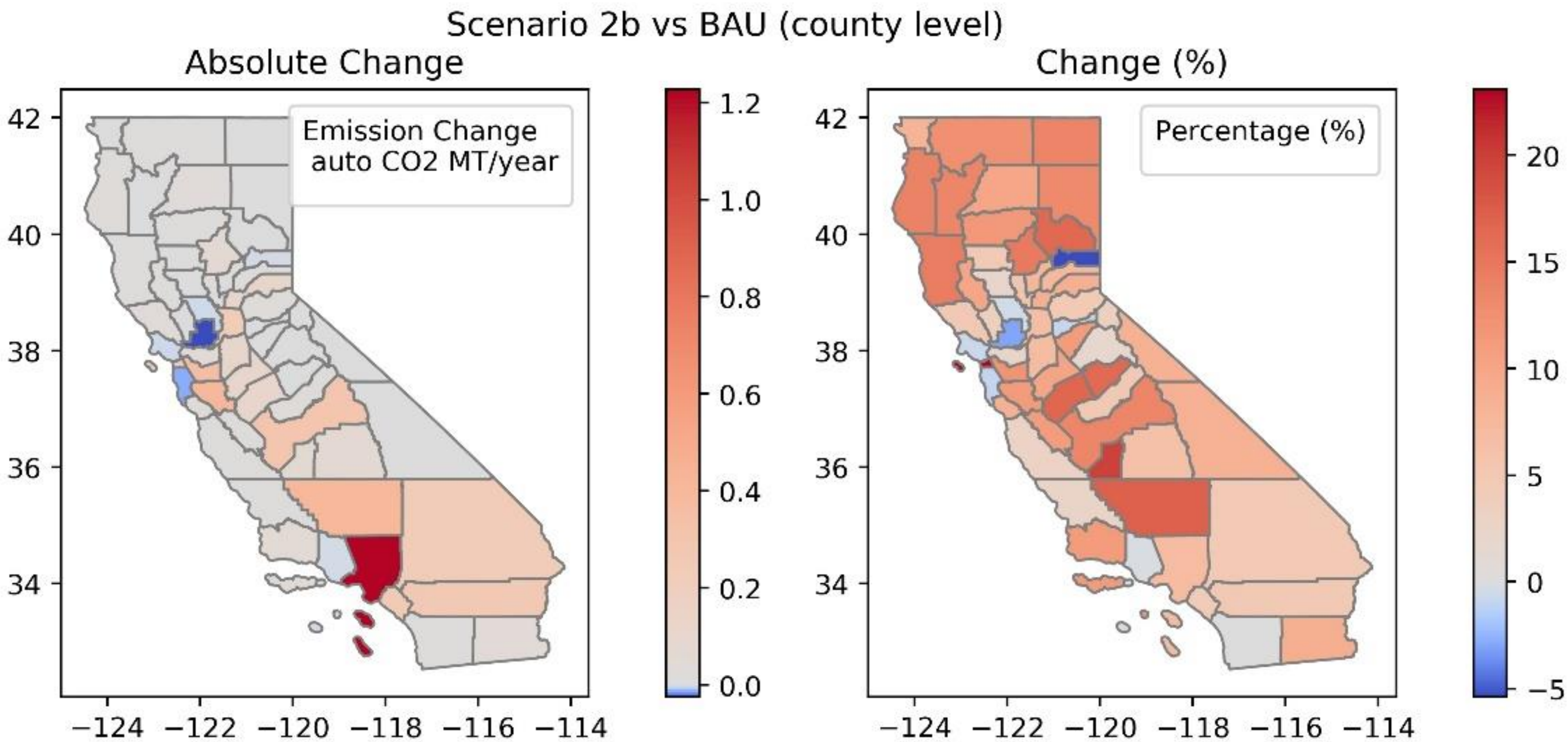

Figure 22. Comparison of Auto CO2 Emissions in Scenario 2b vs. BAU

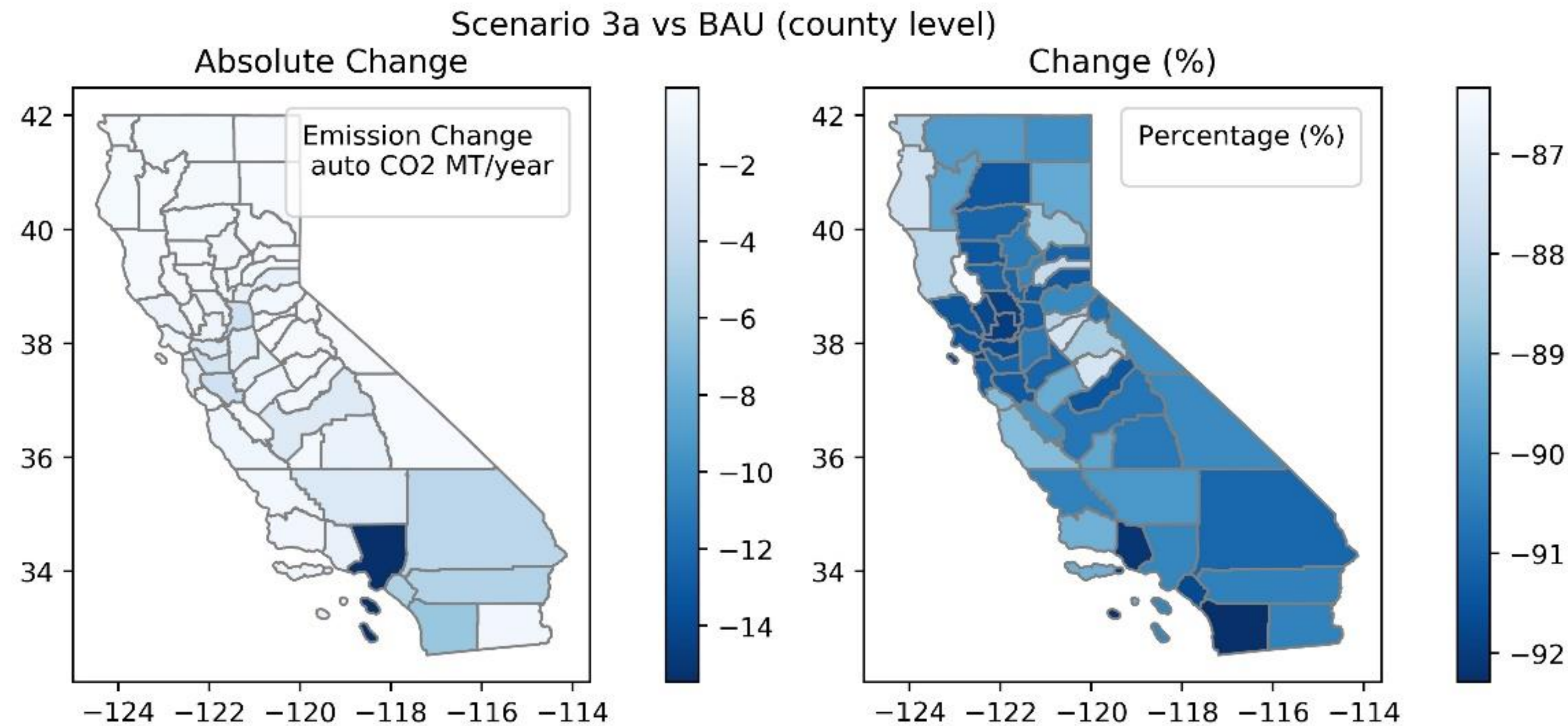

Figure 23. Comparison of Auto CO2 Emissions in Scenario 3a vs. BAU

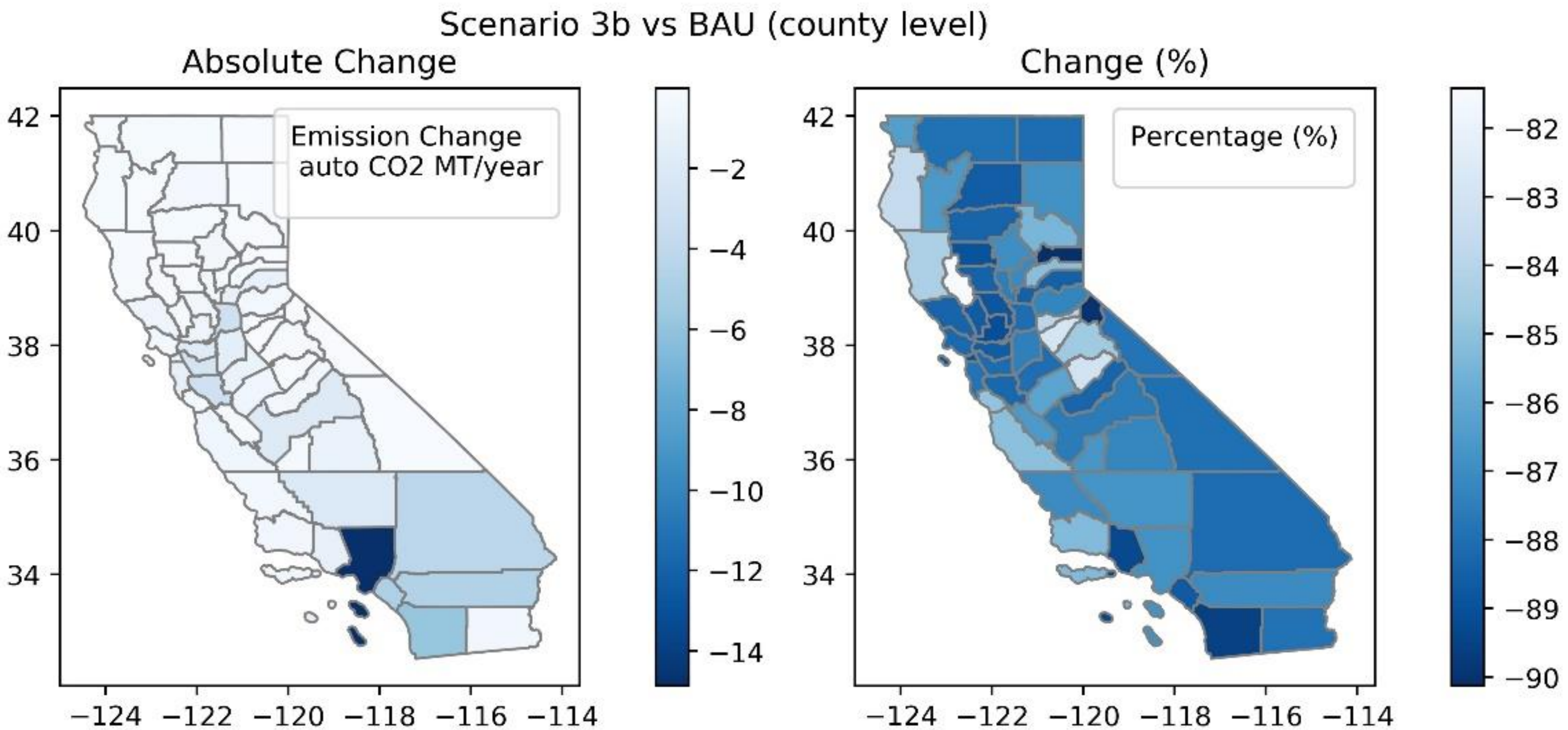

Figure 24. Comparison of Auto CO2 Emissions in Scenario 3b vs. BAU

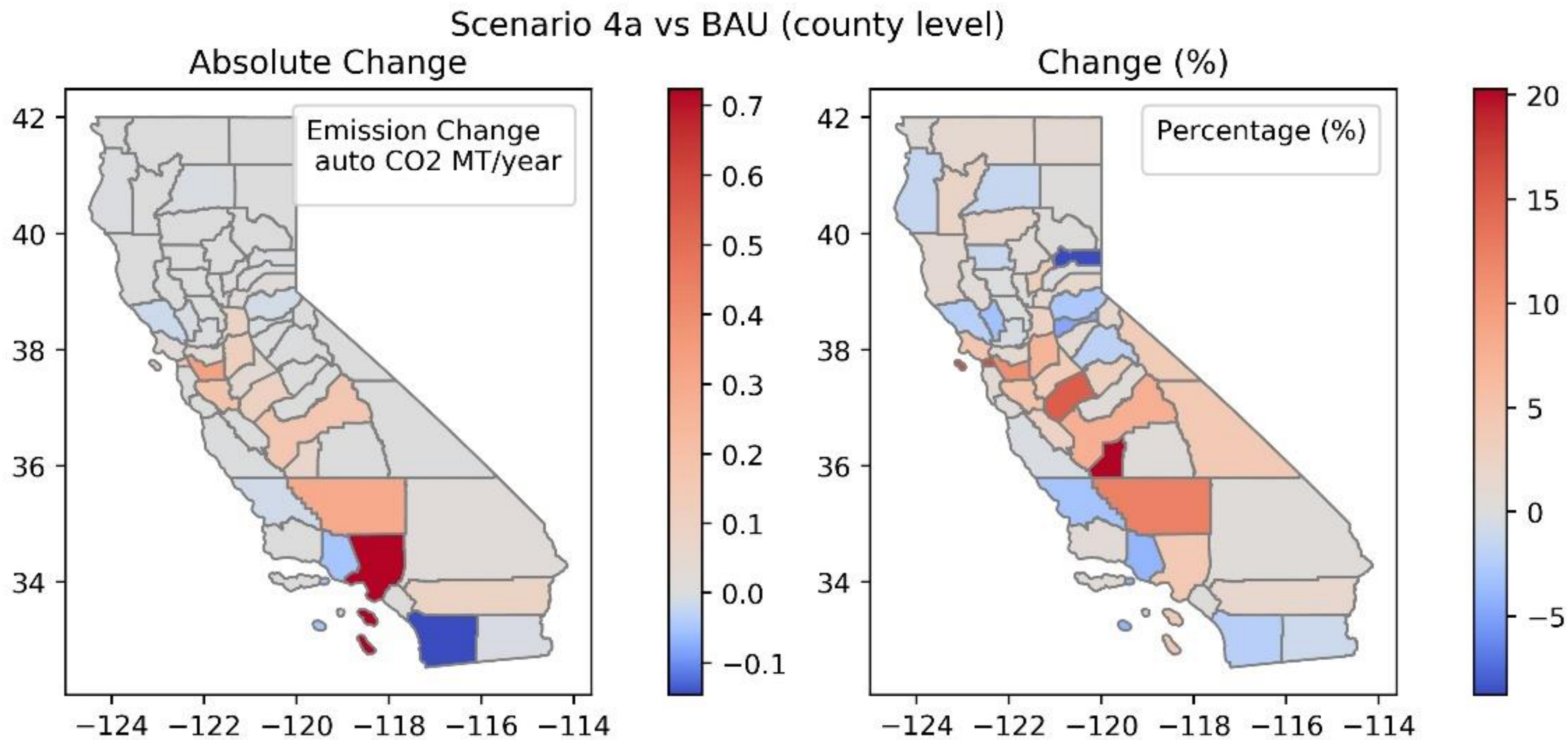

Figure 25. Comparison of Auto CO2 Emissions in Scenario 4a vs. BAU

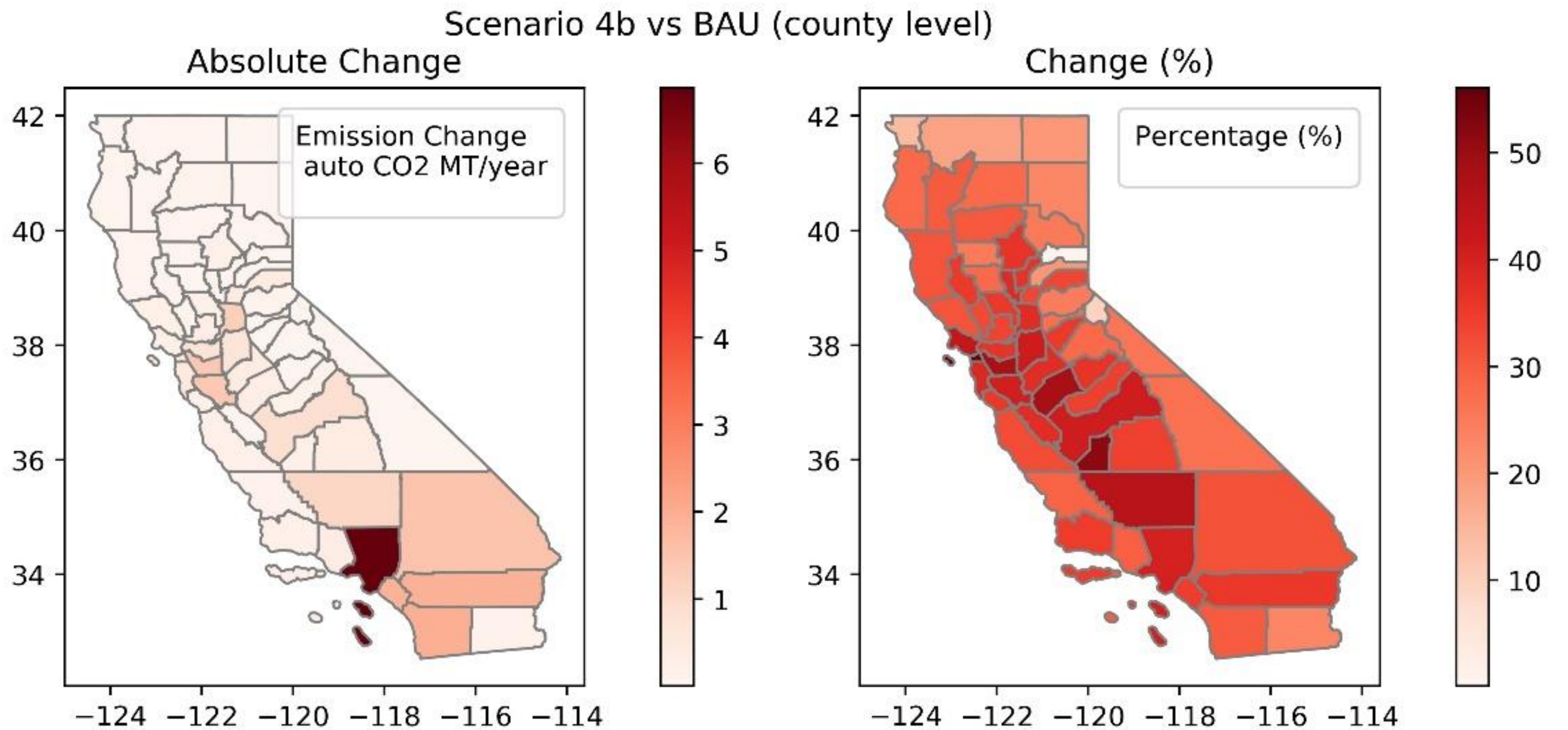

Figure 26. Comparison of Auto CO2 Emissions in Scenario 4b vs. BAU

NCST

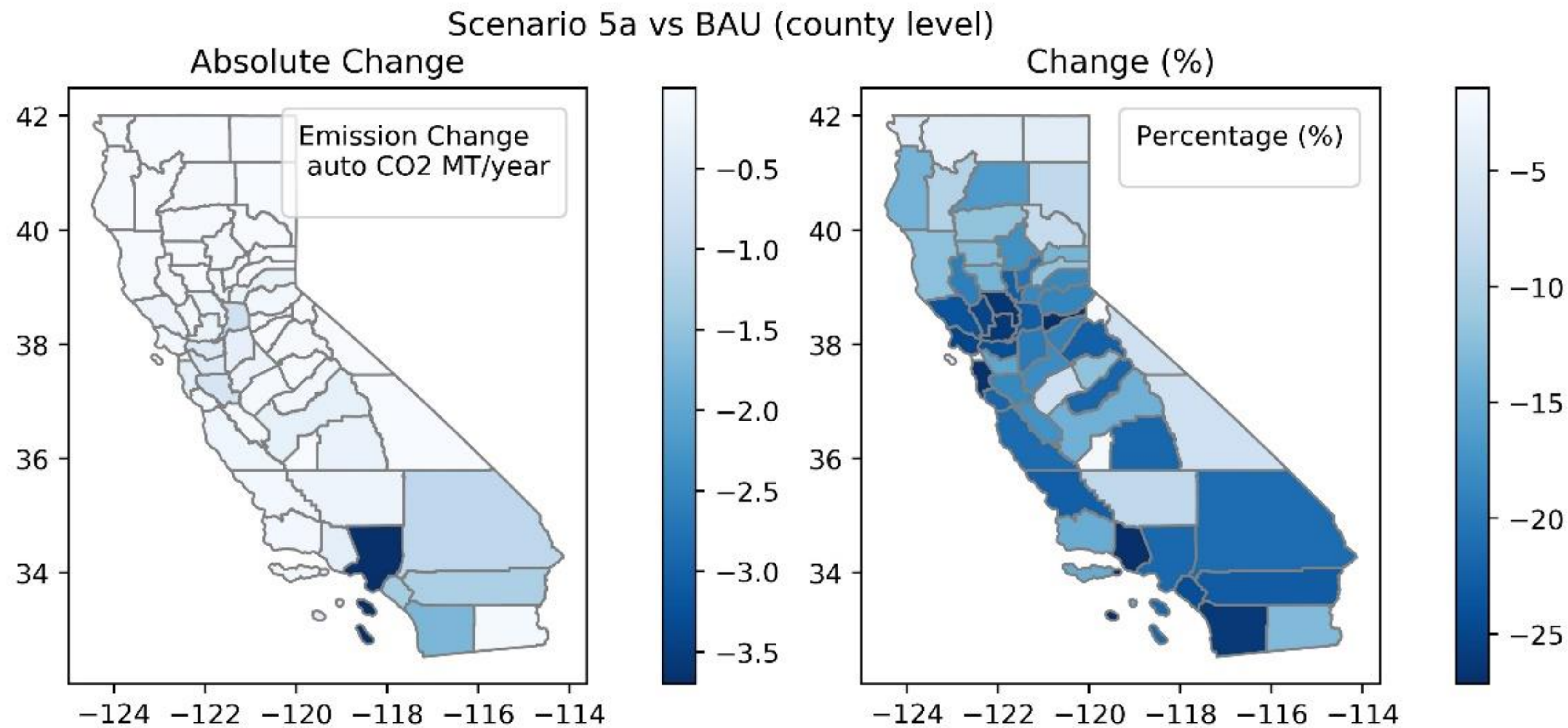

Figure 27. Comparison of Auto CO2 Emissions in Scenario 5a vs. BAU

