Democratization of Electric Vehicle Charging Infrastructure: Analyzing EV Adoption by Vehicle and Household Characteristics Using Synthetic Populations

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A Research Report from the National Center for Sustainable Transportation

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16. Abstract

The path to transportation decarbonization will rely heavily on electric vehicles (EVs) in the United States. EV diffusion forecasting tools are necessary to predict the impacts of EVs on local energy demand and environmental quality. Few EV adoption models operate at a fine spatial scale and those that do still rely on aggregated demographic information. This adoption model is one of the first attempts to employ a synthetic population to examine EV distribution at a fine spatial and demographic scale. Using a synthetic population at the Census-Tract-level, enriched with household fleet body types and home-charging access, the researchers consider the effect of vehicle body type on EV spatial distribution and home-charging access in California. The project examines two EV body type mixes in a high electrification scenario where 8 million EVs are distributed across 6 million households in California: a "Small Vehicles" scenario where 6 million EVs are passenger cars and 2 million EVs are trucks, sport utility vehicles (SUVs), or vans and a "Large Vehicles" scenario with 4 million of each category. The authors find that an electrification scenario with more electric trucks and SUVs serves to distribute electrified households more evenly throughout the state, shifting them from urban to rural counties, while there is little impact on home-charging access.

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NCST

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EXECUTIVE SUMMARY

The path to transportation decarbonization will rely heavily on electric vehicles (EVs) in the United States. EV diffusion forecasting tools are necessary to predict the impacts of EVs on local energy demand and environmental quality, yet few EV adoption models operate at a fine spatial scale. Those that do still rely on aggregated instead of local demographic information. To examine EV adoption at fine spatial and demographic scale, we develop an adoption model that employs a synthetic population, one of the first attempts of its kind. We develop a representative set of households for the state of California, enrich this population with additional variables, then use this population to forecast EV adoption in two scenarios by vehicle body type.

We develop a synthetic population at the resolution of Census Tract levels to accurately represents regional totals for various sociodemographic variables, such as income, housing, and vehicle count, while also containing a representative set of individual households. Then we enriched this synthetic population with vehicle body types (for the two most-driven vehicles in a household) and access to home-charging.

We focus our analysis on vehicle body type preference, enriching households in our synthetic population with vehicle body types and considering scenarios in which the EV body type offerings differ. Body type preference is important to consider with regards to EV adoption because it changes which households adopt EVs, how they use EVs, and how they charge EVs. SUVs and trucks are more likely to belong to rural households and less likely to be used for commuting when compared to sedans. Yet, they will likely have larger energy needs as they will be larger and less efficient than sedans. Most EVs sold to-date are sedans, but many EV SUVs and trucks are quickly entering the market. As the mix of EV body types changes, EVs will concentrate in different areas and be used differently.

We consider the effect of vehicle body type on EV spatial distribution and home-charging access in California. We examine two EV body type mixes in a high electrification scenario for California: one with a low number of EV trucks, SUVs, and vans and one with a high number. Both scenarios are termed high electrification because we consider 8 million EVs distributed across 6 million households. In the first scenario, “Small Vehicles,” 6 million EVs are EVs are passenger cars and 2 million EVs are trucks, SUVs, or vans. In the second scenario, “Large Vehicles,” there are 4 million EVs of each category.

We find that an electrification scenario with more electric trucks and SUVs serves to distribute electrified households more evenly throughout the state. Households with one or two EVs shift from major population centers like Los Angeles and San Francisco to lower-density communities

around the state especially in Northern California and the Central Valley. Home-charging access changes marginally between the two scenarios, increasing in both (1) urban and rural counties and (2) disadvantaged and non-disadvantaged communities. This likely occurs because the households that can own SUVs and trucks are also more likely to live in single-family homes.

Introduction

Decarbonizing transportation will require replacing current vehicles with zero-emission vehicles, particularly plug-in electric vehicles (EVs). Essential to climate change mitigation, EVs are also critical to decreasing local air pollution which disproportionately harms disadvantaged communities (DACs) and communities of color. While EV adoption has accelerated worldwide in the last decade, EVs in the United States heavily concentrate in the cities and wealthy suburbs of California and other states that have aggressively pushed for electrification. Today's EVs are also disproportionately likely to be used for commuting, likely both because they are cheaper to operate per mile and because EV manufacturing has focused on cars rather than trucks and sport utility vehicles (SUVs). The continuing expansion of private transportation electrification will require expanding the appeal of EVs in rural areas and for non-commute uses.

Most US EV studies focus on broad regional analysis either of individual states or the whole country, but infrastructure planning requires a more granular scale understanding of how EVs will be spatially distributed and who will have access to them. Synthetic population modelling makes it possible to address these needs by creating detailed and representative data about households at a fine spatial scale. Forecasting EV spatial distribution is also important because EVs can have significant and possibly negative effects on local grids (*1*). As new EV body types enter the market, the risk of these effects increases. Newer, larger electric trucks and SUVs will have greater energy needs and will amplify both the positive and adverse effects of today's EVs. Finally, while many studies examine electrifying the first vehicle in a household, few look at electrifying the rest of a household fleet. Multi-EV households face additional charging constraints and have the potential to exacerbate local energy supply shortfalls.

To understand where EVs will be purchased and how they will be used, it is vital to have an accurate picture of the relationships between households and vehicle types throughout the study area. EVs in the US are currently concentrated in homogenous, high-income households, but middle-income households will make the majority in the future (*2*). These consumers will be more heterogeneous and more limited by factors such as income, home ownership, home type, and vehicle preference. To include this information in our analysis, we developed a synthetic population of California households at the level of Census Tracts. Population synthesis is often used for agent-based transportation models, but this is one of its first applications in EV diffusion. It is the only way to consider EV adoption at the household-level. To ensure that the environmental and economic benefits of EVs are equitably distributed, it is important to examine EV adoption at fine spatial and demographic scale.

In this report, we present a Census-Tract-level synthetic population of California households designed for use in EV adoption modeling and use this dataset to compare two EV adoption scenarios. This paper follows a five-stage modelling process shown in Figure 1. First, we generate a synthetic population of households for California at the spatial resolution of Census Tracts; this population accurately represents regional totals for various sociodemographic variables while also containing a representative set of individual households. Second, we assign body type to each vehicle in all household fleets. Third, we assign the ability to charge an EV at home based on housing type and tenure. Fourth, we assign households an adoption likelihood score based on their ability to afford relatively new, expensive vehicles and their ability to integrate EVs into their household fleet. Finally, we simulate the electrification of the first and second vehicles in these households.

We apply this model to examine how the first 8 million EVs in California will be distributed in two scenarios: a “Small Vehicles” scenario when passenger cars outnumber large vehicles 3:1 and a “Large Vehicles” scenario when larger EVs account for half the new EVs in the state. We group larger vehicles like light-duty trucks, SUVs, and vans under the category “trucks and SUVS” and sedans and small hatchbacks under “passenger cars”. While we focus on California in this paper, we rely exclusively on data available throughout the US, and the process can be modified for any US region.

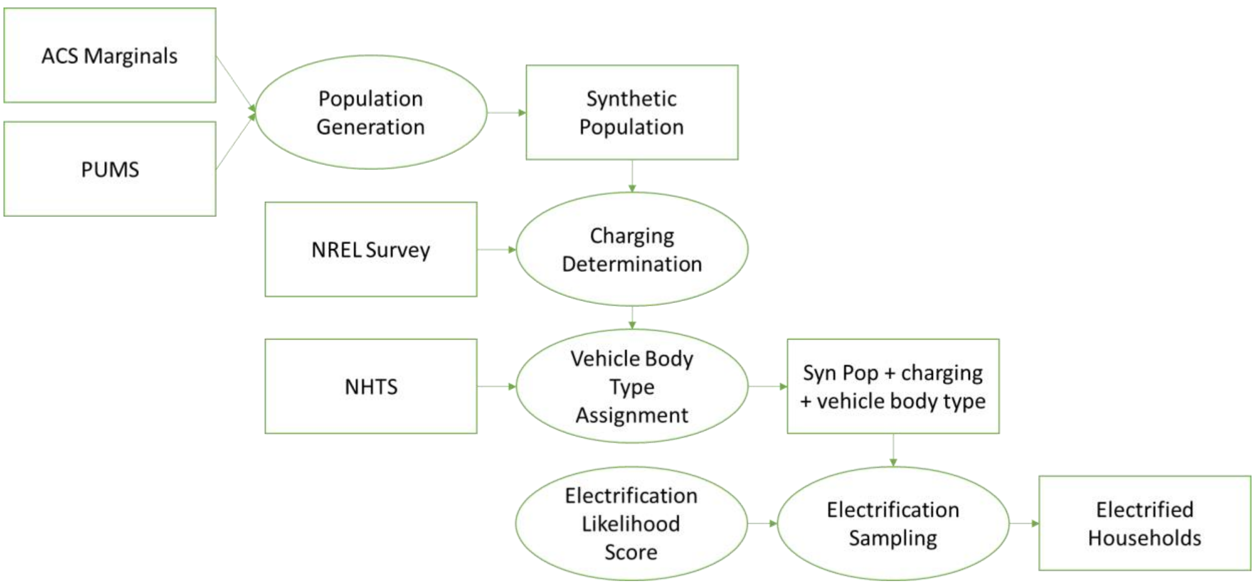

Figure 1. The five-stage modeling process. Datasets are represented by boxes and processes by circles. The final output is a list of households with 1-2 EVs. Key - ACS: American Community Survey, PUMS: ACS Public Use Microdata Samples, NREL Survey: National Renewable Energy Laboratory Survey on home-charging and NHTS: National Household Travel Survey.

Background

Existing EV adoption studies generally work at coarse spatial scales or with highly aggregated models of the population. Reviews of these studies identify three main categories of methods: aggregate models for adoption by country or state, disaggregate models for adoption by household category within a country or state, and agent-based models that examine household and individual choices, with a trend towards disaggregated and agent-based models in recent years (*3*, *4*). These recent models more frequently operate at the household-level with agents assigned randomly to demographic categories (*5*–*7*), or with representative agents developed through synthetic population methods (*8*–*10*). While disaggregated models work at a finer level of spatial precision than aggregate national models, they are generally still too coarse to use for local infrastructure planning.

Modeling a representative set of households at the Census Tract level enables us to link regional variation in home-charging access and demographics to EV ownership, and to effects on local electricity demand. Many of the household-level models can account for changing vehicle attributes and policy over time, but often they cannot identify spatial clustering of EV adoption in the US (*5*–*12*). The few existing models that work at a very fine spatial scale exclusively use the aggregate characteristics of study sites to assign EVs rather than addressing household EV adoption directly (*13*). This paper extends the disaggregated approach to focus on households and intraregional adoption variability at fine spatial resolution.

