Highly Resolved Projections of Passenger Electric Vehicle Charging Loads for the Contiguous United States

Results From and Methods Behind Bottom-Up Simulations of County-Specific Household Electric Vehicle Charging Load (Hourly 8760) Profiles Projected Through 2050 for Differentiated Household and Vehicle Types

Arthur Yip, Christopher Hoehne, Paige Jadun, Catherine Ledna, Elaine Hale, and Matteo Muratori

National Renewable Energy Laboratory

NREL is a national laboratory of the U.S. Department of Energy
Office of Energy Efficiency & Renewable Energy
Operated by the Alliance for Sustainable Energy, LLC

This report is available at no cost from the National Renewable Energy Laboratory (NREL) at www.nrel.gov/publications.

Contract No. DE-AC36-08GO28308

Technical Report
NREL/TP-5400-83916
June 2023

Highly Resolved Projections of Passenger Electric Vehicle Charging Loads for the Contiguous United States

Results From and Methods Behind Bottom-Up Simulations of County-Specific Household Electric Vehicle Charging Load (Hourly 8760) Profiles Projected Through 2050 for Differentiated Household and Vehicle Types

Arthur Yip, Christopher Hoehne, Paige Jadun, Catherine Ledna, Elaine Hale, and Matteo Muratori

National Renewable Energy Laboratory

Suggested Citation
Yip, Arthur, Christopher Hoehne, Paige Jadun, Catherine Ledna, Elaine Hale, and Matteo Muratori. 2023. *Highly Resolved Projections of Passenger Electric Vehicle Charging Loads for the Contiguous United States: Results From and Methods Behind Bottom-Up Simulations of County-Specific Household Electric Vehicle Charging Load (Hourly 8760) Profiles Projected Through 2050 for Differentiated Household and Vehicle Types*. Golden, CO: National Renewable Energy Laboratory. NREL/TP-5400-83916. https://www.nrel.gov/docs/fy23osti/83916.pdf.

NREL is a national laboratory of the U.S. Department of Energy
Office of Energy Efficiency & Renewable Energy
Operated by the Alliance for Sustainable Energy, LLC

This report is available at no cost from the National Renewable Energy Laboratory (NREL) at www.nrel.gov/publications.

Contract No. DE-AC36-08GO28308

Technical Report
NREL/TP-5400-83916
June 2023

National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, CO 80401
303-275-3000 • www.nrel.gov

NOTICE

This work was authored by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Strategic Analysis Team. The views expressed herein do not necessarily represent the views of the DOE or the U.S. Government.

This research was performed in part using high-performance computational resources sponsored by the Department of Energy's Office of Energy Efficiency and Renewable Energy and located at the National Renewable Energy Laboratory.

Cover Photos by Dennis Schroeder: (clockwise, left to right) NREL 51934, NREL 45897, NREL 42160, NREL 45891, NREL 48097, NREL 46526.

Abstract

This report documents enhancements made to the Transportation Energy & Mobility Pathway Options™ (TEMPO) model to project spatially, demographically, and temporally resolved national-scale electric vehicle (EV) charging load profiles and describes three scenarios and corresponding data sets created for the National Renewable Energy Laboratory's (NREL's) demand-side grid (dsgrid) project in support of bulk power systems modeling. In brief, TEMPO was enhanced to disaggregate national and annual energy demand projections into household- and county-level projections of passenger EV hourly charging load profiles (8760 profiles), accounting for consumer, travel, and temperature variations that impact EV energy demand. In alignment with NREL's forward-looking grid modeling, three scenarios for EV adoption covering 2020–2050 were created—*Annual Energy Outlook (AEO) Reference Case*, *Electrification Futures Study (EFS) High Electrification*, and *All EV Sales by 2035*—and associated data sets have been included in the dsgrid platform for public use.

Acknowledgments

We would like to thank our reviewers, Kara Podkaminer, Ookie Ma, Sam Baldwin, Kevin Lynn, Patrick Brown, Wesley Cole, and Eric Wood, for their insightful comments and discussion. We are also grateful for Michael Deneen's copy editing. We extend special thanks to Ookie Ma, who shared his IPF code to generate household data; Meghan Mooney, Daniel Thom, Lixi Liu, and Carlos Bianchi for their help with dsgrid; and Brian Bush for his help with TEMPO.

