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NAtional Vehicle Itinerary GenerATor (NAVIGAT)

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Acronyms and Abbreviations

ACS	American Community Survey
BEV	Battery Electric Vehicles
BILD AQ	Benefits of Infrastructure in Large-scale Deployment: Air Quality
BTS	Bureau of Transportation Statistics
CBSA	Core-Based Statistical Areas
CNT	Center for Neighborhood Technology
DOE	Department of Energy
DAC	Disadvantaged Communities
EV	Electric Vehicle
FCEV	Fuel Cell Electric Vehicles
GEMS	Geo-Economic Multi-Modal System
HB	Home-Based
HEV	Hybrid electric vehicles
HIFLD	Homeland Security Homeland Infrastructure Foundation-Level Data
HPMS	Highway Performance Monitoring System
ICEV	Internal Combustion Engine Vehicle
JOET	Joint Office for Energy and Transportation
LBNL	Lawrence Berkeley National Laboratory
LEHD	Longitudinal-Employer Household Dynamics
LODES	LEHD Origin-Destination Employment Statistics
MNL	Multinomial Logit
NEVI	National Electric Vehicle Infrastructure program
NHB	Non-Home-Based
NHTS	National Household Travel Survey
OSM	OpenStreetMap
PHEV	Plug-in Hybrid Electric Vehicles
NREL	National Renewable Energy Laboratory
GEMS	Geo-Economic Multi-Modal System
VMT	Vehicle Miles Travelled
WAC	Workplace Area Characteristics
TEMPO	Transportation Energy & Mobility Pathway Options Model
TSDC	Transportation Secure Data Center

Executive Summary

In this study, a large-scale passenger vehicle mile travelled (VMT) simulator, called **NAtional Vehicle Itinerary GenerATor (NAVIGAT),** is developed by LBNL and NREL researchers to simulate **household-owned passenger vehicle** movements within the whole U.S. at census tract level resolution (including all 50 states and Washington D.C.). NAVIGAT adopts a modeling framework resembling the traditional travel demand models that are often applied in a regional context, combined with a data-driven approach that estimates model parameters using various national-level data sources. Using NAVIGAT, the vehicle movements can be tracked throughout the network at the census tract level given a technology adoption scenario input also mapped to the census tract level. NAVIGAT outputs can support the estimation of key transportation and environmental metrics, including changes in on-road emissions, air quality, and the health impacts on nearby communities. These changes may result from shifts in technology adoption driven by factors such as the deployment of charging infrastructure, adoption incentives, and fluctuations in fuel or vehicle prices.

Data and Methodology Overview

A previously developed national-scale geospatial typology is adopted to capture the spatial variability of travel demand across the nation, and to generate vehicle flows under various transportation scenarios while maintaining a reasonable computational speed. The major functionalities developed in NAVIGAT are illustrated in **Figure ES-1**. The observed travel demand is generated from 2017 National Household Travel Survey (NHTS) data and aggregated by geospatial typology for national application and imputation for census tracts without observed data. The demand generation rate is multiplied by the American Community Survey (ACS) population to generate total demand at the census tract level. The travel demand is distributed across the entire network using destination choice and route selection models. The fractions of flows are used to split observed “through” traffic—travel that occurs in tracts outside the origin or destination tract of the trip—to corresponding home locations. Both in-state travel and cross-state spillover travel are modeled in NAVIGAT, and calibrated to align with observed daily VMT from Highway Performance Monitoring System (HPMS) data.

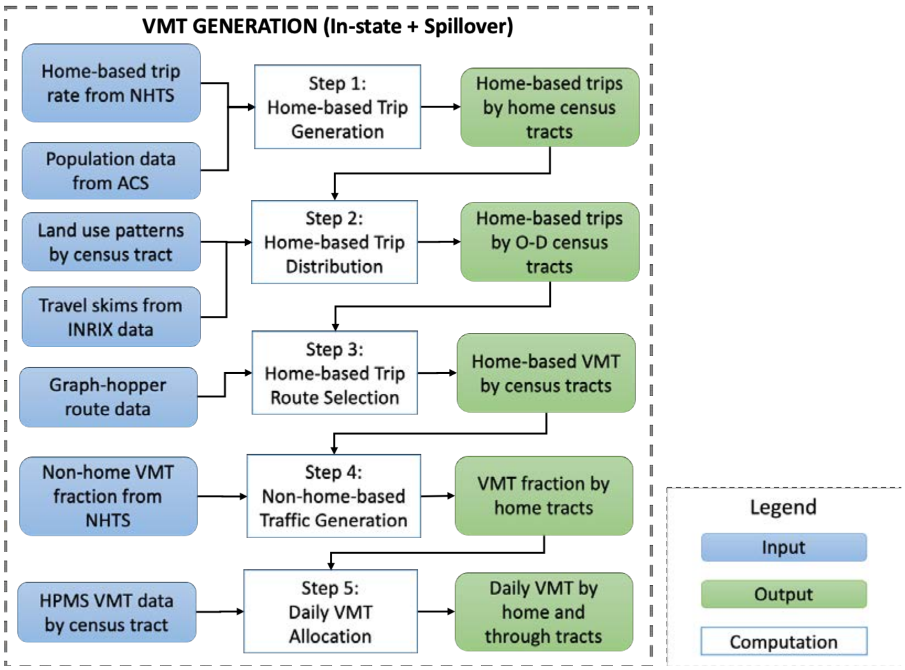


Figure ES - 1. Workflow of NAVIGAT

The major national-scale data sources that are used for each module in NAVIGAT are summarized in **Table ES-1**. Most of these data sources are publicly available and are updated periodically, facilitating future updates and maintenance of the model.

Table ES - 1. Summary of major data sources of NAVIGAT

Module	Element	Data Source	Reference
Trip Generation	Population	2018 ACS 5-year estimates	(U.S. Census Bureau, 2018)
	Trip rate	2017 NHTS	(Federal Highway Administration, 2017)
Trip distribution	Destination choice	2017 NHTS	(Federal Highway Administration, 2017)
	Travel time and distance skims	INRIX trip OD data	Proprietary
	Job count	LEHD LODES7 data workplace area characteristics (WAC)	(U.S. Census Bureau. Longitudinal-Employer Household Dynamics Program., 2022)
	Opportunity count (school, hospital, etc.)	U.S. Department of Homeland Security Homeland Infrastructure Foundation-Level Data (HIFLD).	(U.S. Department of Homeland Security, 2020)
	Bus accessibility	Center for Neighborhood Technology (CNT) All Transit database	(Center for Neighborhood Technology, 2022)

	Rail accessibility	Bureau of Transportation Statistics (BTS) rail nodes database	(U.S. Department of Transportation Bureau of Transportation Statistics., 2020)
Route generation	Route generation	GraphHopper shortest-path routes using OpenStreetMap (OSM) network for entire U.S.	(Geofabrik, 2018; GraphHopper, 2021)
VMT allocation	Tract-level VMT	2017 Highway Performance Monitoring System (HPMS) data	(Federal Highway Administration, 2020)
TEMPO interface	DAC boundary	2022 Joint Office definition	(Joint Office of Energy and Transportation, 2022)

A Case Study of Charging Infrastructure Impact Assessment

The capability of NAVIGAT is demonstrated through a case study that assesses the operational impacts of long-term growth in EV ownership. A model linkage between NAVIGAT and an EV adoption model is developed to simulate changes in electrified VMT throughout the network under alternative EV adoption scenarios. The Transportation Energy & Mobility Pathway Options (TEMPO) model developed by NREL can provide long-term EV adoption rates at the county-level, downscaled to census tract level, and projected under various charging deployment, incentive, pricing, or other policy scenarios. NAVIGAT applies these TEMPO-generated EV adoption rates as inputs and then tracks EV movements within the network to quantify the EV VMT penetration at the census tract level. Finally, a U.S. West Coast case study, which contains California (CA), Oregon (OR) and Washington (WA) is presented to demonstrate the model capabilities. The case study compares EV adoption and penetration in 2018 (the base year) with projections for 2032, assuming public charging infrastructure is maintained at current-day deployment levels.

NAVIGAT is applied to generate the passenger vehicle VMT for the three states, including both in-state and spillover travel (including all cross-state travel among three states, and spillover trips originated from the three states to the rest of the nation). The VMT results for all passenger travel linked to home tracts in the three states are illustrated in **Figure ES-2**. A total of 1.58 billion daily VMT are simulated in the three-state region, with about 6.8% of VMT generated from inter-state spillover travel.

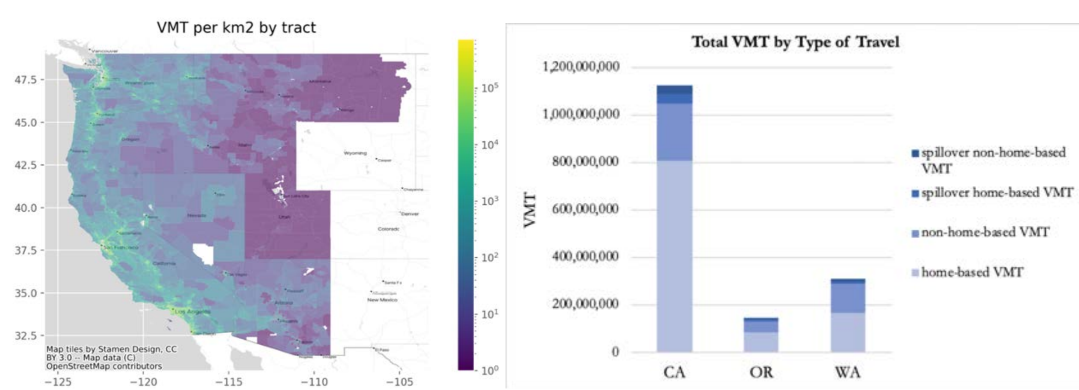
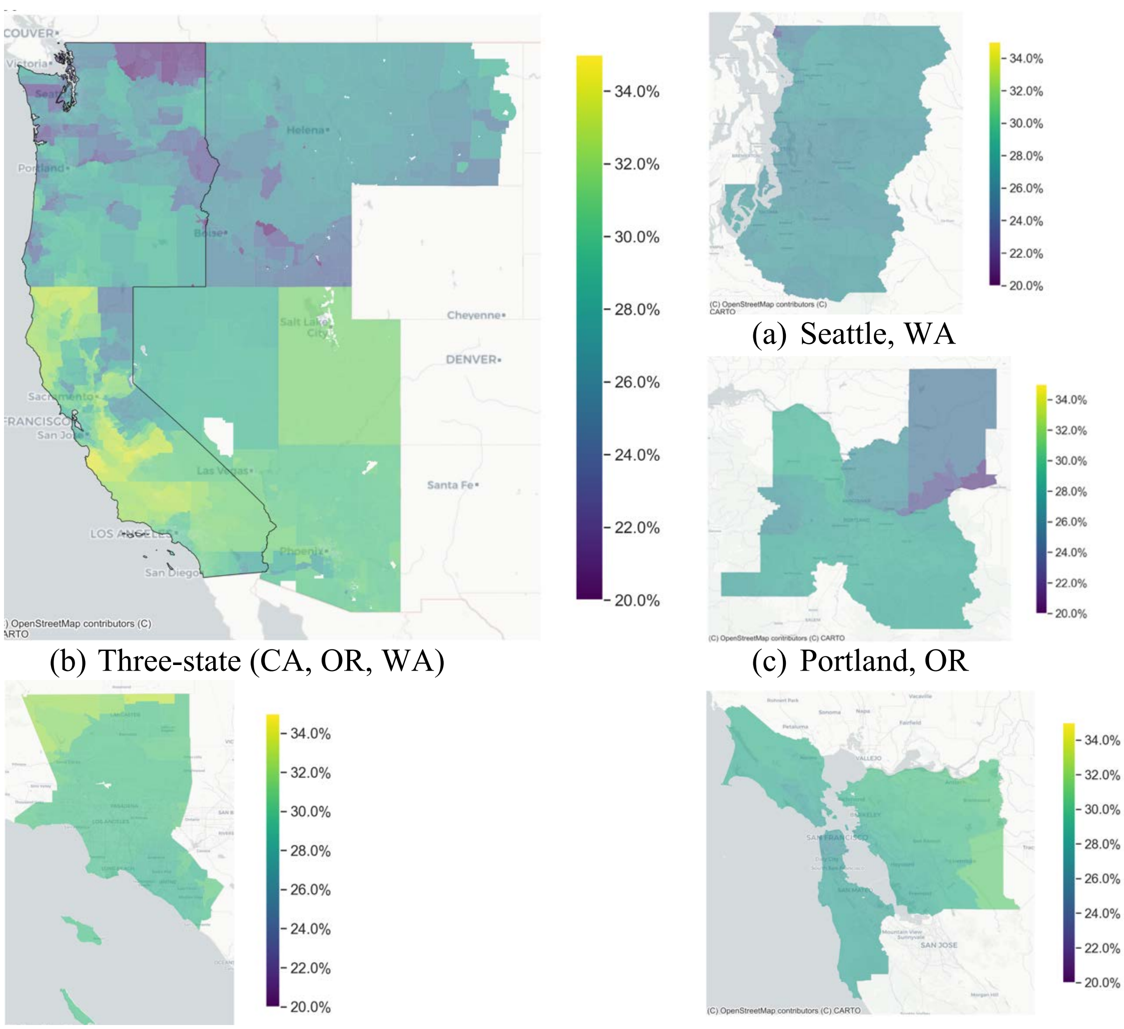


Figure ES - 2. Simulated passenger vehicle VMT originated from CA, OR, WA

Current NAVIGAT implementation is static, in that it assumes the total amount of VMT generated in the system is fixed, and represent the demand from current population. Under this assumption, **Figure ES-3** illustrates the spatial pattern of EV VMT penetration rate change by "through" census tracts (where travel is taking place) from the 2018 base year to the projected 2032 level. Comparing the base year (2018) to the forecast year (2032), the EV adoption rate and EV VMT penetration rate increases throughout the region. Most census tracts have additional 25-35% of EV VMT being electrified by 2032, similar to changes in EV adoption rates. EV VMT penetration rates see a higher increment in CA than in OR and WA, potentially attributed to the more mature EV market and infrastructure in CA. By 2032, a total of 340 million VMT will be electrified (including spillover to neighboring states) by 2032 under the TEMPO projection of EV adoption (**31.7%** of the passenger fleet will be EVs), accounting for 30.7% of total passenger VMT in the region. This is much higher than 12.4 million electrified VMT in 2018, which only accounts for 1.1% of all passenger VMT. The NAVIGAT can be calibrated to better capture future year population and VMT projection if such national-level forecast data is made available to the team.



(a) Seattle, WA

(b) Three-state (CA, OR, WA)

(c) Portland, OR

(d) Los Angeles, CA

(e) San Francisco, CA

Figure ES - 3. Changes in EV VMT penetration (increased EV adoption scenario – base year scenario)

While a model like TEMPO can generate projected changes in EV adoption, travel behavior, and energy consumption, NAVIGAT fills a critical gap in our understanding of where those new EVs in the network will be utilized by providing a spatially explicit model. For example, in this comparison between scenarios, 8.6% of the VMT from the additional EVs adopted are generated in the home tract where the vehicles are adopted, whereas 91.4% are generated outside of the home tract. Similarly, for the additional VMT being electrified under the forecast scenario, 1.4% of VMT comes from EVs adopted in other states that are spilled over to through states. Without a tool like NAVIGAT, an understanding of where the utilization of new technology is likely to occur would not be possible. A tool like NAVIGAT not only helps with understanding the utilization of new technology but also helps with understanding variations of their utilization from different policies and assumptions.

Conclusion

In this study, the NAVIGAT tool is developed to assess the operational impacts of large-scale technology adoption at a high spatial resolution -- specifically, at the census tract level. The modeling capability has full coverage of the continental U.S. NAVIGAT generates privately-owned light duty passenger VMT for selected U.S. states or regions, and can be used to investigate the operational impacts under pre-defined technology adoption scenarios. The results from NAVIGAT provide key inputs for downstream emission, air quality, health and equity analyses. It can also be applied in analyses designed to inform policy and planning decisions, such as transportation infrastructure siting and assessing the impacts of heterogeneous technology adoption across subpopulation groups. The case study in this report demonstrates the model capability to generate state-level passenger VMT under various transportation scenarios, and the pipeline can be easily applied at the national level to support large-scale transportation analysis.

The NAVIGAT tool can be used by federal agencies and state Departments of Transportation (DOTs) to assess the potential operational impacts of technology adoption at the household level. The tool may also be helpful to local planning organizations or transportation authorities who lack in-house expertise or resources to develop their travel demand model but need a screening tool for assessing the community impacts of technology adoption scenarios. By integrating NAVIGAT with technology adoption models, the tool can support and investigate the potential impacts of alternative policy, investment, and infrastructure plans on technology adoption and subsequent penetration into daily travel activities. By integrating NAVIGAT with air quality, public health and urban climate models, the NAVIGAT tool can support understanding of the environmental, public health, and climate impacts of technology adoption in the transportation sector on communities as well as potential equity implications. Currently, the NAVIGAT tool focuses on travel made by auto mode, but the functionality can readily be extended to other modes of transportation through continued refinement and if national data sources become available. The existing methodology can be adapted to investigate technology adoption scenarios for transit, school buses, or freight systems (which requires national operation data for those sectors), or potential behavior shift in travel if paired with national-scale travel mode choice models.

1. Introduction and Model Overview

The transportation and energy sectors in the U.S. are experiencing fast and widespread changes driven, in part, by advancements in technology and infrastructure, including the proliferation of electric vehicles (EVs), low-carbon building technologies, and EV charging stations (Muratori et al., 2023). This transition is being accelerated by key federal policies and legislation such as the Bipartisan Infrastructure Law (BIL) and the Inflation Reduction Act (IRA), which provide historic financial support for build-out of large-scale EV public charging infrastructure and funds investment in renewable energy production and grid updates through grants and tax credits (Yarmuth, 2022; U.S. DOT Volpe Center, 2024)

This changing landscape has raised the need for modeling tools with the aim of forecasting the adoption of new technologies, assessing their impacts on operations (Schmidt et al., 2022), public health, and environmental outcomes (Peters et al., 2020). In many prior studies, the primary metric used to articulate progress in the impacts of technology is often the adoption rate itself, with assignment of that benefit metric to the location where that adoption occurs, including studies in real estate (Zheng et al., 2023), agriculture (Yang et al., 2022), household goods (Lagomarsino et al., 2023) and some in EVs (Afandizadeh et al., 2023). However, in the domain of transportation, technology adoption alone is not sufficient to portray all relevant impacts of the technology deployment. New technologies will be used to fulfill travel needs of various households across the network, with potential environmental and health impacts in surrounding neighborhoods (Antonczak et al., 2023), not just in the residence location where the new vehicle technology has been adopted. Therefore, it is not only the location of the newly adopted technology that is important to forecast but also their operation as they move across the network.