Vehicle preference and local demographics can be connected to predict where EV ownership will concentrate as different EV body types enter the market. To date, most EVs purchased are passenger cars despite US consumers favoring larger trucks and SUVs (*14*, *15*). With improvements in battery technology and increases in demand, many electric models of SUVs and trucks are set to launch over the next decade. The impact on EV adoption is uncertain, but likely to significantly change the ways EVs are used. Passenger cars are used for commuting at a higher rate than trucks and SUVs, and EVs are used for commuting at an even higher rate than internal combustion engine vehicle (ICEV) passenger cars (*13*). Consequently, significant changes in the body types of EVs available might substantially change the ways EVs are used and charged (*16*). Commute trips are predictable and stays at destinations are long enough that they are currently a major source of EV charging. However, EVs that are not used for commuting may not have access to a comparable charging option away from home. In this study, we explore the differences in the spatial pattern of EV adoptions between a scenario where EV production remains focused on passenger cars and one where electric trucks and SUVs make up a much larger share than they do now.

In addition to its relevance to charging infrastructure planning, the spatial distribution of EV ownership is tightly linked to equity concerns about access to EVs and the distribution of local air quality benefits. EV ownership is currently highest in cities and wealthy suburbs, and EV ownership rates in rural parts of California are extremely low (*13*). Existing studies of EV ownership in DACs have found that in areas with low incomes and relatively high EV ownership rates, these EVs are purchased by wealthier households that are generally not representative of the area as a whole (*17*). While EVs currently have much higher purchase prices than comparable ICEVs, the price difference is dropping, largely because batteries are becoming less expensive. Still, new vehicles of all types are primarily owned by wealthier households, so the wide availability of used EVs may be a precondition of expanding EV ownership among low-income households. While purchase price remains a significant barrier, the economic and environmental benefits of EVs are unlikely to be equitably distributed without policy intervention.

Data

Data used in this paper comes from three main nationwide sources, which ensures that the methods described in this paper are applicable beyond California. The 2015–2019 five-year American Community Survey (ACS) summary tables and associated Public Use Microdata Samples (PUMS) were used for synthetic population generation (*18*, *19*). ACS aggregated estimates by Census Tracts were used for marginal distributions while the PUMS served as sample data. Home-charging probabilities were taken from a nationwide National Renewable Energy Laboratory (NREL) survey on residential charging access (*20*).

The 2017 National Household Travel Survey, or NHTS (*21*), was used to model the body types of household vehicles. This survey contains demographic, travel behavior, and vehicle ownership data from 113,973 households drawn from throughout the United States. Table 1 summarizes the NHTS variables and categories examined when developing the vehicle assignment models.

Table 1. Summary of NHTS household data used to develop models for vehicle body type assignment

Variable	Category	1 Vehicle	2 Vehicle	3 Vehicle	4+ Vehicle
	Total	38,838	49,398	17,972	7,765
Vehicle 1	Car	23,789	23,874	8,555	3,703
	SUV	9,736	14,987	5,055	2,102
	Truck	3,400	7,431	3,255	1,507
	Van	1,913	3,106	1,107	453
Vehicle 2	Car	-	23,827	8,525	3,792
	SUV	-	11,887	4,313	1,773
	Truck	-	11,119	4,107	1,781
	Van	-	2,565	1,027	419
Census Region	West	18,916	12,088	4,695	2,133
	Northeast	10,920	7,529	2,450	941
	Midwest	12,025	7,984	2,805	1,236
	South	33,274	21,797	8,022	3,455
Population Density (persons per sq mi)	0-99	12,796	7,237	3,645	1,914
	100-499	14,419	8,780	3,832	1,807
	500-999	7,456	4,901	1,768	787
	1,000-1,999	10,131	6,919	2,285	927
	2,000-3,999	13,660	9,526	3,019	1,115
	4,000-9,999	14,054	10,030	2,966	1,058
	Over 10,000	2,619	2,005	457	157
Housing Tenure	Own	65,761	41,930	16,510	7,321
	Rent	9,374	7,468	1,462	444

Variable	Category	1 Vehicle	2 Vehicle	3 Vehicle	4+ Vehicle
Household Size	1	6,583	5,206	1,027	350
	2	41,410	30,145	8,485	2,780
	3	12,207	5,985	4,471	1,751
	4 or more	14,935	8,062	3,989	2,884
Worker Count	0	19,043	14,427	3,505	1,111
	1	23,025	16,012	5,210	1,803
	2	28,295	18,320	7,173	2,802
	3 or more	4,772	639	2,084	2,049
Household Income	< $25k	6,154	4,641	1,119	394
	$25-35k	5,323	3,921	1,041	361
	$35-50k	8,218	5,859	1,755	604
	$50-75k	14,354	9,727	3,289	1,338
	$75-100k	12,506	8,107	3,047	1,352
	$100-125k	10,350	6,414	2,728	1,208
	$125-150k	5,927	3,579	1,586	762
	$150-200k	5,975	3,605	1,578	792
	>$200k	6,328	3,545	1,829	954

Methodology

This study is divided into the following modules: population synthesis & home-charging determination, vehicle body type assignment, and electrification.

Population Synthesis & Home-Charging Determination

Household-level models are most useful when the data they are built on is an accurate representation of the population being studied. As complete regional population data is generally unavailable, many activity-based travel demand models begin by generating a synthetic model of the region's population (*22*–*24*). The population generation process uses a sample dataset of household-level microdata and regional distributions for variables for the population being modeled to generate a representative population, which is input into successive stages of the model.

The synthetic population used in this paper was generated using the population synthesizer PopGen (*25*), an open-source program developed by the Mobility Analytics Research Group at Arizona State University. This software controls for both individual- and household-level distributions in the synthesis process by using iterative proportional fitting (IPF) and iterative proportional updating (IPU) algorithms. IPF is a process for generating weights for a seed dataset that produce marginal distributions most closely matching the respective marginal distributions for a range of demographic variables. In this study, the seed dataset is drawn from the PUMS, which contains detailed information about a set of real households surveyed as part of ACS, with spatial data at the level of Public Use Microdata Areas (PUMAs). Our marginal distributions are counts of households and people for individual Census Tracts in the ACS. IPU extends IPF by matching marginal distributions for both households and people simultaneously; IPU alternates between person-level and household-level IPF steps in order to minimize the total error. IPF is a well-established method for synthetic population generation, and the combined IPF-IPU approach is an increasingly popular solution for the need to match multiple levels of seed data (*25*, *26*). In this study, we utilize a synthetic population model at a broader spatial aggregation level, rather than the typical parcel level used in most activity-based travel demand simulations. Additionally, our method incorporates Monte Carlo simulation, which is central to our analysis but not typically associated with synthetic populations. These key methodological choices are crucial for understanding the approach and results of this study.

The ACS and PUMS datasets served as the marginal and sample seed data (*18*, *19*). The following household variables and levels were used:

- Vehicle Count (None, 1, 2, 3 or 4+)
- Income (< $10k, $10-15k, $15-25k, $25-35k, $35-50k, $50-75k, $75-100k, $100-125k, $125-150k, $150-200k, > $200k)
- Housing Type (Single-Family Detached, Single-Family Attached, Apartment, or Mobile Home)
- Housing Tenure (Own or Rent)
- Worker Count (None, 1, 2, 3+)
- Household Size (1, 2, 3, 4+)
- Additionally, one person-level variable was included: gender/age status which had three levels: adult female, adult male, and minor.

Synthetic population generation is the only way to examine interactions between several important variables for electrification, since the ACS does not contain cross-tabulations for many of the household variables we use. Income, vehicle count, housing type, and tenure are well-known predictors of both EV adoption and access to home-charging (*2*, *12*, *20*, *27*). Workplace charging is the most utilized type of charging after home charging and regular trips are well-suited for limited-range EVs, thus we use worker count as a proxy in this synthetic population (*12*, *28*, *29*). Lastly, household size is a crucial variable to include as it's an important indicator for vehicle body type preference (*30*).

Most current users of EVs charge their vehicles at home, and the ability to charge at home is strongly linked to EV adoption (*12*, *31*). To incorporate home-charging access into our EV adoption model, we use information from a NREL study (*20*) based on a nationwide survey of residential charging capability to randomly assign home charging based on housing type and tenure. The study estimates the fraction of households that can or could charge an EV at home under a range of circumstances. Homeowners are assumed to be able to install chargers if space is available, so their home-charging probability is set based on the share of vehicles that either already park near electricity, could possibly install a charger at their parking location, or could change their parking to a location where they could install a charger. Renters are assumed not to be able to modify their property, so people who already can or could park near electricity are considered. The following charging probabilities were used to randomly assign home charging ability based on housing type and tenure:

- Single detached: Own (89%) and Rent (72%)
- Single attached: Own (70%) and Rent (53%)
- Apartment: Both (25%)
- Mobile Home: Both (59%)

Vehicle Body Type Assignment

The vehicle assignment module generates vehicle body types in a household fleet. The available types included passenger cars, SUVs, light-duty trucks, and vans. Single-vehicle and multi-vehicle households were considered separately, using data from the NHTS (*21*).

A single multinomial logistic (MNL) model was used for single-vehicle households while two sequential MNL models were used to predict the body types of the two most-driven vehicles in a multi-vehicle household. Vehicles in multi-vehicle households were ordered by decreasing vehicle miles travelled (VMT), such that the most-driven vehicle was classified as vehicle one. In cases where the same annual travel was reported for multiple vehicles, vehicle model year was used to break ties, with newer vehicles ranked higher. This ordering was chosen because EVs generally have lower operating costs than ICEVs and are more likely to be used for high-mileage activities like commuting.

Model variables were selected using a 10-fold cross-validation process minimizing mean residual deviance to ensure that the models provided useful predictions both in-sample and out-of-sample. Population density and household size were selected for all three models. Both multi-vehicle household models also included household vehicle count, while the second vehicle model included the first vehicle type as in input. The assignment models were applied to each household generated in the previous module. Figure 2 depicts the workflow of the assignment process.

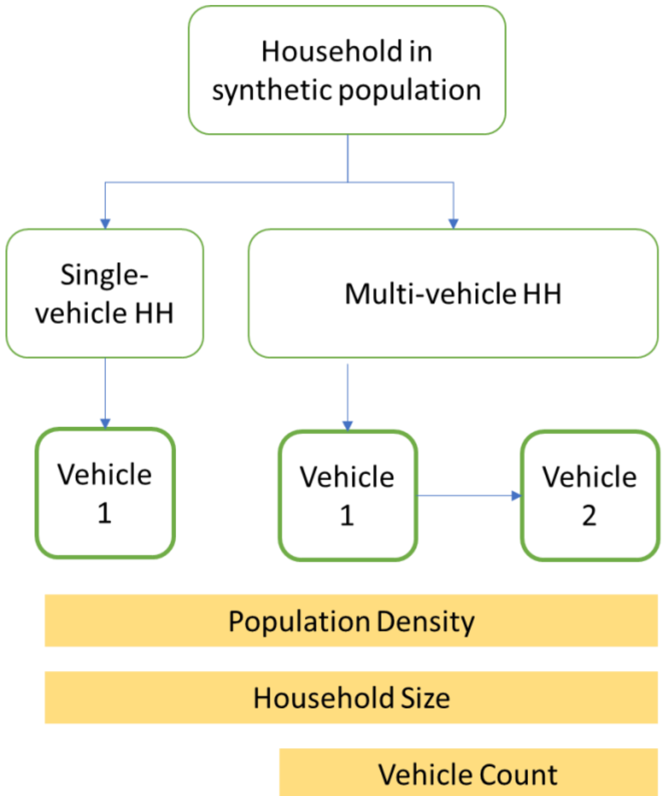

Figure 2. Vehicle body type assignment workflow. Each vehicle-holding household in the synthetic population is classified as a single- or multi-vehicle household and separate models are applied to each type. Body type of the first vehicle is determined before the second vehicle is assigned in multi-vehicle households. Input demographic variables are listed in yellow.