List of Acronyms

ACS	American Community Survey
AEO	Annual Energy Outlook
ATB	Annual Technology Baseline
BEV	battery electric vehicle
DCFC	direct current fast charging
EPA	U.S. Environmental Protection Agency
dsgrid	demand-side grid
EFS	Electrification Futures Study
EIA	U.S. Energy Information Administration
EV	plug-in electric vehicle, including both plug-in hybrid electric vehicles and battery electric vehicles, and excluding hybrid electric vehicles and fuel cell electric vehicles
IPF	iterative proportional fitting
L1	Level 1 electric vehicle charging
L2	Level 2 electric vehicle charging
LDV	light-duty vehicle
NHTS	National Household Travel Survey
NREL	National Renewable Energy Laboratory
PUMS	Public Use Microdata Sample
TEMPO	Transportation Energy & Mobility Pathway Options model
VMT	vehicle miles traveled (typically in units of miles/year/vehicle)
ZEV	zero-emission vehicle

Executive Summary

Vehicle electrification is increasing in speed and scale, with widespread light-duty vehicle (LDV) electrification moving from a question of "if" to "when" and "where." Vehicle electrification will increase electricity consumption by a substantial but manageable amount, with multiple studies projecting that full electrification of the light-duty vehicle stock would account for 13%–29% of future aggregate U.S. load (Mai et al. 2018; Fox-Penner, Gorman, and Hatch 2018; Milovanoff et al. 2020). However, for energy system planning and design, "*when* and *where* electric vehicle (EV) charging occurs will be as critical as *how much* electricity is needed" (Muratori and Mai 2020), especially in the transitional medium-term horizon.

Significant spatial and temporal heterogeneity in EV loads across the United States is expected due to variations in travel behavior, vehicle ownership preferences (e.g., pickup trucks or compact sedans), and technology adoption. Spatiotemporal differences in EV energy use also arise from weather impacts. For example, the energy used by the same EV to drive a mile can change by up to 50%–100% in very cold temperatures. Overall, these factors combine to result in major spatial and temporal variations in EV electricity demand, which heavily impacts charging needs and implications for the electricity system. In addition, patterns in these factors are expected to change in future scenarios. This report describes how the Transportation Energy & Mobility Pathway Options™ (TEMPO) model was enhanced to project spatially, demographically, and temporally resolved passenger EV charging demand.

TEMPO is a comprehensive transportation demand model from the National Renewable Energy Laboratory (NREL) used to explore long-term scenarios of energy use across the entire U.S. transportation sector (Muratori, Jadun, et al. 2021). TEMPO simulates travel demand, household vehicle ownership, mode choice, and technology choice, for both passenger travel and freight transport. TEMPO models heterogeneous passenger travel demand, vehicle ownership, travel mode choice, and technology preferences and choices by categorizing U.S. households according to socio-demographics and geographic characteristics. Here we document the methodologies and assumptions used to enhance TEMPO's resolution, which was previously limited to the national scale and annual level, in order for TEMPO to simulate spatially, demographically, and temporally resolved household EV charging loads. This process is organized into four steps:

1. Spatially disaggregating and harmonizing TEMPO's demographically resolved household and vehicle input data to enable county-level TEMPO simulations for households and their passenger light-duty EVs for the contiguous United States, projected through 2050.
2. Capturing spatially and temporally resolved effects of temperature on EV energy use for a specific weather year.
3. Developing spatially resolved vehicle electrification scenarios that determine the extent of EV adoption in each county.
4. Simulating week-long trip energy consumption schedules, applying charging strategies, and generating hourly EV charging load profiles for different scenarios.

Using these enhancements, TEMPO generated annual hourly load projections for household EV charging for all counties in the contiguous United States, projected through 2050 for a set of vehicle electrification scenarios. The resulting data sets have been included in the NREL demand-side grid (dsgrid)[1] repository. The scenarios are:

A. *AEO Reference Case*, aligned with passenger light-duty EV adoption in the Reference Case in the 2018 U.S. Energy Information Administration (EIA) Annual Energy Outlook (AEO) (EIA 2019), which was used to calibrate the TEMPO model.