To properly account for the transportation operation of such emerging technologies, operation modeling tools need to account for sufficient spatial variation at a large scale. Granular, local forecasts of where and how new vehicle technologies operate are vital to, for example, forecast the need for new infrastructure at locations other than the owners' residential or workplace location (Gulbahar et al., 2023). This is key given that there is evidence that residential proximity to higher-volume roads is linked to a plethora of negative health outcomes (Health Effects Institute, 2010). Antonczack et al. (Antonczak et al., 2023) illustrate, using data at the census tract level, that there are racial and income inequities in the characteristics of populations living near highways in the U.S., highlighting the need for granular forecasts of the impact of the decarbonization agenda on road traffic characteristics. Additionally, the magnitude of the energy transition will give rise to decisions affecting multiple states and even the full nation, which calls for the development of modeling tools that are scalable and offer both depth and breadth, to explore outcomes at a granular, local level but also covering large regions. However, existing studies mostly focus on addressing these issues on a regional scale at fine resolution, such as EV charging behavior at a census tract level in California (Li and Jenn, 2022); or use highly aggregated data or models for larger scale analysis, such as forecasting the health and environmental impacts of truck electrification at the corridor level (McNeil et al., 2024).

So far, there is a lack of such a scalable modeling capability that can simulate the operational impacts of emerging privately-owned light-duty vehicle technologies both at large-scale (national or multi-state level) and at high spatial resolution due to challenges with the availability of large-scale, high-resolution data and modeling capabilities at the national level. Previous studies have either investigated EV travel behavior at a census tract level limited to a single state such as

California (Javid and Nejat, 2017) or Virginia (Jia and Chen, 2021); or have covered several states or the full U.S. in a more aggregated manner, such as state-level resolution (Vergis and Chen, 2015; Jenn et al., 2018; Zambrano-Gutiérrez et al., 2018) or simply consider the large-scale adoption of the technology without accounting for the operational level impacts (Muratori et al., 2021; Sinton et al., 2024). Modeling efforts which manage to provide both granular resolution and a wide area of application are still largely missing. Therefore, there is an urgent need for a **large-scale** tool to look into operational impacts of emerging technologies and new infrastructure with higher spatial coverage, to align with the federal- and state-scale investments or deployment projects, including spillover effects on neighboring regions and states. **High spatial resolution** also needs to be maintained to capture the spatial variation under those scenarios and investigate local impacts on, for example, disadvantaged communities.

This study fills the gap through the development of a large-scale VMT simulator using a data-driven approach. The **NAtional Vehicle Itinerary GenerATor (NAVIGAT)** for **household-owned light-duty vehicles**, is developed by LBNL researchers to simulate vehicle movements at the network level. The modeling framework resembles the traditional four-step travel demand models that are widely applied in a regional context (Davidson et al., 2007; Miller, 2023), with key model structures and parameters informed and estimated with national-level data sources. Specifically, a national-scale geospatial typology developed in a prior study (Popovich et al., 2021) is adopted to capture the spatial variation in travel demand across the nation and generate vehicle flows under various transportation scenarios while maintaining a reasonable computational speed. The travel demand was then distributed to the entire network using destination choice and route selection models, and the fraction of flows are used to split observed "through" traffic, or travel in tracts that may be outside the origin or destination tract of the trip, to corresponding home locations. Both in-state travel and cross-state spillover travel are modeled in NAVIGAT and calibrated to align with observed daily VMT from Highway Performance Monitoring System (HPMS) data (Federal Highway Administration, 2020). Using NAVIGAT, simulated vehicle movements can be tracked throughout the network at the census tract level given a technology adoption scenario input that is also mapped to the census tract level. Outputs from NAVIGAT can support the estimation of common transportation and environmental metrics, such as on-road emission changes, air quality, and health impacts on surrounding communities resulting from changes in technology adoption. These changes in technology adoption capture variations of charging infrastructure deployment, adoption incentives, changes in fuel prices or vehicle prices, or other factors, and NAVIGAT helps to translate how those policy factors may affect system performance in different aspects through tracking the utilization of technologies.

The NAVIGAT tool can be used by federal agencies and state Departments of Transportation (DOTs) to assess the potential operational impacts of technology adoption at the household level. The tool may also be helpful to local planning organizations or transportation authorities who lack in-house expertise or resources to develop their travel demand model but need a screening tool for assessing the community impacts of technology adoption scenarios. By integrating NAVIGAT with technology adoption models, the tool can support and investigate the potential impacts of alternative policy, investment, and infrastructure plans on technology adoption and subsequent penetration into daily travel activities. By integrating NAVIGAT with air quality, public health and urban climate models, the NAVIGAT tool can support understanding of the environmental, public health, and climate impacts of technology adoption in the transportation sector on communities as well as potential equity implications. Currently, the NAVIGAT tool focuses on travel made by auto mode, but the functionality can readily be extended to other modes of transportation through continued refinement and if national data sources become available. The existing methodology can be adapted to investigate technology adoption scenarios for transit, school buses, or freight systems (which requires national operation data for those sectors), or potential behavior shift in travel if paired with national-scale travel mode choice models.

1.1 Technical Background

Popovich et al. (2021) developed a national typology at the census tract level designed to capture transportation demand and cost variation across all census tracts in the U.S. (Popovich et al., 2021). Specifically, the purpose of the typology is to group regions into clusters that exhibit similar geo-economic drivers of the relationship between geographic attributes on the one hand, and transportation demand and travel costs on the other. Specifically, the typology is intended to ensure that the trip-generation rate, network characteristics, and transportation cost drivers/supply constraints are relatively homogeneous within each category. The categorization results in a two-layer typology referred to as **'microtypes'** (at the neighborhood level, defined based on census tracts) and **'geotypes'** (at the regional level, defined based on core-based statistical areas [CBSAs] or counties). The two-layered typology of micro-geotypes represents common geographic and system combinations across the whole U.S. The micro-geotype typology can be applied as a useful tool to segment travel demand at the census tract level, and capture major variation in traffic operation under different settings with different degrees of urban versus rural characteristics. It is especially pertinent to a large-scale model at a multi-state or national level, particularly because of the coverage across more rural areas. Travel data for rural areas are often sparse and lack heterogeneity (Isserman, 2005), applying micro-geotypes can help increase the sample size for rural areas and impute travel attributes for areas that lack sufficient observed data. The definitions of microtypes and geotypes can be explored on FHWA's website (Federal Highway Administration, 2023) and downloaded from the DOT DataHub (U.S. Department of Transportation, 2022). Examples of micro-geotype designations for the San Francisco Bay Area (or SF Bay) are illustrated in Figure 1 and Figure 2 below.

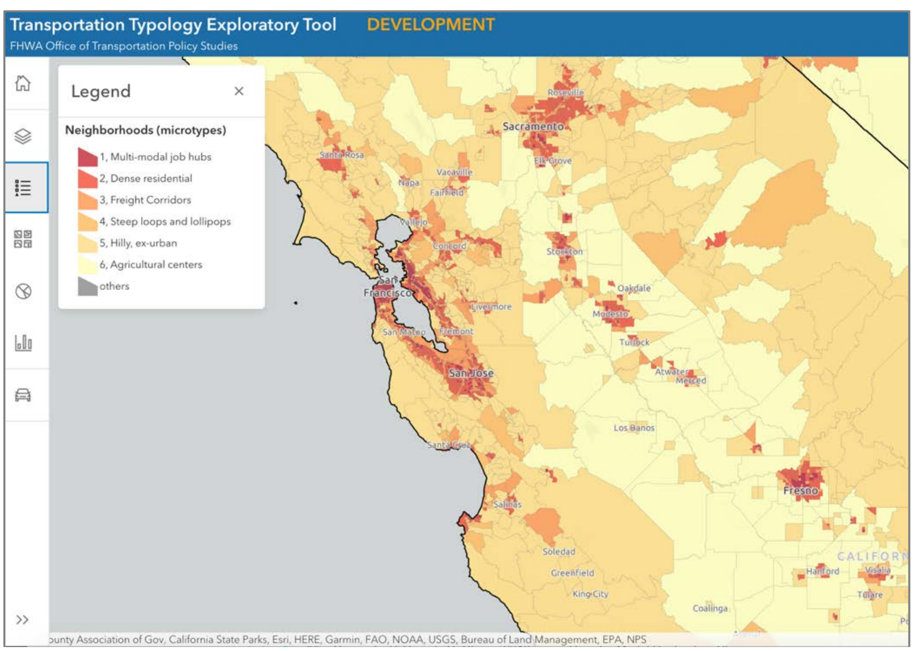


Figure 1. Example of microtype designation

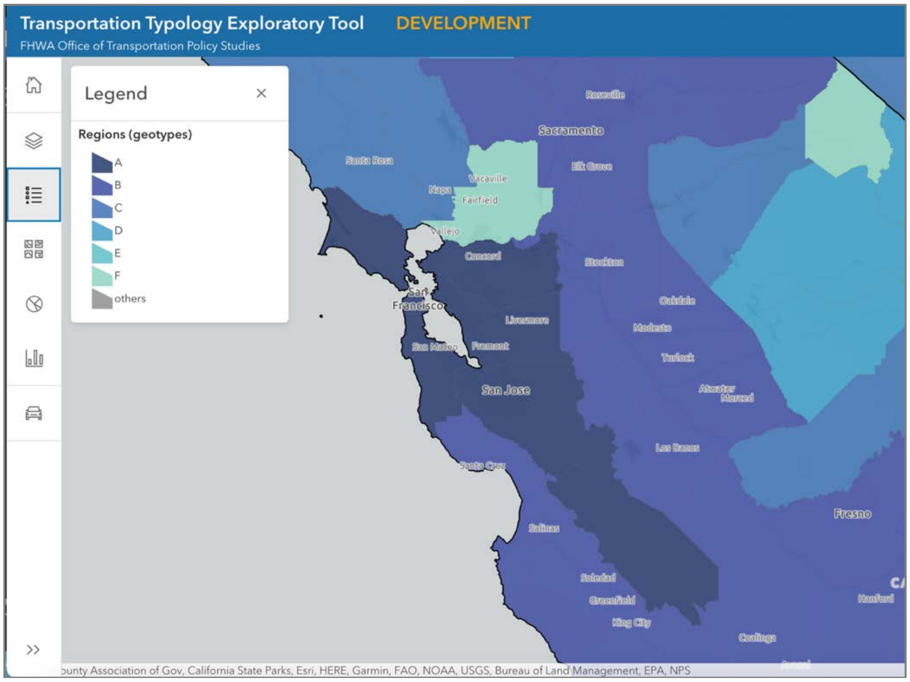


Figure 2. Example of geotype designation (A, B, F – urban areas with different centricity, C, D, E – rural areas with different commute patterns)

1.2 Model Overview

In this analysis, the travel demand characteristics by micro-geotype are leveraged and used to generate traffic volumes at the census tract level. The major functionalities developed in NAVIGAT are illustrated in Figure 3. Within the model, five functional modules were developed to estimate travel demand by census tract and the distribution of that demand to the network, including travel both within the target state or across state boundaries (referred to as '**spillover**' in the following sections). The five major components are listed below:

1. **A home-based trip generation module**, which predicts the total home-based trips for each home census tract, for both in-state and spillover travel.
2. **A home-based trip distribution module**, which predicts the destination choices for demand by various activity types, income groups, and home locations.
3. **A home-based trip route assignment module**, which generates the route for each origin-destination (O-D) pair. The VMT accumulation in each through-tract along the route was then calculated by multiplying through-distance and trip frequency within a given tract.
4. **A non-home-based traffic generation module,** which generates the non-home-based VMT as a fraction of home-based VMT to the same destination. Results from steps 3 and 4 were combined to generate the fraction of daily VMT by home tracts in each through census tract.
5. **A VMT allocation module**, which combines observed daily VMT in each census tract from HPMS and the VMT fraction from step 4, to generate the total daily VMT in each census tract, attributed to various home census tracts.

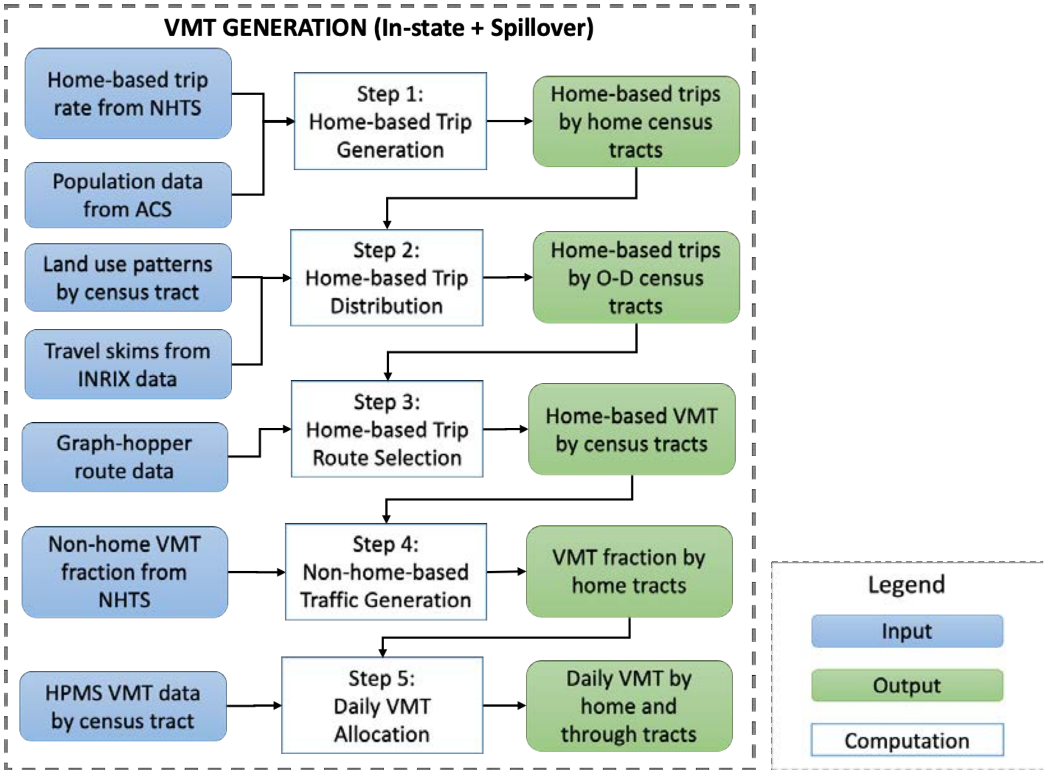


Figure 3 NAtional Vehicle Itinerary GenerATor (NAVIGAT) workflow

The major national-scale data sources that are used for each module in NAVIGAT are summarized in Table 1. The majority of the data sources are publicly available and are updated periodically, facilitating future updates and maintenance of the model.

Table 1. Summary of major data sources of NAVIGAT

Module	**Element**	**Data Source**	**Reference**
Trip Generation	Population	2018 ACS 5-year estimates	(U.S. Census Bureau, 2018)
	Trip rate	2017 NHTS	(Federal Highway Administration, 2017)
Trip distribution	Destination choice	2017 NHTS	(Federal Highway Administration, 2017)
	Travel time and distance skims	INRIX trip OD data	Proprietary
	Job count	LEHD LODES7 data workplace area characteristics (WAC)	(U.S. Census Bureau. Longitudinal-Employer Household Dynamics Program., 2022)
	Opportunity count (school, hospital, etc.)	U.S. Department of Homeland Security Homeland Infrastructure Foundation-Level Data (HIFLD).	(U.S. Department of Homeland Security, 2020)

	Bus accessibility	Center for Neighborhood Technology (CNT) All Transit database	(Center for Neighborhood Technology, 2022)
	Rail accessibility	Bureau of Transportation Statistics (BTS) rail nodes database	(U.S. Department of Transportation Bureau of Transportation Statistics., 2020)
Route generation	Route generation	GraphHopper shortest-path routes using OpenStreetMap (OSM) network for entire U.S.	(Geofabrik, 2018; GraphHopper, 2021)
VMT allocation	Tract-level VMT	2017 Highway Performance Monitoring System (HPMS) data	(Federal Highway Administration, 2020)
TEMPO interface	DAC boundary	2022 Joint Office definition	(Joint Office of Energy and Transportation, 2022)

The input-output relationship of the NAVIGAT tool is illustrated in Figure 4, as a demonstration of how each input data were utilized in the modeling pipeline.