Electrification

Finally, we use this synthetic population of households and vehicles to explore the differences in spatial distribution of EVs between two scenarios for light-duty vehicle electrification. The EV assignment process follows the process outlined in Figure 3. Households are first separated into groups based on the body type of their first vehicle. First EVs are assigned using a weighted random sampling process, using weights prioritizing households that can more easily afford to buy an EV. Next, EV households are sorted into new groups based on the body type of their second vehicle and the random sampling process is repeated to assign second EVs. To explore a wide range of possible outcomes, we run the entire process repeatedly as a Monte Carlo simulation. Our results represent the average value across 100 Monte Carlo replicates, and we also assessed the range of results across simulations to get a sense of the uncertainty in the model.

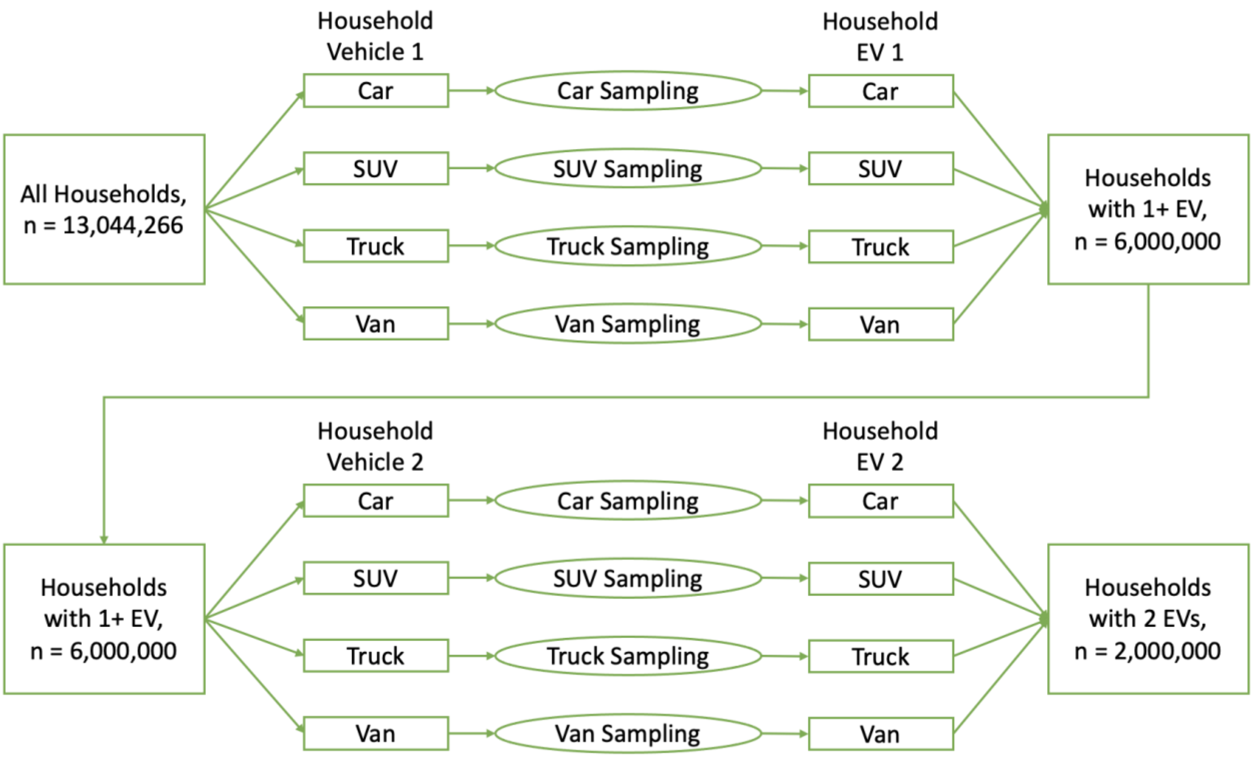

Figure 3. Vehicle electrification workflow. First and second vehicles are considered separately, and only households that have been assigned an EV as their first vehicle are considered for receiving an EV as their second vehicle.

We consider two electrification scenarios that match California's target of having 8 million EVs on the road by 2030 (a milestone on the path to 100% light-duty ZEV sales by 2035) but are differentiated by the mix of body types purchased (*32*). The "Small Vehicles" scenario posits that EV production will continue to emphasize small commute vehicles (*13*); in this scenario, we assign 6 million electric sedans and small hatchbacks, 1 million electric SUVs, and half a million each of electric trucks and vans. The second scenario considers a more mixed future where EV production more closely matches the ICEV fleet; in this scenario, we assign 4 million electric passenger cars, 2 million electric SUVs, and 1 million each are trucks and vans. In both cases, we assign 6 million EVs as first vehicles and 2 million EVs as second vehicles to households that already have an EV.

Households were chosen for electrification using a weighted random sampling process. Weights reflect the likelihood that a household could afford to purchase an EV, the benefit that they would get from having an EV, and the barriers that they might face when choosing an EV over an ICEV. Because forecasting vehicle purchase decisions a decade early involves a great deal of uncertainty, the EV adoption model is kept relatively simple and emphasizes variables existing studies identify as key controls on EV adoption. Income is chosen as the largest driver because most of the EVs will be relatively new in 2030: the path to 8 million EVs requires sales to increase rapidly in the last few years of the decade and most of these vehicles will still be very new in 2030. Weights are higher for households with more vehicles because they may more easily incorporate a limited-range EV into their household fleet since they will have backup ICEVs (*33*). The ability to charge vehicles at home greatly increases the convenience of owning an EV, so households with EV charging capability and single-family detached houses, which generally have larger garages, are assigned higher weights. Finally, households with workers are given a slightly higher weight because EVs' lower operating costs and possible ability to recharge at commute destinations makes them particularly suited for commute use. While the barriers to adopting a first EV are likely different from the barriers to adding a second EV if you already own one, we use the same sampling weights for both assignments in the interest of simplicity.

Electrification weights are divided into four categories: income, which controls 50% of each household's sampling weight; vehicle count, 20%; housing type / home charging, 20%; and all other variables, which together control 10% of the household weight. The full set of weights within each category is shown in Table 2. Each household's overall sampling weight is equal to the sum of the weights across all values. For example, a household with an income of $100,000 (20% weight), 3 household vehicles (16%), containing multiple workers employed outside the home (5%), and who own (5%) a single-family detached house (10%) with charging available (10%), would have a total electrification weight of 66%. This weight would make them twice as likely to be selected for electrification as a household with a weight of 33% if only one household was being selected. However, the scenarios in this study cover nearly half of all households in California, and resultingly many lower-weight households will be selected.

Table 2. Household Electrification Weights

Category	Variable	Value	Score	Weight
Income (50%)	Household Income	Less than $10,000	1	2%
		$10,000 to $14,999	1	2%
		$15,000 to $24,999	2	4%
		$25,000 to $34,999	2	4%
		$35,000 to $49,999	4	8%
		$50,000 to $74,999	6	12%
		$75,000 to $99,999	8	16%
		$100,000 to $124,999	10	20%
		$125,000 to $149,999	15	30%
		$150,000 to $199,999	20	40%
		$200,000 or more	25	50%
Vehicle Count (20%)	Total Household Vehicles	No vehicle available	1	2%
		1 vehicle available	1	2%
		2 vehicles available	4	8%
		3 vehicles available	8	16%
		4 or more vehicles available	10	20%
Housing Type and Charging (20%)	Housing Type	Mobile Home	1	1%
		Apartment	2	2%
		Single-Family Attached	5	5%
		Single-Family Detached	10	10%
	Home Charging Ability	No home charging	1	1%
		Home charging available	10	10%
All Others (10%)	Housing Tenure	Rent	1	3%
		Own	2	5%
	Workers	No workers	1	2%
		1 worker	3	5%
		2 workers	3	5%
		3 or more workers	3	5%

Results

Synthetic Population & Charging Determination

The results of the population synthesis are summarized in Table 3. Overall, the synthetic population performed well at replicating known aggregate distributions in the actual population. The number of households synthesized exactly matched the total number of households in the state for ACS estimates at 13,044,266 households. All household-level synthesized marginals were extremely accurate and within -0.06–0.1% of the statewide values despite a total of 7,040 distinct constraints. At the PUMA level, synthesized household marginals were within -0.4%- 0.5% of actual marginals. At the Census-Tract-level, synthesized marginals were also generally small: median error was under 2.5% for all household variables and the 90th percentile error was under 20% for all variables. The population generation was more imprecise with the person-level marginals and underpredicted individuals, despite matching the household size variable. Dividing the category *4-or-more Person Household* into separate groups could resolve this, but person-level accuracy was not essential for our household-level adoption model.

Households in the synthetic population were randomly assigned home-charging access based on the process described in the Methods section. Ultimately, 63.9% of synthesized households were assigned access to residential charging, with 58.6% of DAC and 65.4% of non-DAC households having access.