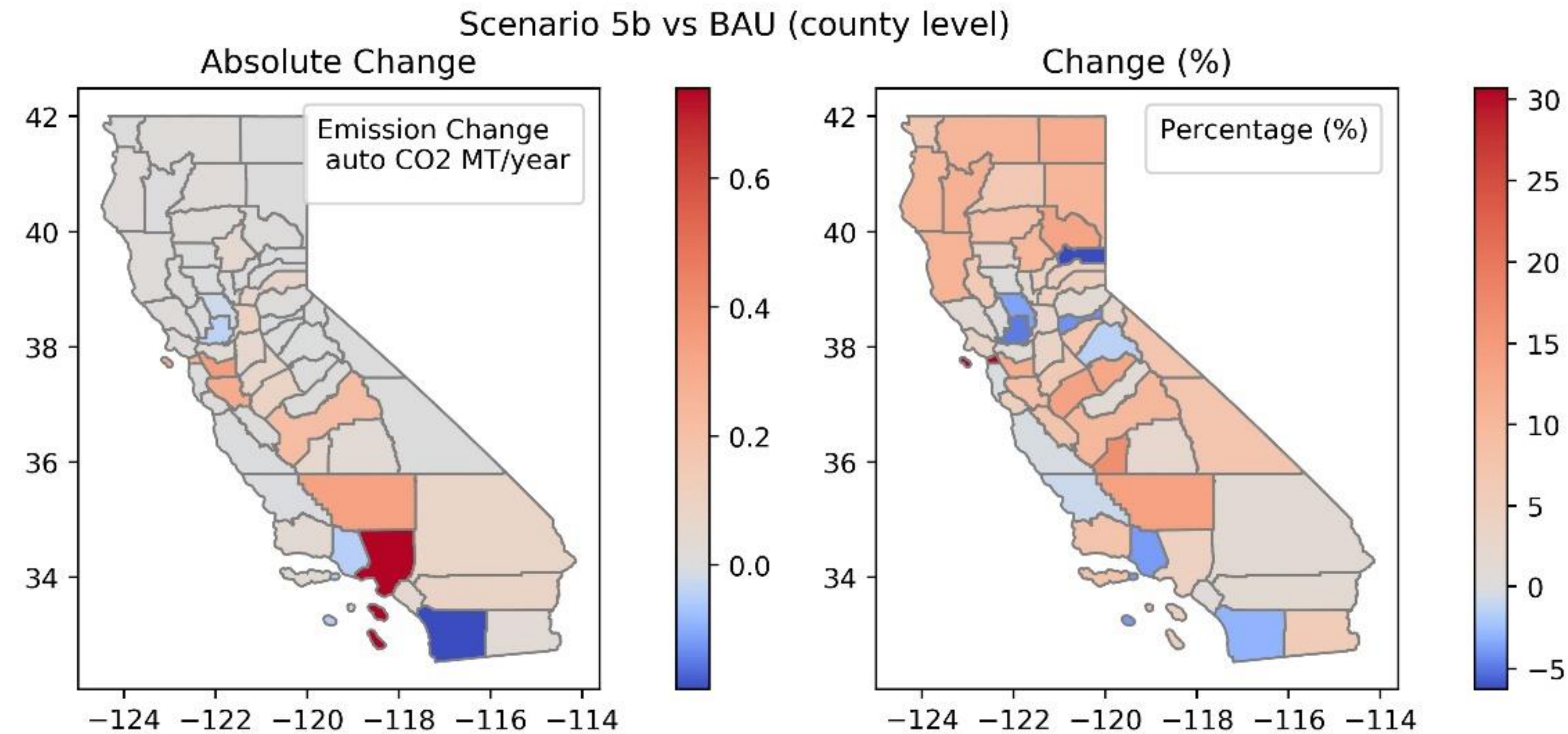

Figure 28. Comparison of Auto CO2 Emissions in Scenario 5b vs. BAU

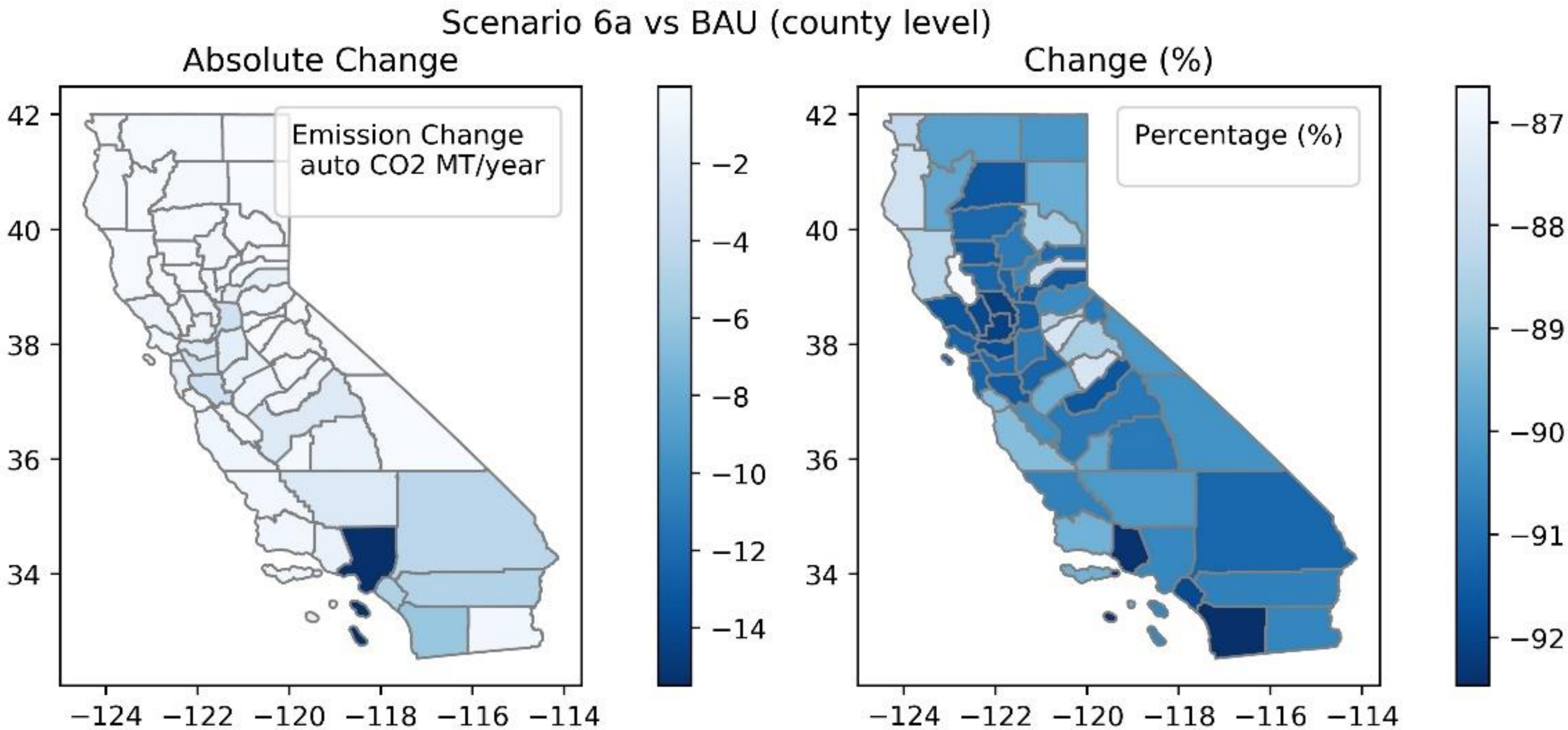

Figure 29. Comparison of Auto CO2 Emissions in Scenario 6a vs. BAU

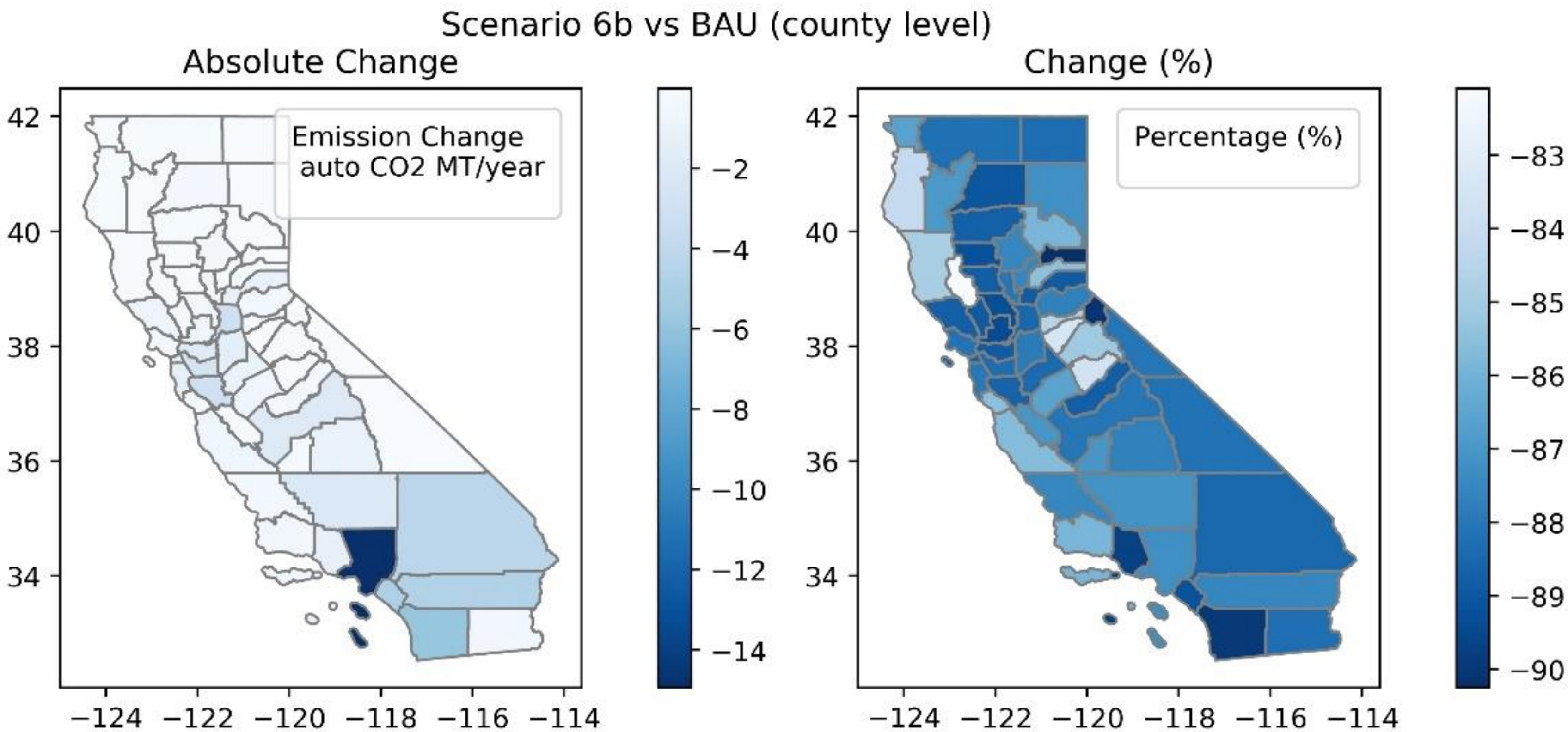

Figure 30. Comparison of Auto CO2 Emissions in Scenario 6b vs. BAU

According to the emission results, we observe a certain increase in auto pollutants in the private CAV and shared CAV scenarios, while both the private CAV + ZEV and shared CAV + ZEV scenarios yield lower levels of pollutant emissions. With the high penetration rate of ZEVs, we observed a dramatic reduction in auto emissions compared to the baseline (BAU) scenario.