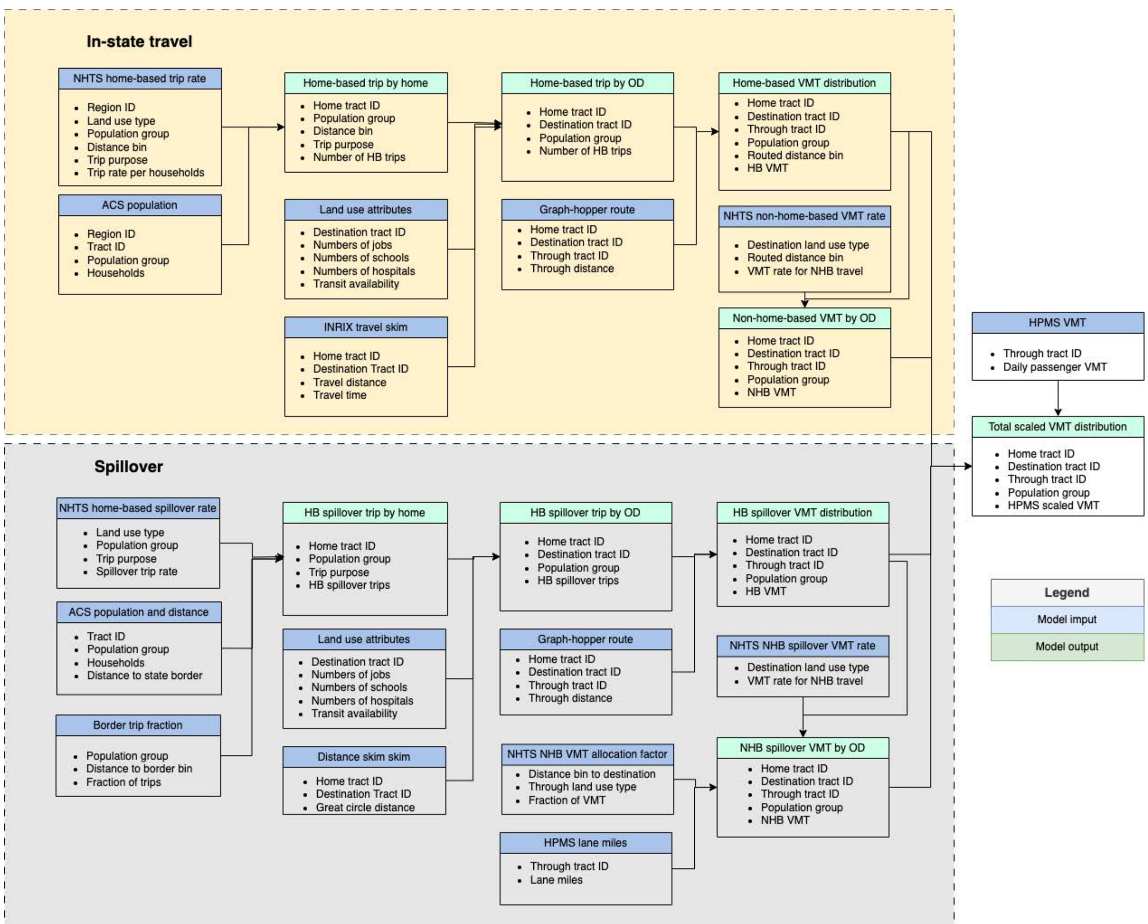


Figure 4. I-O Structure of NAVIGAT

After generating the total VMT by home- and through-tracts, the linkage between NAVIGAT and technology adoption scenarios can be established to estimate the VMT penetration of specific technology adoption scenarios at the census tract level. The results from this integration then serve as inputs for downstream emission and air quality analyses for light-duty passenger vehicles.

2. VMT Generation and Parameter Estimation

In this section, the technical details of NAVIGAT module development and parameter estimation are provided. The major components of NAVIGAT include home-based trip generation, destination choice, route choice, non-home-based VMT generation, and VMT output allocation and calibration. The detailed methodology of both in-state and spillover travel is introduced for each component. The outcome from NAVIGAT includes **census-tract-level passenger vehicle daily VMT** in the baseline year 2018, attributed to home census tracts and segmented by household income groups.

2.1 Home-based Trip Generation

In this study, the travel demand is first generated for home-based (HB) travel, including trips that start or end at home. The non-home-based (NHB) travel (e.g., at-work dining) is assumed to be proportional to demand for home-based travel at activity destinations and is essentially assigned to various home census tracts in the later part of the modeling framework. The HB trip generation in this project resembles a traditional four-step model, which estimates total home-based trips by multiplying the **average trip rates** per household under different land use types and **the number of households** in each home census tract. The major data source for estimating the travel demand is the 2017 National Household Travel Survey (NHTS) (Federal Highway Administration, 2017) and 2018 American Community Survey (ACS) 5-year estimates (U.S. Census Bureau, 2018). The majority of the trips considered in this model are short-distance trips within 150 miles (99.5% of all passenger auto trips suggested by NHTS data), which are informed by the data to represent daily routine travel and do not cover long-distance road trips above 300 miles. Therefore, the model is more suited for assessing the operations of technology adoption in a routine travel setting, while the range constraints for long-distance road trips needs to be investigated through future work supported by additional data gathering. Since 2017 NHTS data only represents a small portion of all trips and is sparsely distributed across the U.S., the trip data is aggregated into the spatial cluster level, or the micro-geotype level, as introduced above. The trip generation at the census tract level is then estimated using the ACS household data at the census tract level, multiplied by the trip generation rates from NHTS.

2.1.1 In-state Home-based Trip Generation

Regarding household inputs, census tract level household counts from the 2018 American Community Survey (ACS) 5-year estimates are used (U.S. Census Bureau, 2018). The households were aggregated into three income groups: high-income (annual income>=$125,000), median-income (annual income $50,000-125,000), and low-income (annual income <$50,000). Each household group has different trip generate rates for various trip purposes.

Trip and household data from the 2017 NHTS were used to derive trip generation rates. The weighted home-based trip counts by household income group, trip purpose, home location type by micro-geotype and NHTS region, and travel destination location type by micro-geotype were generated from the trip table. For NHTS region, census division boundary is used where only public sample is available (Westat, 2017), except for California and Texas where add-on data is available to the team from Transportation Secure Data Center (TSDC) (National Renewable Energy Laboratory, 2023) and Texas Department of Transportation during the project period. The weighted number of households by income group were generated from the household table. The trip generation rate is calculated using the following equation:

$$HBTR_{i,p,h,g,r}^{NHTS} = \frac{HBTC_{i,p,h,g,r}^{NHTS}}{HH_{i,r}^{NHTS}} \tag{1}$$

Where,

- i = income group (high, median, low)
- p = trip purpose (work, school, medical, leisure, home, other)
- h = micro-geotype specifications of home census tract
- g = micro-geotype specifications of travel destination census tract
- r = NHTS region (by regions requested add-on data or use census division for states without add-on) (Westat, 2017)
- $HBTC_{i,p,h,g,r}^{NHTS}$ = home-based trip count from 2017 NHTS (scaled by trip weights)
- $HH_{i,r}^{NHTS}$ = household count from 2017 NHTS (scaled by household weights)
- $HBTR_{i,p,h,g,r}^{NHTS}$ = home-based trip rate based on 2017 NHTS

For each home census tract o under a specific micro-geotype and NHTS region among all U.S. tracts O, the ACS 2018 5-year estimated household count $HH_{i,o}^{ACS}$ is multiplied by the trip generation rate $HBTR_{i,p,h,g,r}^{NHTS}$ under each selected home micro-geotype and NHTS region to generate the final trip generation within each home census tract using the following equation:

$$HBT_{i,p,o,g} = HBTR_{i,p,h,g,r}^{NHTS} * HH_{i,o}^{ACS} \ \forall \{o \in O | h, r\} \tag{2}$$

Where,

- O = the set of all home census tracts in the U.S.
- $HH_{i,o}^{ACS}$ = household count by income group and tract from the ACS 2018 5-year estimates
- $HBT_{i,p,o,g}$= in-state home-based trips generated at census tract level

The final output from this step is the daily home-based trip generation by: (1) home census tract, (2) destination land use typology, (3) income group, and (4) trip purpose. The total trips originated from each home census tract is illustrated using a California example in Figure 5. The majority of the trips were generated from major cities along the coast, such as San Francisco and Los Angeles.

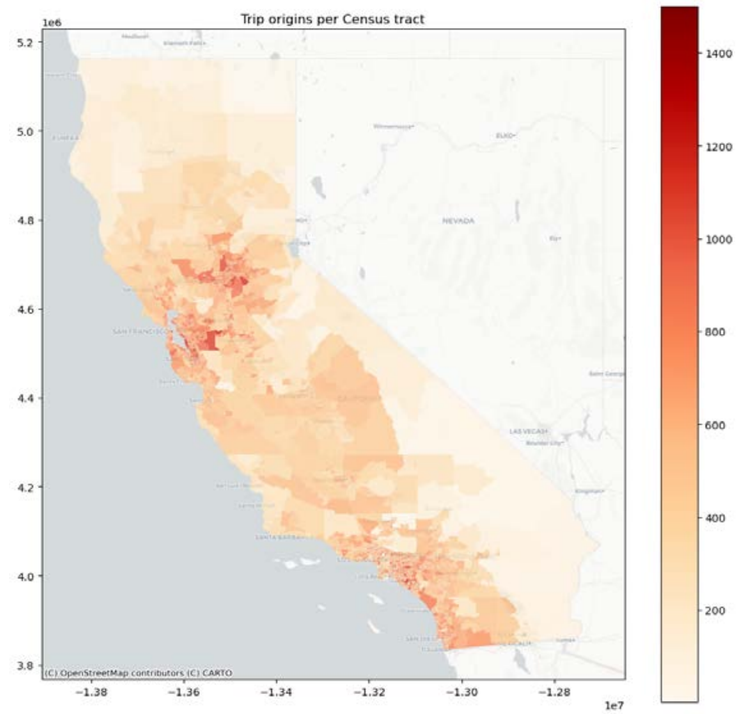


Figure 5. Trip origins by census tract (CA example)

2.1.2 Spillover Home-based Trip Generation

In the spillover VMT generator, similar to in-state travel, the travel demand is first generated for home-based travel, including trips that start or end at home. The non-home-based VMT (e.g., sightseeing at and around the destination) is assumed to be proportional to the VMT for home-based travel to their out-of-state destination, so that non-home-based travel is therefore assumed to be larger the farther from home to trip destination is. The home-based spillover trip generation estimates total home-based trips by multiplying the **average trip rate** per household under different land use types (micro-geotype) with **the number of households** in each home census tract. Those trips are then assigned to potential home census tracts based on their proximity to the nearest states, as most of the cross-state travel occur for households living close to other states.

The major data source for estimating the travel demand is the 2017 National Household Travel Survey (NHTS) (Federal Highway Administration, 2017). Sample trips from NHTS are labeled as spillover trips if the trip's origin state or destination state is different from the home state. In total, 6,126 home-based trips and 16,597 total trips are selected from the NHTS national dataset to estimate the model parameters for the spillover VMT generator. In addition, as those trips only represent a small portion of all trips and are sparsely distributed across the U.S., all the spillover trip data within the U.S. are aggregated into the spatial cluster level, or the micro-geotype level, as introduced above. Similar to the EV VMT generator, the spillover trip generation in each state is then estimated using the demographic data from the American Community Survey (ACS) at the census tract level, multiplied by the trip generation rate from NHTS.

The weighted home-based trip counts by household income group, trip purpose, home location type by micro-geotype, and travel destination location type by micro-geotype were generated from the trip table. The weighted households by income group were generated from the household table. The trip generation rate is calculated using the following formula:

$$SHBTR_{i,p,h}^{NHTS} = \frac{SHBTC_{i,p,h}^{NHTS}}{HH_i^{NHTS}} \tag{3}$$

Where,

- i = income group (high, medium, low)
- p = trip purpose (work, school, medical, leisure, home, other)
- h = micro-geotype specifications of home census tract
- $SHBTC_{i,p,h}^{NHTS}$= weighted spillover home-based trip count from 2017 NHTS
- HH_i^{NHTS} = weighted household count by income-group from 2017 NHTS
- $SHBTR_{i,p,h}^{NHTS}$= spillover home-based trip rate based on 2017 NHTS

For a selected home state st, the total ACS household count $HH_{i,o}^{ACS}$ for all tracts under a specific micro-geotype h and income group i, is multiplied by the $SHBTR_{i,p,h}^{NHTS}$ under selected home micro-geotype to generates the final trip generation within each home tract using the following equation.

$$SHBT_{i,p,st} = \sum_{o \in \{O|st\}} HH_{i,o}^{ACS} * SHBTR_{i,p,h}^{NHTS} \tag{4}$$

Where,

- $SHBT_{i,p,st}$= total spillover home-based trips in selected state

The final output from this step is the total home-based trips by: (1) income group and (2) trip purpose within selected state, with home census tract still needing to be assigned based on proximity to the state border. As households living near the state border are more likely to make cross-state trips, the total spillover trips from a selected state were proportionally assigned to home census tracts based on the distance of those census tracts to the nearest out-of-state tracts. The probability of home tract location is defined as fractions of trips $f_{i,db}$ by income group i and distance to border bin db (distance between centroids of each in-state tract to nearest out-of-state destination tract). The $f_{i,db}$ by income group and distance to out-of-state destinations is illustrated in Figure 6 below, which is estimated from the sample NHTS spillover trips using census tract information. The final spillover trips $SHBT_{i,p,o}$ were generated by randomly assigning all $spillover\ trips_{i,p,st}$ to home tracts o based on $f_{i,db}$ and assigning distance bin db of each tract.

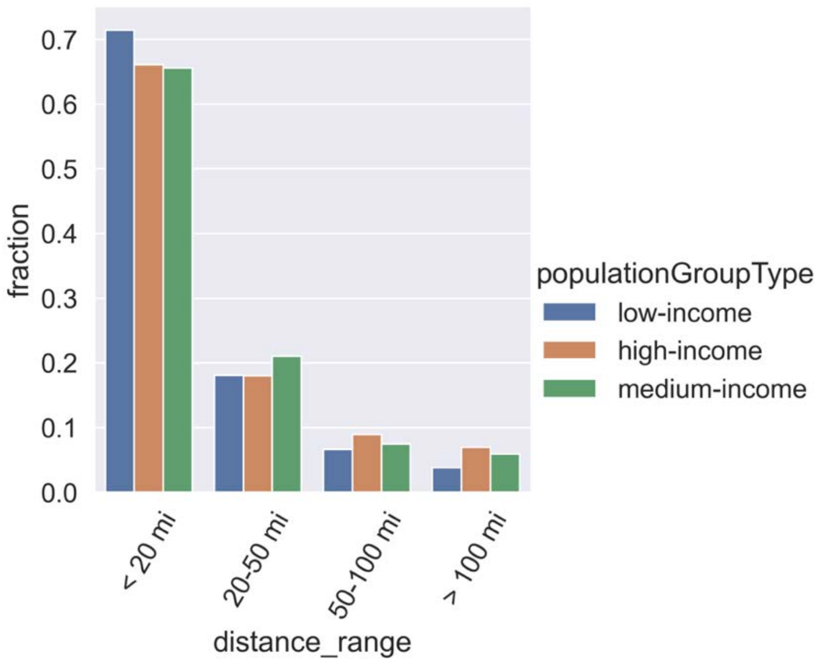


Figure 6. Fraction of spillover trips attributed to home location by distance bins between home location and out-of-state trip location

Using the methodology described above, the spillover trips are allocated to home census tracts based on their proximity to out-of-state destinations. The spillover trip count by census tract within CA is provided in Figure 7 below as an example.

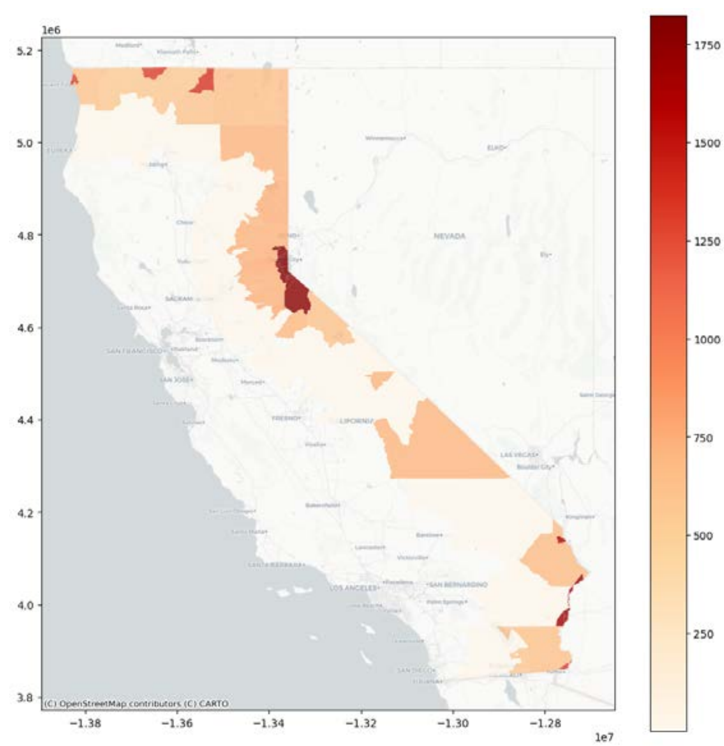


Figure 7. Spillover trip count by home census tracts from CA

2.2 Home-based Trip Distribution and Destination Choice

After the home-based trip generation step, the trips were distributed to various destination census tracts using an availability-constraint destination choice model. Destination choice models are formulated as discrete choice models, typically logit models (Bernardin et al., 2018). This approach addresses the incorrect demand elasticities of the traditional gravity model by allowing for a wide range of explanatory variables. In this study, a destination choice model is estimated using a multinomial logit model (MNL), which is often used for this type of analysis (Bernardin et al., 2018) and is easy to apply. The destination choice model is developed for home-based trips, with the origin location set to home census tract, and inbound/outbound destination census tract for various traveler categories for various trip purposes. The destination choice model takes demographic characteristics, travel characteristics, and land use patterns as major inputs, and predicts the destination census tract selection among potential destination census tract choice set. In the following sections, the technical details of the model, including: (1) data source preparation, (2) model formulation and structure, (3) model application for in-state travel, and (4) spillover destination choice model application will be discussed.

2.2.1 Data Source Preparation

The major data preparation steps for the destination choice model include: (1) generating the travel time and distance skims between all O-D pairs, (2) generating the choice set or the dependent variable, and (3) selecting the explanatory factors or independent variables. The 2017 NHTS trips data is used as the major data source for developing the destination choice model, with additional land use and travel characteristics data gathered from various data sources. The major data sources used to generate the dependent variable and independent variables are summarized in Table 2 below, with geographical resolution at the census tract level.