Table 3. Results of Population Synthesis

Category Definition	Actual	Synthesized	% Difference
	Household-Level Variables		
Vehicle Count			
No vehicle available	927,957	928,868	0.10%
1 vehicle available	3,968,129	3,970,574	0.06%
2 vehicles available	4,851,748	4,850,047	-0.04%
3 vehicles available	2,113,467	2,112,552	-0.04%
4 or more vehicles available	1,182,965	1,182,225	-0.06%
Income			
Less than $10,000	628,526	628,675	0.02%
$10,000 to $14,999	534,197	534,600	0.08%
$15,000 to $24,999	975,904	976,534	0.06%
$25,000 to $34,999	979,245	979,608	0.04%
$35,000 to $49,999	1,363,211	1,363,587	0.03%
$50,000 to $74,999	2,022,818	2,022,914	0.00%
$75,000 to $99,999	1,620,466	1,620,323	-0.01%
$100,000 to $124,999	1,264,447	1,264,273	-0.01%
$125,000 to $149,999	904,574	904,010	-0.06%
$150,000 to $199,999	1,164,827	1,164,136	-0.06%
$200,000 or more	1,586,051	1,585,606	-0.03%
Housing Type			
Single detached	7,593,962	7,593,417	-0.01%
Single attached	928,948	929,069	0.01%
Apartment	4,058,922	4,059,455	0.01%
Mobile Home	462,434	462,325	-0.02%
Housing Tenure			
Own	7,154,580	7,154,175	-0.01%
Rent	5,889,686	5,890,091	0.01%
Worker Count			
No workers	3,068,280	3,070,902	0.09%
1 worker	4,850,157	4,848,943	-0.03%
2 workers	3,854,073	3,852,977	-0.03%
3 or more workers	1,271,756	1,271,444	-0.02%
Household Size			
1-person household	3,106,104	3,105,827	-0.01%
2-person household	3,967,889	3,967,706	0.00%
3-person household	2,177,312	2,176,903	-0.02%
4-or-more person household	3,792,961	3,793,830	0.02%

Category Definition		Actual	Synthesized	% Difference
		Person-Level Variables		
Gender/Age				
	Adult Female	15,345,949	13,708,293	-10.67%
	Adult Male	14,915,402	13,590,113	-8.89%
	Minor	9,022,146	8,887,204	-1.50%

Vehicle Body Type Assignment

Table 4 and Table 5 summarize the coefficients, standard errors, and residual deviance for all vehicle assignment models. Three models were developed, one for single vehicle households (Table 4) and two for the first two vehicles in a multi-vehicle household (Table 5). “Cars” were used as the reference vehicle type and the base category for each variable is listed in parentheses. A “-“ entry indicates that a particular explanatory variable was not an input for a particular model.

The model parameters indicate that passenger cars are generally the most preferred vehicle type while vans are the least. As household size increases, SUVs and vans gain preference over trucks. While cars are preferred to larger vehicles with increasing population density, trucks are more popular than other large vehicle types at low densities. The relationship between vehicle count and earlier vehicles is more complex with some preference for mixed vehicle type households. The results of applying these models to the synthetic population is depicted in Table 4.

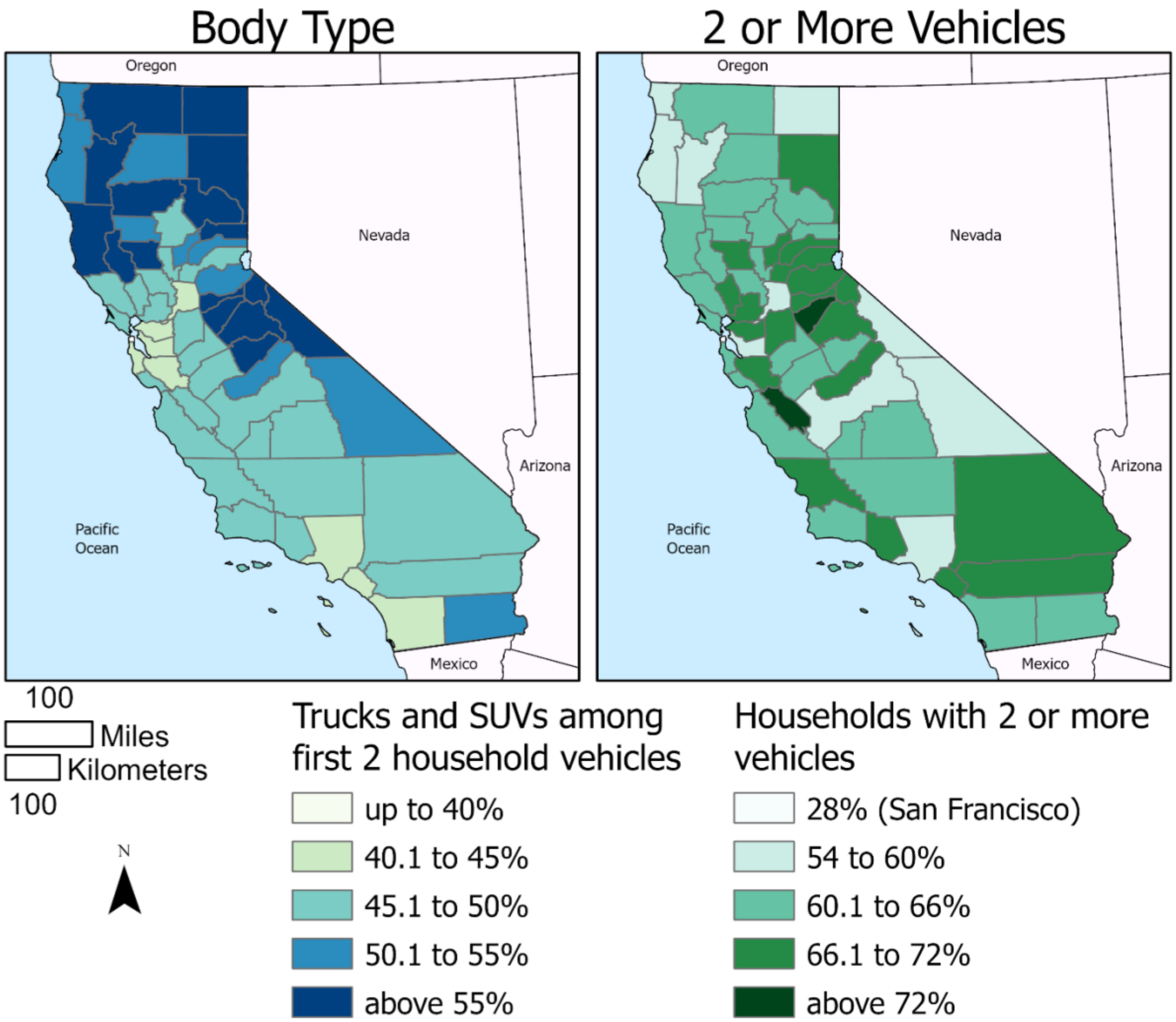

Figure 4. County-level percent of "trucks and SUVs" in first two vehicles in a household (left) and percent of households with two or more vehicles (right)

Table 4. Single-vehicle household vehicle body type assignment model

Variable	Level	SUV	Truck	Van
Constant		-0.8849 (0.00147)	-0.7798 (0.00157)	-2.5946 (0.00257)
Household Size (Base = 1)	**2**	0.1672 (0.00094)	-0.286 (0.00164)	0.6703 (0.00191)
	3	0.2461 (0.00131)	-0.3737 (0.00253)	0.9453 (0.00238)
	4 or more	0.6272 (0.00132)	-0.1471 (0.00257)	1.9429 (0.00199)
Population Density (Base = 0-99)	**100-499**	-0.0259 (0.00185)	-0.9801 (0.00234)	-0.1448 (0.00313)
	500-999	-0.0245 (0.00201)	-1.0041 (0.00266)	0.1242 (0.00322)
	1,000-1,999	-0.1508 (0.00182)	-1.4517 (0.00254)	-0.7045 (0.00343)
	2,000-3,999	-0.216 (0.00166)	-1.6152 (0.0022)	-0.4437 (0.00284)
	4,000-9,999	-0.354 (0.00162)	-1.5449 (0.00202)	-0.8332 (0.00285)
	Over 10,000	-0.3355 (0.00176)	-2.4712 (0.00329)	-0.563 (0.003)
Residual Deviance			70,144,428	
AIC			70,144,488	

Table 5. Multi-vehicle household vehicle body type assignment models

Variable	Level	Vehicle 1 SUV	Vehicle 1 Truck	Vehicle 1 Van	Vehicle 2 SUV	Vehicle 2 Truck	Vehicle 2 Van
Constant		-0.6041 (0.00158)	-0.4205 (0.00171)	-1.9947 (0.00292)	-0.7289 (0.00183)	0.6735 (0.00151)	-2.0323 (0.0032)
Household Size (Base = 1)	2	0.2866 (0.00146)	-0.1303 (0.00164)	0.0542 (0.00285)	0.2434 (0.00169)	-0.5079 (0.00141)	-0.0114 (0.00306)
	3	0.2533 (0.00154)	-0.1602 (0.00176)	0.1202 (0.00302)	0.3873 (0.00175)	-0.7582 (0.00155)	0.2062 (0.00318)
	4 or more	0.5711 (0.00149)	-0.2621 (0.00172)	1.3697 (0.00279)	0.5714 (0.00171)	-0.6501 (0.00148)	0.9906 (0.00301)
Population Density (Base = 0-99)	100-499	-0.0182 (0.0011)	-0.4095 (0.00123)	-0.2244 (0.00182)	-0.0837 (0.00122)	-0.4981 (0.0011)	-0.1316 (0.00195)
	500-999	-0.075 (0.00124)	-0.7742 (0.00153)	-0.3679 (0.00209)	-0.203 (0.00135)	-0.9781 (0.00134)	-0.4504 (0.00228)
	1,000-1,999	-0.2053 (0.00115)	-0.9769 (0.00143)	-0.434 (0.00192)	-0.2441 (0.00124)	-1.2213 (0.00127)	-0.4395 (0.00207)
	2,000-3,999	-0.2618 (0.00106)	-1.0362 (0.00129)	-0.4774 (0.00176)	-0.3755 (0.00116)	-1.5186 (0.00119)	-0.4959 (0.00189)
	4,000-9,999	-0.4675 (0.00106)	-1.1824 (0.00128)	-0.6666 (0.00175)	-0.4624 (0.00115)	-1.5919 (0.00118)	-0.5347 (0.00186)
	Over 10,000	-0.5946 (0.0015)	-1.702 (0.00234)	-0.5985 (0.00239)	-0.551 (0.00157)	-2.0829 (0.00209)	-0.7171 (0.00267)
Vehicle Count (Base = 2)	3	-0.0848 (0.00071)	0.1725 (0.00092)	-0.2975 (0.00124)	-0.1651 (0.00076)	-0.0484 (0.00083)	-0.1016 (0.00127)
	4 or more	-0.2292 (0.00096)	0.3261 (0.00115)	-0.5676 (0.00164)	-0.1824 (0.001)	0.02 (0.00108)	-0.208 (0.00163)
Earlier vehicles (Contin-uous)	SUV	-	-	-	0.0893 (0.00074)	0.3324 (0.00079)	-0.3471 (0.00131)
	Truck	-	-	-	0.4411 (0.00091)	-0.4621 (0.00117)	-0.1563 (0.00167)
	Van	-	-	-	-0.269 (0.00133)	0.1473 (0.00135)	-0.3458 (0.00203)
Residual Deviance			144,344,683			145,192,253	
AIC			144,344,755			145,192,325	

Impact of Body Type on the Spatial Distribution of EVs

The tools developed in this paper—a synthetic population optimized for EV adoption enriched with vehicle body type usable for any US geography—are unique among EV adoption models and will be developed further for future projects. In this project, we employ these tools to analyze the impact of different EV body type mixes on EV distribution in California. Both scenarios result in a large share of California households receiving at least one electric vehicle, as we consider a high electrification future with 6M out of California's 13M households electrified. While the share of electrified households changes minimally in some aggregate views, there are significant local differences in EV clustering that are interesting to consider.