The spatial pattern of emission distribution is similar with that of auto VMT. This is because areas with higher VMT would generate higher criteria pollutants, and the CSTDM framework assumes that high zero-emission vehicle penetration would not alter travel demand and the powertrain option is not considered a factor affecting travel patterns.

Consistent with the VMT distribution, in the private CAV and shared CAV scenarios, the Sacramento, the San Francisco Bay Area, the Greater Los Angeles and San Diego regions yield most of the absolute change in emissions (as expected, as these are proportional to the total amount of travel). The San Joaquin valley experiences the highest percentage change. The private CAV + pricing and shared CAV + pricing scenarios achieve a substantial containment of total emissions, though the real abatement of GHG and other criteria pollutant emissions is achieved in the ZEV scenarios.

Discussion

Many metropolitan planning organizations and other transportation agencies have adopted activity-based models to support transportation planning decisions and evaluate infrastructure projects. The classical four-step trip-based models (including trip generation, trip distribution, model choice, and route assignment) have produced some effective analyses in the past. However, as a simplified method for travel demand forecasting, four-step models consider aggregated travel choices and cannot entirely reflect the reality of travel-related decision-making by individuals and households.

Activity-based models, such as the CSTDM, overcome those limitations, by modeling household organization and individuals' activity participation and travel choices for the entire population. In details, these models generate a synthetic population of households and individuals and forecast activity participation and travel choices for the entire population in the model area. While activity-based models provide many benefits in terms of their increased ability to model realistic individual behaviors and forecast the resulting travel demand impacts, they have several limitations that affect their use when forecasting the range of potential impacts from CAV deployment.

First, a general limitation in modeling CAV deployment impacts is that while alternatives to owning and driving a private vehicle are becoming increasingly available, whether and how these services and technologies will be accessible to the various segments of the population in different areas remains unknown. Similarly, research to date only provides limited insights into the behavioral changes that these alternative solutions might cause.

Another limitation is rooted in the activity-based modeling framework in general. In this project, our assumption is that the statewide activity-based model can capture the impacts of

CAVs through the changes in the travel behavior of the population. The fundamental behavioral assumptions rely on how people would perceive CAVs in the future and how they would adjust their corresponding daily travel behavior. While we implement a number of changes in the modeling framework to account for the behavioral changes prompted by CAV availability, we hold constant many other functions, estimated coefficients, and constants in the model.

Third, we use a model that was estimated, calibrated, and validated using survey data from past years, while many uncertainties remain about the future. This includes changes in lifestyle, technology, urban form, and policy that might modify the underlying behavioral framework with which individuals make choices in their everyday life. This is also caused by the introduction of new CAV travel modes, which will bring drastic changes to the transportation system, household organization, and individuals' activities and choices. Thus, there is no guarantee that the equations estimated for the model using data from the past will hold true in the future, given advanced in-vehicle technologies, intelligent transportation systems, and new household vehicle ownership options.

The estimations of the model coefficients usually remains valid for modeling applications to scenarios that fit in a certain range of applicability. When we introduce into the model modified assumptions and a new technology that will likely cause large modifications in individual behaviors, as it is the case of CAVs, the assumptions about behaviors (and calibration procedures for the model base year) that form the basis for the model might no longer hold true. The model assumptions and calibration practices usually adopted in the development of activity-based models might actually limit the amount of change in forecasted travel demand, constraining the results to a range that is more conventional and closer to the base scenario. This type of problem is not unusual in travel demand forecasting models, especially in cases when the model is somewhat over-fitted to replicate the observed traffic volumes in the base scenario during the calibration and validation processes.

Further, if CAVs cause a reduction in the friction of distance in a future dominated by vehicle automation, CAV deployment may well lead to modifications in land use that are not accounted for in this study. In particular, if traveling in a CAV is easier, more pleasant, more suitable for conducting other activities while traveling, and induces less fatigue, individuals may choose to live further from work locations and other frequent destinations, if this can lead to lower housing costs and/or access to better amenities.

This relocation phenomenon is not easy to measure today. For example, respondents might tend to underreport their intention to move farther away from their regular trip destinations when participating in stated preference surveys. However, in the future when facing an economic choice and while experiencing the benefits of travel in CAVs, they might modify their willingness to pay for housing units vs. location/accessibility. This might lead to further increases in travel distances and average VMT that are not accounted for in any of the scenarios presented in this project. These effects could be partially compensated, though, by the reduced need for parking in a CAV-dominated future. The reduced need for parking could open additional land for redevelopment purposes in the central core of cities and allow for more efficient use of space, in particular in US cities where a very high percentage of total land is allocated to roadways and parking. Overall, the resulting impacts of land use changes associated with CAV deployment likely point to higher VMT and increased auto travel. However, as land use effects are not accounted for in this project, all estimates of CAV travel impacts in this study are likely a substantial underestimation of the true future impacts of CAV deployment.

It should be also noted that in this project we are ignoring the disruption to transportation and the whole society caused by the COVID19 pandemic. Travel behavior choices might be different from the pre-COVID era, with long-term effects on telecommuting, car dependency, and activity patterns that are still difficult to predict at the time of writing this report. It is possible that more telecommuting, private car ownership, and urban sprawl may occur in the near future, as a result of the pandemic.

One additional limitation affecting the results from this study is that the model seems to be designed and calibrated so that travel cost is prioritized. However, the impacts of changes in travel time might not be fully captured in terms of the decision-making associated with travel choices. The results in the mode shifts in the scenarios indicate a substantial decrease in transit trips, as well as long-distance rail and in-state air travel, and the model seems to be sensitive to factors affecting mode choice. However, the total trip volume in all scenarios does not show sizable differences. This is probably because the model is designed to meet total trip volumes, and it might over-rely on constants introduced in the calibration stage to fulfill this purpose. This limits the amount of change in total trips even if major changes occur in the underlying engines of travel in future scenarios. This would not be surprising, considering that one of the most important purposes for which travel demand forecasting models are designed and used is to forecast the impacts of new travel alternatives on mode choice, while forecasting the impacts of a revolutionary technology such as CAVs that might increase the topic amount of travel in future scenarios is usually outside of the scope for which these models are designed. Additional investigation of these topics and evaluation of the model elasticities and overall ability to forecast the potential impacts of CAV deployment are recommended in future research.

Despite the many limitations that might affect our results, this study provides important evidence to inform policy frameworks to advance a sustainable CAV deployment in California, as well as in other parts of the country and abroad. In particular, the study systematically discusses the many impacts that CAVs might have on future society and transportation, including those that could not be empirically assessed in the modeling application. The discussion of the literature and the range of impacts observed in the scenario forecasts point to the importance of policies that can mitigate negative externalities from CAV deployment.

CAVs might lead to many desirable outcomes, including increased safety, reduced traffic fatalities and increased mobility for those with unmet mobility needs, and they will considerably increase the quality of life especially of individuals with disabilities and mobility impairments. But they might also cause a sharp increase in the use of automobiles, together with the risk of increased car dependence of society, decreased demand for public transit, and reductions in active travel.

It will be important for California policymakers to account for these impacts when designing future policies, including in the development and update of the Sustainable Communities Strategies mandated by SB 375 and integrated in the Regional Transportation Plans, which also focus on the explicit coordination of land use and transportation. While land use impacts of CAVs were only discussed in theory in this study and based on the review of the previous literature, and could not be empirically modeled in the CSTDM framework, coordinating land use development to prevent some of the non-desirable outcomes of CAV deployment—e.g., the increase in suburban sprawl and low-density development—will be one of the upmost priorities in the future. It will be extremely important to rein in some of the potential modifications induced by CAV deployment, that we design strategies to reduce VMT and meet the reduction targets in the state.

More broadly, several potential strategies could be deployed to mitigate the eventual negative externalities associated with CAV deployment. These include (Circella et al., 2017):

- Establish programs that result in driverless vehicle deployment as shared rather than privately-owned vehicles, such that they will be subject to the Clean Miles Standard and considerably reduce emissions by 2030;
- For privately-owned CAVs, adopt a rapid timeline for vehicle electrification.
- Develop a clear incentive system for pricing the climate impacts of travel—consider charging drivers using a GHG/passenger-mile basis;
- Create programs that deploy CAVs to address first-last mile gaps connecting more riders to line haul transit;
- Ensure CAV fleets include a range of vehicle types, so that demand can be right-sized and consume less energy;
- Encourage local planning jurisdictions to work to integrate CAVs into complete streets planning, so that CAVs improve livability, safety, and comfort on surface streets;
- Ensure local planning efforts are rooted in direct community engagement so that community members can weigh in on how the introduction of CAVs can improve accessibility and affordability to goods and services, particularly among historically underserved populations.

Some of these strategies have been explicitly discussed in this report, including electrification, sharing, and pricing. For the reasons discussed previously in this section, the range of travel demand forecasts in this project are likely to be affected by the model being too sensitive to (and demand too elastic with respect to) travel costs and demand being too inelastic with respect to changes in other factors. Still, even if a certain overestimation of the impacts of pricing is in place, the direction of the forecasted impacts is certainly correct. The study highlights the potential of strategies including pricing to reduce total demand, especially in the most congested areas, and of electrification (and/or transition to other zero-emission vehicles) to sharply reduce tailpipe emissions, especially in locations such as the San Joaquin Valley and Southern California, which are facing the most dramatic problems with air quality and concentration of pollutants. Similar considerations could be derived for other potential policy levers that can alter the final impacts that will derive from the deployment of CAVs.

Conclusions

This report presents a detailed review of the scientific literature on the impacts that connected and automated vehicles (CAVs) could have on transportation and discusses a set of future scenarios including CAV deployment under various assumptions through the application of the California Statewide Travel Demand Model. The study was designed to support CARB's efforts to understanding the potential impacts of the introduction and rapid adoption of CAVs in California.

Recent studies have discussed how the development and deployment of CAVs will likely not happen as fast as previous studies suggested, because of the many challenges in this process, including in the areas of vehicles and technologies, systems and services, and users and society. Nevertheless, researchers have been investigating the factors influencing the adoption and willingness to pay for CAVs, as well as the likely impacts that CAV deployment will have on future travel. CAV availability will remarkably influence society, modifying the way people live, travel, shop, socialize, and participate in various activities. Therefore, modeling the impacts of CAV deployment is an important step to prepare stakeholders for the changes that this new technology will bring.

CAV deployment will likely cause the sequential spreading of various effects that can be summarized into: (1) first-order effects that include the possible effects of CAVs on short- to medium-term changes, such as travel cost/time, road capacity, and their resulting travel choices; (2) second-order effects that include the impacts of CAVs on medium- to long-term choices such as household vehicle ownership and willingness to share, location choices, land use, and urban form; and (3) third-order implications of CAV deployment that include indirect effects of these changes, including impacts on energy consumption, GHG emissions, social equity, and the economy.

Previous studies have highlighted the likely changes associated with CAV deployment. Those studies can inform the likely ranges of forecasted impacts, and then better account for the effect of CAVs on the future of our society including land use and environmental impacts. Regarding equity implications, this study simulates the impacts on travel behavior of CAVs through changes in travel cost, parking cost, drivers' licenses, value of travel time and road capacity, among many other factors. However, the changes in those parameters cannot fully capture the responses to CAVs of passengers with disabilities. In the scenario without CAVs, individuals with mobility impairments may show less elasticity to the change in travel cost or parking cost due to a disability to drive, for example. However, CAVs will free them from worrying about these limitations. Thus, the effects of travel cost and parking fees should be recalibrated to truly represent their response to CAVs. For example, a dedicated research among disadvantaged populations will be important to identify the most challenging barriers and their real attitudes toward CAVs before the actual deployment of CAVs.

In this study, the research team simulated a set of future scenarios for year 2050 using the CSTDM Version 3.0 to explore the potential impacts of the deployment of CAVs as well as the potential integration of CAV deployment with various travel assumptions and policies, such as high electrification of transportation and the introduction of road pricing. The comparison of the travel forecasts in these scenarios with the baseline 2050 scenario (business as usual, or "no change") from Caltrans, highlights some important impacts of CAV deployment: these include likely increases in total travel demand, VMT and pollutant emissions. Still, some concerns remain on the actual ability of this modeling framework to realistically forecast some of the changes associated with CAV deployment.

The results show how public transit, active modes, long-distance rail and in-state air travel could experience a significant reduction in their mode share and total number of trips in a future dominated by CAVs, if sufficient policies are not implemented. According to the model results, the total number of trips would be less impacted than VMT and VHT, which are found to be rather sensitive to auto travel costs. This difference in sensitivity might be partially an artifact of the specific modeling assumptions and structure of the CSTDM framework and not entirely a realistic feature of future transportation, and more research is recommended to investigate the topic.

Even considering these limitations, the results highlight how the eventual implementation of pricing strategies and congestion pricing policies could have a significant impact in mitigating the travel demand increases caused by the CAV deployment. The study also shed light into the benefit of mitigating emissions that ZEV policies would bring into the transportation system. The results from this study help inform the California Air Resources Board on the likely impacts that CAV deployment could cause on transportation, and inform policy making, including the development of Sustainable Community Strategies, the Advanced Clean Cars II regulation, and other transportation and CAV planning efforts statewide.

References

Abrantes, Pedro A L, and Mark R Wardman. 2011. "Meta-Analysis of UK Values of Travel Time: An Update." *Transportation Research Part A: Policy and Practice* 45 (1): 1–17. https://doi.org/10.1016/J.TRA.2010.08.003.

Ala, Mani Venkat, Hao Yang, and Hesham Rakha. 2016. "Modeling Evaluation of Eco–Cooperative Adaptive Cruise Control in Vicinity of Signalized Intersections." *Transportation Research Record: Journal of the Transportation Research Board* 2559 (1): 108–19. https://doi.org/10.3141/2559-13.

Ambühl, Lukas, Francesco Ciari, and Monica Menendez. 2016. "What about Space? A Simulation Based Assess-Ment of AVs Impact on Road Space in Urban Areas." In *16th Swiss Transport Research Conference*. Monte Verita / Ascona. http://www.strc.ch/2016/Ambuehl_EtAl.pdf.

Arbib, James, and Tony Seba. 2017. "Rethinking Transportation 2020-2030." www.rethinkx.com.