Table 2. Summary of destination choice model data sources

Category	Attribute	Data Source	Reference
Dependent variable	Chosen destination	2017 NHTS	(Federal Highway Administration, 2017)
Independent variable	Travel time and distance	INRIX trip OD data	Proprietary
	Demographic characteristics	2017 NHTS	(Federal Highway Administration, 2017)
	Travel purposes	2017 NHTS	(Federal Highway Administration, 2017)
	Job count	LEHD LODES7 data workplace area characteristics (WAC)	(U.S. Census Bureau. Longitudinal-Employer Household Dynamics Program., 2022)
	Opportunity count (school, hospital, etc.)	U.S. Department of Homeland Security Homeland Infrastructure Foundation-Level Data (HIFLD).	(U.S. Department of Homeland Security, 2020)

	Bus accessibility	Center for Neighborhood Technology (CNT) All Transit database	(Center for Neighborhood Technology, 2022)
	Rail accessibility	Bureau of Transportation Statistics (BTS) rail nodes database	(U.S. Department of Transportation Bureau of Transportation Statistics., 2020)

First, the travel distance and time skims are generated for the entire U.S., state-by-state, using passive O-D data collected from smartphone devices. The INRIX trip data collected during January 2020 is used to generate daily travel skims[1], which contains origin, destination, travel distance and time information. However, there are still many census tracts with no trips collected requiring imputation. For the remaining O-D pairs without observed distance and travel time, the values are imputed for those O-D pairs within each state. For travel distance, the routed distance is imputed using the linear regression line between routed and great circle trip distance as shown in Figure 8. Regarding travel time, the observed average speed curve by distance from INRIX data and imputed routed distance are used to impute the travel time, where longer trips tend to have faster average speeds and travel time increments are not linear. After the value imputation, the travel distance and time skims are generated for all census tracts for each state, and are used as key inputs in developing the destination choice model below.

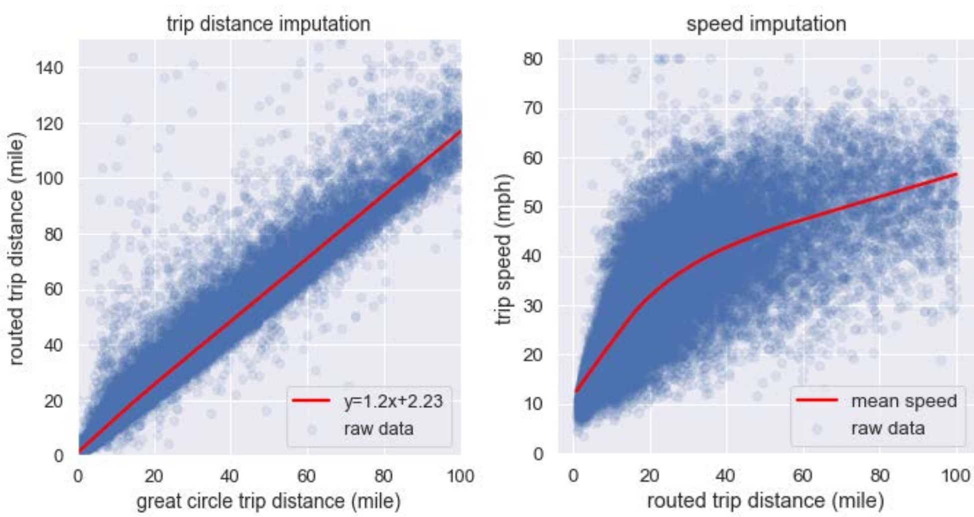


Figure 8 Travel skim imputation (with CA data as an example)

Next, the destination choice sets were generated for home-based auto trips. Unlike other discrete choice problems with limited choice sets, such as mode choice models, the number of possible destination alternatives for a trip is very large (Pozsgay and Bhat, 2001). Including all the potential destinations would be computationally intensive and challenging, so a subset of alternative zones is often drawn from the universal choice set for each trip. In this analysis, a choice set of 10 destination tracts is assigned to each trip. The one chosen destination at the census tract level is collected from the 2017 NHTS data. Additional 9 non-chosen destination tracts are randomly

[1] The data from the first week of January is excluded due to the influence of the holiday, as the travel trends may not be representative. The data from Feb to June 2020 are also excluded due to potential impacts of COVID-19 and travel restrictions across the U.S.

drawn from all census tracts, constrained by: (1) their land use type and (2) travel time to origin location. Regarding the land use constraint, the micro-geotype of the chosen destination g is used to filter candidate census tracts. So if a selected trip ended in a high-density urban area, the potential non-chosen alternatives should also be the dense urban areas. After this step, the census tracts with the same land use type will be kept as potential destinations, but some of them may be far away from the home location and rarely selected. In this case, a travel-time-based survival function is estimated for remaining destinations, with nearby census tracts having a higher survival probability compared to farther tracts. The survival function is estimated using an exponentiated Weibull distribution of travel time from 50,000 observed trips from INRIX data. The probability density function for exponentiated Weibull distribution of travel time is listed below:

$$f(t,a,k) = ak[1 - exp(-t^k)]^{a-1} exp(-t^k) t^{k-1} \tag{5}$$

Where,

- t = the trip travel time (hour)
- a, k = exponentiation parameter and shape parameter of the distribution

The estimated parameters of the travel time distribution are $a = 0.354$ and $k = 1.136$. The survival probability sp under travel time t equals 1 minus the cumulative probability under time t, which follows the formula below:

$$sp(t,a,k) = 1 - [1 - exp(-t^k)]^a \quad (t > 0, a > 0, k > 0) \tag{6}$$

After estimating the survival function, the survival probability is computed for all potential destination tracts based on their imputed travel time to the origin home tracts. The 9 non-chosen destinations were then drawn from all samples based on the weighting of survival probabilities. The candidate destination tracts with higher survival probabilities are more likely to be selected for the destination choice model. Finally, if fewer than 9 candidate destinations were left after applying the land use constraint (not enough tracts in specific land use type), the constraints will be softened to only include the survival function and ensure a sufficient number of destinations being added to the choice set.

Finally, for destination choice models, the common explanatory variables include impedance, accessibility, psychological boundaries, and other destination qualities, as well as traveler attributes (Bernardin et al., 2018). Considering the data availability and application feasibility, the research team selected household income group, travel purpose, travel distance, travel time, employment, opportunity counts, and transit availability as the final factors to be considered in the destination choice model, with corresponding data sources summarized in Table 2 above.

2.2.2 Model Formulation and Estimation

In this study, the utility function of the destination choice model adopts a typical formulation used in empirical destination choice studies (Pozsgay and Bhat, 2001), which is shown below:

$$U_{qod} = \boldsymbol{\beta} \cdot \boldsymbol{x}_{qod} + \gamma log(\boldsymbol{\delta} \cdot \boldsymbol{v}_d) + \varepsilon_{qod} \tag{7}$$

Where,

- q = trip id
- o = originate home tract

- d = destination census tract
- $\boldsymbol{x}_{qod}$ = a vector of exogenous variables (refers to travel time, distance and transit accessibility in this study)
- $\boldsymbol{\beta}$ = a vector of coefficients for x_{qod}
- $\boldsymbol{v}_d$ = a vector of proxy size variables for destination d (refers to employment size and opportunity count at destination in this study)
- $\boldsymbol{\delta}$ = a vector of weighting factor (reflecting contribution of different size variables)
- γ = presence of common unobserved zonal attributes (1 – no unobserved factor, 0 – all zonal factors are unobserved)
- ε_{qod} = random error follows Gumbel distribution

The probability of choosing a specific destination d among a set of destinations D for trip q starting/ending at o is defined as:

$$f_{qod} = \frac{U_{qod}}{\sum_{d \in D} U_{qod}} \tag{8}$$

The list of variables and model specifications that can maximize the model performance (or adjusted ρ^2 in this case) are chosen. To account for the heterogeneity of built environment and travel patterns among households with different income levels, the geotype of home location and income group is used for market segmentation. For each geotype and income group, a set of destination choice parameters is estimated. The samples from geotype D and E (rural areas) were combined due to low sample size in each geotype and potential similarity in travel patterns. The destination choice models are estimated and evaluated using the PandasBiogeme package in Python (Bierlaire, 2020). The final estimated parameters are listed in Table 3 below:

Table 3. Summary of destination choice parameters

Variable	Description	Geotype A - Highly Polycentric Urban			Geotype B - Polycentric Urban			Geotype C - High Disperse Monocentric Rural			Geotype D+E - Monocentric Rural			Geotype F - Monocentric Urban		
		Low-inc	Med-inc	High-inc	Low-inc	Med-inc	High-inc	Low-inc	Med-inc	High-inc	Low-inc	Med-inc	High-inc	Low-inc	Med-inc	High-inc
B_time	Coefficient of travel time	-1.07 ***	-2.06 ***	-1.48 ***	-2.56 ***	-3.7 ***	-3.09 ***	-2 ***	-2.69 ***	-2.12 ***	-3.19 ***	-2.16 ***	-0.228	-2.13 ***	-1.86 ***	-2.74 ***
B_distance	Coefficient of routed travel distance	-0.143 ***	-0.099 ***	-0.101 ***	-0.087 ***	-0.040 ***	-0.044 ***	-0.075 ***	-0.038 ***	-0.057 ***	-0.038 ***	-0.041 ***	-0.071 ***	-0.106 ***	-0.079 ***	-0.060 ***
B_transit	Coefficient of transit availability	-0.143	-0.234 ***	-0.233 ***	0.028	-0.057	-0.345	0.094 *	-0.073	-0.158 *	-0.132 *	0.035	-0.295 **	0.176 *	-0.068	-0.237 *
B_job	Coefficient of (job count * work trip)2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
B_edu	Coefficient of (school count * school trip)	255 *	236 **	426 **	125	253 ***	868 **	249 *	255 **	479 *	61	255 *	256	276	255 *	263
Gamma	Coefficient for unobserved land use factors	0.585 ***	0.642 ***	0.687 ***	0.535 ***	0.6 ***	0.664 ***	0.607 ***	0.637 ***	0.702 ***	0.629 ***	0.65 ***	0.745 ***	0.55 ***	0.657 ***	0.69 ***
Sample size		3661	6103	4908	5053	6707	3044	5683	6676	2309	4623	5431	1703	1897	2777	1246
adjusted ρ^2		0.341	0.324	0.32	0.198	0.189	0.196	0.199	0.171	0.187	0.133	0.131	0.145	0.266	0.233	0.241

Note: * p<0.05, ** p<0.01, *** p<0.001

[2] The coefficient of the job term in the log sum is pre-defined as 1 to facilitate the model estimation

As shown in Table 3, overall, the destination choice model parameters look reasonable across all market segments, with distance and travel time negatively affecting the utility of the destination. The destination choice models for rural areas (geotypes C-E) tends to have lower goodness-of-fit, potentially as a result of fewer observations (especially for high-income groups) and lack of observable influential factors that can capture the dynamics of destination choice in rural areas. Those limitations can be addressed if more data become available for those land use types allowing for further inspection of their travel patterns. Based on existing model results, in most cases, the numbers of education opportunities significantly increase the utility of the destination for medium- and high-income households with school trips, while impacts on low-income households tends to be less notable. On the other hand, transit accessibility leads to increased utility for low-income groups in several cases, while almost always yields disutility for high-income groups. In summary, households living under different built environments with different income levels show different preferences towards destinations, leading to diverse travel patterns being captured across U.S. with mixed land use typology and mixed households from various income groups.

2.2.3 Model Application

After estimating the destination choice model and travel skims, the generated trips from Section 2.1 were allocated to potential destination tracts following similar steps as model estimation. First, for all trips originating from the same tracts with the same purpose by travelers in the same income group, a set of 10 potential destination tracts are selected based on the land use cluster constraints and survival probabilities. If less than 10 destinations are identified, the land use constraint is incrementally relaxed to gather enough destinations for decision-making. Next, the probability of choosing individual destinations is calculated using estimated model parameters, travel characteristics and destination characteristics. Finally, the trips are allocated to potential destinations based on the probability of choosing each destination. After this step, the daily O-D demand matrix by home tract, destination tract, travel purpose and income group are generated for all home-based trips, and are used to generate the through VMT in the next step. The trip counts by destination tracts illustrated for a California example in Figure 9, which shows similar trends as Figure 5 but often with higher trip concentration in certain areas potentially due to more centralized work/activity opportunities.

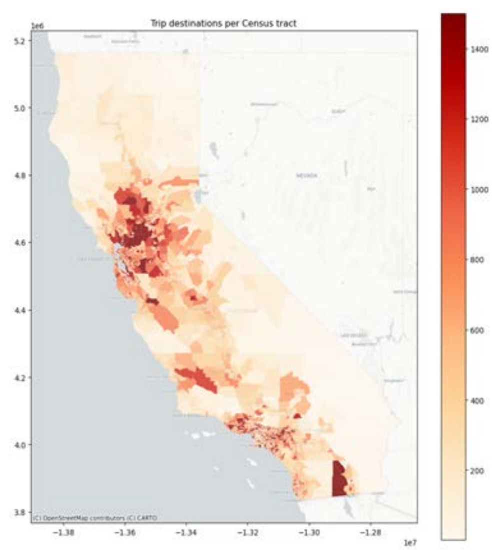


Figure 9. Trip destinations by census tract (CA example)

2.2.4 Spillover Destination Model Estimation and Application

Separate sets of destination choice models are estimated for spillover trips to accommodate potentially different travel patterns and destination preferences for cross-state travel. In general, the workflow and data sources are consistent with the methodology described in Sections 2.2.1 and 2.2.2. The NHTS spillover samples used for trip rate in Section 2.1.2 are also applied to estimate the destination choice model, for all spillover trips within 300 miles from origin tracts[3]. There are a few modifications and adjustments made to account for the characteristics of spillover trips and lower sample size, which are listed below:

1. **Data source:** due to the lack of observed cross-state trips and available travel time/distance from INRIX data (most trips from INRIX data set are split by long stops and idling periods, which leads to a disproportionate representation of shorter, mostly local, trips in the INRIX data if taken at face value), INRIX data is not used for generating travel skims of spillover trips. Instead, great circle distances of O-Ds are used to represent the trip impedance.
2. **Model specification:** due to insufficient sample size for market segment by geotype, the spillover destination choice models are only estimated by income group for the entire U.S.
3. **Model constraints:** the out-of-state constraint is added for all candidate destinations. In addition, the land use typology constraints of destination are removed due to lack of significant variation across different land use types. Finally, as only distance is used for travel impedance, the survival function is re-estimated using great circle distance (with $a = 0.697$ and $k = 60.29$).

The estimated coefficients of the spillover destination choice model are summarized in Table 4 below. The coefficients of education and entertainment are significant at 90% confidence level for some income groups, so they are still kept in the final estimation. Compared to low- and medium-income groups, high-income households have lower disutility towards travel distance, and a higher coefficient on education and entertainment opportunities, suggesting some differences in destination preferences among different population groups.

Table 4. Summary of spillover destination choice parameters

Variable	Description	Low-income	Med-income	High-income
B_distance	Coefficient of great circle distance	-0.0247***	-0.0204***	-0.0138***
B_transit	Coefficient of transit availability	-0.0708	-0.217**	-0.00522
B_job	Coefficient of (job count * work trip)[4]	1	1	1
B_edu	Coefficient of (school count * school trip)	216	0	255
B_ent	Coefficient of (parks count * leisure trips)	0.624	43.3	102
Gamma	Coefficient for unobserved land use factors	0.566***	0.707***	0.777***
Sample size		1599	2324	1122
adjusted ρ^2		0.436	0.381	0.32

Note: * p<0.05, ** p<0.01, *** p<0.001

Finally, the spillover destination choice models were implemented similarly to in-state travel, using estimated coefficients above and new set of constraints. A sample out-of-state destination distribution for California residents is illustrated in Figure 10 below, with most of destinations fall

[3] The 300-mile buffer is applied to reduce the file size requirement for distance skims, as file size increase exponentially to distance range. This filter does not significantly affect the sample size being chosen, as 95% of spillover samples are less than 300 miles distance.

[4] The coefficient of the job term in the log sum is pre-defined as 1 to facilitate the model estimation

into neighboring states and a small fraction of destinations can reach non-neighboring states like Utah and Idaho.

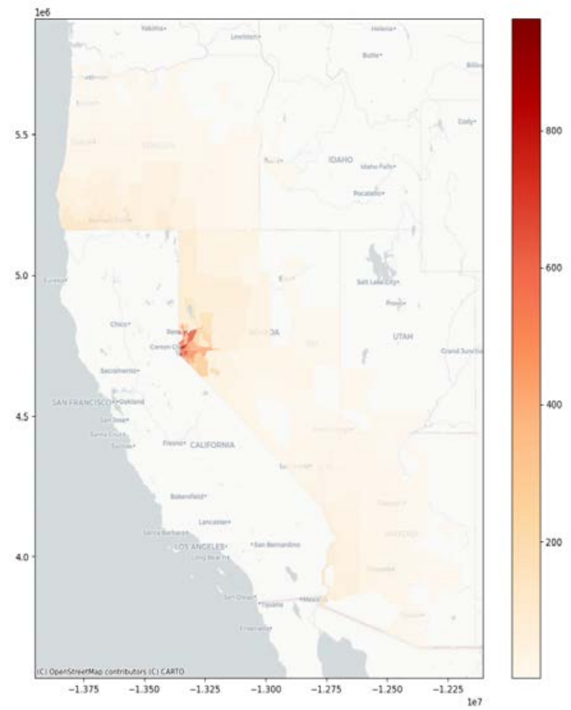


Figure 10. Spillover trip count by destination census tracts from CA

2.3 Route Generation

The VMT throughput in each census tract, for both in-state and spillover home-based trips, can be estimated by combining the O-D matrix with their trajectories. In this study, the team adopted a shortest-path approach to generate vehicle trajectories for all the trips. The shortest-path routes between pairs of census tract centroids are generated by GraphHopper direction API and open-source OpenStreetMap (OSM) network (Geofabrik, 2018; GraphHopper, 2021), with missing routes imputed using an open-source shortest-path router from an R package 'stplanr' and OSM network (Lovelace and Ellison, 2019). A sample of shortest-path routes from 500 unique O-D pairs is illustrated in Figure 11. Finally, the VMT accumulation during the day is aggregated by origin, destination, and through census tracts for further analysis. The in-state home-based VMT and spillover home-based VMT are denoted as $HB\,VMT_{i,o,d,c}$ and $SHB\,VMT_{i,o,d,c}$ respectively, aggregated by income group i, home tract o, destination tract d and through tract c.