Two body type mixes were analyzed: a "Small Vehicles" scenario with 6M private cars and 2M private trucks and a "Large Vehicles" scenario with 4M of each. Statewide electrification by demographic categories, such as income level and worker count, did not vary significantly between the two scenarios. Figure 5 depicts the average electrification by demographic categories. Error bars are not shown because the range of scenarios is <1.2% for all income levels and <0.5% for all levels of all other variables.

Despite the slight differences in statewide variables, the body mix changes translate to large intraregional variation. The spatial differences are apparent when looking at two key metrics: the number of households that "electrify"—get at least one EV—and the number of two-EV households.

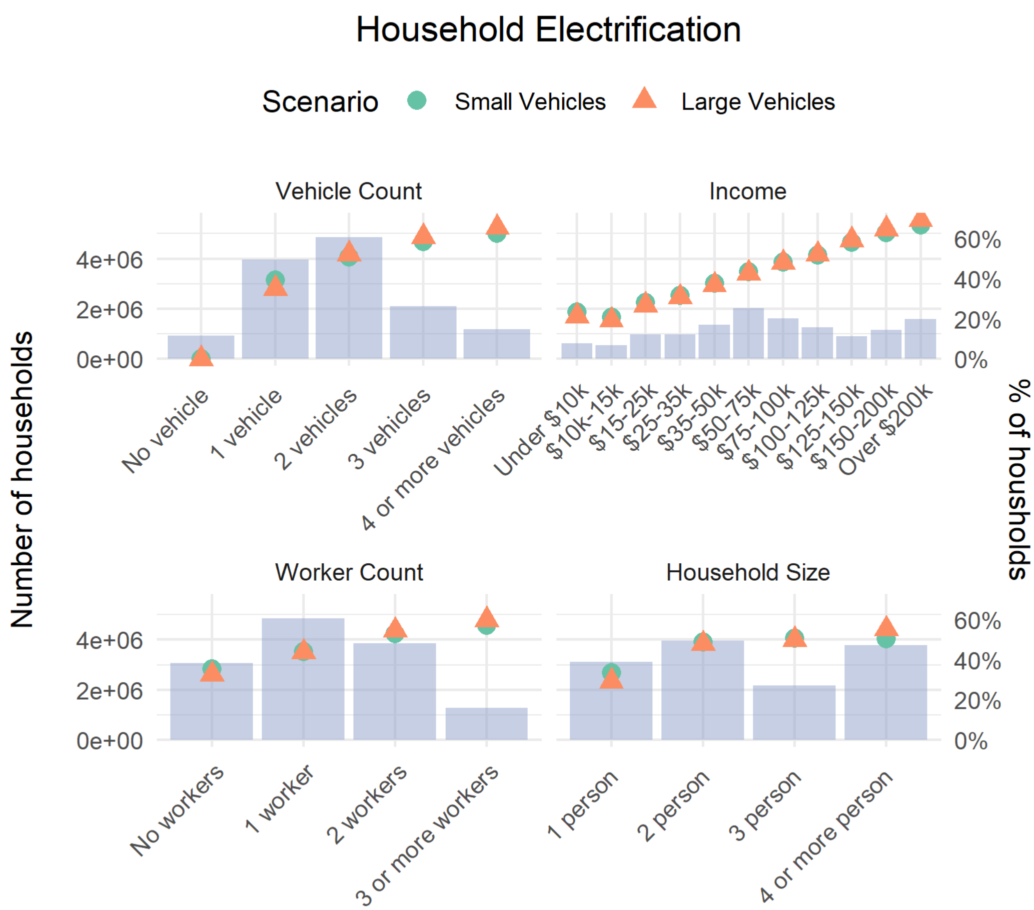

Figure 5. Statewide average electrification in Small and Large Vehicles scenarios across various demographic categories.

Electrified Households

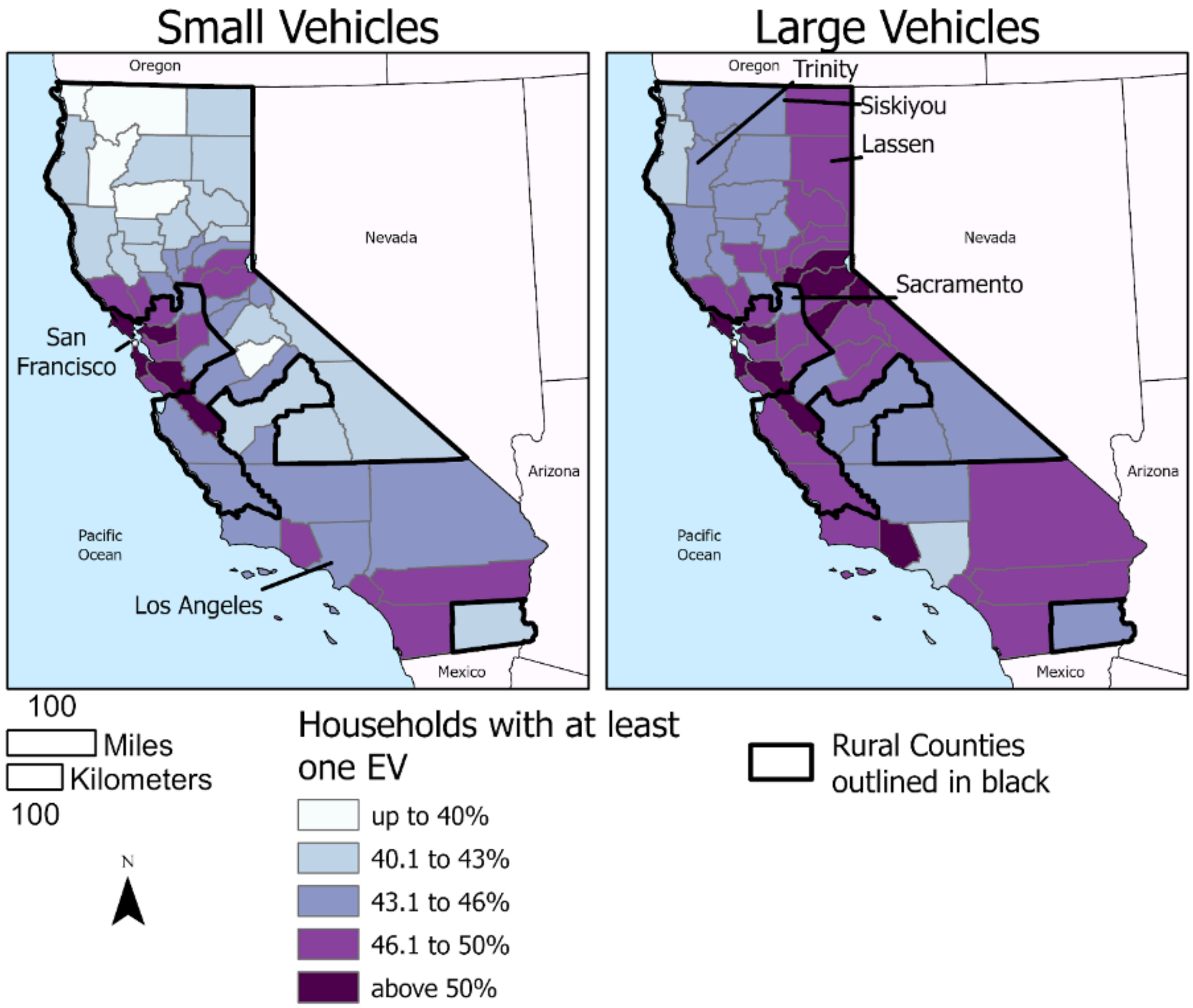

Figure 6. County-level household electrification in the Small Vehicles (left) and Large Vehicles (right) scenarios with rural counties outlined.

Moving from the Small Vehicles to Large Vehicles scenario distributes EV households more uniformly across California and shifts EVs from urban to rural counties (Figure 6). Los Angeles and San Francisco counties experience the largest drop in electrification with about 48,000 (-1.5%) and 9,000 (-2.6%) fewer EV households (% of households electrified) respectively, but other counties in the San Francisco Bay and Los Angeles areas remain largely the same with electrification rates ranging from 47-52%. In contrast, northern California counties like Siskiyou, Lassen, or Trinity counties experience as much as a 7% increase in electrified households.

The Small Vehicles scenario has a greater share of households in urban counties electrified at 46.2% compared to rural counties' 44.5%. The opposite is true in the Large Vehicles scenario, where 47.3% of rural county and 45.8% of urban county households have at least one electric vehicle. The Sacramento-Tahoe region (Figure 7) especially highlights this trend. While electrification is high in the Small Vehicles scenario - certain tracts around Placerville have 50–54% electrification rates—electrification in these same tracts jumps 5-7% in the large vehicles scenario.

Electrification in DAC households is similar in both cases with slightly more electrified households in the Small Vehicles scenario with 40.2% instead of 39.9%. Both figures are significantly lower than the state overall, indicating that the environmental benefits of EVs are not equitably distributed in these cases. This result is not surprising as income is the largest driver in our electrification model. Notably, households in DACs that have electrified so far generally are not representative of their surrounding communities and often have higher incomes. (*17*). However, it is important to note that changes in commutes and other travel patterns will have important effects on local criteria pollutants, which itself is an input to DAC status, and further gains may be found by providing financial support for low-income and DAC households to purchase EVs.

In certain areas of the state, DACs have higher electrification rates in the Large Vehicles scenario along with DAC-neighboring communities. This is the case in both the San Francisco Bay and the Central Valley areas (Figure 8 and Figure 9). Certain DACs in the Bay near San Jose and Fremont have about 50% electrification in the Small Vehicles scenario and have an additional 7% in the Large Vehicles scenario. Likewise, some tracts east of these cities start at about 50 or 55% electrification in the Small Vehicles scenario and an additional 10-11% in the Large Vehicles scenario. The scenario differences are even more stark when examining Central Valley DACs. In the Small Vehicles scenario, most of these communities only achieve electrification in the 30 to low-40% range but with the introduction of larger EVs, many of these tracts can electrify an additional 9-10%.