ARTRAC. 2019. "Connected Automated Driving Roadmap." https://www.ertrac.org/uploads/documentsearch/id57/ERTRAC-CAD-Roadmap-2019.pdf.

Asgari, Hamidreza, and Xia Jin. 2019. "Incorporating Attitudinal Factors to Examine Adoption of and Willingness to Pay for Autonomous Vehicles." *Transportation Research Record* 2673 (8): 418–29.

Alexander, Serena, Asha Weinstein Agrawal, and Benjamin Y. Clark. 2021. "Local Climate Action Planning as a Tool to Harness the Greenhouse Gas Emissions Mitigation and Equity Potential of Autonomous Vehicles and On-Demand Mobility."

Auld, Joshua, Vadim Sokolov, and Thomas S Stephens. 2017. "Analysis of the Effects of Connected–Automated Vehicle Technologies on Travel Demand." *Transportation Research Record: Journal of the Transportation Research Board* 2625 (1): 1–8. https://doi.org/10.3141/2625-01.

Adnan, Nadia, et al. "How trust can drive forward the user acceptance to the technology? In-vehicle technology for autonomous vehicle." Transportation research part A: policy and practice 118 (2018): 819-836.

Bahrami, Sina, Daniel Vignon, Yafeng Yin, and Ken Laberteaux. 2021. "Parking management of automated vehicles in downtown areas." Transportation Research Part C: Emerging Technologies 126 (2021): 103001.

Bansal, Prateek, and Kara M Kockelman. 2018. "Are We Ready to Embrace Connected and Self-Driving Vehicles? A Case Study of Texans." *Transportation* 45 (2): 641–75. https://doi.org/10.1007/s11116-016-9745-z.

Bansal, Prateek, and Kara M Kockelman. 2017. "Forecasting Americans' Long-Term Adoption of Connected and Autonomous Vehicle Technologies." *Transportation Research Part A: Policy and Practice* 95 (January): 49–63. https://doi.org/10.1016/J.TRA.2016.10.013.

Bills, Tierra. 2020. "On Transportation Equity Implications of Connected and Autonomous Vehicles (CAV) A Review of Methodologies."

Bansal, Prateek, Kara M Kockelman, and Amit Singh. 2016. "Assessing Public Opinions of and Interest in New Vehicle Technologies: An Austin Perspective." *Transportation Research Part C: Emerging Technologies* 67 (June): 1–14. https://doi.org/10.1016/J.TRC.2016.01.019.

Barbaresso, Jim, Gustave Cordahi, Dominie Garcia, Christopher Hill, Alex Jendzejec, Karissa Wright, and Booz Allen Hamilton. 2014. "USDOT's Intelligent Transportation Systems (ITS) ITS Strategic Plan, 2015-2019."

Barkenbus, Jack N. 2010. "Eco-Driving: An Overlooked Climate Change Initiative." *Energy Policy* 38 (2): 762–69. https://doi.org/10.1016/J.ENPOL.2009.10.021.

Beal, Craig Earl, and J. Christian Gerdes. 2013. "Model Predictive Control for Vehicle Stabilization at the Limits of Handling." *IEEE Transactions on Control Systems Technology* 21 (4): 1258–69. https://doi.org/10.1109/TCST.2012.2200826.

Becker, Felix, and Kay W Axhausen. 2017. "Literature Review on Surveys Investigating the Acceptance of Automated Vehicles." *Transportation* 44 (6): 1293–1306. https://doi.org/10.1007/s11116-017-9808-9.

Begg, Davdi. 2014. "A 2050 Vision for Londion: What Are the Implications of Driverless Transport." https://www.transporttimes.co.uk/Admin/uploads/64165-transport-times_a-2050-vision-for-london_aw-web-ready.pdf.

Bellem, Hanna, Thorben Schönenberg, Josef F Krems, and Michael Schrauf. 2016. "Objective Metrics of Comfort: Developing a Driving Style for Highly Automated Vehicles." *Transportation Research Part F: Traffic Psychology and Behaviour* 41: 45–54. https://doi.org/10.1016/j.trf.2016.05.005.

Bierstedt, Jane, Aaron Gooze, Chris Gray, Josh Peterman, Leon Raykin, and Jerry Walters. 2014. "Effects of Next-Generation Vehicles on Travel Demand and Highway Capacity EFFECTS OF NEXT-GENERATION VEHICLES ON TRAVEL DEMAND AND HIGHWAY CAPACITY." https://orfe.princeton.edu/%7B~%7Dalaink/Papers/FP_NextGenVehicleWhitePaper012414.pdf.

Bierstedt, Jane, Aaron Gooze, Chris Gray, Josh Peterman, Leon Raykin, and Jerry Walters. 2014. "Effects of Next-Generation Vehicles on Travel Demand and Highway Capacity." *FP Think Working Group*, 10–11.

Bösch, Patrick M, Felix Becker, Henrik Becker, and Kay W Axhausen. 2018. "Cost-Based Analysis of Autonomous Mobility Services." *Transport Policy* 64 (May): 76–91. https://doi.org/10.1016/J.TRANPOL.2017.09.005.

Bösch, Patrick M, Francesco Ciari, and Kay W Axhausen. 2016. "Autonomous Vehicle Fleet Sizes Required to Serve Different Levels of Demand." *Transportation Research Record* 2542 (4): 111–19. https://doi.org/10.3929/ethz-b-000104743.

Brown, Austin, Jeffrey Gonder, and Brittany Repac. 2014. "An Analysis of Possible Energy Impacts of Automated Vehicles." In, 137–53. Springer, Cham. https://doi.org/10.1007/978-3-319-05990-7_13.

Burns, Lawrence D. 2013. "Sustainable Mobility: A Vision of Our Transport Future." *Nature* 497 (7448): 181–82. https://doi.org/10.1038/497181a.

Burns, Lawrence D, William C Jordan, Jordan Analytics, and Bonnie A Scarborough. 2013. "Transforming Personal Mobility." New York: Hogan Hall.

California Department of Motor Vehicles. n.d. "Driverless Testing of Autonomous Vehicles." Accessed February 25, 2019. https://www.dmv.ca.gov/portal/dmv/detail/vr/autonomous/auto.

California Department of Motor Vehicles (CA DMV). n.d. "Testing of Autonomous Vehicles." Accessed February 25, 2019. https://www.dmv.ca.gov/portal/dmv/detail/vr/autonomous/testing.

Calvert, S C, W J Schakel, and J W C van Lint. 2017. "Will Automated Vehicles Negatively Impact Traffic Flow?" *Journal of Advanced Transportation* 2017. https://doi.org/10.1155/2017/3082781.

Chapin, Tim, Lindsay Stevens, Jeremy Crute, Jordan Crandall, Anne Rokyta, and Alexandria Washington. 2016. "Envisioning Florida's future: Transportation and land use in an automated vehicle world." Florida State University Department of Urban & Regional Planning.

Chen, Danjue, Soyoung Ahn, Madhav Chitturi, and David A. Noyce. 2017. "Towards Vehicle Automation: Roadway Capacity Formulation for Traffic Mixed with Regular and Automated Vehicles." *Transportation Research Part B: Methodological* 100: 196–221. https://doi.org/10.1016/j.trb.2017.01.017.

Chen, T Donna, Kara M Kockelman, and Josiah P Hanna. 2016. "Operations of a Shared, Autonomous, Electric Vehicle Fleet: Implications of Vehicle and Charging Infrastructure Decisions." *Transportation Research Part A: Policy and Practice* 94: 243–54. https://doi.org/10.1016/j.tra.2016.08.020.

Cohen, Stuart, S. Shirazi, and T. Curtis. 2017. "Can We Advance Social Equity with Shared, Autonomous and Electric Vehicles?." Institute of Transportation Studies at the University of California, Davis.

Chester, Mikhail V, and Arpad Horvath. 2009. "Environmental Assessment of Passenger Transportation Should Include Infrastructure and Supply Chains." *Environmental Research Letters* 4 (2): 024008. https://doi.org/10.1088/1748-9326/4/2/024008.

Childress, Suzanne, Brice Nichols, Billy Charlton, and Stefan Coe. 2015. "Using an Activity-Based Model to Explore Possible Impacts of Automated Vehicles." In *Transportation Research Board Annual Meeting*. Washington D.C. https://psrc.github.io/attachments/2014/TRB-2015-Automated-Vehicles-Rev2.pdf.

Choi, Ji-Eun, and Sang-Hoon Bae. 2013. "Development of a methodology to demonstrate the environmental impact of connected vehicles under lane-changing conditions." Simulation 89, no. 8: 964-976.

Circella, Giovanni, Chris Ganson and Caroline Rodier. 2017. "Keeping Vehicle Use and Greenhouse Gas Emissions in Check in a Driverless Vehicle World." 3 Revolutions Policy Briefs. University of California, Davis, April 2017; available at https://3rev.ucdavis.edu/sites/g/files/dgvnsk6431/files/files/page/k.pdf.

Cohen, Tom, and Clémence Cavoli. 2019. "Automated Vehicles: Exploring Possible Consequences of Government (Non) Intervention for Congestion and Accessibility." *Transport Reviews* 39 (1): 129–51.

Committee, S A E On-Road Automated Vehicle Standards, and others. 2014. "Taxonomy and Definitions for Terms Related to On-Road Motor Vehicle Automated Driving Systems." *SAE International*.

Coppola, Pierluigi, and Fulvio Silvestri. 2019. "Autonomous Vehicles and Future Mobility Solutions." In *Autonomous Vehicles and Future Mobility*, 1–15. Elsevier.

Cottam, Bobby J. 2018. "Transportation Planning for Connected Autonomous Vehicles: How It All Fits Together." *Transportation Research Record: Journal of the Transportation Research Board* 2672 (51): 12–19. https://doi.org/10.1177/0361198118756632.

Crute, Jeremy, William Riggs, Timothy Stewart Chapin, and Lindsay Stevens. 2018. Planning for autonomous mobility. American Planning Association.

Cunneen, Martin, Martin Mullins, and Finbarr Murphy. 2019. "Autonomous Vehicles and Embedded Artificial Intelligence: The Challenges of Framing Machine Driving Decisions." *Applied Artificial Intelligence* 33 (8): 706–31.

Cunneen, Martin, Martin Mullins, Finbarr Murphy, Darren Shannon, Irini Furxhi, and Cian Ryan. 2020. "Autonomous Vehicles and Avoiding the Trolley (Dilemma): Vehicle Perception, Classification, and the Challenges of Framing Decision Ethics." *Cybernetics and Systems* 51 (1): 59–80.

Cyganski, Rita, Eva Fraedrich, and Barbara Lenz. 2015. "Travel-Time Valuation for Automated Driving: A Use Case-Driven Study." In *Annual Meeting of the Transportation Research Board*. Washington D.C. https://core.ac.uk/download/pdf/31016556.pdf.

Dang, Ruina, Jianqiang Wang, Shengbo Eben Li, and Keqiang Li. 2015. "Coordinated Adaptive Cruise Control System With Lane-Change Assistance." *IEEE Transactions on Intelligent Transportation Systems* 16 (5): 2373–83. https://doi.org/10.1109/TITS.2015.2389527.

Daziano, Ricardo A, Mauricio Sarrias, and Benjamin Leard. 2017. "Are Consumers Willing to Pay to Let Cars Drive for Them? Analyzing Response to Autonomous Vehicles." *Transportation Research Part C: Emerging Technologies* 78 (May): 150–64. https://doi.org/10.1016/J.TRC.2017.03.003.

de Almeida Correia, Gonçalo Homem, and Bart van Arem. "Solving the User Optimum Privately Owned Automated Vehicles Assignment Problem (UO-POAVAP): A model to explore the impacts of self-driving vehicles on urban mobility." Transportation Research Part B: Methodological 87 (2016): 64-88.

de Almeida Correia, Gonçalo Homem, Erwin Looff, Sander van Cranenburgh, Maaike Snelder, and Bart van Arem. "On the impact of vehicle automation on the value of travel time while performing work and leisure activities in a car: Theoretical insights and results from a stated preference survey." Transportation Research Part A: Policy and Practice 119 (2019): 359-382.

Department for Transport. 2016. "Research on the Impacts of Connected and Autonomous Vehicles on Traffic Flow: Summary Report," no. May 2016. http://people-places.co.uk/wp-content/uploads/impacts-of-connected-and-autonomous-vehicles-on-traffic-flow-summary-report.pdf.

Diakaki, Christina, Markos Papageorgiou, Ioannis Papamichail, and Ioannis Nikolos. 2015. "Overview and Analysis of Vehicle Automation and Communication Systems from a Motorway Traffic Management Perspective." *Transportation Research Part A: Policy and Practice* 75: 147–65. https://doi.org/10.1016/j.tra.2015.03.015.

Diels, Cyriel, and Jelte E Bos. 2016. "Self-Driving Carsickness." *Applied Ergonomics* 53 (March): 374–82. https://doi.org/10.1016/J.APERGO.2015.09.009.

Dixit, Vinayak V, Sai Chand, and Divya J Nair. 2016. "Autonomous Vehicles: Disengagements, Accidents and Reaction Times." Edited by Jun Xu. *PLOS ONE* 11 (12): e0168054. https://doi.org/10.1371/journal.pone.0168054.

Dokic, Jadranka, Beate Müller, and Gereon Meyer. 2015. "European roadmap smart systems for automated driving." European Technology Platform on Smart Systems Integration 39.

Duarte, Fábio, and Carlo Ratti. 2018. "The impact of autonomous vehicles on cities: A review." Journal of Urban Technology 25, no. 4: 3-18.

Elbanhawi, Mohamed, Milan Simic, and Reza Jazar. 2015. "In the Passenger Seat: Investigating Ride Comfort Measures in Autonomous Cars." *IEEE Intelligent Transportation Systems Magazine* 7 (3): 4–17. https://doi.org/10.1109/MITS.2015.2405571.

Elliott, David, Walter Keen, and Lei Miao. 2019. "Recent Advances in Connected and Automated Vehicles." *Journal of Traffic and Transportation Engineering (English Edition)*.

Fagnant, Daniel J, and Kara M Kockelman. 2014. "The Travel and Environmental Implications of Shared Autonomous Vehicles, Using Agent-Based Model Scenarios." *Transportation Research Part C: Emerging Technologies* 40: 1–13. https://doi.org/10.1016/j.trc.2013.12.001.

Fagnant, Daniel J., Kara M. Kockelman, and Prateek Bansal. 2015. "Operations of Shared Autonomous Vehicle Fleet for Austin, Texas, Market." *Transportation Research Record* 2536: 98–106. https://doi.org/10.3141/2536-12.

Fagnant, Daniel J, and Kara Kockelman. 2015. “Preparing a Nation for Autonomous Vehicles: Opportunities, Barriers and Policy Recommendations.” *Transportation Research Part A: Policy and Practice* 77 (July): 167–81. https://doi.org/10.1016/J.TRA.2015.04.003.

Fagnant, D.J. and Kockelman, K.M., 2018. Dynamic ride-sharing and fleet sizing for a system of shared autonomous vehicles in Austin, Texas. Transportation, 45(1), pp.143-158.

Favarò, Francesca, Sky Eurich, and Nazanin Nader. 2018. “Autonomous Vehicles' Disengagements: Trends, Triggers, and Regulatory Limitations.” *Accident Analysis and Prevention* 110 (January): 136–48. https://doi.org/10.1016/J.AAP.2017.11.001.

Fraedrich, Eva, and Barbara Lenz. 2014. “Automated Driving.” *Transportation Research Record: Journal of the Transportation Research Board* 2416 (1): 64–72. https://doi.org/10.3141/2416-08.

Gkartzonikas, Christos, and Konstantina Gkritza. 2019. “What Have We Learned? A Review of Stated Preference and Choice Studies on Autonomous Vehicles.” *Transportation Research Part C: Emerging Technologies* 98 (January): 323–37. https://doi.org/10.1016/J.TRC.2018.12.003.

Gong, Siyuan, and Lili Du. 2018. “Cooperative Platoon Control for a Mixed Traffic Flow Including Human Drive Vehicles and Connected and Autonomous Vehicles.” *Transportation Research Part B: Methodological* 116: 25–61. https://doi.org/10.1016/j.trb.2018.07.005.