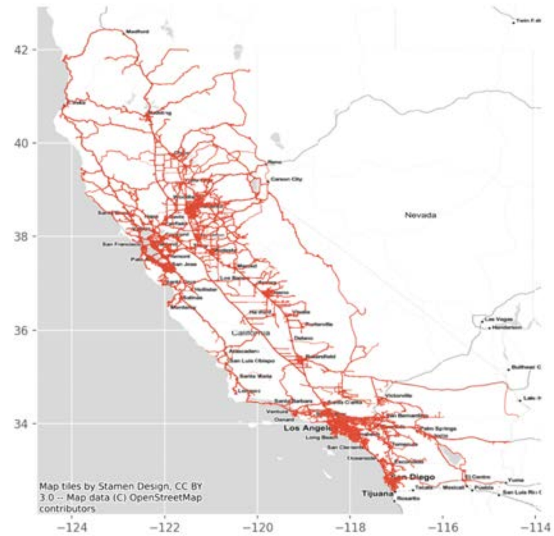


Figure 11. **Sample shortest-path routes from 500 O-D pairs provided by GraphHopper**

The routed trip length distribution of all home-based travel (both in-state and spillover) is demonstrated using the California example in Figure 12 below. The majority of the trips are short-distance trips within 150 miles.

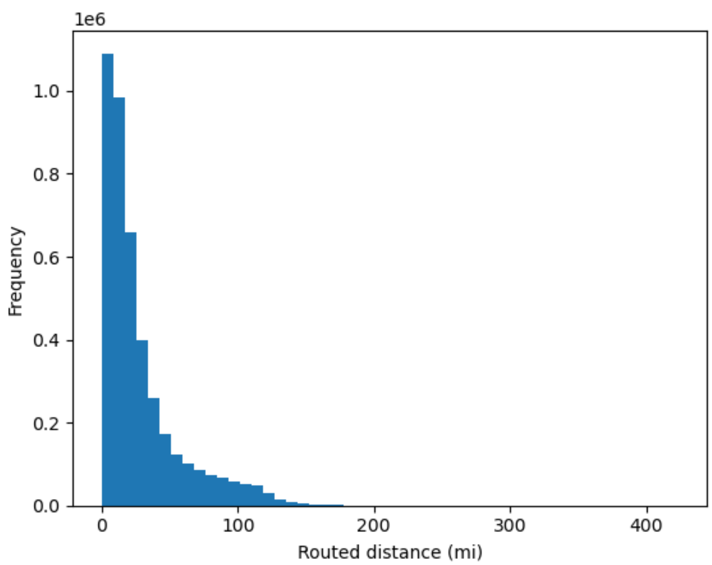


Figure 12. Routed trip length distribution of in-state and spillover trips (CA example)

2.4 Non-home-based (NHB) VMT Generation

The non-home-based (NHB) VMT is generated proportional to home-based VMT, assuming each mile of home-based trips ended in a specific destination will yield some level of NHB activities on average at that destination. The NHB VMT is then allocated to through tracts surrounding each destination. The major reason for this assumption is due to the extreme complexity of performing both the non-home origin location selection and destination choices for non-home activities (and the lack of data for estimating both location choices). The 2017 NHTS data are used to generate the ratio between NHB and HB VMT. Then the home-based VMT from Section 2.3, combined with the NHB VMT ratio, is used to compute the NHB VMT at the tract level. The NHB spillover VMT is generated following similar assumptions, with further simplification on model constraints and path traversal to maintain computational feasibility. The step-by-step methodology of in-state and spillover VMT is provided below.

2.4.1 In-state NHB VMT Generation

First, the methodology of in-state NHB VMT simulation is described below, which is performed through three preliminary steps: (1) estimate NHB VMT generation rate per unit of HB travel; (2) calculate total through NHB VMT at the tract-level, and (3) assign through NHB VMT to potential home locations.

2.4.1.1 Step 1: Generate NHB Trip VMT Generation Rate

The NHB VMT originated at a certain location is generated using a rate-based approach for each mile of HB travel to the same location, and the NHB VMT generation rate is estimated using 2017 NHTS data. Under a specific micro-geotype g in NHTS region r, there are $HB\ VMT_{l,g}^{NHTS}$ miles of home-based auto trips arriving at this land use cluster within the distance bin l. There are also $NHB\ VMT_{l,g}^{NHTS}$ miles of non-home-based auto trips that departed from this land use type, and are away from home within distance bin l when they departed from micro-geotype g in NHTS region r. So, for the home-based trips to micro-geotype g in NHTS region r within distance bin l, the NHB VMT generation rate is calculated using the following equation:

$$NHBR_{l,g,r} = \frac{HB\ VMT_{l,g,r}^{NHTS}}{NHB\ VMT_{l,g,r}^{NHTS}} \tag{9}$$

Where,

- $NHBR_{l,g,r}$ = non-home-based VMT generation rate for land use type g and distance bin l in NHTS region r
- l = distance bin between home and destination for home-based travel (1 - less than 5 miles, 2 - between 5 to 10 miles, 3 - between 10 to 20 miles, 4 - above 20 miles)
- $HB\ VMT_{l,g,r}^{NHTS}$ = home-based VMT from 2017 NHTS
- $NHB\ VMT_{l,g,r}^{NHTS}$= NHB VMT from 2017 NHTS

2.4.1.2 Step 2: Generate Through NHB VMT

From Section 2.3, for a given home census tract o in NHTS region r and a destination census tract d, there are $\{HB\ VMT_{i,o,d,1}, HB\ VMT_{i,o,d,2}, \dots, HB\ VMT_{i,o,d,C}\}$ miles of home-based VMT traversing through a set of census tracts C from income group i. The micro-geotype of d is g and the travel distance between o and d falls into bin l. So, for those through census tracts, the NHB VMT $\{NHB\ VMT_{i,o,d,1}, NHB\ VMT_{i,o,d,2}, \dots, NHB\ VMT_{i,o,d,3}\}$ can be generated as a result of home-based VMT between o and d using the following equation. This is based on the assumption that home-based VMT and non-home-based VMT tagged to the destination d will share the same travel space (and essentially adopts the same routes).

$$NHB\ VMT_{i,o,d,c} = NHBR_{l,g,r} * HB\ VMT_{i,o,d,c}\ for\ \{o \in O|r\} \quad (10)$$

Where,

- o, d = home and destination tracts, and d has micro-geotype as g
- i = household income-group
- c = through census tract between $o, d.\ c \in C$
- r =NHTS region
- $HB\ VMT_{i,o,d,c}$ = home-based VMT
- $NHB\ VMT_{i,o,d,c}$= NHB VMT

2.4.1.3 Step 3: Identify Home Tracts

Finally, the $NHB\ VMT_{o,d,c}$ needs to be linked with various home locations o' that may or may not be o[5]. So, the last step is to assign the non-home-based VMT to potential home census tracts, given the relative contribution of VMT from various home tracts to a specific destination. First, the total $NHB\ VMT_{i,O,d,c}$ within through-census-tract c to the destination d by income group i is generated by aggregating $NHB\ VMT_{i,o,d,c}$:

$$NHB\ VMT_{i,O|r,d,c} = \sum_{o \in O|r} NHB\ VMT_{i,o,d,c} \quad (11)$$

Where,

- $NHB\ VMT_{i,O|r,d,c}$= NHB VMT originated at d, through c, by income group i, from all potential home tracts O within region r

Next, for each home-based destination census tract d, the home-based VMT fraction $f^{o'd}$ by home census tracts o' are calculated to show the relative VMT attributed to each home tract:

$$f^{o'd} = \frac{HB\ VMT_{o',d}}{\sum_{o' \in O|r} HB\ VMT_{o',d}} \quad (12)$$

Where,

- $HBVMT_{o',d}$= home-based VMT between o' and d (combining VMT from all income levels)
- $f^{o'd}$ = fraction of allocating NHB VMT from d to potential home tract o'

Finally, the total NHB VMT $NHB\ VMT_{i,O,d,c}$ through c to destination d by income group i is assigned to each home tract o' using the fraction $f^{o'd}$, so that the NHB VMT from home o' and departed from d traversing tract c by income group i is $NHB\ VMT_{i,o',d,c}$:

---

[5] If the home location is also O for non-home-based VMT (same as home-based VMT), that means the home and non-home trips from the same home tracts are using the same routes for different purposes, which are not realistic in most cases.

$$NHB\ VMT_{i,o',d,c} = NHB\ VMT_{i,O,d,c} * f^{o'd} \quad (13)$$

Where,

- $NHB\ VMT_{i,o',d,c}$ = NHB VMT from home o', departed from d, traversing tract c, by income group i

2.4.2 Spillover NHB VMT Generation

For spillover NHB VMT, a simplified approach is adopted compared to in-state NHB VMT due to insufficient observations to account for variation in travel patterns. In general, the spillover NHB VMT simulator is composed of two steps: (1) a VMT generation step to generate total NHB VMT at out-of-state origins attributed to census tracts in the home states, and (2) a VMT distribution step to distribute through VMT to out-of-state census tract surrounding origins.

For spillover NHB VMT generation, a similar fraction-based method is adopted, with the distance bin segmentation removed due to lack of observed variation in NHB VMT generation across different distance ranges. In this case, using 2017 NHTS data, under a specific micro-geotype g, there are $SHB\ VMT_g^{NHTS}$ miles of spillover home-based auto trips arriving at this land use cluster. There are also $SNHB\ VMT_g^{NHTS}$ miles of NHB auto trips departed from this land use type. So, for the spillover home-based trips to g, the NHB VMT ratio is calculated using the following equation (assuming spillover NHB trips are generated as a fraction of spillover home-based trips):

$$SNHBR_g = \frac{SNHB\ VMT_g^{NHTS}}{SHB\ VMT_g^{NHTS}} \quad (14)$$

Where,

- $SNHBR_g$ = spillover NHB VMT ratio for land use type g (applied to whole U.S.)
- $SHB\ VMT_g^{NHTS}$ = spillover home-based VMT to g from 2017 NHTS
- $SNHB\ VMT_g^{NHTS}$ = spillover NHB VMT from g from 2017 NHTS

From Section 2.3, for a given home census tract o and an out-of-state entry point d, there are $SHB\ VMT_{i,o,d}$ miles of home-based VMT. The land use type of d is g. So, for the out-of-state entry point d, the total NHB VMT $SNHB\ VMT_{i,o,d}$ can be generated as a result of home-based VMT between o and d using the following equation.

$$SNHB\ VMT_{i,o,d} = SNHBR_g * SHB\ VMT_{i,o,d} \quad (15)$$

Where,

- o, d = home tract and out-of-state entry point tract, and d has micro-geotype as g
- $SHB\ VMT_{i,o,d}$ = spillover home-based VMT between o, d by income group i
- $SNHB\ VMT_{i,o,d}$ = total spillover NHB VMT originated from out-of-state entry point d and attributed to home tract o and income group i

Next, the total generated NHB VMT will be allocated to through tracts C surrounding the out-of-state entry point d using a radius-based method as illustrated in Figure 13 below. With this method, the out-of-state destinations for each spillover NHB trip were not specified. Rather, the spillover

NHB VMT was assigned based on proximity to out-of-state entry points, with the attribution factor generated from NHTS spillover trips.

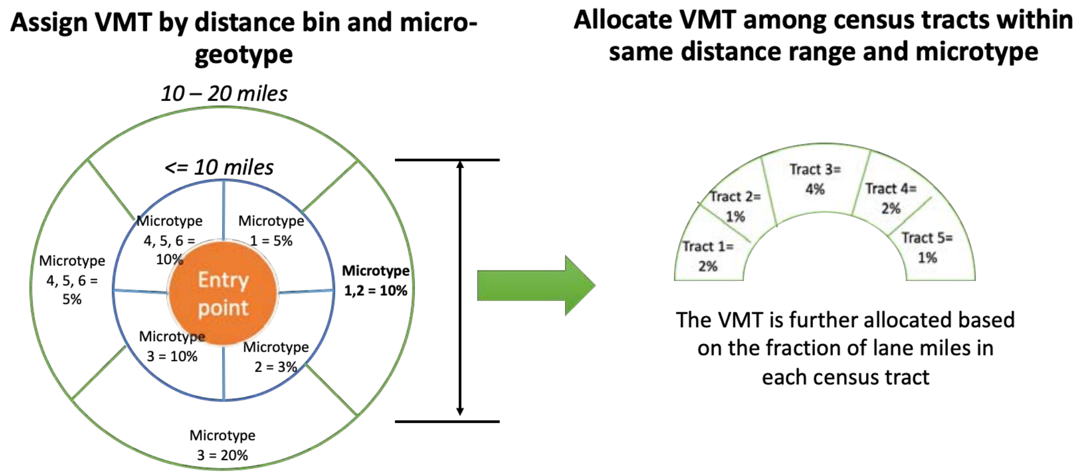


Figure 13. Radius-based method for allocating spillover NHB VMT to through tracts

First, the spillover NHB VMT, $SNHB\ VMT_{i,o,d}$, entering out-of-state point d will be spread to a set of nearby tracts $C^{m,ls} = \{c_1^{m,ls}, c_2^{m,ls}, \ldots, c_N^{m,ls}\}$, based on the land use type m and distance bin ls between $c_n^{m,ls}$ to d, using VMT fraction $f_{m,ls}$ estimated from NHTS. The distribution of $f_{m,ls}$ is shown in Figure 14 below, with a higher amount of VMT travel through microtypes 3 – 6 (highway, suburb and rural areas). Therefore, the total spillover NHB VMT will be assigned to the set of through tracts $C^{m,ls}$ using the following equation:

$$SNHB\ VMT_{i,o,d,C^{m,ls}} = SNHB\ VMT_{i,o,d} * f_{m,ls} \tag{16}$$

Where,

- o, d = home tract and out-of-state entry point tract
- m = micro-geotype of through tract
- ls = distance bin between through tracts and entry point d (bin 1 = 0-5 mile, bin 2 = 5-10 mile, bin 3 = 10-20 mile, bin 4 = 20-50 mile, bin 5 = 50 -100 mile, bin 6 = >100 mile)
- $f_{m,ls}$ = spillover NHB VMT allocation factor
- $SNHB\ VMT_{i,o,d,C^{m,ls}}$ = spillover NHB VMT from home tract c, enter d and traverse $C^{m,ls}$

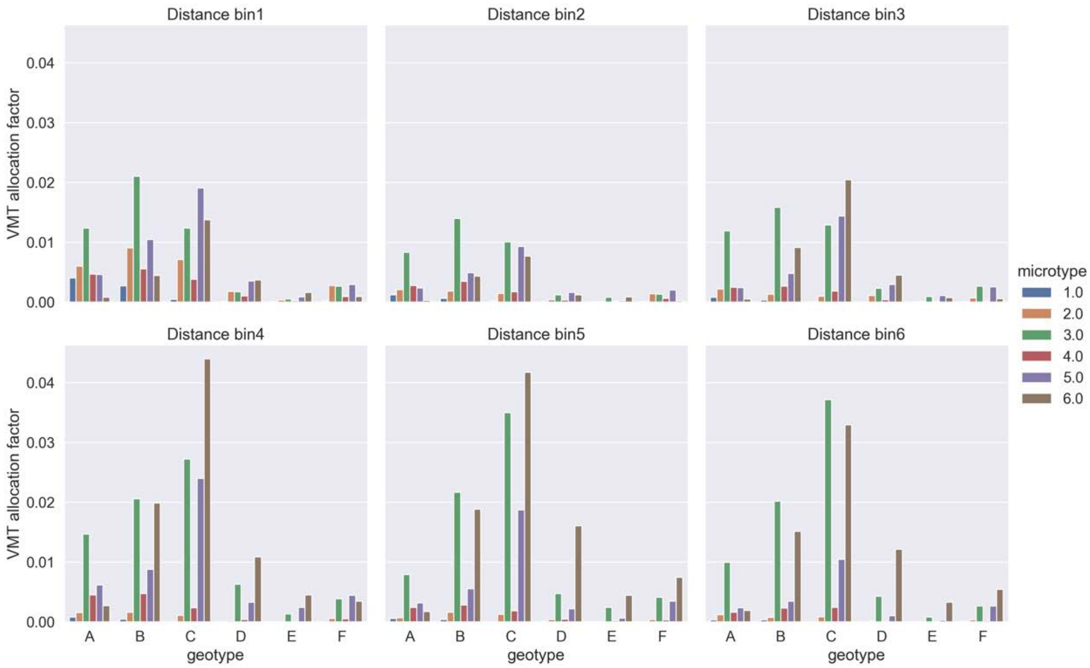


Figure 14. Spillover NHB VMT allocation factor

Finally, the spillover NHB VMT was further allocated to each tract c among the set of through tracts $C^{m,ls}$ to generate tract-level spillover NHB VMT, $SNHB\ VMT_{i,o,d,c}$. The allocation of spillover NHB VMT within $C^{m,ls}$ b is based on fraction of lane miles lm_c of tract c among all tracts in $C^{m,ls}$. The tract-level lane miles were estimated from 2017 Highway Performance Monitoring System (HPMS) data (Federal Highway Administration, 2020).

$$SNHB\ VMT_{i,o,d,c} = \frac{lm_c}{\sum_{c \in C^{m,ls}} lm_c} * SNHB\ VMT_{i,o,d,C^{m,ls}} \quad (17)$$

Where,

- lm_c = lane miles in through tract c
- $SNHB\ VMT_{i,o,d,c}$ = spillover NHB VMT originating from out-of-state entry point d, traversing tract c, and attributed to home tract o and income group i

Finally, combining both home-based and non-home-based VMT by home location and traversing tracts, for both in-state and spillover trips, all the through-VMT can be linked to various home locations. As a result, NAVIGAT is able to track all the through traffic to their home location, and the EV penetration can be then translated into corresponding proportional EV movements through the network.

2.5 Allocating Daily Through VMT to Home Tracts

As described from Section 2.1 to Section 2.4, the total passenger vehicle demand by home locations, as well as the potential through traffic and VMT accumulation, was generated at the census tract level. However, directly applying those VMT results to represent network-level congestion may lead to the following bias in VMT simulation:

1. The results are based on shortest-path trajectory, without considering the re-distribution of traffic due to congestion. The actual traffic can be more dispersed as alternative routes being used in many cases.
2. Due to the low spatial coverage of NHTS data and accumulation error during each step, the estimated through traffic may be very different from observed traffic.