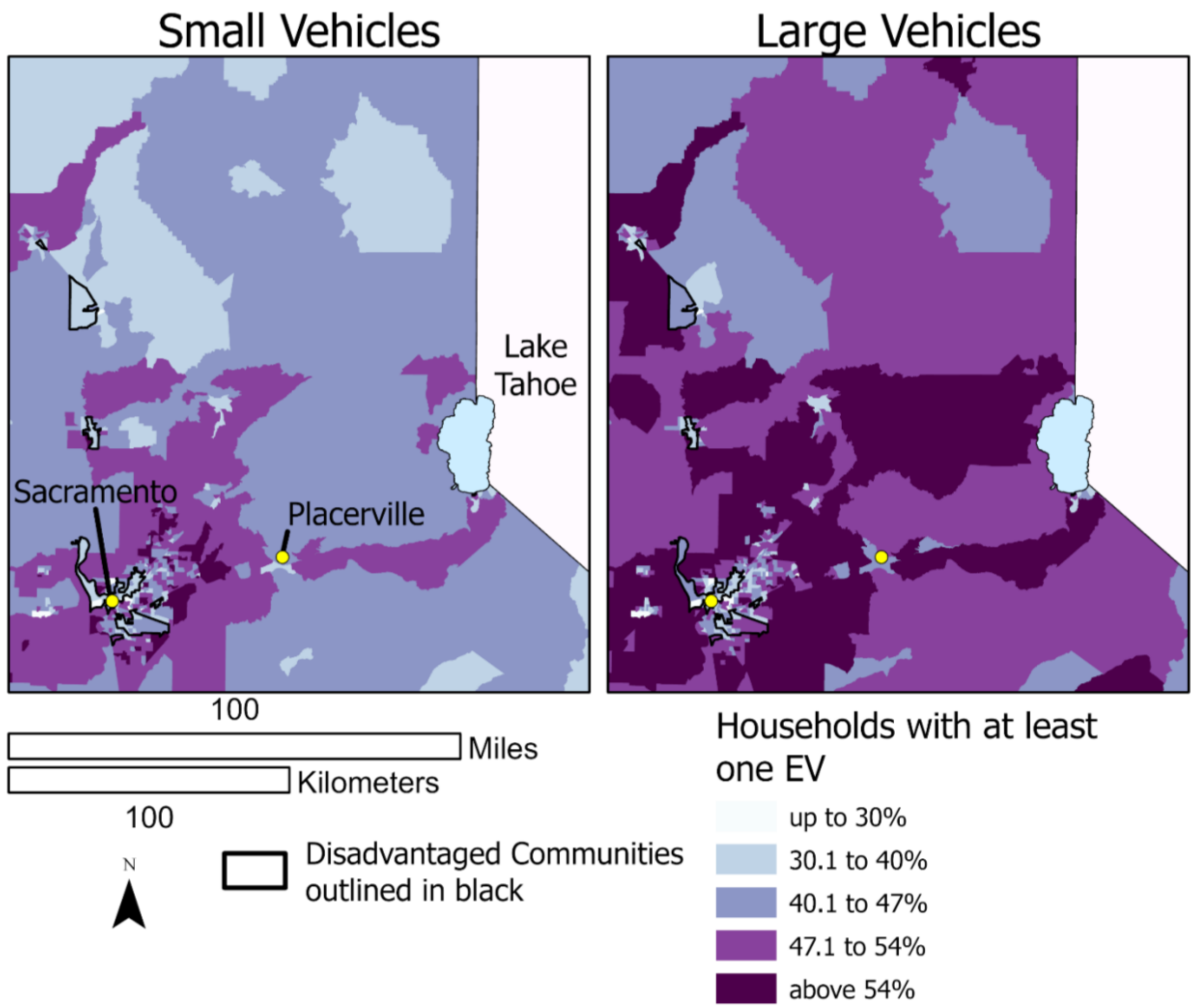

Figure 7. Electrification by Census Tract for the Sacramento-Tahoe region. Disadvantaged communities are outlined.

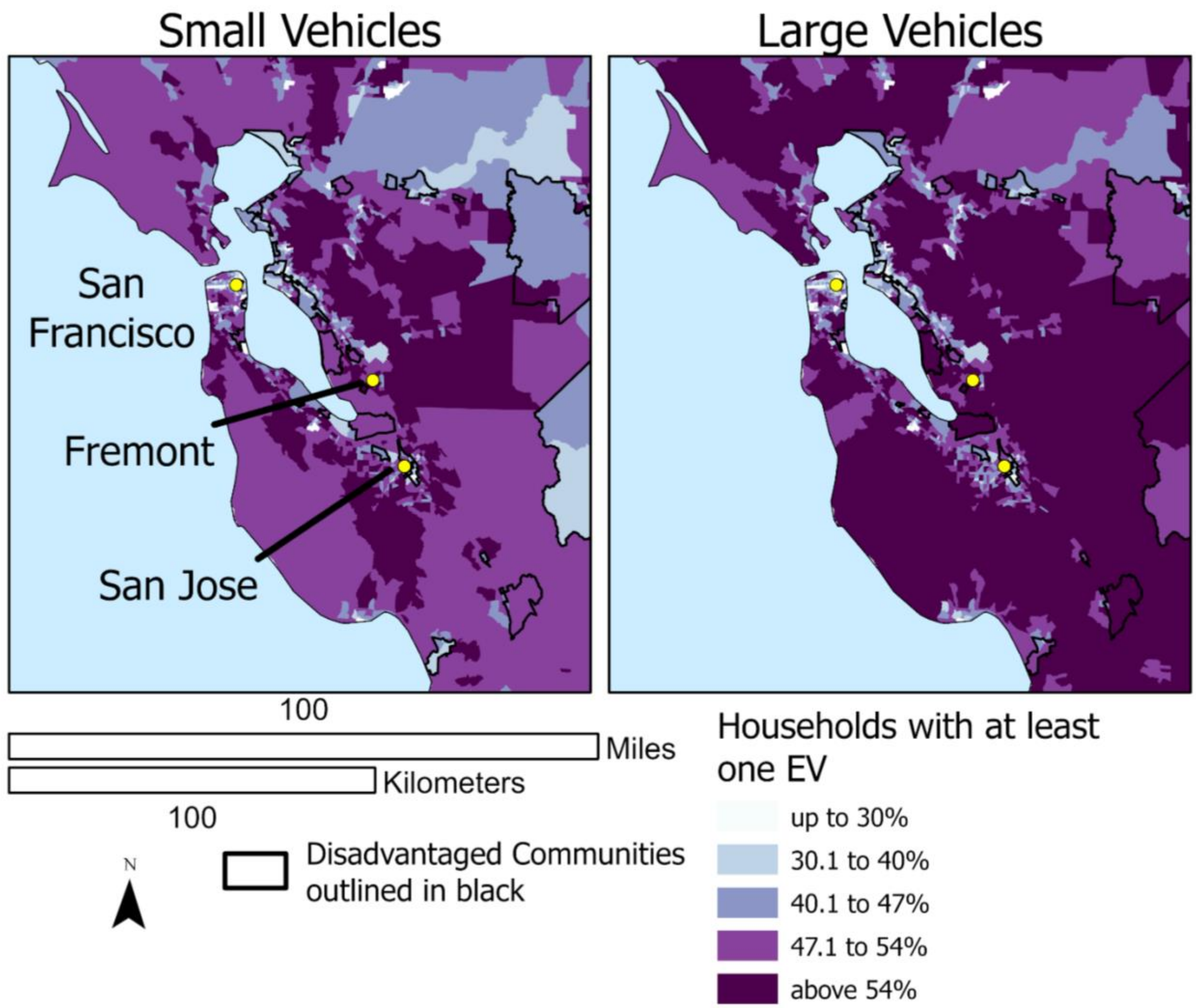

Figure 8. Electrification by Census Tract for the San Francisco Bay region. Disadvantaged communities are outlined.

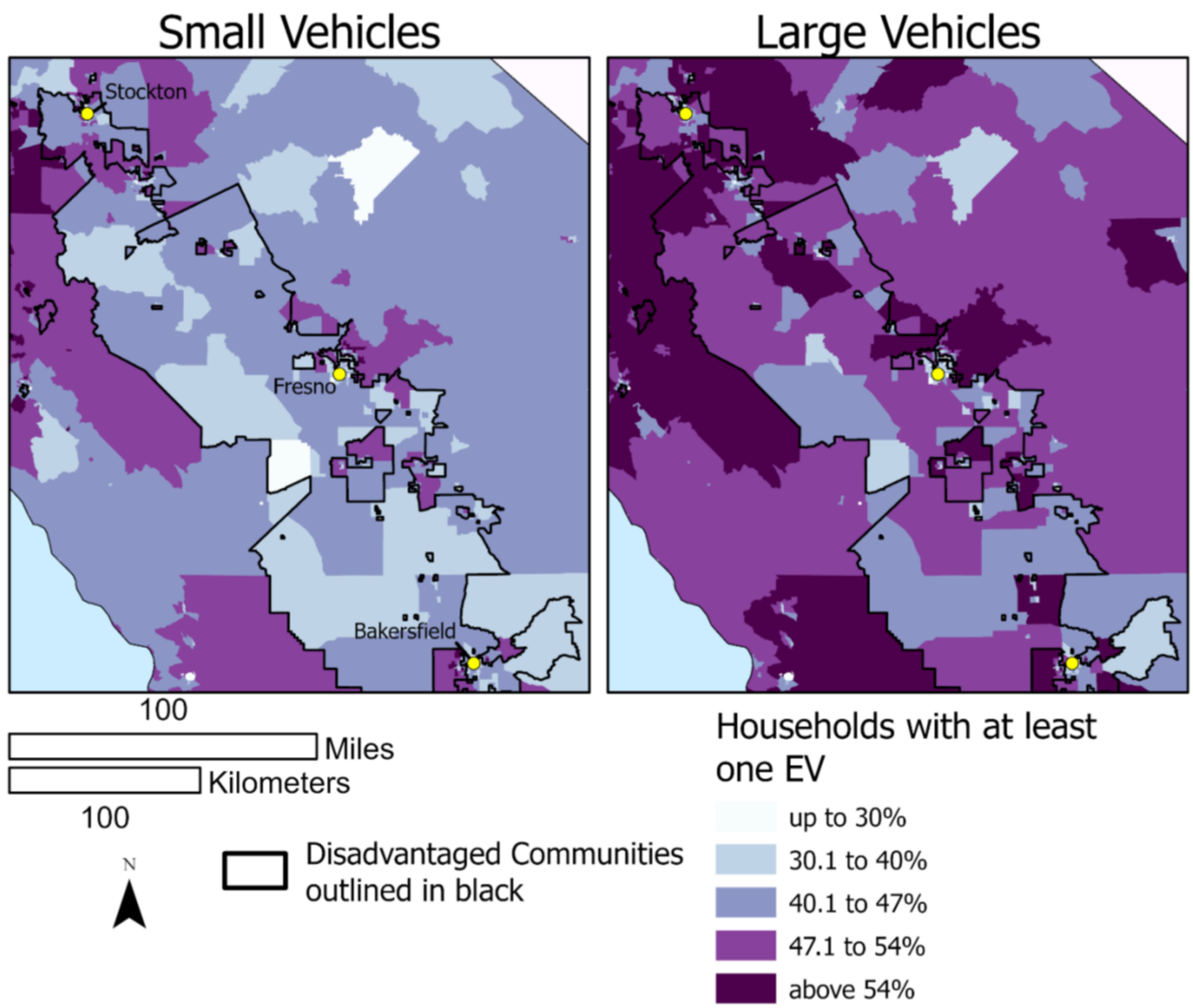

Figure 9. Electrification by Census Tract for the Central Valley region. Disadvantaged communities are outlined.