Grush, Bern. 2016. “Driverless Cars Ahead: Ontario Must Prepare for Vehicle Automation.” http://rccao.com/research/files/RCCAO_Vehicle-Automation_OCT2016_WEB.pdf.

Goodall, Noah J. 2014"Ethical decision making during automated vehicle crashes." Transportation Research Record 2424.1: 58-65.

Gucwa, Michael. 2014. "Mobility and energy impacts of automated cars." In Proceedings of the automated vehicles symposium, San Francisco.

Haboucha, Chana J, Robert Ishaq, and Yoram Shiftan. 2017. “User Preferences Regarding Autonomous Vehicles.” *Transportation Research Part C: Emerging Technologies* 78 (May): 37–49. https://doi.org/10.1016/J.TRC.2017.01.010.

Harb, Mustapha, Yu Xiao, Giovanni Circella, Patricia L Mokhtarian, and Joan L Walker. 2018. “Projecting Travelers into a World of Self-Driving Vehicles: Estimating Travel Behavior Implications via a Naturalistic Experiment.” *Transportation* 45 (6): 1671–85. https://doi.org/10.1007/s11116-018-9937-9.

Harb, Mustapha, Jai Malik, Giovanni Circella, and Joan Walker. *Forthcoming*. "A Glimpse of the Future: Simulating Life with Personally-Owned Autonomous Vehicles”, *Transportation Research Record*.

Harper, Corey D, Chris T Hendrickson, Sonia Mangones, and Constantine Samaras. 2016. “Estimating Potential Increases in Travel with Autonomous Vehicles for the Non-Driving, Elderly and People with Travel-Restrictive Medical Conditions.” *Transportation Research Part C: Emerging Technologies* 72 (November): 1–9. https://doi.org/10.1016/J.TRC.2016.09.003.

Hatipoglu, Cem, Umit Ozguner, and Keith A. Redmill. 2003. "Automated lane change controller design." IEEE transactions on intelligent transportation systems 4, (1): 13-22.

Hawkins, Jason, and Khandker Nurul Habib. 2019. "Integrated Models of Land Use and Transportation for the Autonomous Vehicle Revolution." *Transport Reviews* 39 (1): 66–83. https://doi.org/10.1080/01441647.2018.1449033.

Hohenberger, Christoph, Matthias Spörrle, and Isabell M Welpe. 2016. "How and Why Do Men and Women Differ in Their Willingness to Use Automated Cars? The Influence of Emotions across Different Age Groups." *Transportation Research Part A: Policy and Practice* 94 (December): 374–85. https://doi.org/10.1016/J.TRA.2016.09.022.

Hoogendoorn, Raymond, Bart van Arem, and Serge Hoogendoorn. 2014. "Automated Driving, Traffic Flow Efficiency, and Human Factors." *Transportation Research Record: Journal of the Transportation Research Board* 2422 (2422): 113–20. https://doi.org/10.3141/2422-13.

Howard, Daniel, and Danielle Dai. 2014. "Public Perceptions of Self-Driving Cars: The Case of Berkeley, California." In *Presented at 93rd Annual Meeting of Transportation Research Board*. Washington, DC. https://www.ocf.berkeley.edu/%7B~%7Ddjhoward/reports/Report.

Hulse, Lynn M, Hui Xie, and Edwin R Galea. 2018. "Perceptions of Autonomous Vehicles: Relationships with Road Users, Risk, Gender and Age." *Safety Science* 102 (February): 1–13. https://doi.org/10.1016/J.SSCI.2017.10.001.

Ian Wallis Associates. 2014. "Car Passenger Valuations of Quantity and Quality of Time Savings." New Zealand.

IHS Automative. 2014. "Emerging Technologies: Autonomous Cars- Not If, but When." Colorado. https://supplierinsight.ihsmarkit.com/_assets/sampledownloads/auto-tech-report-emerging-tech-autonomous-car-2013-sample_1404310053.pdf.

International Transport Forum (ITF). 2015. "Urban Mobility System Upgrade–How Shared Self-Driving Cars Could Change City Traffic." Paris.

Ipsos MORI. 2014. "Public Attitudes to Science 2014." www.ipsos-mori.com.

Jing, Peng, Hao Huang, Bin Ran, Fengping Zhan, and Yuji Shi. 2019. "Exploring the Factors Affecting Mode Choice Intention of Autonomous Vehicle Based on an Extended Theory of Planned Behavior—A Case Study in China." *Sustainability* 11 (4): 1155.

Johnson, B. 2015. "Disruptive Mobility." https://www.investmentbank.barclays.com/content/dam/barclaysmicrosites/ibpublic/documents/investment-bank/global-insights/barclays-disruptive-mobility-pdf-120115-459kb.pdf.

Jaller, Miguel, Elham Pourrahmani, Caroline Rodier, Neil Maizlish and Michael Zhang.2020 Active Transportation and Community Health Impacts of Automated Vehicle Scenarios: An Integration of the San Francisco Bay Area Activity Based Travel Demand Model and the Integrated Transport and Health Impacts Model (ITHIM).

Kamal, Md. Abdus Samad, Akira Ohata, Kazuyuki Aihara, Jun-ichi Imura, and Tomohisa Hayakawa. 2014. “A Vehicle-Intersection Coordination Scheme for Smooth Flows of Traffic Without Using Traffic Lights.” *IEEE Transactions on Intelligent Transportation Systems* 16 (3): 1136–47. https://doi.org/10.1109/tits.2014.2354380.

Kamalanathsharma, Raj Kishore, and Hesham A Rakha. 2016. “Leveraging Connected Vehicle Technology and Telematics to Enhance Vehicle Fuel Efficiency in the Vicinity of Signalized Intersections.” *Journal of Intelligent Transportation Systems: Technology, Planning, and Operations* 20 (1): 33–44. https://doi.org/10.1080/15472450.2014.889916.

Kelley, Scott B, Bradley W Lane, and John M DeCicco. 2019. “Pumping the Brakes on Robot Cars: Current Urban Traveler Willingness to Consider Driverless Vehicles.” *Sustainability* 11 (18): 5042.

Khan, Sakib Mahmud. 2019. “Connected and Automated Vehicles in Urban Transportation Cyber-Physical Systems.”

Khondaker, Bidoura, and Lina Kattan. 2015. “Variable Speed Limit: A Microscopic Analysis in a Connected Vehicle Environment.” *Transportation Research Part C: Emerging Technologies* 58: 146–59. https://doi.org/10.1016/j.trc.2015.07.014.

Kolarova, Viktoriya, Felix Steck, Rita Cyganski, and Stefan Trommer. 2018. “Estimation of the Value of Time for Automated Driving Using Revealed and Stated Preference Methods.” *Transportation Research Procedia* 31 (January): 35–46. https://doi.org/10.1016/J.TRPRO.2018.09.044.

König, M, and L Neumayr. 2017. “Users’ Resistance towards Radical Innovations: The Case of the Self-Driving Car.” *Transportation Research Part F: Traffic Psychology and Behaviour* 44 (January): 42–52. https://doi.org/10.1016/J.TRF.2016.10.013.

Koopman, Philip, and Michael Wagner. 2017. “Autonomous Vehicle Safety: An Interdisciplinary Challenge.” *IEEE Intelligent Transportation Systems Magazine* 9 (1): 90–96. https://doi.org/10.1109/MITS.2016.2583491.

Kröger, Lars, Tobias Kuhnimhof, and Stefan Trommer. 2018. “Does Context Matter? A Comparative Study Modelling Autonomous Vehicle Impact on Travel Behaviour for Germany and the USA.” *Transportation Research Part A: Policy and Practice*, April. https://doi.org/10.1016/J.TRA.2018.03.033.

Krueger, Rico, Taha H Rashidi, and John M Rose. 2016. “Preferences for Shared Autonomous Vehicles.” *Transportation Research Part C: Emerging Technologies* 69 (August): 343–55. https://doi.org/10.1016/J.TRC.2016.06.015.

Kuderer, Markus, Shilpa Gulati, and Wolfram Burgard. 2015. “Learning Driving Styles for Autonomous Vehicles from Demonstration.” *Proceedings - IEEE International Conference on Robotics and Automation* 2015-June (June): 2641–46. https://doi.org/10.1109/ICRA.2015.7139555.

Kuhr, James, Natalia Ruiz Juri, Chandra Bhat, Jackson Archer, Jennifer Duthie, Edgar Varela, Maitri Zalawadia, Thomas Bamonte, Arash Mirzaei, and Hong Zheng. 2017. "Travel Modeling in an Era of Connected and Automated Transportation Systems: An Investigation in the Dallas-Fort Worth Area."

Kyriakidis, M, R Happee, and J C F de Winter. 2015. "Public Opinion on Automated Driving: Results of an International Questionnaire among 5000 Respondents." *Transportation Research Part F: Traffic Psychology and Behaviour* 32 (July): 127–40. https://doi.org/10.1016/J.TRF.2015.04.014.

Kyriakidis, Miltos, Joost C F de Winter, Neville Stanton, Thierry Bellet, Bart van Arem, Karel Brookhuis, Marieke H Martens, et al. 2019. "A Human Factors Perspective on Automated Driving." *Theoretical Issues in Ergonomics Science* 20 (3): 223–49.

LaMondia, Jeffrey J, Daniel J Fagnant, Hongyang Qu, Jackson Barrett, and Kara Kockelman. 2016. "Shifts in Long-Distance Travel Mode Due to Automated Vehicles: Statewide Mode-Shift Simulation Experiment and Travel Survey Analysis." *Transportation Research Record: Journal of the Transportation Research Board* 2566 (1): 1–11. https://doi.org/10.3141/2566-01.

Lavieri, Patrícia S, Venu M Garikapati, Chandra R Bhat, Ram M Pendyala, Sebastian Astroza, and Felipe F Dias. 2017. "Modeling Individual Preferences for Ownership and Sharing of Autonomous Vehicle Technologies." *Transportation Research Record: Journal of the Transportation Research Board* 2665 (1): 1–10. https://doi.org/10.3141/2665-01.

Vine, Scott Le, Alireza Zolfaghari, and John Polak. 2015. "Autonomous Cars: The Tension between Occupant Experience and Intersection Capacity." *Transportation Research Part C: Emerging Technologies* 52: 1–14. https://doi.org/10.1016/j.trc.2015.01.002.

Lavieri, Patrícia S., and Chandra R. Bhat. 2019 "Modeling individuals' willingness to share trips with strangers in an autonomous vehicle future." Transportation research part A: policy and practice 124: 242-261.

Lefèvre, Stéphanie, Ashwin Carvalho, and Francesco Borrelli. 2016. "A Learning-Based Framework for Velocity Control in Autonomous Driving." *IEEE Transactions on Automation Science and Engineering* 13 (1): 32–42. https://doi.org/10.1109/TASE.2015.2498192.

Levin, Michael W, and Stephen D Boyles. 2016. "A Multiclass Cell Transmission Model for Shared Human and Autonomous Vehicle Roads." *Transportation Research Part C: Emerging Technologies* 62: 103–16. https://doi.org/10.1016/j.trc.2015.10.005.

Levin, Michael W, and Stephen D Boyles. 2016. "Effects of Autonomous Vehicle Ownership on Trip, Mode, and Route Choice." *Transportation Research Record: Journal of the Transportation Research Board* 2493: 29–38. https://doi.org/10.3141/2493-04.

Lewis-Evans, B, D De Waard, K A Brookhuis - Accident Analysis, and Undefined 2010. n.d. "That's Close Enough—A Threshold Effect of Time Headway on the Experience of Risk, Task Difficulty, Effort, and Comfort." *Elsevier*. https://www.sciencedirect.com/science/article/pii/S0001457510001508.

Li, Ruijie, Xiaobo Liu, and Yu (Marco) Nie. 2018. “Managing Partially Automated Network Traffic Flow: Efficiency vs. Stability.” *Transportation Research Part B: Methodological* 114 (2018): 300–324. https://doi.org/10.1016/j.trb.2018.06.004.

Li, Xiaopeng, Amir Ghiasi, Zhigang Xu, and Xiaobo Qu. 2018. “A Piecewise Trajectory Optimization Model for Connected Automated Vehicles: Exact Optimization Algorithm and Queue Propagation Analysis.” *Transportation Research Part B: Methodological* 118: 429–56. https://doi.org/10.1016/j.trb.2018.11.002.

Liang, Xiao, Gonçalo Homem de Almeida Correia, and Bart van Arem. 2016. “Optimizing the Service Area and Trip Selection of an Electric Automated Taxi System Used for the Last Mile of Train Trips.” *Transportation Research Part E: Logistics and Transportation Review* 93 (2016): 115–29. https://doi.org/10.1016/j.tre.2016.05.006.

Litman, Todd. 2017. *Autonomous Vehicle Implementation Predictions*. Victoria Transport Policy Institute Victoria, Canada.

Lin, Patrick. "Why ethics matters for autonomous cars." Autonomous driving. Springer, Berlin, Heidelberg, 2016. 69-85.

Liu, Jun, Kara M Kockelman, Patrick M Boesch, and Francesco Ciari. 2017. “Tracking a System of Shared Autonomous Vehicles across the Austin, Texas Network Using Agent-Based Simulation.” *Transportation* 44 (6): 1261–78. https://doi.org/10.1007/s11116-017-9811-1.

Malokin, Aliaksandr, Giovanni Circella, and Patricia L. Mokhtarian. "How do activities conducted while commuting influence mode choice? Using revealed preference models to inform public transportation advantage and autonomous vehicle scenarios." *Transportation Research Part A: Policy and Practice* 124 (2019): 82-114.

Ma, Jiaqi, Jia Hu, Ed Leslie, Fang Zhou, Peter Huang, and Joe Bared. 2019. “An Eco-Drive Experiment on Rolling Terrains for Fuel Consumption Optimization with Connected Automated Vehicles.” *Transportation Research Part C: Emerging Technologies* 100 (March): 125–41. https://doi.org/10.1016/j.trc.2019.01.010.

Matthaei, Richard, Andreas Reschka, Jens Rieken, Frank Dierkes, Simon Ulbrich, Thomas Winkle, and Markus Maurer. 2015. “Autonomous Driving.” *Handbook of Driver Assistance Systems: Basic Information, Components and Systems for Active Safety and Comfort*, 1519–56. https://doi.org/10.1007/978-3-319-12352-3_61.

Menon, Nikhil, Natalia Barbour, Yu Zhang, Abdul Rawoof Pinjari, and Fred Mannering. 2019. “Shared Autonomous Vehicles and Their Potential Impacts on Household Vehicle Ownership: An Exploratory Empirical Assessment.” *International Journal of Sustainable Transportation* 13 (2): 111–22.

Meyer, Gereon. 2019. “European Roadmaps, Programs, and Projects for Innovation in Connected and Automated Road Transport.” In *Road Vehicle Automation 5*, 27–39. Springer.

Meyer, Jonas, Henrik Becker, Patrick M Bösch, and Kay W Axhausen. 2017. "Autonomous Vehicles: The next Jump in Accessibilities?" *Research in Transportation Economics* 62 (June): 80–91. https://doi.org/10.1016/J.RETREC.2017.03.005.

Milakis, Dimitris, Maaike Snelder, Bert van Arem, Bert van Wee, and G Homem de Almeida Correia. 2017. "Development and Transport Implications of Automated Vehicles in the Netherlands: Scenarios for 2030 and 2050." *European Journal of Transport and Infrastructure Research* 17 (1). https://repository.tudelft.nl/islandora/object/uuid:154a5dd5-3296-4939-99c7-776e3ba54745?collection=research.

Milakis, Dimitris, Bart van Arem, and Bert van Wee. 2017. "Policy and Society Related Implications of Automated Driving: A Review of Literature and Directions for Future Research." *Journal of Intelligent Transportation Systems* 21 (4): 324–48. https://doi.org/10.1080/15472450.2017.1291351.

National Cooperative Highway Research Program (NCHRP). 2012. "Travel Demand Forecasting: Parameters and Techniques." Washington, D.C.: National Academies Press. https://doi.org/10.17226/14665.