In this study, the observed census-tract level VMT from 2017 Highway Performance Monitoring System (HPMS) data is adopted as the benchmark of the daily traffic accumulation within each census tract (Federal Highway Administration, 2020). The estimation bias can be directly shown in the pair plot between HPMS VMT and unscaled NAVIGAT estimated VMT, both at the census tract level (Figure 15). Although unscaled NAVIGAT predicted VMT shows a similar trend as HPMS data, the discrepancy at the tract-level cannot be ignored. In addition, the unscaled NAVIGAT predicted VMT tend to be higher than observed values, potentially due to slight over-estimation of longer-distance trips. In this case, the O-D and through traffic from Section 2.1 to Section 2.4 is only used as the VMT allocation factors for each through-census tract associated with their potential home tracts. The final VMT by through tract and home tract is calculated by multiplying the HPMS VMT at tract level, with home VMT allocation factor from NAVIGAT.

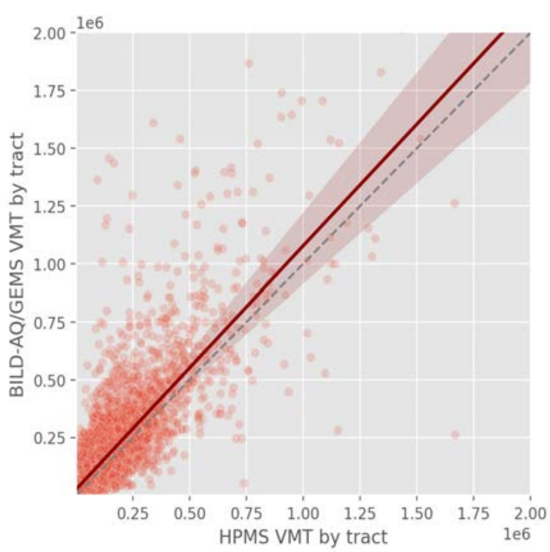


Figure 15. Correlation between HPMS daily VMT and simulated VMT (with CA example)

The first step of the VMT allocation is to combine and aggregate VMT from all sources, including the in-state and spillover home-based and non-home-based travel, for a selected state and neighboring states. In this case, a through tract c in state st can contain volumes from: (1) in-state home-based and non-home-based travel, (2) egress spillover home-based travel from selected state st, and (3) ingress spillover home-based and NHB travel from neighboring states (with spillover VMT simulated). For spillover travel, the out-of-state trip locations are selected within a 300-mile radius of the home location. The assumption is made after screening spillover trips from NHTS and observing that 95% of spillover trips in the NHTS are within this distance range. For a selected through census tract c in the U.S., VMT are combined and aggregated by home tracts, through tracts and income groups (combining all destinations) using the following equation:

$$VMT_{i,o,c} = \sum_{all\ d} (HB\ VMT_{i,o,d,c} + SHB\ VMT_{i,o,d,c} + NHB\ VMT_{i,o,d,c} + SNHB\ VMT_{i,o,d,c}) \tag{18}$$

Where,

- $VMT_{i,o,c}$ = total VMT from all travel types that traverse c, home tract o and income group i.

The next step of the VMT allocation is to construct the VMT allocation factor for each through census tract to various home locations, from both in-state and spillover travel (so the home tract o can be within the same state as c, or from another state that has spillover travel to c). This VMT allocation factors is defined as:

$$\theta_{i,o,c} = \frac{VMT_{i,o,c}}{\sum_{all\ o} \sum_{all\ i} VMT_{i,o,c}} \tag{19}$$

Where,

- $\theta_{i,o,c}$ = VMT allocation factor for through census tract c attributed to home tract o and income group i.

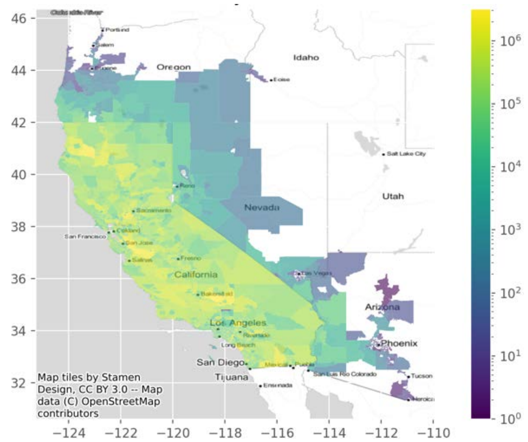
Finally, the observed VMT in tract c from HPMS were assigned to each home tract o and income group i can be generated as follows:

$$VMT_{i,o,c}^{HPMS} = \theta_{i,o,c} * VMT_c^{HPMS} \tag{20}$$

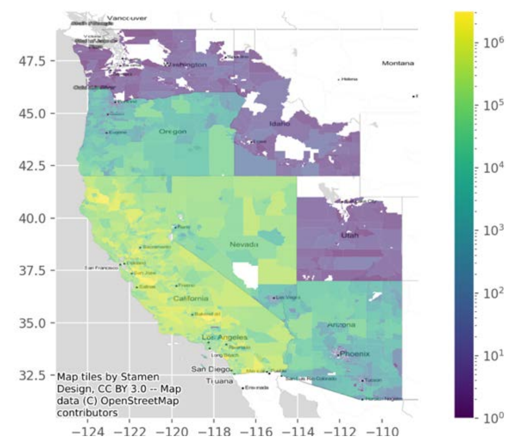
Where,

- VMT_c^{HPMS}= observed VMT in census tract c from HPMS
- $VMT_{i,o,c}^{HPMS}$ = allocated observed VMT to home tract o and income group i

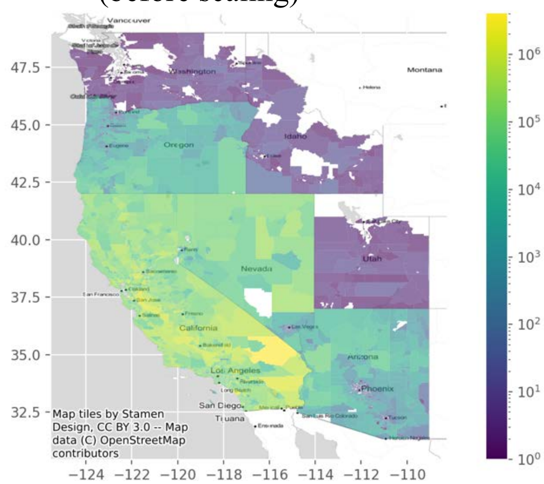
The final outcome from NAVIGAT is the **through VMT based on observed HPMS data, attributed to home location and income group**. An example of through-tract VMT both before-and-after scaling for CA alone (without ingress spillover VMT from other states) is illustrated in Figure 16 below. In general, the VMT distribution before and after scaling shows similar trends, with scaled VMT showing more distinction between urban and rural tracts. In the next section, the results from an example case study of NAVIGAT using this scaled VMT will be presented using large-scale charging infrastructure deployment and EV adoption.



(a) Tract-level VMT with HB spillover (before scaling)



(b) Tract-level VMT with HB and NHB spillover (before scaling)



(c) VMT with state spillover after scaling by HPMS VMT

Figure 16. VMT generation and scaling (with CA example)

3. A Case Study of Increased EV Adoption in Three Western States

With the support of the U.S. Department of Energy, Vehicle Technologies Office, and the U.S. Joint Office for Energy and Transportation (JOET), Lawrence Berkeley National Laboratory (LBNL) and the National Renewable Energy Laboratory (NREL) have developed the BILD AQ framework (Benefits of Infrastructure in Large-scale Deployment: Air Quality), an integrated simulation pipeline that leverages the core analytic capabilities of each laboratory to quantify air quality and public health impacts of charging infrastructure investment scenarios. BILD AQ is currently designed to assess the distribution of air quality outcomes between disadvantaged communities (DACs) and non-DACs resulting from state NEVI plans (National Electric Vehicle Infrastructure program), and can be used for state deployment planning and JOET Justice40 program evaluation.

Under BILD AQ, a linkage between NAVIGAT and an EV adoption model is developed to simulate the electrified VMT throughout the network under a given EV adoption scenario. The Transportation Energy & Mobility Pathway Options (TEMPO) model developed by NREL (Muratori et al., 2021) can simulate long-term EV adoption rates at the county level, downscaled to the census tract level projected under various charging deployment, incentive, pricing, or other policy scenarios. TEMPO also has the capability to simulate passenger travel demand, trip choice and energy consumption, but these capabilities were not used for this study. NAVIGAT is applied to provide spatially resolved VMT distributed to the transportation network, which are scalable at the national scale and still maintain key aggregation level to be integrated with TEMPO. NAVIGAT applies those EV adoption rates as inputs and tracks EV movement within the network to quantify the EV VMT penetration at the census tract level. The VMT generated by EVs versus internal combustion engine vehicle (ICEVs) under different adoption scenarios can be used by downstream emission, air quality and health models, as is the case in the BILD AQ modeling framework, to investigate the potential environmental and health impacts from passenger vehicle electrification.

The current modeling approach assumes that EVs will be used to replace existing travel with personal vehicles, and does not model any behavior shifts that might be due to different EV utilization patterns, such as potential impacts on trip generation, mode choice, destination, and route choice (in essence, it is assumed that historic data on trip generation, mode choice, destination and route choice can all be relied upon in projecting future driving VMT patterns in the context of either ICEs or EVs). This simplification is motivated by the application of NAVIGAT in modeling EV VMT under a large-scale transportation electrification conversion context, where EVs transition to being the primary vehicles used for general transportation needs. There is a dearth of representative EV travel behavior data available and a lack of consensus on how EVs may replace ICEVs at a large scale. For example, Raghavan and Tal (Srinivasa Raghavan and Tal, 2021) identify complex substitution effects between ICEVs and BEVs within multi-vehicle households, where driving patterns of ICEVs and BEVs vary by preferences and vehicle characteristics. They also highlight the current research gap and caution against drawing conclusions about EV driving behavior and mobility patterns from observational data, where observations are based on small numbers of early adopters.

Many other studies have investigated EV operation based on stated preference surveys and observational data, and a common finding across these analyses is the prevalence of shorter distance trips in EV driving (Kessler and Bogenberger, 2016; Weldon et al., 2016; Jensen and

Mabit, 2017; Habla et al., 2021). However, those studies are based on profiles of mainstream ICE users and early adopters of EVs, while under more mature markets such as Germany, range anxiety is much lessened and EV driving over longer distances is becoming more common (Niklas et al., 2020). Therefore, there is no clear conclusions on how EVs may be used under potential future wide-scale adoption scenarios. In this study, our focus is on modeling predominantly short distance trips within 100 miles (see Figure 12), which can be supported by current EV technologies as suggested by the aforementioned studies. Furthermore, we project future scenarios where the concern of range anxiety may dissipate as the EV market matures and charging infrastructure becomes more prevalent, which is supported by the literature (Niklas et al., 2020). This assumption allows us to showcase our modeling framework, which remains flexible, allowing for updates and testing of alternative assumptions when new data that showcases different behavioral patterns of EVs become available.

3.1 Integration with TEMPO

The TEMPO model can generate vehicle stock composition for all light-duty passenger vehicles at the county level under various forecast years and EV policy, incentive or infrastructure deployment scenarios. New methods were used for this study to downscale county-level outputs to the census tract level. In this study, the NAVIGAT model assumes EVs and non-EVs are used homogeneously by the same population within the same tract for their passenger vehicle operations on the network (e.g., there is no behavior differences in route choice and destination choice between EV and non-EV vehicles driven by the same population), so that the EV penetration at the vehicle level form a model like TEMPO is used to infer EV penetration at the network level in NAVIGAT. This is a simplifying assumption, but is intended to reflect the fact that as EVs penetration increases more and more, the marginal difference pertaining to how early adopters use them compared to non-EVs is likely to shrink, as people will still need to accomplish the same activities as always, but will do so by relying more and more on EVs.

The vehicle technologies available in TEMPO for household vehicle adoption include ICEVs (internal combustion engine vehicles), BEVs (battery electric vehicles) with different ranges, HEV (hybrid electric vehicles), PHEVs (plug-in hybrid electric vehicles) with different all-electric ranges, and FCEVs (fuel cell electric vehicles). For a given analysis year y and scenario s, the TEMPO-generated household vehicle stock within a census tract o is represented as $\{veh_{y,s,o}^{ICEV}, veh_{y,s,o}^{HEV}, veh_{y,s,o}^{PHEV25}, veh_{y,s,o}^{PHEV50}, veh_{y,s,o}^{FCEV}, veh_{y,s,o}^{BEV}\}$, which sums up to total number of vehicles, $veh_{y,s,o}$. The market share of each vehicle type is notated as $\{ms_{y,s,o}^{ICEV}, ms_{y,s,o}^{HEV}, ms_{y,s,o}^{PHEV25}, ms_{y,s,o}^{PHEV50}, ms_{y,s,o}^{FCEV}, ms_{y,s,o}^{BEV}\}$.

NAVIGAT output is then leveraged to select all of the through census tracts $C = \{1, 2, \dots, c\}$ with $\{VMT_{i,o,1}^{HPMS}, VMT_{i,o,2}^{HPMS}, \dots, VMT_{i,o,c}^{HPMS}\}$ VMT linked to home tract o and income group i. With the current assumption that EVs are used homogeneously across income groups and the total amount of VMT remains unchanged during the simulation period, the electrified VMT can be estimated by multiplying VMT with EV market share directly. First, the EV adoption rate can be calculated by combining all EVs available from TEMPO:

$$ms_{y,s,o}^{Elec} = ms_{y,s,o}^{BEV} + ms_{y,s,o}^{FCEV} + ms_{y,s,o}^{PHEV50} * \mu_1 + ms_{y,s,o}^{PHEV25} * \mu_2 \quad (21)$$

Where,

- μ_1 and μ_2 are electrified VMT fraction for PHEVs with 50-mile and 25-mile all-electric range (Based on TEMPO estimation, PHEVs with 25 and 50 miles of range had electrified VMT fraction of 22% and 62%, respectively)

The electrified VMT in through tract c due to EV adoption in home tract o can be calculated by multiplying VMT to EV adoption rates as following:

$$VMT_{y,s,o,c}^{Elec} = \sum_{all\ i} VMT_{i,o,c}^{HPMS} * ms_{y,s,o}^{Elec} \tag{22}$$

The conventional-fuel VMT is then calculated as:

$$VMT_{y,s,o,c}^{Fuel} = \sum_{all\ i} VMT_{i,o,c}^{HPMS} - VMT_{y,s,o,c}^{Elec} \tag{23}$$

For all the through census tracts under analysis year y and scenario s, the total conventional and electrified VMT can be generated by summing up VMT linked to all home tracts (located in selected state or from neighboring states):

$$VMT_{y,s,c}^{Elec} = \sum_{all\ o} VMT_{y,s,o,c}^{Elec} \tag{24}$$

$$VMT_{y,s,c}^{Fuel} = \sum_{all\ o} VMT_{y,s,o,c}^{Fuel} \tag{25}$$

Therefore, for a specific through tract c within the network under analysis year y and scenario s, the EV penetration rate pr can be calculated as:

$$pr_{y,s,c}^{Elec} = \frac{VMT_{y,s,c}^{Elec}}{VMT_{y,s,c}^{Elec} + VMT_{y,s,c}^{Fuel}} \tag{26}$$

The BILD AQ pipeline considers the changes in EV adoption and VMT changes between different EV adoption scenarios for downstream study and impact assessments. If we are comparing two scenarios s_1 and s_0 (base), the changes in EV adoption, conventional VMT, electrified VMT and EV penetration rate in year y at the census tract level can be calculated as follows:

$$\Delta ms_{y,o}^{Elec} = \Delta ms_{y,s_1,o}^{Elec} - \Delta ms_{y,s_0,o}^{Elec} \tag{27}$$

$$\Delta VMT_{y,c}^{Elec} = VMT_{y,s_1,c}^{Elec} - VMT_{y,s_0,c}^{Elec} \tag{28}$$

$$\Delta VMT_{y,c}^{Fuel} = VMT_{y,s_1,c}^{Fuel} - VMT_{y,s_0,c}^{Fuel} \tag{29}$$

$$\Delta pr_{y,c}^{Elec} = \Delta pr_{y,s_1,c}^{Elec} - \Delta pr_{y,s_0,c}^{Elec} \tag{30}$$

3.2 A West Coast Case Study

The capability of this integration between TEMPO and NAVIGAT is demonstrated here through a U.S. West Coast case study, which contains California (CA), Oregon (OR) and Washington (WA). The case study compares the EV adoption and penetration in a base year (2018) to a future year (2032), under the assumption that existing public charging infrastructure is held fixed at current-day levels. This is simply a demonstration of how the NAVIGAT functionality can take an arbitrary set of EV adoption input scenarios and allocate them to changes in utilization of the vehicles on the network.

3.2.1 NAVIGAT VMT Simulation Results and Trends

First, we present the NAVIGAT VMT simulator itself in the case study region. Recall that total VMT and travel patterns (destination and route choice) are assumed fixed in the application of NAVIGAT to assess the impact of technology adoption scenarios on where those new vehicle types are utilized on the network. Therefore, overall VMT generated in NAVIGAT, as presented in this subsection, is used, and simply allocated to different vehicle and technology types, in the case study scenario examples to follow in the next subsections.

The VMT generation methods described in Section 2 are applied to generate the passenger vehicle VMT for the three states (both in-state and spillover). The VMT results for all passenger travel linked to home tracts in the three states are illustrated in Figure 17. A total of 1.58 billion daily vehicle miles are simulated in the three-state region, with about 6.8% of VMT coming from inter-state travel (or 'spillover travel' in NAVIGAT simulation).