Two-EV Households

Two-EV households are also more evenly distributed across the state in the Large Vehicles scenario (Figure 10). Both rural and urban counties have similar rates with 15.5% and 15.3% of households owning two EVs. In contrast, rural counties have 13.8% and urban counties have 15.4% of households owning two EVs in the Small Vehicles scenario. Again, there is a negligible difference in statewide DAC figures in the two scenarios with 11.6% and 11.9% of households in the Large and Small Vehicles scenario doubly-electrified.

Similar patterns continue in the San Francisco Bay area (Figure 11). DACs in this region have two-EV electrification rates ranging from about 2 to 25-26% in each scenario, but with significant Census-Tract-level variation between the scenarios. Some DACs have 2% fewer households with two-EVs while others have up to 8% more in the Large Vehicles scenario. Like the single-EV case, larger EVs serve to move EVs away from densely populated areas and into sparser populated ones.

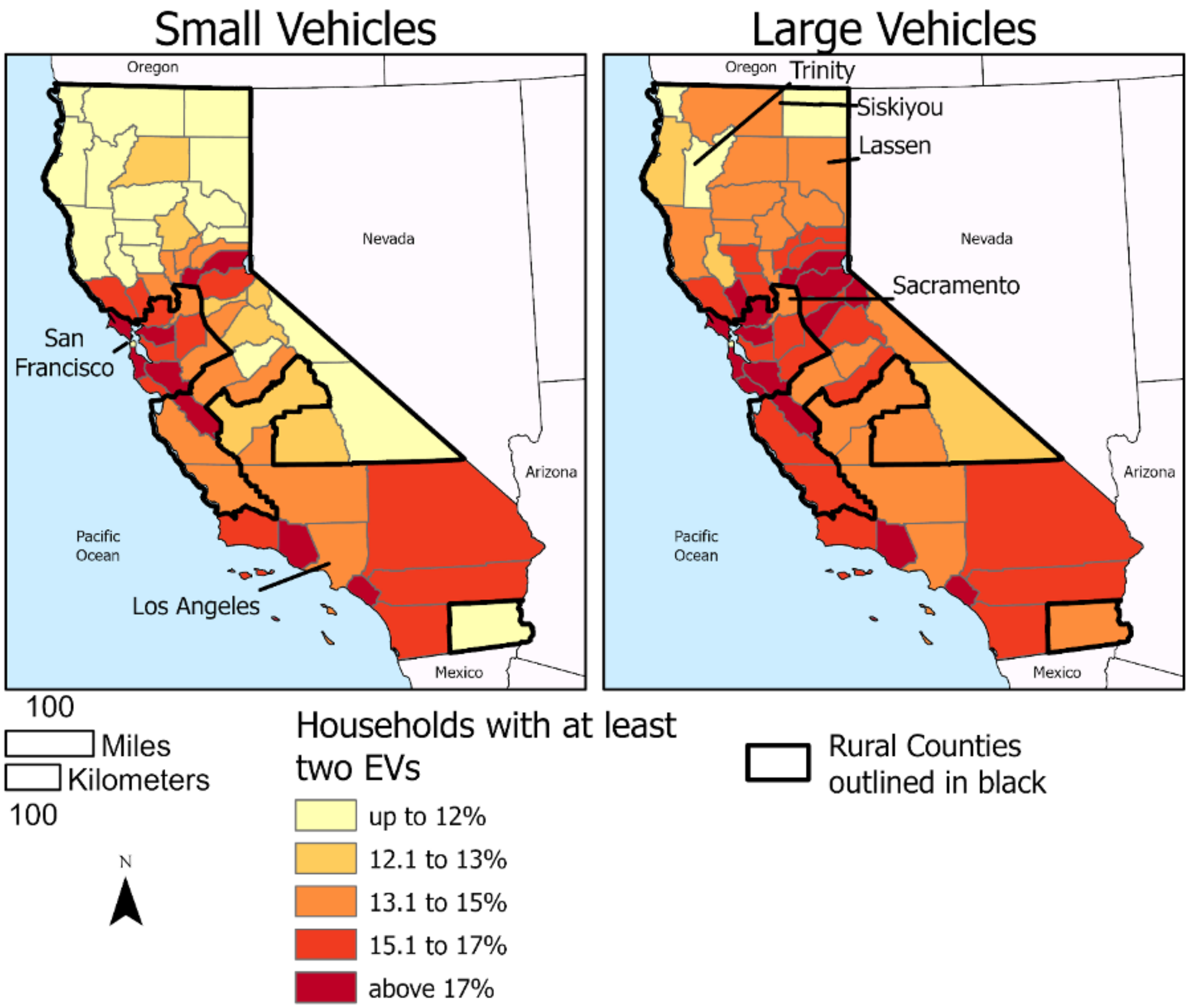

Figure 10. County-level household two-EV electrification in the Small Vehicles (left) and Large Vehicles (right) scenarios with rural counties outlined.

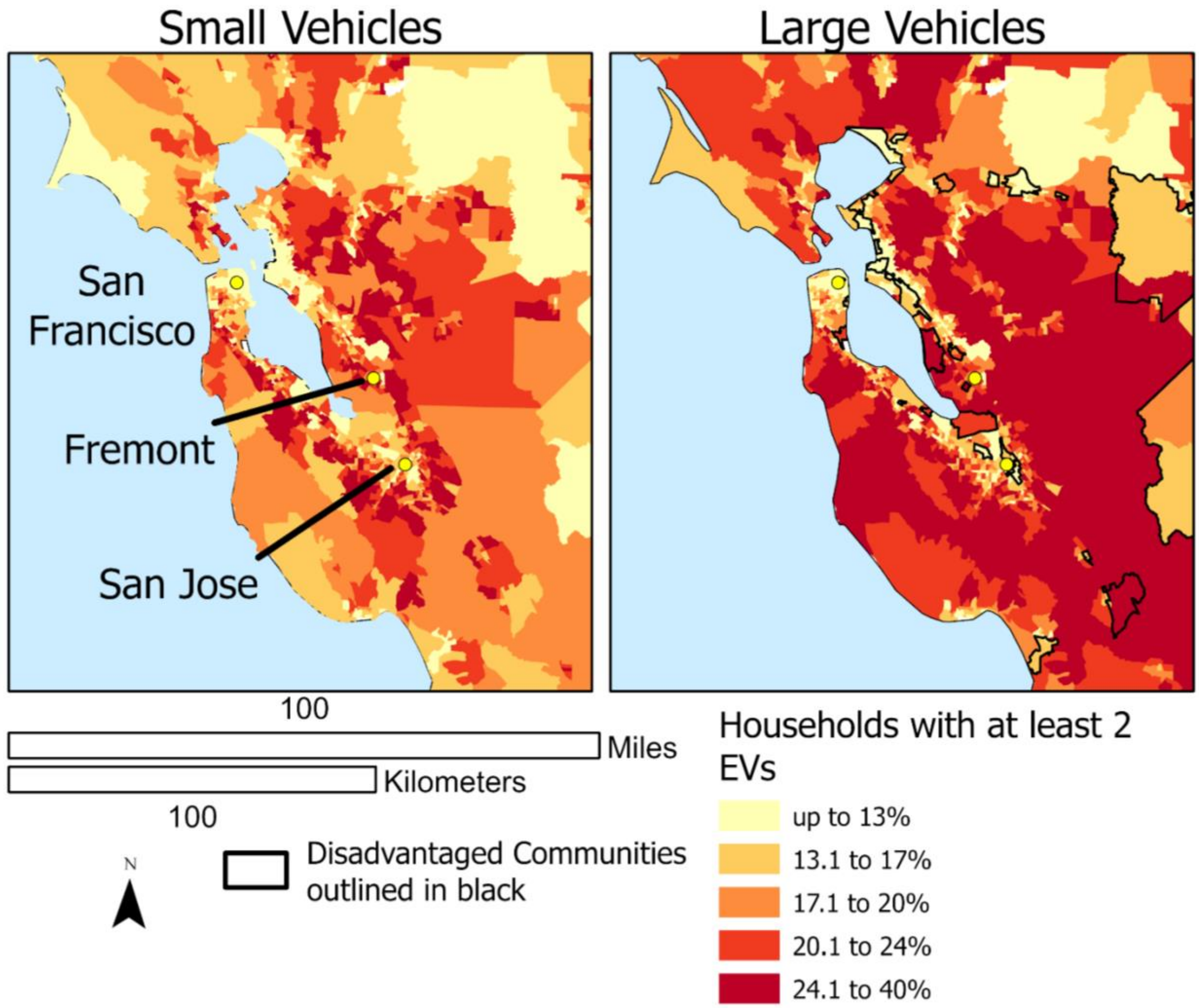

Figure 11. Two-EV electrification by Census Tract for the San Francisco Bay region. Disadvantaged communities are outlined.

Home-Charging

Home-charging access does not change drastically between the two scenarios for electrified households or two-EV households. Rural households generally have higher levels of home-charging access when compared to urban households. Moving from the Small Vehicles to Large Vehicles scenario causes access to home-charging to slightly rise in both rural and urban counties, for both electrified households in general and two-EV households. In the Small Vehicles scenario, 71.6% of urban electrified households and 79% of rural electrified households have home-charging while these figures rise to 72.5% and 79.4% respectively. Similarly for two-EV households, 79.9% of urban and 84.6% of rural households have home-charging in the Small Vehicles scenario while 80.7% of urban and 84.9% of rural households have home-charging in the Large Vehicles scenario. Home-charging access is similar or rises between the two scenarios regardless of urban/rural classification because households with trucks and SUVs tend to live in housing types with greater home-charging access. An important caveat for these figures is that they do not consider charger congestion in two-EV households. Thus, while these households may be able to charge an EV, they still may not be able to meet all their charging needs at home.

A similar trend continues for DAC and non-DAC communities. While DAC households have lower access to charging than non-DAC households, moving from the small to large vehicles scenario increases home-charging access rates for both groups, with a smaller increase in DAC households than non-DAC households. In the small vehicles scenario, 69.2% (73.2%) of DAC (non-DAC) households have home-charging access while 69.9% (74.2%) of them have access in the large vehicles scenario. Access in two-EV DAC (non-DAC) households is similar with 78.2% (80.9%) in the small vehicles and 78.8% (81.7%) in the large vehicles scenarios having access. While access may be rising, it is important to note that it is likely because EVs are shifting towards households with single-family homes who also tend to be more affluent and own SUVs and trucks.