Nazari, Fatemeh, Mohamadhossein Noruzoliaee, and Abolfazl (Kouros) Mohammadian. 2018. "Shared versus Private Mobility: Modeling Public Interest in Autonomous Vehicles Accounting for Latent Attitudes." *Transportation Research Part C: Emerging Technologies* 97 (December): 456–77. https://doi.org/10.1016/J.TRC.2018.11.005.

Nordhoff, Sina, Miltos Kyriakidis, Bart Van Arem, and Riender Happee. 2019. "A Multi-Level Model on Automated Vehicle Acceptance (MAVA): A Review-Based Study." *Theoretical Issues in Ergonomics Science* 20 (6): 682–710.

Nourinejad, Mehdi, Sina Bahrami, and Matthew J Roorda. 2018. "Designing Parking Facilities for Autonomous Vehicles." *Transportation Research Part B: Methodological* 109: 110–27. https://doi.org/10.1016/j.trb.2017.12.017.

Ohnemus, Michael, and Anthony Perl. 2016. "Shared Autonomous Vehicles: Catalyst of New Mobility for the Last Mile?" *Built Environment* 42 (4): 589–602. https://doi.org/10.2148/benv.42.4.589.

Panagiotopoulos, Ilias, and George Dimitrakopoulos. 2018. "An Empirical Investigation on Consumers' Intentions towards Autonomous Driving." *Transportation Research Part C: Emerging Technologies* 95 (October): 773–84. https://doi.org/10.1016/J.TRC.2018.08.013.

Payre, William, Julien Cestac, and Patricia Delhomme. 2014. "Intention to Use a Fully Automated Car: Attitudes and a Priori Acceptability." *Transportation Research Part F: Traffic Psychology and Behaviour* 27 (November): 252–63. https://doi.org/10.1016/J.TRF.2014.04.009.

Pourrahmani, Elham, Miguel Jaller, Neil Maizlish and Caroline Rodier. "Health Impact Assessment of Connected and Autonomous Vehicles in San Francisco, Bay Area." *Transportation Research Record* 2674.10 (2020): 898-916.

Piao, Jinan, Mike McDonald, Nick Hounsell, Matthieu Graindorge, Tatiana Graindorge, and Nicolas Malhene. 2016. “Public Views towards Implementation of Automated Vehicles in Urban Areas.” *Transportation Research Procedia* 14 (January): 2168–77. https://doi.org/10.1016/J.TRPRO.2016.05.232.

Pudāne, Baiba, Eric J E Molin, Theo A Arentze, Yousef Maknoon, and Caspar G Chorus. 2018. “A Time-Use Model for the Automated Vehicle-Era.” *Transportation Research Part C: Emerging Technologies* 93 (August): 102–14. https://doi.org/10.1016/J.TRC.2018.05.022.

Pudāne, Baiba, Eric J E Rataj Michałand Molin, Niek Mouter, Sander van Cranenburgh, and Caspar G Chorus. 2018. “How Will Automated Vehicles Shape Users’ Daily Activities? Insights from Focus Groups with Commuters in the Netherlands.” *Transportation Research Part D: Transport and Environment*, December. https://doi.org/10.1016/J.TRD.2018.11.014.

Rashidi, Taha H, Ali Najmi, Ahsan Haider, Charlotte Wang, and Fatemeh Hosseinzadeh. 2020. “What We Know and Do Not Know about Connected and Autonomous Vehicles.” *Transportmetrica A: Transport Science* 16 (3): 987–1029.

Rasouli, Amir, and John K Tsotsos. 2019. “Autonomous Vehicles That Interact with Pedestrians: A Survey of Theory and Practice.” *IEEE Transactions on Intelligent Transportation Systems*.

Re, L Del, F Allgöwer, L Glielmo, and C Guardiola. 2010. *Automotive Model Predictive Control: Models, Methods and Applications*. https://books.google.com/books?hl=en&lr=&id=tC4DCAAAQBAJ&oi=fnd&pg=PR2&dq=model+predictive+control+vehicle&ots=P0VIswA1J9&sig=Bb32GjU24bw3aqsE69jKtuGsbj0.

Rödel, Christina, Susanne Stadler, Alexander Meschtscherjakov, and Manfred Tscheligi. 2014. “Towards Autonomous Cars: The Effect of Autonomy Levels on Acceptance and User Experience.” In *Proceedings of the 6th International Conference on Automotive User Interfaces and Interactive Vehicular Applications - AutomotiveUI ’14*, 1–8. New York, New York, USA: ACM Press. https://doi.org/10.1145/2667317.2667330.

Rodier, Caroline, Elham Pourrahmani, Miguel Jaller, and Joel Freedman. 2019. “Automated Vehicles Scenarios: Simulation of System Level Travel Effects in the San Francisco Bay Area.” In *Presented at Transportation Research Board Annual Meeting*. Washington D.C.

SAE On-Road Automated Vehicle Standards Committee, 2020. Taxonomy and Definitions for Terms Related to Cooperative Driving Automation for On-Road Motor Vehicles. SAE International: Warrendale, PA, USA.

Kim, Sung Hoo, Giovanni Circella, and Patricia L. Mokhtarian. 2019. "Identifying latent mode-use propensity segments in an all-AV era." Transportation Research Part A: Policy and Practice 130: 192-207. https://doi.org/10.1016/j.tra.2019.09.015.

Saffarian, M., J. C.F. De Winter, and R. Happee. 2012. “Automated Driving: Human-Factors Issues and Design Solutions.” *Proceedings of the Human Factors and Ergonomics Society*, 2296–2300. https://doi.org/10.1177/1071181312561483.

Santos, A, N McGuckin, H Y Nakamoto, D Gray, and S Liss. 2011. “Summary of Travel Trends: 2009 National Household Travel Survey,” June. https://trid.trb.org/view/1107370.

Schakel, Wouter J., Bart Van Arem, and Bart D. Netten. 2010. “Effects of Cooperative Adaptive Cruise Control on Traffic Flow Stability.” *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC*, no. Idm: 759–64. https://doi.org/10.1109/ITSC.2010.5625133.

Schlossberg, Marc, Adam Millard-Ball, Elizabeth Shay, and William Billy Riggs. 2018. "Rethinking the street in an era of driverless cars."

Schoettle, Brandon, and Michael Sivak. 2014. “A Survey of Public Opinion about Autonomous and Self-Driving Vehicles in the U.S., the U.K., and Australia.” Ann Arbor, Michigan. http://www.umich.edu/%7B~%7Dumtriswt.

Shabanpour, Ramin, Nima Golshani, Ali Shamshiripour, and Abolfazl (Kouros) Mohammadian. 2018. “Eliciting Preferences for Adoption of Fully Automated Vehicles Using Best-Worst Analysis.” *Transportation Research Part C: Emerging Technologies* 93 (August): 463–78. https://doi.org/10.1016/J.TRC.2018.06.014.

Shanker, Ravi, Gregory Locraft, and Simon Flannery. 2013. “Autonomous Cars: Self-Driving the New Auto Industry Paradigm.” https://orfe.princeton.edu/%7B~%7Dalaink/SmartDrivingCars/PDFs/Nov2013MORGAN-STANLEY-BLUE-PAPER-AUTONOMOUS-CARS：-SELF-DRIVING-THE-NEW-AUTO-INDUSTRY-PARADIGM.pdf.

Shladover, Steven, Dongyan Su, and Xiao-Yun Lu. 2013. “Impacts of Cooperative Adaptive Cruise Control on Freeway Traffic Flow.” *Transportation Research Record: Journal of the Transportation Research Board* 2324 (Idm): 63–70. https://doi.org/10.3141/2324-08.

Siebert, Felix Wilhelm, Michael Oehl, and Hans Rüdiger Pfister. 2014. “The Influence of Time Headway on Subjective Driver States in Adaptive Cruise Control.” *Transportation Research Part F: Traffic Psychology and Behaviour* 25 (PART A): 65–73. https://doi.org/10.1016/j.trf.2014.05.005.

Silberg, Gary, Mitch Manassa, Kevin Everhart, Deepak Subramanian, Micheal Corley, Hugh Fraser, and Vivek Sinha. 2013. “Self-Driving Cars: Are We Ready?” https://home.kpmg/content/dam/kpmg/pdf/2013/10/self-driving-cars-are-we-ready.pdf.

Simoni, Michele D, Kara M Kockelman, Krishna M Gurumurthy, and Joschka Bischoff. 2019. “Congestion Pricing in a World of Self-Driving Vehicles: An Analysis of Different Strategies in Alternative Future Scenarios.” *Transportation Research Part C: Emerging Technologies* 98 (January): 167–85. https://doi.org/10.1016/J.TRC.2018.11.002.

Singleton, Patrick A. 2019. “Discussing the ‘Positive Utilities’ of Autonomous Vehicles: Will Travellers Really Use Their Time Productively?” *Transport Reviews* 39 (1): 50–65. https://doi.org/10.1080/01441647.2018.1470584.

Sivak, Michael, and Brandon Schoettle. 2012. “Eco-Driving: Strategic, Tactical, and Operational Decisions of the Driver That Influence Vehicle Fuel Economy.” *Transport Policy* 22 (July): 96–99. https://doi.org/10.1016/J.TRANPOL.2012.05.010.

Snyder, Ryan. 2018. "Street Design Implications of Autonomous Vehicles." Public Square.

Soteropoulos, Aggelos, Martin Berger, and Francesco Ciari. 2019. "Impacts of Automated Vehicles on Travel Behaviour and Land Use: An International Review of Modelling Studies." *Transport Reviews* 39 (1): 29–49. https://doi.org/10.1080/01441647.2018.1523253.

Stephens, T S, J Gonder, Y Chen, Z Lin, C Liu, and D Gohlke. 2016. "Estimated Bounds and Important Factors for Fuel Use and Consumer Costs of Connected and Automated Vehicles."

Taeihagh, Araz, and Hazel Si Min Lim. 2019. "Governing Autonomous Vehicles: Emerging Responses for Safety, Liability, Privacy, Cybersecurity, and Industry Risks." *Transport Reviews* 39 (1): 103–28.

Talebpour, Alireza, and Hani S Mahmassani. 2016. "Influence of Connected and Autonomous Vehicles on Traffic Flow Stability and Throughput." *Transportation Research Part C: Emerging Technologies* 71: 143–63. https://doi.org/10.1016/j.trc.2016.07.007.

Treiber, Martin., and Arne Kesting. 2013. *Traffic Flow Dynamics: Data, Models and Simulation*. Springer.

Treiber, Martin, and Arne Kesting. 2013. *Traffic Flow Dynamics*. Berlin, Heidelberg: Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-32460-4.

U.S. Department of Transportation, and Federal Highway Administration. 2009. "2009 National Household Travel Survey." 2009. https://nhts.ornl.gov.

Van Arem, Bart, Cornelie JG Van Driel, and Ruben Visser. 2006. "The Impact of Cooperative Adaptive Cruise Control on Traffic-Flow Characteristics." *IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS* 7 (4): 429. https://doi.org/10.1109/TITS.2006.884615.

Van den Berg, Vincent AC, and Erik T. Verhoef. "Autonomous cars and dynamic bottleneck congestion: The effects on capacity, value of time and preference heterogeneity." Transportation Research Part B: Methodological 94 (2016): 43-60.

Vanderwerf, Joel, Steven Shladover, and Mark A Miller. 2004. "Conceptual Development and Performance Assessment for the Deployment Staging of Advanced Vehicle Control and Safety Systems." https://escholarship.org/uc/item/8hg3b55r.

Wadud, Zia. 2017. "Fully Automated Vehicles: A Cost of Ownership Analysis to Inform Early Adoption." *Transportation Research Part A: Policy and Practice* 101 (July): 163–76. https://doi.org/10.1016/J.TRA.2017.05.005.

Wadud, Zia, Don MacKenzie, and Paul Leiby. 2016. "Help or Hindrance? The Travel, Energy and Carbon Impacts of Highly Automated Vehicles." *Transportation Research Part A: Policy and Practice* 86: 1–18. https://doi.org/10.1016/j.tra.2015.12.001.

Walker, Jonathan, and Charlie Johnson. 2016. "Peak Car Ownership: The Market Opportunity of Electric Automated Mobility Services." http://www.rmi.org/peak_car_ownershipEDITORIAL/DESIGN.

Wang, Kailai, and Gulsah Akar. 2019. "Factors affecting the adoption of autonomous vehicles for commute trips: an analysis with the 2015 and 2017 Puget Sound Travel Surveys." Transportation Research Record 2673, no. 2: 13-25.

Wang, Zhaodong, Xiqun Michael Chen, Yanfeng Ouyang, and Meng Li. 2015. “Emission Mitigation via Longitudinal Control of Intelligent Vehicles in a Congested Platoon.” *Computer-Aided Civil and Infrastructure Engineering* 30 (6): 490–506. https://doi.org/10.1111/mice.12130.

Wilson, R.E., and J.A. Ward. 2011. “Car-Following Models: Fifty Years of Linear Stability Analysis – a Mathematical Perspective.” *Transportation Planning and Technology* 34 (1): 3–18. https://doi.org/10.1080/03081060.2011.530826.

Wischhof, L., A. Ebner, and H. Rohling. 2005. “Information Dissemination in Self-Organizing Intervehicle Networks.” *IEEE Transactions on Intelligent Transportation Systems* 6 (1): 90–101. https://doi.org/10.1109/TITS.2004.842407.

Wu, Changxu, Guozhen Zhao, and Bo Ou. 2011. “A Fuel Economy Optimization System with Applications in Vehicles with Human Drivers and Autonomous Vehicles.” *Transportation Research Part D: Transport and Environment* 16 (7): 515–24. https://doi.org/10.1016/j.trd.2011.06.002.

Xu, Zhigang, Kaifan Zhang, Haigen Min, Zhen Wang, Xiangmo Zhao, and Peng Liu. 2018. “What Drives People to Accept Automated Vehicles? Findings from a Field Experiment.” *Transportation Research Part C: Emerging Technologies* 95 (October): 320–34. https://doi.org/10.1016/J.TRC.2018.07.024.

Yang, Kaidi, S. Ilgin Guler, and Monica Menendez. 2016. “Isolated Intersection Control for Various Levels of Vehicle Technology: Conventional, Connected, and Automated Vehicles.” *Transportation Research Part C: Emerging Technologies* 72: 109–29. https://doi.org/10.1016/j.trc.2016.08.009.

Yap, Menno D, Gonçalo Correia, and Bart van Arem. 2016. “Preferences of Travellers for Using Automated Vehicles as Last Mile Public Transport of Multimodal Train Trips.” *Transportation Research Part A: Policy and Practice* 94 (December): 1–16. https://doi.org/10.1016/J.TRA.2016.09.003.

Ye, Lanhang, and Toshiyuki Yamamoto. 2018. “Modeling Connected and Autonomous Vehicles in Heterogeneous Traffic Flow.” *Physica A: Statistical Mechanics and Its Applications* 490: 269–77. https://doi.org/10.1016/j.physa.2017.08.015.

Zakharenko, Roman. 2016. "Self-driving cars will change cities." Regional science and urban economics 61: 26-37.

Zhang, Tingru, Da Tao, Xingda Qu, Xiaoyan Zhang, Rui Lin, and Wei Zhang. 2019. “The Roles of Initial Trust and Perceived Risk in Public’s Acceptance of Automated Vehicles.” *Transportation Research Part C: Emerging Technologies* 98: 207–20.

Zhang, Wenwen, and Subhrajit Guhathakurta. 2018. “Residential Location Choice in the Era of Shared Autonomous Vehicles.” *Journal of Planning Education and Research*, May, 0739456X1877606. https://doi.org/10.1177/0739456X18776062.

Zhang, Wenwen, and Subhrajit Guhathakurta. 2017. “Parking Spaces in the Age of Shared Autonomous Vehicles: How Much Parking Will We Need and Where?” *Transportation Research Record: Journal of the Transportation Research Board* 2651 (1): 80–91. https://doi.org/10.3141/2651-09.

Zhang, Wenwen, Subhrajit Guhathakurta, Jinqi Fang, and Ge Zhang. 2015. “Exploring the Impact of Shared Autonomous Vehicles on Urban Parking Demand: An Agent-Based Simulation Approach.” *Sustainable Cities and Society* 19: 34–45. https://doi.org/10.1016/j.scs.2015.07.006.