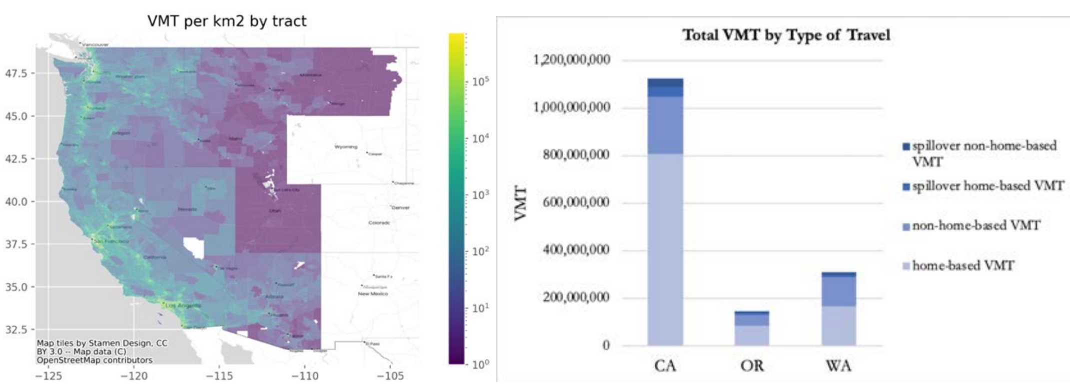


Figure 17. Simulated passenger vehicle VMT originated from CA, OR, WA

The spatial distribution of VMT by home location and through location are illustrated in Figure 18 using households from Portland, Oregon (the tracts with very low VMT are removed in the figure to focus in the key aspects of the outcomes). With the trip distribution functionality in NAVIGAT, the VMT are distributed across the network. Some of the VMT also traverses WA state to the north, as an example of the spillover effect of vehicle ownership in one state propagating to network VMT in neighboring states.

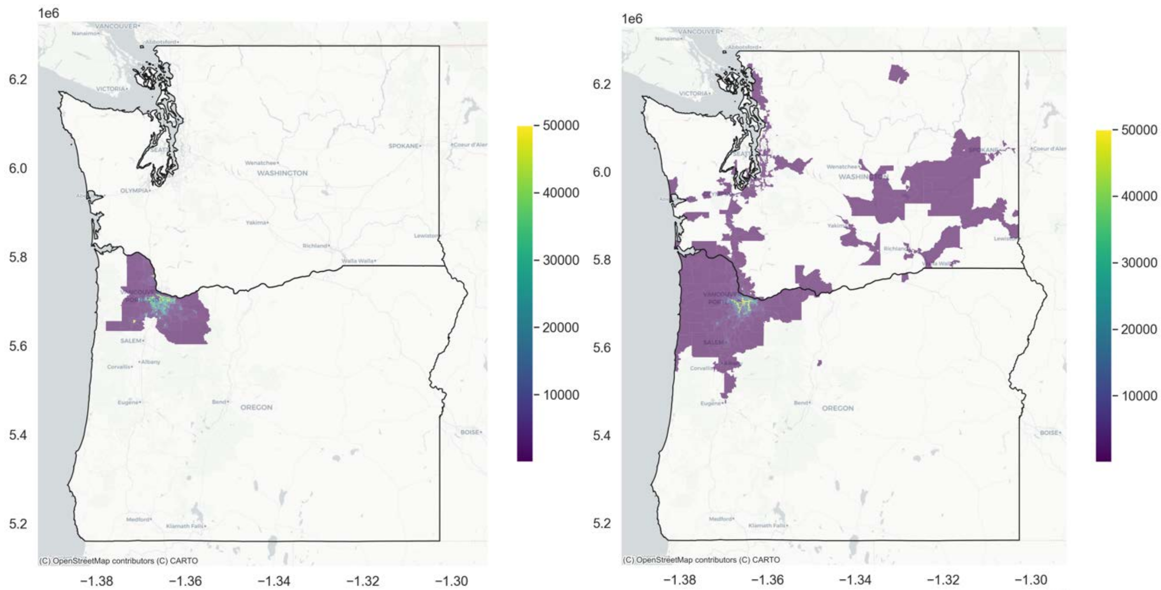
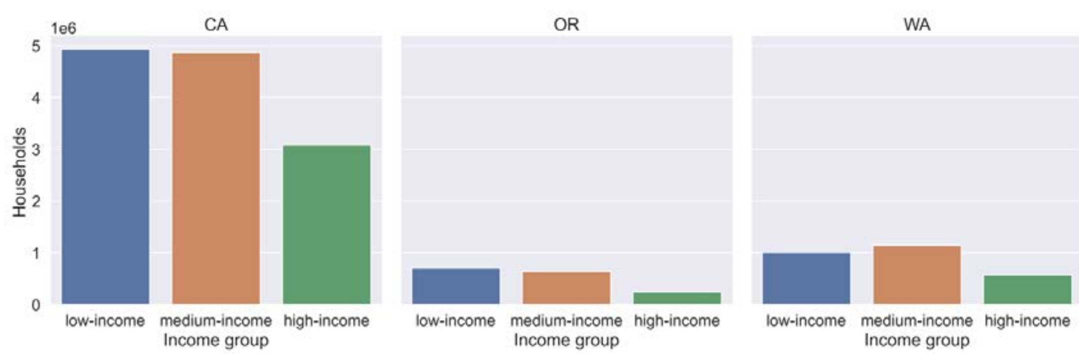
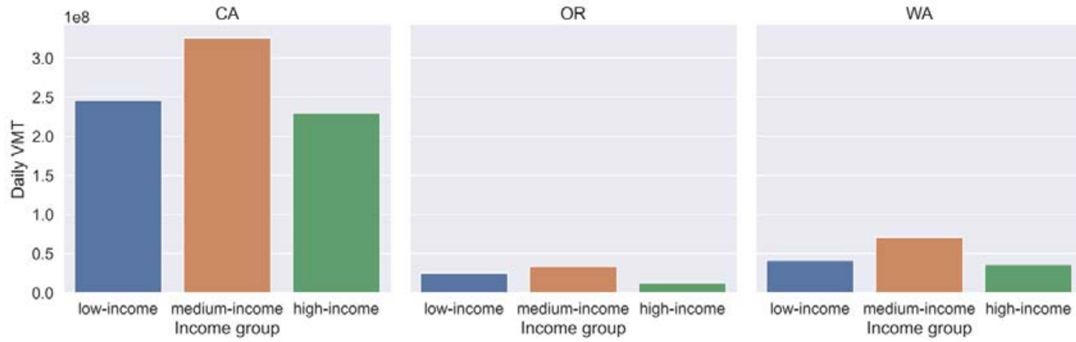


Figure 18. Total daily VMT from all passenger vehicle travels per land area, including originated VMT grouped by home tracts (left) and distributed VMT by through tracts (right) (min 10 miles/km²)

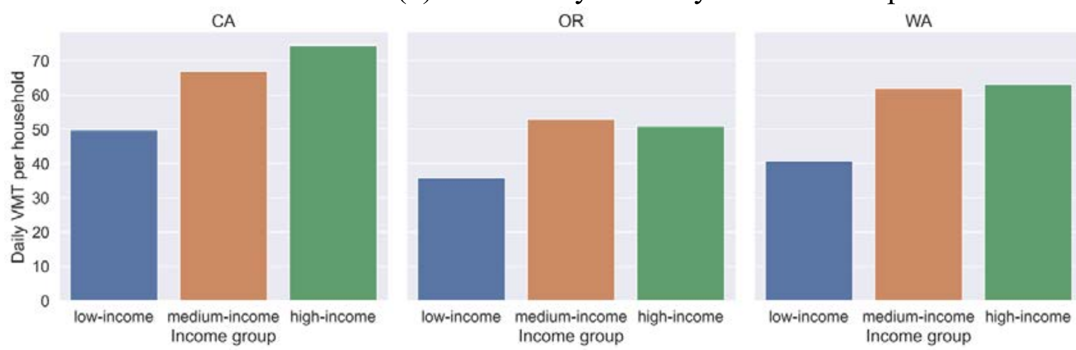
Given the resolution of NAVIGAT, the daily VMT by income group can also be investigated (based on their home location). In this case study example, as presented in Figure 19, for all three states low-income households with annual income less than 50k have the lowest daily VMT per household (around 30-50 mile/day/household). For WA and CA, high-income households (annual income >125k) have the highest daily VMT per household, and for OR, the medium- and high-income households have similar daily VMT. Even though high-income households account for the lowest fraction of the population in all three states (Figure 19a), they contribute disproportionally to total VMT (Figure 19c), while the reverse is true for low-income households.



(a) Households by Income Group



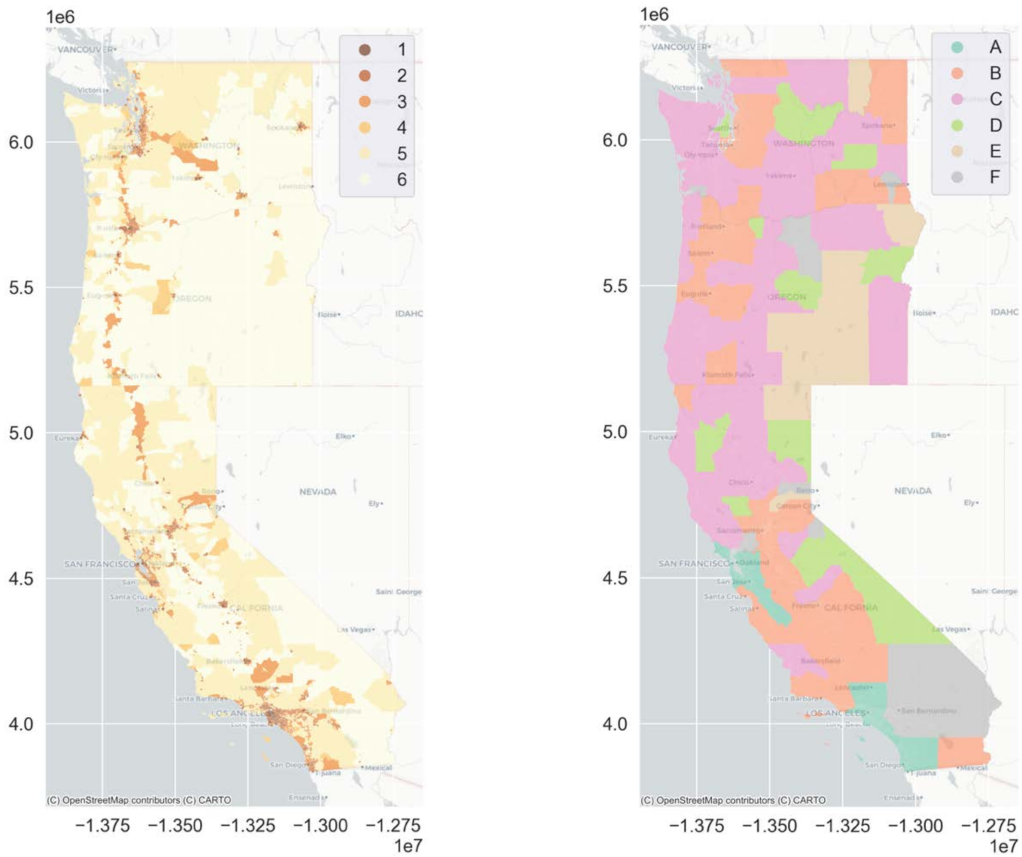
(b) Total Daily VMT by Income Group



(c) Daily VMT per Household by Income Group

Figure 19. Household and daily VMT by income group

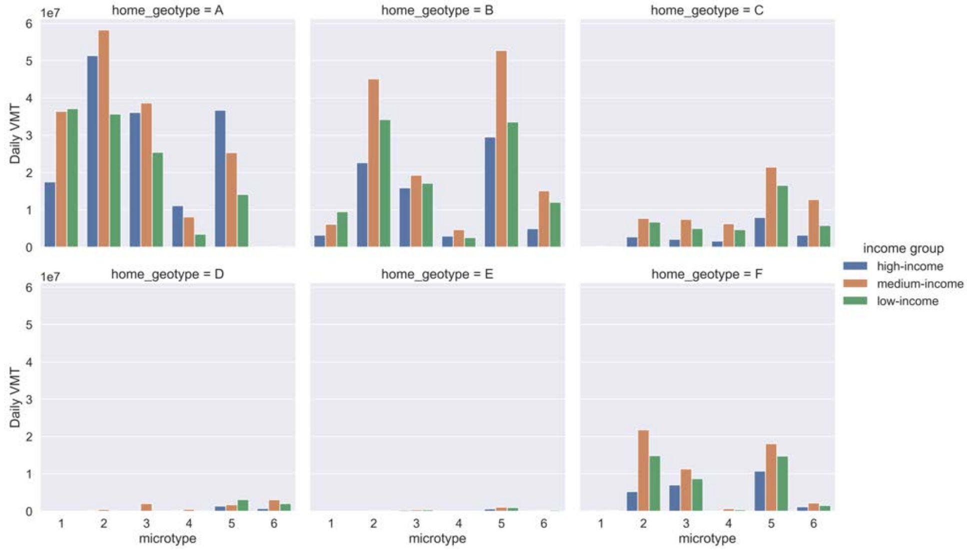
Using NAVIGAT, variation in VMT across land-use types can also be investigated. The typology from Popovich et al (Popovich et al., 2021) of all the CA, OR and WA census tracts is provided in Figure 20 as a reference, with the majority of land area classified as microtypes 5 and 6 (suburban and rural areas). Census tracts along major highway corridors are classified as microtype 3, and high-density urban areas fall into microtypes 1 and 2. Regarding geotypes, two major metropolitan areas, including San Francisco and Los Angeles, are classified as geotype A – urban areas with high commute centricity. The rest of the region mostly fall into geotypes B and C, which are polycentric urban areas and rural areas with monocentric commute patterns.



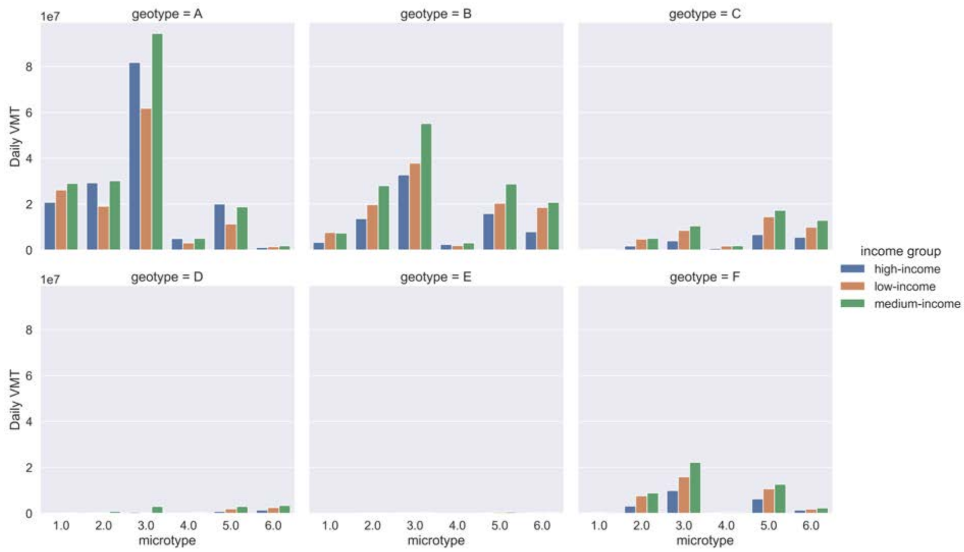
(a) Microtype distribution of study area (b)Geotype distribution of study area

Figure 20. Geospatial typology of the study area

The passenger VMT aggregated by typology of home census tracts and through census tracts are illustrated in Figure 21. Figure 21a shows that the spatial allocation of home location and through location are different, with the majority of VMT originating from microtypes 2 and 5 (residential areas), but more often traveling through microtype 3 (census tracts containing major highways/arterials). Regarding regional differences, Figure 21b shows that a higher portion of VMT are generated within urban areas (geotypes A, B, and F), and a lower fraction of VMT originate from, or travel through, rural regions such as geotypes C, D, and E.



(a) VMT by home tract typology and income group



(b) VMT by through tract typology and income group

Figure 21. Total VMT by census tract typology

3.2.2 TEMPO EV Adoption Scenarios for Case Study

The EV adoption scenarios for 2018 (base year) and a forecast year (2032) are used to estimate EV VMT across the network. The forecast year scenario assumes scenario changes in the relative purchase price and operating costs of different vehicle technologies, but holds current-day charging infrastructure fixed. To provide an overview of the scenario used for the case study, the EV adoption rate by home tracts in the base year 2018 are illustrated in Figure 22. Comparing the base year (2018) to the forecast year (2032), Figure 23 shows the EV adoption change from the TEMPO scenario.

As shown in Figure 24, in the base year, EV penetration is much higher in California (1.7% statewide) compared to Oregon and Washington (0.7% and 0.8% respectively). Looking at the change in EV adoption between the base year and forecast year (Figure 23), we see that most census tracts have additional 30-35% of EVs electrified by 2032, even with public charging infrastructure held fixed at current-day levels. This is due to input assumptions which assume reductions in EV cost, increases in EV fuel efficiency, and improvements in residential charging availability. The EV adoption rates see higher increment in CA than OR and WA, potential as a result of more mature EV market and widespread EV infrastructure. In total, **12 million EVs** will be adopted in the three states by 2032 in this example forecast scenario, accounting for **31.7%** of the passenger fleet, which is a large increase compared to only **578,596 EVs** and **1.5%** of passenger fleet in 2018.