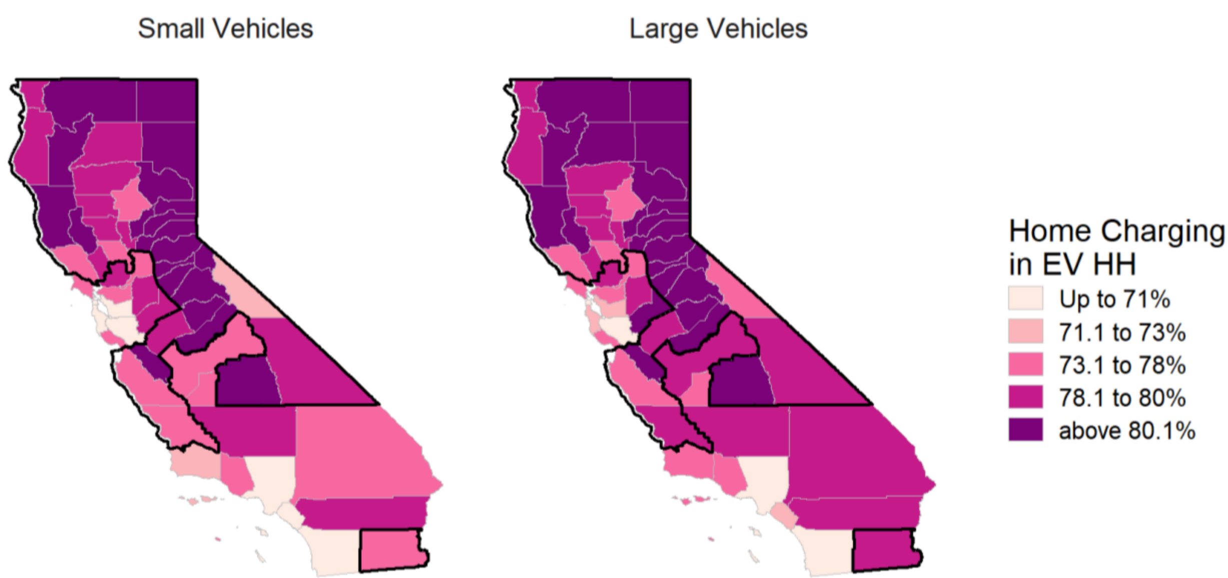

Figure 12. Home-charging access in electrified households. Rural counties are outlined.

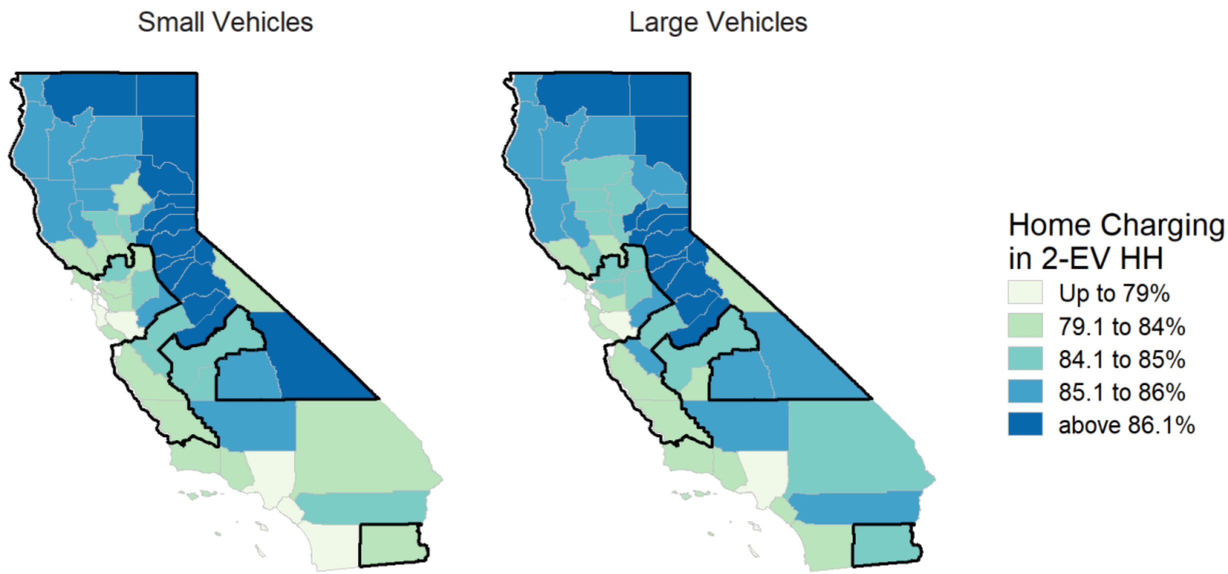

Figure 13. Home-charging access in two-EV households. Rural counties are outlined.

Implications

While the aggregate differences in electrification between rural and urban counties or DACs and non-DACs is not large between the two body type scenarios, the specific spatial variation can have important implications. Most apparent is the impact on regional charging infrastructure and energy demand. Not only will larger EVs be distributed more widely than smaller ones, but they will necessarily require more energy to charge. Combined with differences in the ways these vehicles are used, this could result in drastically different charging patterns. While Level 1 charging is widely available, larger EVs that are used to commute or are driven often may find little benefit from low-speed charging and instead require Level 2 charging. Any increase in electrification in smaller communities due to the availability of larger EVs could have outsized, magnified impacts on local electric demand due to these factors.

Vehicle body type preference is an important driver of the distribution of EVs in this model, thus more complex models of vehicle body type assignment could be incorporated in the future to discover additional fine-scale regional patterns. This paper utilizes the NHTS to create a model flexible enough for any US geography, but specific regional vehicle data could be introduced to capture local vehicle trends. Additionally, more sophisticated vehicles assignment models could be substituted to improve body type assignment accuracy. Mixed logit or multiple discrete-continuous extreme value (MDCEV) models are just a few of the alternatives available. Moreover, we plan to integrate vehicle age in future model versions to target households with a propensity for frequent vehicle purchases.

Finally, the electrification model can be further developed to consider additional scenarios or policy implications. Incorporating household vehicle purchase decisions—which households purchase vehicles often and whether they are new or used vehicles—will be important in further refining this model. The electrification methodology we develop can be modified to test the impact of various policy scenarios on EV adoption, such as subsidies or incentives that reduce the burden of low-income households purchasing and owning an EV or increased incentives for multi-unit EV charging which will allow apartment dwellers to more easily access EVs.

Conclusion

The availability of EVs in all body types is essential to decarbonizing personal transportation. Thus far, most EVs have been passenger cars, but future electric trucks and SUVs will be critical to bringing EVs to more communities, to rural areas, and for non-commute uses. A greater variety of body styles will hasten the transition to zero-emission vehicles and help distribute their environmental benefits, but special attention is needed for their impact on local energy demand and equity. The synthetic population developed in this paper is uniquely suited to examine EV adoption at both fine spatial and demographic scales. By enriching this synthetic population with both vehicle body type and home-charging access, we have developed a tool to help predict electrification at the local level anywhere in the United States. This level of resolution is necessary to plan for charging infrastructure and anticipate environmental justice concerns. As EVs are critical to greenhouse gas emissions reduction and local air quality, it is critical to ensure that the environmental benefits of EVs are equitably distributed.

Changing EV body types will dramatically change charging demand. While EV adoption so far has concentrated in densely populated urban centers, increases in electric SUV and truck sales has the potential to expand EV ownership in sparser suburban and rural areas. Combined with the greater energy needs of these vehicles due to larger battery sizes and lower energy efficiencies, larger EVs have the potential to stress local electric grids without proper forecasting tools. The change in the EV market highlights the need for more modelling to predict energy demand.

When considering a high electrification scenario for California with 8M EVs and 6M households electrified, we find that EVs shift away from huge population centers like Los Angeles and San Francisco and increase in lower-density communities around the state especially in Northern California and the Central Valley. In future modelling, we will consider vehicle age, as most of the 8M EVs in 2030 will come from new car sales. Additionally, more research is needed on commute patterns and vehicle usage which will greatly impact the energy needs of new EVs and access to workplace-charging. Lastly, we plan to incorporate more extensive modelling of chargers and charging events. While we consider access to home-charging, more work is needed on charger congestion in multi-EV households, workplace charging, and public charging and the total charging needed for electrification.

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Data Summary

Products of Research

Data used in this report come from three main sources: the 2015–2019 five-year American Community Survey (ACS) and associated Public Use Microdata Samples (PUMS), a nationwide National Renewable Energy Laboratory (NREL) survey on residential charging access, and the 2017 National Household Travel Survey (NHTS). This report uses an earlier version of the NREL survey that was provided upon request prior to its publication. These data sources were used to generate a synthetic population of households for California.

Data Format and Content

The data are in multiple formats.

2015-2019 ACS Summary Tables: CSV tables for regional totals for household variables (Vehicle Count, Income, Housing Type, Housing Tenure, Worker Count, and Household Size) and individual variables (Gender and Age)

2015-2019 ACS PUMS: Comma delimited (CSV) set of records from individual people or housing units that are representative at the public use microdata area (PUMA) level.

2017 NHTS: CSV files with household, individual, and vehicle characteristics and travel behaviors.

NREL survey: CSV file with housing type and corresponding home charging availability probabilities.

Synthetic Population: CSV file with following variables:

- scenario: body type electrification mix considered
- geo: census tract geographic identifier
- unique_id_in_geo: unique identifying number
- ev1: probability of the first vehicle being electric
- ev2: probability of the second vehicle being electric
- workers: number of workers in the household
- vehicles: number of vehicles in the household
- tenure: household tenure (own or rent)
- income: household income
- size: household size
- veh1: vehicle body type of the first vehicle in the household, augmented variable
- veh2: vehicle body type of the second vehicle in the household, augmented variable
- charging: access to home charging (Y = Yes/N = No), augmented variable

Data Access and Sharing

2015-2019 ACS Summary Tables: The following ACS tables were used and are available at data.census.gov:

- B08203 – Worker count and vehicle count marginals
- B25124 – Housing tenure, household size, and housing type
- B19001 – Income
- B01001 – Gender and Age

The tables were retrieved using the R package "tidycensus"

> Walker K, Herman M (2022*). tidycensus: Load US Census Boundary and Attribute Data as 'tidyverse' and 'sf'-Ready Data Frames*. R package version 1.2.2.9000, https://walker-data.com/tidycensus/

2015-2019 ACS PUMS: Available at https://www2.census.gov/programs-surveys/acs/data/pums/2020/5-Year/

2017 NHTS: Available at https://nhts.ornl.gov/

NREL survey: Data table and supporting presentation available at https://github.com/tramadoss/ev-syn-pop/tree/main/nrel

Synthetic Population: Data table available at: https://doi.org/10.25338/B8T066. Documentation available at https://github.com/tramadoss/ev-syn-pop/

Reuse and Redistribution

There are no restrictions on the use of the data. Data should be cited using the following suggested citation:

> Ramadoss, Trisha; Tal, Gil; Davis, Adam (2023). Synthetic population – Democratization of electric vehicle charging infrastructure [Dataset]. Dryad. https://doi.org/10.25338/B8T066