Zhang, Wenwen, Subhrajit Guhathakurta, and Elias B Khalil. 2018. “The Impact of Private Autonomous Vehicles on Vehicle Ownership and Unoccupied VMT Generation.” *Transportation Research Part C: Emerging Technologies* 90 (May): 156–65. https://doi.org/10.1016/J.TRC.2018.03.005.

Zhao, Li, and Jian Sun. 2013. “Simulation Framework for Vehicle Platooning and Car-Following Behaviors Under Connected-Vehicle Environment.” *Procedia - Social and Behavioral Sciences* 96 (Cictp): 914–24. https://doi.org/10.1016/j.sbspro.2013.08.105.

Zhou, Mofan, Xiaobo Qu, and Sheng Jin. 2017. “On the Impact of Cooperative Autonomous Vehicles in Improving Freeway Merging: A Modified Intelligent Driver Model-Based Approach.” *IEEE Transactions on Intelligent Transportation Systems* 18 (6): 1422–28. https://doi.org/10.1109/TITS.2016.2606492.

Zhu, Wen Xing, and H M Zhang. 2018. “Analysis of Mixed Traffic Flow with Human-Driving and Autonomous Cars Based on Car-Following Model.” *Physica A: Statistical Mechanics and Its Applications* 496: 274–85. https://doi.org/10.1016/j.physa.2017.12.103.

Zmud, Johanna, Ipek N Sener, and Jason Wagner. 2016. “Consumer Acceptance and Travel Behavior Impacts of Automated Vehicles.” https://d2dtl5nnlpfr0r.cloudfront.net/tti.tamu.edu/documents/PRC-15-49-F.pdf.

Zmud, Johanna, Ipek N Sener, Jason Wagner, J Zmud, and D C Washington. 2016. “Self-Driving Vehicles Determinants of Adoption and Conditions of Usage.” *Transportation Research Record: Journal of the Transportation Research* 2565: 57–64. https://doi.org/10.3141/2565-07.

Zmud, Johanna, Tom Williams, Maren Outwater, Mark Bradley, Nidhi Kalra, and Shelley Row. 2018. *Updating Regional Transportation Planning and Modeling Tools to Address Impacts of Connected and Automated Vehicles, Volume 2: Guidance*. Washington, D.C.: Transportation Research Board. https://doi.org/10.17226/25332.

Zohdy, Ismail H, and Hesham A Rakha. 2016. “Intersection Management via Vehicle Connectivity: The Intersection Cooperative Adaptive Cruise Control System Concept.” *Journal of Intelligent Transportation Systems: Technology, Planning, and Operations* 20 (1): 17–32. https://doi.org/10.1080/15472450.2014.889918.

Zwaneveld, P J, and Bart van Arem. 1997. “Traffic Effects Of Automated Vehicle Guidance Systems: A Literature Survey,” no. INRO-VVG 1997-17 (December).

Data Summary

Products of Research

This study used three main data and information sources. First, the study conducted a comprehensive literature review to identify the key factors to be considered when modeling connected and automated vehicles (CAVs). The team identified the factors and used the literature to identify quantitative measures for such factors and incorporate them in the design of assumptions and modeling scenarios. Second, the team conducted a workshop with experts to synthesize the existing knowledge, fill in the gaps from the literature and create consensus among team members about the most salient impacts of CAVs. Finally, the team conducted the modeling. There are two main components for the modeling exercise. One refers to the use and implementation of the California Statewide Travel Demand Model (CSTDM) Version 3.0; and the other uses the modeling results to conduct additional analyses and the post-processing of the scenarios.

Following the structure and implementation of CSTDM, the team analyzed the baseline and projected scenarios from the California Department of Transportation (Caltrans) for the year 2050. Additionally, and based on the assumptions and scenarios described in this report, the team implemented changes to the CSTDM, and generated the input data to use for the specific scenarios. The team implemented the model and analyzed the results. Additionally, there were scenarios for which the team did not explicitly run the CSTDM. Rather, the team conducted post-processing of the scenario results (e.g., assumption of the use of zero emission vehicles). For the various scenarios, the team used emission factor rates from the EMFAC and Vision models, and estimated changes in emissions for each scenario with respect to the reference year and business as usual scenario.

Data Format and Content

There are a number of datasets generated by the project.

Scenario input data and parameters:

1. Parameters: This data includes the emission factors per vehicle type (light-, medium-, and heavy-duty). The data file uses comma-separated values (CSV) and excel formats.
2. Scenario input data: For each of the scenarios used in the model, the project generated a set of input data for the CSTDM. These sets contain multiple scripts and other files required to run and implement the CSTDM.

CSTDM Output data: These data include the outputs from the CSTDM for the different scenarios. The loaded networks are also generated resulting from the traffic assignment step of the model.

Post-Processing scenarios: As mentioned above, the team also evaluated a number of scenarios building on model outputs and scenario assumptions. The post-processing steps are carried out mainly using intermediate and final results, including trip tables by mode and loaded networks.

Shape files: The team used geographic information systems (GIS) to develop geographic representation of results. The corresponding shapefiles and maps are generated based on the model outputs, using CUBE, ArcGIS and Python.

Data Access and Sharing

Interested individuals will be able to access the data available through the Dryad data repository and should contact the Principal Investigator, Dr. Giovanni Circella, prior to accessing the data. The data should not be hosted in other locations and should only use the data on Dryad. There is no private or confidential information in the data generated by this project. However, interested individuals must follow Caltrans guidelines when accessing results from the CSTDM V3.0. Emission rates from EMFAC and Vision are publicly available from the California Air Resources Board.

Reuse and Redistribution

Dr. Giovanni Circella and the other co-authors of the work (identified in this final report) hold the intellectual property rights to the data generated by the project. CSTDM data and emission rates are subject to intellectual property rights from Caltrans and the Air Resources Board.

Data will not be able to be transferred to other data archives besides the ones approved by the PI and Co-PIs.

The data can be used by anyone with proper referencing to the authors using the suggested citation:

> Sun, Ran et al. (2021), Emissions impact of connected and automated vehicle deployment in California - model results, Dryad, Dataset, https://doi.org/10.25338/B86926

Appendix A

Table 21. Behavioral and Technological Factors to Be Considered in the Modeling of CAVs impacts (Source: Kuhr et al., 2017)

<table>
<tr><th>Category</th><th>Factor</th><th>Impact</th></tr>
<tr><td rowspan="5">Travel demand</td><td>Trip making rates</td><td>• Total number of trips</td></tr>
<tr><td>Vehicle ownership</td><td>• Modal split
• Trip making rates</td></tr>
<tr><td>Residential choice</td><td>• Location of home-based-trip origins</td></tr>
<tr><td>Activity location choice</td><td>• Location of trip destinations</td></tr>
<tr><td>Modal split</td><td>• Trips by mode
• Number of vehicles on the road</td></tr>
<tr><td>Traffic Assignment</td><td>Route selection paradigms for CAVs</td><td>• Path choice &resulting travel times
• Modal split (indirectly)</td></tr>
<tr><td rowspan="3">System Performance</td><td>Vehicle fleet characteristics</td><td>• Arterial and freeway performance
• Residential location choice (Indirect)</td></tr>
<tr><td>Automation</td><td rowspan="2">• Headways
• Traffic control strategies
• Safety
• Indirect: Arterial and highway performance
• Indirect: Modal Split</td></tr>
<tr><td>Communications</td></tr>
</table>

Table 22. Summary of Modeling Practice

Study	Areas	Type of Models	Research Questions	Assumptions	Main findings
Fagnant and Kockelman. (2014)	Developed a model for a hypothetical gridded-like city	Agent-based-Model	Finding the impacts of different SAV relocation strategies Investigate the potential impacts of SAVs in vehicle ownership, VMT, and environment.	- Changes in trip generation (Double, Half, Quarter) - Centralization of trip (more centralized, less centralized) - Service area (Greater vs. smaller area) - Return-home trip by SAV - Peak congestion - SAV demand (Greater AM and PM Peak) - relocation strategies - Limiting number of SAVs	Each SAVs can replace 10-11 conventional cars, serving 31-41 travelers par day with average waiting time of 20 minutes VMT can be increased by 4.9% to 10.7%
Gucwa (2014)	San Francisco, USA	Activity-based Model (MTC ABM)	Finding the magnitude of the effect from the reduced generalized cost of travel (in mode choice)?	+100% road capacity	+2% VMT
				-100% VOT for private AVs	+13% VMT
				+10% to 100% road capacity and -25% to 100% VOT	+4% to 15% VMT
Childress et al. (2015)	Seattle, USA	Activity-based Model (PSRC's SoundCast)	Finding the range of behavioral impacts from AVs (Mode and Trip-Choice Model Capacity changes for freeways and major arterials)	30% road capacity (all freeway and major arterials)	+4% VMT, -4% VHT
				+30% road capacity and -35% VOT	+5% VMT, -2% VHT
				+30% road capacity and -35% VOT and -50% parking cost	+20% VMT, 17% VHT, -0.3% in PT share, -1.6% in walk share

Study	Areas	Type of Models	Research Questions	Assumptions	Main findings
				SAVs with the cost of 1.65$/mile	+35% VMT, -41% VHT, +4% in PT share, +5% in walk share
International Transport Forum (2015)	Lisbon, Portugal	Agent-based model	Examining the impacts of SAVs and pooled SAVs	Replacement of all motorized trips by SAVs (with/without high-capacity transit) Replacement of all motorized trips by pooled SAVs (with/without high-capacity transit)	+44% to +89% VKT; −84% to −89% parking spaces −77% to −83% vehicles +6% to +22% VKT; −93% to −94% in parking spaces −87% to −90% vehicles
Zhang et al. (2015)	Hypothetical city (10 miles * 10-mile city with gridded like network)	Agent-based model	Understanding the impacts of SAVs on urban parking for various fleet size and passenger wait time	2% of trips with SAVs	-90% parking demand
Fagnant, Kockelman, and Bansal (2015)	Austin, TX, USA	Agent-based model (MATSim) and used the sample of trips from the regional model	Exploring the impact of SAVs at lower market penetration	Replace 1.3% of regional trips	SAVs can replace 9 conventional vehicles, +8% VMT
Levin, and Boyles (2015)	Downtown Austin	Multi-class (VOT-based) four-step model	Exploring the impact of AVs on trip, mode, and route choice	Various parking price	
Boesch, Ciari, and Axhausen (2016)	Zurich, Switzerland	Agent-based model (MATSim)	Exploring the fleet size requires for serving different level of demand	Replace all private vehicle trips by SAVs	-90% vehicle

Study	Areas	Type of Models	Research Questions	Assumptions	Main findings
Chen, Kockelman, and Hanna (2016)	Hypothetical city (based on Austin, TX)	discrete-time agent-based model	Exploring the management of fleet of electric SAVs	10% of trips served by SAVs	+7% empty VMT, −87% vehicles
				10% of trips served by electric SAVs (with recharge time and vehicle range)	+7% to +14% empty VMT; −85% to −73% vehicles
Correia, Homem, and van Arem (2016)	Delft, Netherlands	Traffic assignment	Exploring the impact of replacing privately owned conventional vehicles with AVs on traffic delays and parking demand	Replacement of private vehicles with private AVs in households	+17% VMT, +3% in car share, -5.9% in PT trips
				Replacement of private vehicles with private AVs in households, Free parking everywhere	20% VMT, +7.8% in car share, -14% in PT trips
				Replacement of private vehicles with private AVs in households, - %50 VOT	49% VMT, +9% in car share, -21% in PT trips
LaMondia et al. (2016)	Michigan, USA	statewide (trip generation and mode choice)	Exploring the impact of AVs on long-distance trip modal split	AV cost is twice as the cost of conventional vehicle, AV VOT is three-quarter of conventional car VOT	401-500 long distance: -26.2% in personal vehicle trip volume and -25.1% in airline trip volume
Meyer et al. (2017)	Switzerland	Travel demand model (macroscopic)	Investigating the changes in accessibilities provided by deployment of AVs and SAVs?	+80% road capacity outside urban areas, +40% in urban areas (private AVs)	Minor gains in accessibility for rural municipalities, no change/small decrease in greater cities
				+80% road capacity outside urban areas, +40% in in urban areas (SAVs)	Moderate accessibility gains in rural municipalities, decrease in larger agglomerations

Study	Areas	Type of Models	Research Questions	Assumptions	Main findings
Liu et al. (2017)	Austin, TX, USA	Agent-based model (MATSim), using the result of activity-based model as an input	Exploring the impact of the operation of SAVs on travel mode choice	−50% VOT, $0.5/mile operating costs for SAVs	50.9 SAV mode share, +9.8% empty VMT; SAV fleet = 17% of travelers.
				−50% VOT, $0.75/mile operating costs for SAVs	12.9 SAV mode share, +13.2% empty VMT; SAV fleet = 15% of travelers.
				−50% VOT, $1/mile operating costs for SAVs	10.5 SAV mode share, +15.7% empty VMT; SAV fleet = 13% of travelers.
				−50% VOT, $1.25/mile operating costs for SAVs	9.2 SAV mode share, +15.1% empty VMT; SAV fleet = 13% of travelers.
Zhang and Guhathakurta (2017)	Atlanta, USA	Agent-based model (with discrete event simulator)	Examining the impact of SAVs on urban parking	5% of market penetration, −100% parking cost, $0.5/minute operating costs (carsharing) and $0.3/minute (ridesharing)	−4.5% in parking land
Auld, Sokolov, and Stephens (2017)	Chicago, USA	Activity-based model (POLARIS)	Exploring the behavioral and operational effect of CAVs	+12% to 77% road capacity	+1% to +4% VMT
				−25% to −75% VOT, 20% market share of private AVs	+2% to +18% VMT
				−25% to −75% VOT, 75% market share of private AVs	+10% to +59% VMT
				+3% road capacity, −25% VOT, 20% market share of private AVs	+2.7% in VMT
				+77% road capacity, −75% VOT, 100% market share of private AVs	+79% in VMT

Study	Areas	Type of Models	Research Questions	Assumptions	Main findings
Kröger, Kuhnimhof, and Trommer (2018).	Germany and USA	A spatial travel demand model	How different context can lead to different AV impacts	-25% VOT for private AVs (7.5% market share)	+3.4% in VKT, +1.3% in car share, −0.2% in PT share
				-25% VOT for private AVs (29.3% market share)	+8.6% in VKT, +3.8 in car share, −0.4% in PT share
				-25% VOT for private AVs (10.1% market share)	+2.4% in VKT, +1% in car share, −0.3% in PT share
				-25% VOT for private AVs (37.6% market share)	+8.6% in VKT, +3.7% in car share, −0.9% in PT share
Zhang, Guhathakurta, and Khalil (2018)	Atlanta, USA	Activity-based model	Understanding the potential for vehicle ownership reduction through AVs	Replacement of private vehicles with private AVs in households determined by min. number of AVs to satisfy travel demand of household members	+13.3% empty VMT, −9.5% vehicles
Zhang and Guhathakurta (2018)	Atlanta, USA	Agent-based model + residential location choice model	Examining the potential changes in residential location choice provided by AVs	(1) AV is not serving other household member when the current trip departs; (2) There is sufficient time for AV to relocate from its location to the origin of the upcoming trip; (3) The potential relocation time is obtained using Google Maps Distance Matrix Application Programming Interface (API) service.	(1) more than 18% of the households can reduce vehicles, while maintaining the current travel patterns. (2) 29.8 unoccupied VMT will be induced per day per reduced vehicles.
Rodier et al. (2019)	San Francisco, USA	Activity-based model	Evaluating the system level traffic effects in San Francisco Bay Area	+100% market penetration, +100% roadway capacity	+1% in drive alone, +8% in Transit, -5% in active mode, 14% VMT
				+100% market penetration, -25% VOT	+1% in drive alone, -5% in Transit, -4% in active mode, 3% VMT