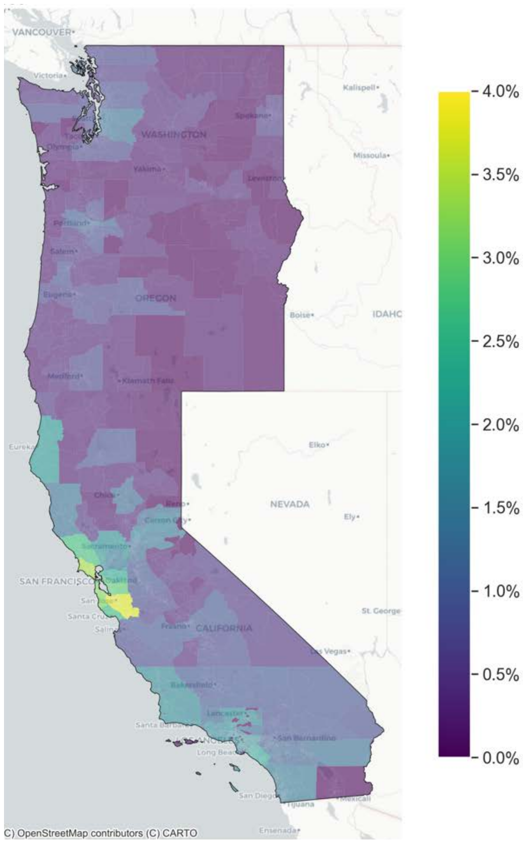
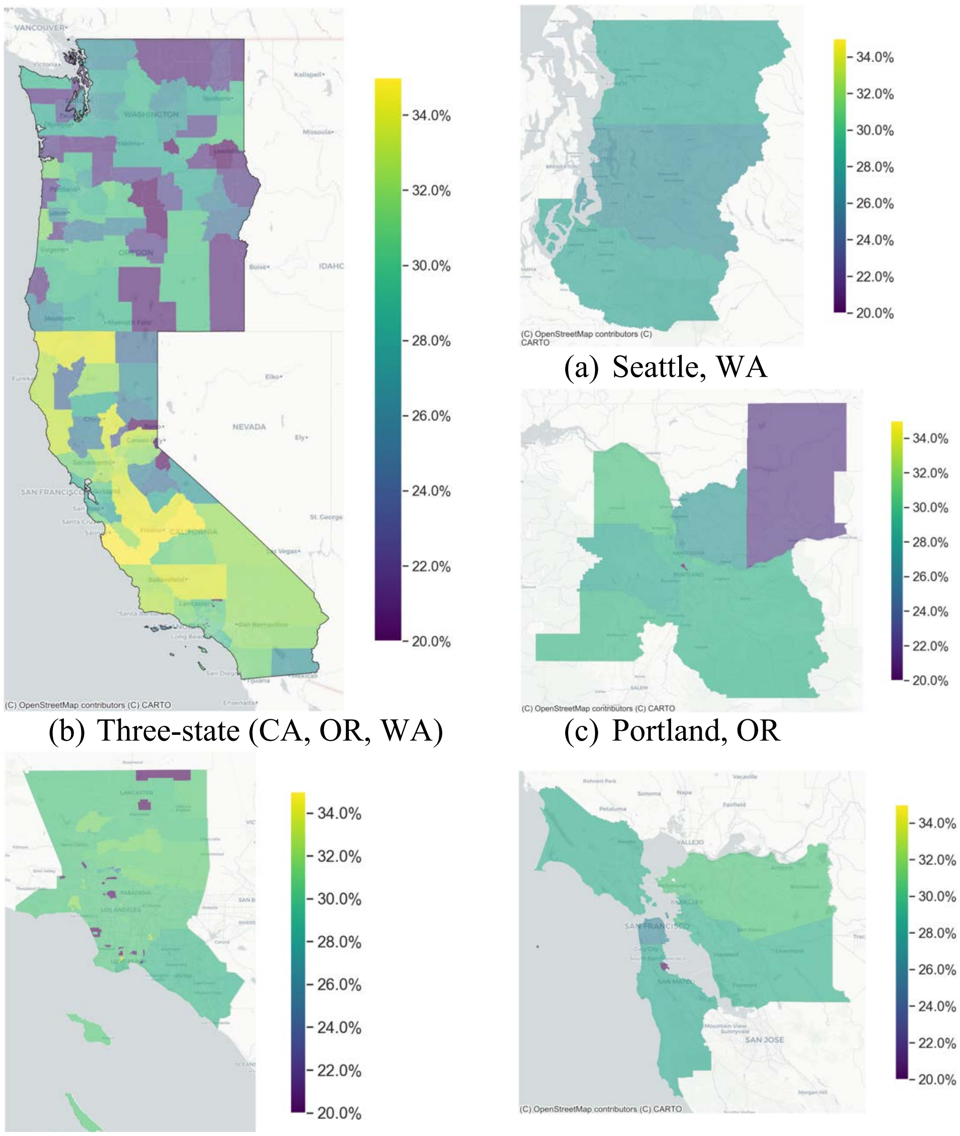


Figure 22. 2018 base year EV adoption scenario in CA, OR, and WA (solid black border indicating the 3-state boundary)



(a) Seattle, WA

(b) Three-state (CA, OR, WA)

(c) Portland, OR

(d) Los Angeles, CA

(e) San Francisco, CA

Figure 23. Changes in EV adoption (increased EV adoption forecast – base year scenario)

3.2.3 NAVIGAT EV VMT Penetration Under Case Study EV Adoption Scenarios

Using the TEMPO scenarios summarized in Section 3.2.2, The EV VMT penetration results are generated for both scenarios from year 2018 and 2032. The EV VMT penetration by through tracts in the base year 2018 is illustrated in Figure 24. Under the low EV adoption level in the three-state region in 2018, most census tracts have EV VMT penetration level under 1%, and only 1.1% of VMT are electrified regionwide. EV VMT penetration is generally higher in California (1.3% statewide) compared to Oregon and Washington (0.5% and 0.6% respectively).

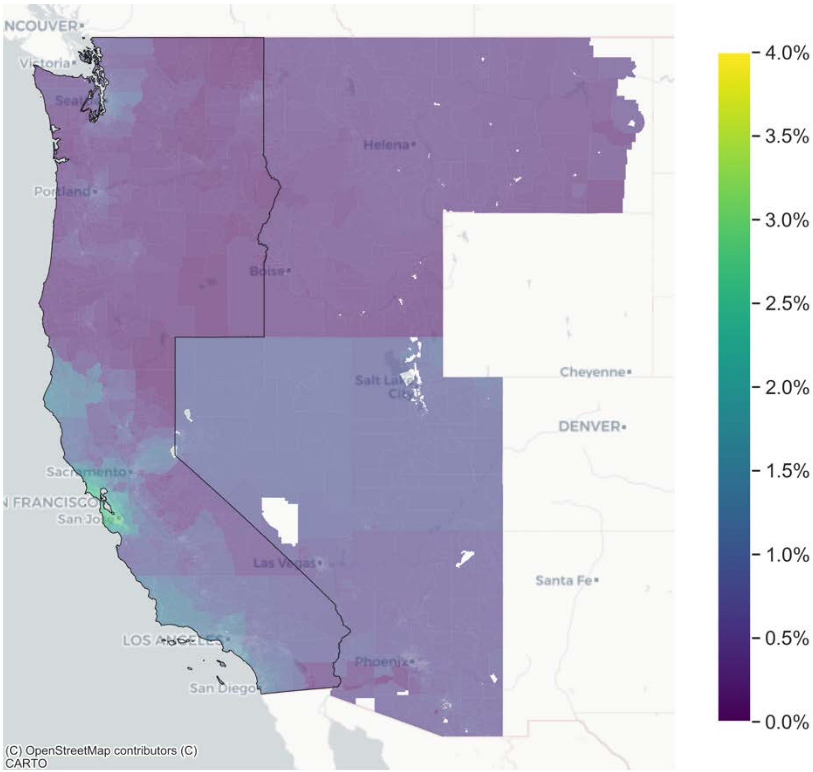
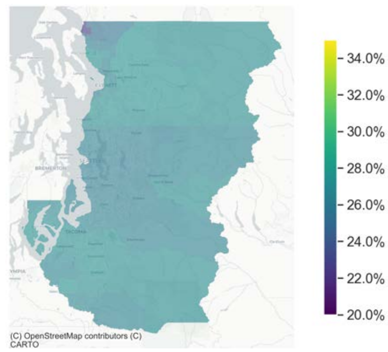
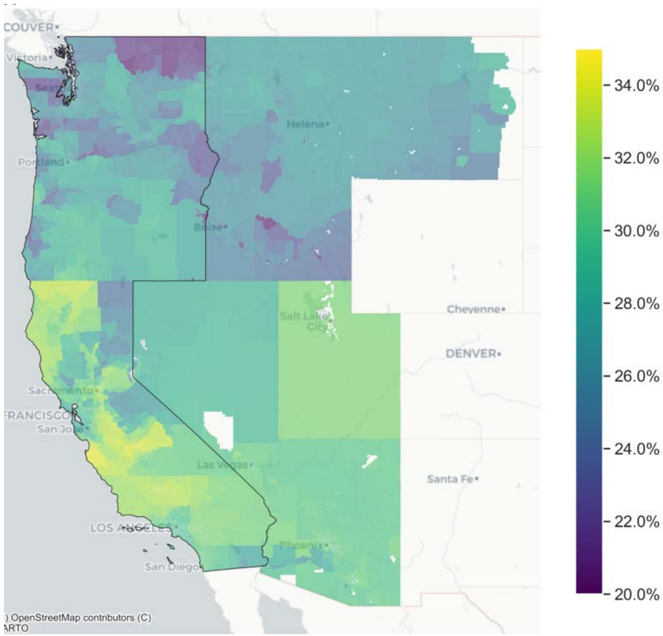


Figure 24. 2018 base year EV VMT penetration (right) in CA, OR and WA (solid black border indicating the 3-state boundary)

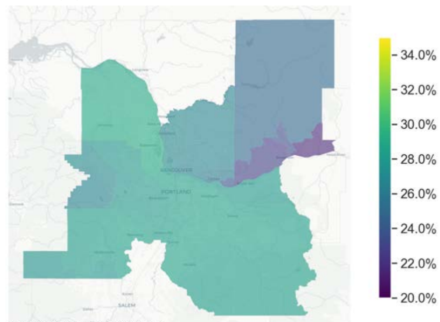
The changes in EV VMT penetration by through census tract are illustrated in Figure 25. Comparing the base year (2018) to the forecast year (2032), the EV adoption rate and EV VMT penetration rate increase throughout the region. Most census tracts have 25-35% of additional EV VMT being electrified by 2032, which is similar to changes in EV adoption. Similar to EV adoption, the EV VMT penetration rates also see higher increments in CA than OR and WA. A total of 340 million miles of VMT will be electrified (including spillover to neighboring states) by 2032 using the TEMPO scenario and accounting for 30.7% of total passenger vehicle VMT in the region, which is much higher than 12.4 million electrified VMT in 2018 and only accounting for 1.1% of all passenger VMT.



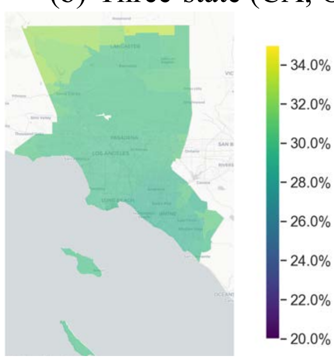
(a) Seattle, WA



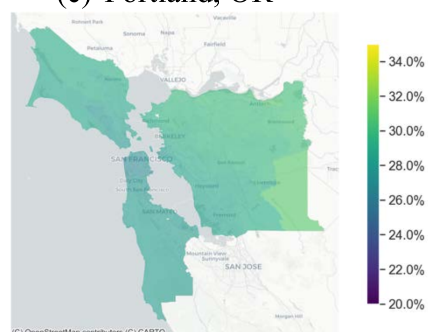
(b) Three-state (CA, OR, WA)



(c) Portland, OR



(d) Los Angeles, CA



(e) San Francisco, CA

Figure 25. Changes in EV VMT penetration (increased EV adoption scenario – base year scenario)

While a model like TEMPO can generate projected changes in EV adoption and can model passenger travel behavior and energy consumption, NAVIGAT fills a critical gap in our understanding of where those new EVs in the network will be utilized. For example, in this comparison between scenarios, 8.6% of the VMT from the additional EVs adopted are generated in the home tract where the vehicles are adopted, whereas 91.4% are generated outside of the home tract. Similarly, for the additional VMT being electrified under the forecast scenario, 1.4% of VMT comes from EVs adopted in other states that are spilled over to through states. Without a tool like NAVIGAT, an understanding of where the utilization of new EVs is likely to occur would not be possible. A tool like NAVIGAT not only helps with understanding the utilization of new technology but also helps with understanding variations of their utilization from different policies and assumptions.

4. Conclusions and Future Works

In this study, a large-scale household-owned passenger vehicle VMT simulator, known as NAVIGAT, is developed to simulate vehicle movement within U.S. at the census tract level resolution. NAVIGAT adopts a modeling framework resembling traditional travel demand models that are often applied in a regional context, combined with a data-driven approach that estimates model parameters using various national-level data sources. NAVIGAT can generate the distribution of passenger vehicle VMT by home, destination and through census tracts, segmented by land use typology and household income groups, for both in-state and cross-state spillover travel. NAVIGAT supports the assessment of operational impacts at the census tract level for selected U.S. states or regions under pre-defined transportation technology and infrastructure scenarios, and provides key inputs for downstream emission, air quality, health and equity analyses. For example, the changes in technology adoption under various policy scenarios (e.g., mandates, purchase incentives, fuel economy standards) and alternative infrastructure plans (e.g., alternative fuel corridor charging and public charging infrastructure siting) can flow through NAVIGAT to account for changes in potential penetration of VMT by technology on the road network due to vehicle operation. By integrating NAVIGAT with more sophisticated travel choice models (e.g., vehicle choice, route choice and charging choice models), the tool can be extended to understand shifts in different types of travel behavior (e.g., induced demand, mode shift, within-household vehicle selection for different trip purposes, rerouting) under various technology adoption scenarios.

The capability of NAVIGAT is demonstrated through an example case study using EV adoption scenarios from a base year '2018' and a forecast year '2032' generated in the TEMPO model for CA, WA and OR, under the assumption that purchase and operating costs may change for the different vehicle technologies in the future, but charging infrastructure is assumed fixed at current day deployment levels. The result shows that a total of 12 million EVs will be adopted in the three states by 2032 in this example forecast scenario, accounting for 31.7% of the passenger fleet, with that adoption allocated to specific tracts and income groups. This is compared to 0.6 million EVs making up 1.5% of the passenger fleet in the base year. Using NAVIGAT, it can be determined that these additional EVs will lead to a total of 340 million miles of VMT being electrified (including spillover to neighboring states) by 2032, accounting for 30.7% of total passenger vehicle VMT in the region. This is compared to 12.4 million miles, and 1.1% of passenger vehicle VMT in the base year. NAVIGAT allows a breakdown of the attribution of these additional electrified vehicle miles based on location type, income groups within census tracts, and any other census-tract specific characteristics of interest. The changes in VMT generated by EVs and ICEVs under different scenarios compared to a baseline can then be used by downstream emission and air quality models for quantifying the environmental and health impacts of large-scale EV deployment. NAVIGAT is capable of providing scalable and tract-level resolution of passenger vehicle flows for state/multistate applications, and can be potential expanded to answer more policy relevant questions, such as improving the locations of EV charging infrastructure plans and assessing the impact of heterogeneous EV adoption across income groups.

While a model like TEMPO can generate projected changes in EV adoption and model passenger travel behavior, VMT and energy consumption, NAVIGAT fills a critical gap in our understanding of where those new EVs in the network will be utilized. For example, in this comparison between scenarios, 8.6% of the VMT from the additional EVs adopted are generated in the home tract where the vehicles are adopted, whereas 91.4% are generated outside of the home tract. Similarly, for the additional VMT being electrified under the forecast scenario, 1.4% of VMT comes from EVs adopted in other states that are spilled over to through states. Without a tool like NAVIGAT, an understanding of where the utilization of new EVs is likely to occur would not be possible.

Finally, the current NAVIGAT methodology can be expanded in the following ways to address more policy-related questions for emerging technology and alternative transportation infrastructure plans on a larger scale, for a broader spectrum of transportation systems, and with higher accuracy and confidence, given the availability of more data and computational resources:

1. **Expansion for broader applications for the entire U.S**: the case study presented here demonstrates NAVIGAT's functionality for a case with three states, but the data and methodology applied in NAVIGAT can support a national-scale application if the upstream technology adoption inputs are available and sufficient computational resources and run time is available. It can also facilitate a broader range of applications and scenario analysis of technology adoption scenarios or infrastructure plans at the census tract level used as inputs.
2. **Expansion to include more transportation modes and vehicle technologies**: the current NAVIGAT model simulates movements of passenger light-duty vehicles. NAVIGAT can be expanded to include additional transportation modes, such as transit, school buses, freight trucks and ride hailing if large-scale data sources for those modes are available.
3. **Further model validation and calibration**: the accuracy of current model estimation can be further improved if more travel data are available, especially for low-density rural areas and spillover travel. Additional travel data in these categories can help the research team capture influential factors and travel preferences in future model revisions.

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Appendix A List of Variables

Table A - 1. List of variables

Variable	Definition
$HBTR$	Home-based trip rate
$HBTC$	Home-based trip count
HH	Number of households
HBT	Home-based trips (in-state)
O	Set of all U.S. census tracts
$SHBTR$	Spillover home-based trip rate
$SHBTC$	Spillover home-based trip count
$SHBT$	Spillover home-based trips
VMT	Vehicle miles travelled
$HB\ VMT$	Home-based VMT (in-state)
$SHB\ VMT$	Spillover home-based VMT
$NHBR$	Non-home-based VMT generation rate
$SNHBR$	Spillover non-home-based VMT generation rate
$NHB\ VMT$	Non-home-based VMT (in-state)
$SNHB\ VMT$	Spillover non-home-based VMT
veh	Number of vehicles from TEMPO
f	Fraction of travel
t	Trip travel time
sp	Survival probability of Weibull distribution
a, k	Exponentiation parameter and shape parameter of the Weibull distribution
β, γ, δ	Estimated destination choice model parameters
x	a vector of exogenous variables varied by origin and destination for destination choice model
v	a vector of proxy size variables for destination used in destination choice model
ε	Error term (random component) in destination choice model
U	Utility (systematic component) in destination choice model
lm	Lane miles
θ	VMT allocation factor (for assigning HPMS VMT to home tracts)
ms	Market share of EVs from TEMPO
pr	EV VMT penetration rate

Table A - 2. List of annotators

Annotator	Definition
i	Income group
p	Trip purpose
h	micro-geotype specifications of home census tract
g	micro-geotype specifications of travel destination census tract
r	NHTS region
o	Home census tract

d	Destination census tract
c	Through census tract
st	Home state
db	Distance bin between selected tracts to nearest state border
q	Trip id
l	Distance bin between home and home-based destination
ls	Distance bin between out-of-state destination and surrounding tracts (for spillover)
s	EV charging infrastructure deployment scenario