Study	Areas	Type of Models	Research Questions	Assumptions	Main findings
				+100% market penetration, reduced per mile cost from 17.9 cents to 14 cents	+1% in drive alone, -4% in Transit, -4% in active mode, 3% VMT
				+100% market penetration, relaxed age restriction between 16-13 years old	+6% in drive alone, -12% in Transit, -4% in active mode, 2% VMT
Khan (2019)	South Carolina, USA	Simulation	Optimizes CAV speed in a situation-aware left-turning considering the follower driver's aggressiveness	600 veh/hr/lane opposite traffic stream	-61% in VHT
				800 veh/hr/lane opposite traffic stream	-23% in VHT
				1000 veh/hr/lane opposite traffic stream	-41% in VHT

Table 23. How Self-Driving Cars Will Transform Cities

Study	Area	Research question	Main findings				
			Urban form	Road Capacity	Lane	Parking Demand	Infrastructure
Guerra, E. (2015). Planning for Cars That Drive Themselves: Metropolitan Planning Organizations, Regional Transportation Plans, and Autonomous Vehicles, Journal of Planning Education and Research 2016, Vol. 36(2) 210 –224	Atlanta			+50%		Reduced operating costs and free parking	
	San Francisco			+10% to +100%			
	Seattle			+0% to +30%			
Heinrichs, D. (2015). Autonomous Driving, Technical, Legal and Social Aspects. Autonomous Driving and Urban Land Use		Fathom potential implications on urban form and land use of a transport system with autonomous vehicles		Increasing road capacity		Reducing parking demand	
DeAngelis, J. (2016). Planning for the Autonomous Vehicle Revolution				Increasing capacity		Parking minimums	Will lead to a decline in street signs, lane striping, and traffic signals
Riggs, M., Boswell, M., Ross, R. (2016), Street plan: Hacking Streetmix for Community-Based	United State	Inform street section planning, design and Traffic			Reducing and combinin g lanes		

Study	Area	Research question	Main findings				
			Urban form	Road Capacity	Lane	Parking Demand	Infrastructure
Outreach on the Future of Streets.		modeling / simulation					
Sisson, P. (2016). Driverless Cars Will Shrink Our Roads and Radically Reshape Urban Space,	San Francisco, United State					200% increase in efficiency	
Smolnicki, Piotr Marek, Jacek Soltys, (2106), Driverless Mobility: The Impact on Metropolitan Spatial Structures, World Multidisciplinary Civil Engineering-Architecture-Urban Planning Symposium 2016			Increasing urban sprawl				
Chapin, T., Stevens, L., Crute, J., Crandall, J., Rokyta, A., Washington, A. (2016). Envisioning Florida's Future: Transportation and Land Use in an Automated Vehicle World. Report prepared for the Florida Department of Transportation.	Florida, United State	Assessing how AV technology might impact the built environment in the coming decades			Narrower traffic lanes, reduce the number of lanes	Increasing efficiency	
Duarte, F. and Ratti, C. (2018). The Impact of Autonomous Vehicles on		Exploring the Impact of AV in cars (more or	Increasing urban sprawl	AV will require %80 fewer cars on			AVs could double the existing average road

Study	Area	Research question	Main findings				
			Urban form	Road Capacity	Lane	Parking Demand	Infrastructure
Cities: A Review, Journal of Urban Technology, VOL. 25, NO. 4, 3–18		fewer cars), parking, urban form (more or less sprawl), infrastructure (more or less road infrastructure)		any given highway. More efficient transportation in cities			infrastructure capacity. Traffic lights could be eliminated with the implementation of distributed systems of traffic data exchange
Crute, J., Riggs, W., Chapin, T., and Stevens, L. (2018). Planning for autonomous mobility, the American Planning Association			Increasing urban sprawl		Lane widths can be reduced to 8 feet	Removing on-street parking decline in the demand for parking	Investing in dedicated AV infrastructure
Snyder, R. (2018). Street design implications of autonomous vehicles				Capacity on freeways will roughly double	Reduced to 8 or 9 feet in lane width	Reducing the amount of on-street parking	Vehicle-to-infrastructure (V2I) capabilities traffic signals may not be needed, and intersections may function like virtual roundabouts
Schlossberg, M., W. Riggs, A., Millard-Ball, and E., Shay (2018). Rethinking the street in an era of driverless cars					Both number and space may be reduced	Parking demand on streets may be reduced	

Table 24. Potential Trip-based Modeling Changes (Source: Zmud et al. 2018)

Model Component	Trip-Based Model Improvement
Sociodemographic	
Land use/demographic model	Adjust accessibility measures
Land use/demographic model	Account for parking reuse
Land use/demographic model	Estimate levels of expanded mobile populations
Market/Fleet	
Fleet composition models	Estimate and forecast types of vehicles and technology
Auto Ownership	
Auto ownership model	Estimate and forecast CAV or manual vehicle ownership
Auto availability model	Estimate and forecast availability of SAVs and carsharing
Trip Generation	
Trip rates	Estimate and forecast rates for expanded mobile populations
Trip rates	Account for zero-occupant vehicle trip generation
Trip rates	Adjust rates within reason for improved accessibility
Trip Distribution	
Impedance to travel	Estimate network cost matrices reflecting CAVs
Impedance to travel	Estimate new friction factor matrices if CAVs affect trip lengths
Mode Choice	
Mode choice model	Design new nesting structure including CAVs, SAVs, and SAV access to transit
Mode choice model	Account for MaaS impacts on multimodal tour plans
Value of time	Account for improved value of time for CAV modes
Network Assignment	
Supply models	Estimate CAV-enhanced capacity on signalized arterial systems
Network capacity	Estimate CAV-enhanced capacity on grade-separated facilities
Path costs; pricing and tolling	Estimate value of time including discounts for CAV passengers

Table 25. Summary of Model Improvement for Activity Based and Dynamic Traffic Assignment Models (Source: Zmud et al. 2018)

Model Component	Disaggregate AB/DTA Model Improvements
Sociodemographic	
Population synthesizer	Control for age and income
Population synthesizer	Add smartphone ownership and education level
Built Environment	
Urban form	Set place type by area type and development type
Mobility	
Vehicle ownership	Add CAVs as an option for households to own
Vehicle ownership	Add purchase cost, incentive policies, parking cost, or accessibility variables to distinguish vehicle type
MaaS	Add carsharing, ride-hailing, bikesharing memberships
Activity Generation and Scheduling	
Activity generation	Lift age restrictions for CAVs, add constraints for persons with disabilities and seniors using conventional vehicles
Activity generation	Adjust value of travel time (VOT) and review induced demand
Activity generation	Add representation of empty car trips
Destination/Location Choice	
Work/school locations	Integrate with land use model to provide sensitivity
Mode Choice	
Mode choice	Add new modes (CAVs, TNCs, shared modes, microtransit)
Mode choice	Adjust VOT for CAVs
Access/egress	Add access and egress modes (TNCs, shared modes, microtransit)
Mode choice	Add dynamic pricing for new modes, adjust parking costs for CAVs
Mode choice	Adjust age and disability restrictions for CAVs
Parking choice	Add parking choice model to include off-site parking
Routing and Traffic Assignment	
Dynamic assignment	Add vehicle-following and speed characteristics for CAVs
Vehicle operations	Parameterize vehicle operating characteristics
Vehicle operations	Track empty vehicles and their travel characteristics
Dynamic assignment	Simulate different levels of CVs in mixed traffic
Dynamic assignment	Simulate nonrecurring congestion with/without CAVs
Pricing	
Cost models	Determine cost per mile for each new mode by time period
Parking costs	Adjust parking cost as demand shifts away from high-cost areas

Table 26. AV Planning Needs and Requirements (Source: Litman,2018)

Impact	Needs	Requirements	Time Period
Become legal	Demonstrated functionality and safety	Define performance, testing and data collection requirements for automated driving on public roads.	2018-25
increase traffic density by vehicle coordination	Road lanes dedicated to vehicles with coordinated platooning capability	Evaluate impacts. Define requirements. Identify lanes to be dedicated to vehicles capable of coordinated operation.	2020-40
Independent mobility for non-drivers	Fully AVs available for sale	Allows affluent non-drivers to enjoy independent mobility.	2020-30s
Automated carsharing /taxi	Moderate price premium. Successful business model.	May provide demand response services in affluent areas. Supports carsharing.	2030-40s
Independent mobility for lower-income population	Affordable AVs for sale	Reduced need for conventional public transit services in some areas.	2040-50s
Reduced parking demand	Major share of vehicles is autonomous	Reduced parking requirements.	2040-50s
Reduced traffic congestion	Major share of urban peak vehicle travel is autonomous.	Reduced road supply.	2050-60s
Increased safety	Major share of vehicle travel is autonomous.	Reduced traffic risk. Possibly increased walking and cycling activity.	2040-60s
Energy conservation and emission reductions	Major share of vehicle travel is autonomous. Walking and cycling become safer.	Supports energy conservation and emission reduction efforts.	2040-60s
Improved vehicle control	Most or all vehicles are autonomous	Allows narrower lanes and interactive traffic controls.	2050-70s
Need to plan for mixed traffic	Major share of vehicles is autonomous.	More complex traffic. May justify restrictions on human-driven vehicles.	2040-60s
Mandated AVs	Most vehicles are autonomous and large benefits are proven.	Allows advanced traffic management.	2060-80s

The Future Street is a conceptual visualization of how our streets of the future may look, and arguably will need to include: opportunities created by the introduction of AVs, smart city technology, urban agriculture, and urban landscape imperatives. It tests the possibilities of dedicating less public space to cars and returning that space to people to use in ways other than driving. Future Street looks at new and different mobility options and ways to live in and enjoy our cities and streets.[6]

[6] Blueprint for Autonomous Urbanism, Second Edition: https://nacto.org/publication/bau2/

Appendix B

Table 27. List of Experts of AV Modeling Expert Group Meeting

Name	Affiliation
Abolfazl (Kouros) Mohammadian	University of Illinois at Chicago
Ali Etezady	Georgia Institute of Technology
Ali Kothawala	University of California, Davis
Arash Mirzaei	North Central Texas Council of Governments
Caroline Rodier	University of California, Davis
Chandra Bhat	University of Texas, Austin
Cinzia Cirillo	University of Maryland
Colin Sheppard	Lawrence Berkeley National Lab
Dan Sperling	University of California, Davis
David Bunch	University of California, Davis
David Greene	University of Tennessee
Deb Niemeier	University of California, Davis
Elham Pourrahmani	University of California, Davis
Farzad Alemi	University of California, Davis
Flavia Tsang	Metropolitan Transportation Commission
Giovanni Circella	University of California, Davis
Grant Matson	University of California, Davis
Greg Rowangould	University of New Mexico
Guy Rousseau	Atlanta Regional Commission
Hani Mahmassani	Northwestern University
Henrik Becker	ETH Zurich
Hui Deng	Southern California Association of Governments
Jai Malik	University of California, Davis
Jeremy Raw	Federal Highway Administration
Lew Fulton	University of California, Davis
Lisa Aultman-Hall	University of Vermont
Mark Bradley	RSG
Melanie Zauscher	California Air Resources Board
Michael Gaunt	University of California, Davis
Michael Zhang	University of California, Davis
Miguel Jaller	University of California, Davis
Mike McCoy	Strategic Growth Council, California (retired)
Monique Stinson	Argonne National Lab
Niloufar Yousefi	University of California, Davis
Norman Marshall	Smart Mobility
Patricia Mokhtarian	Georgia Institute of Technology
Rachel James	FHWA

Name	Affiliation
Ram Pendyala	Arizona State University
Ran Sun	University of California, Davis
Rolf Moeckel	TU Munich
Ronald Milam	Fehr and Peer
Rosa Dominguez-Faus	University of California, Davis
Rosella Picado	WSP
Roy Abboud	Caltrans
Scott Hardman	University of California, Davis
Shengyi Gao	Sacramento Area Council of Governments
Srinivas Peeta	Georgia Institute of Technology
Susan Handy	University of California, Davis
Syche Cai	California Public Utilities Commission
Thomas Rossi	Cambridge Systematics
Vladimir Livshits	Maricopa Association of Governments
Yanmei Ou	Sacramento Area Council of Governments
Zhuo Yao	California Air Resources Board

Table 28. Agenda of Expert Workshop

AGENDA AV MODELING EXPERT GROUP MEETING April 29th and 30th, 2019 Hyatt Place Meeting Room, UC Davis	
Monday, April 29th, 2019	
8:30 a.m.	Registration and Coffee
9:00 a.m.	Welcome to Participants and Introductions
9:15 a.m.	**Session 1: Meeting Introduction - Modeling Travel Demand Impacts of AV Deployment** • Meeting overview and objectives • *When AVs become reality*: Discussion of AV deployment timeline and next steps • *Which AV business models*: Discussion of various business models • *What transition years will look like*: Discussion of transition paths and future implications Short presentations and discussion with expert participants
10:30 p.m.	Coffee Break
10:45 a.m.	**Session 2: The Big Picture - Overall Modeling Structure and Planning Applications** • *Do we have the right tools?* Discussion of model assumptions, future scenarios and data availability • *What we can model and what we cannot:* Model components, limitations and boundaries • *Applications for planning agencies and dealing with uncertainties*: Discussion of applications of modeling frameworks for planning agencies Short presentations and discussion with expert participants
12:30 p.m.	Lunch Break
1:30 p.m.	**Session 3: Impacts on Road Capacity and Changes in the Transportation Network** • *How AVs will affect travel time and safety*: Discussion of the changes in transportation supply and network capacity • *The role of connectivity*: Opportunities offered by V2V and V2I from intersection to network capacity • *Changes in traffic assignment and network modeling*: Modification required to better model CAV deployment Short presentations and discussion with expert participants
3:15 p.m.	Coffee Break

3:30 p.m.	**Session 4: Value of Travel Time and Time-Use/Activity Patterns** • *Changes in value of travel time*: Discussion of the changes in subjective value of time and induced demand • *Individual activity patterns in the era of AV*: Discussion of the modifications required to model the changes in activity patterns (including individuals with reduced mobility) • *How people will use their "saved time"*: How activity-based and other travel demand modeling tools can capture the effects of AVs on individual time use Short presentations and discussion with expert participants
5:15 p.m.	Last Thoughts and Wrap-up of Day 1
6:00 p.m.	Dinner at Our House Restaurant, 808 Second Street, Davis, CA
	Tuesday, April 30th, 2019
8:30 a.m.	Coffee
9:00 a.m.	**Session 5: Mode Choice** • *How to model mode choice in the AV future*: Discussion of modifications to introduce in travel demand models to account for AV options • *New modes enabled by shared mobility and automation*: How to model shared vs. personally-owned automated vehicles, the future of public transportation, new options in individuals' choice set • *How to update existing models*: Discussion of the steps required to update large-scale travel demand models Short presentations and discussion with expert participants
10:45 a.m.	Coffee Break
11:00 a.m.	**Session 6: The Future of Vehicle Ownership** • *Early adopters*: Discussion of the factors affecting AV adoption and willingness to pay • *Cost of AV ownership/use*: How it will differ from the cost of owning/using a conventional vehicle • *Household vehicle ownership*: Discussion of the steps required to update vehicle ownership model components Short presentations and discussion with expert participants
12:30 p.m.	Lunch Break
1:30 p.m.	**Session 7: Long-distance Travel** • *How long-distance travel will change with AVs*: Discussion of changes in long-distance trips • *The future of air travel*: Discussion of conditions under which AVs can become competitive alternatives to air travel and other options (e.g. high speed rail) for long-distance trips Short presentations and discussion with expert participants
2:45 p.m.	Coffee Break

3:00 p.m.	**Session 8: Land Use and Other Long-Term Decisions** • *How residential location choices might change as AVs become available*: Discussion of changes in residential location choices for various AV business models • *Future urban form and location of primary and secondary destinations*: What do we know about future cities (e.g. retail vs. residential space) and the required changes in destination choice models • *The future of parking*: Discussion of the changes in parking infrastructure and curbside management Short presentations and discussion with expert participants
4:30 p.m.	**Wrap-up: Future Travel Demand - GHG, Energy and VMT** • *VMT, GHG and energy impacts*: How will they change, and how to model them • *Future vehicle fleet*: What assumptions to make on efficiency standards, ZEV mandates, etc. Short presentations and discussion with expert participants
5:30 p.m.	Happy Hour and Goodbye