B. *EFS High Electrification*, with passenger light-duty EV adoption in line with the High Electrification scenario in the Electrification Futures Study (EFS) (Mai et al. 2018).

C. *All EV Sales by 2035*, assuming U.S. average passenger light-duty EV sales reaching 50% in 2030 and 100% in 2035, in line with various announced targets.

For each scenario, annual hourly charging profiles are provided for every other year from 2020 through 2050, differentiated by county, household type, and vehicle type.

This report explains TEMPO's county-level disaggregation methodology, incorporation of spatiotemporally specific temperature impacts, development of disaggregate EV sales scenarios, and simulation of EV charging load profiles. It then summarizes aggregate results from all scenarios and focuses on detailed results from the *All EV Sales by 2035* scenario, demonstrating TEMPO's capabilities in simulating when, where, and how much household EVs will be charged in the United States. Figures ES-1 and ES-2 highlight the EV charging load results generated by TEMPO for this report.

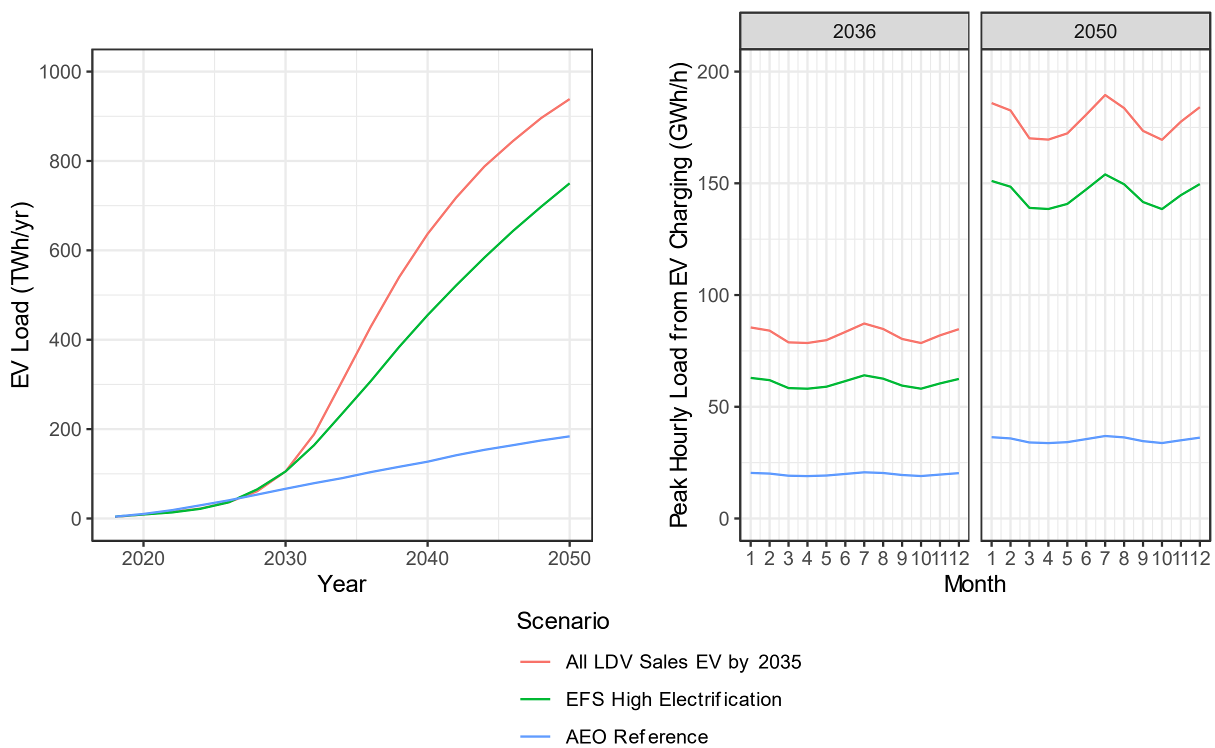

Figure ES-1. Aggregate U.S. annual and peak hourly EV load under three scenarios

[1] https://www.nrel.gov/analysis/dsgrid.html

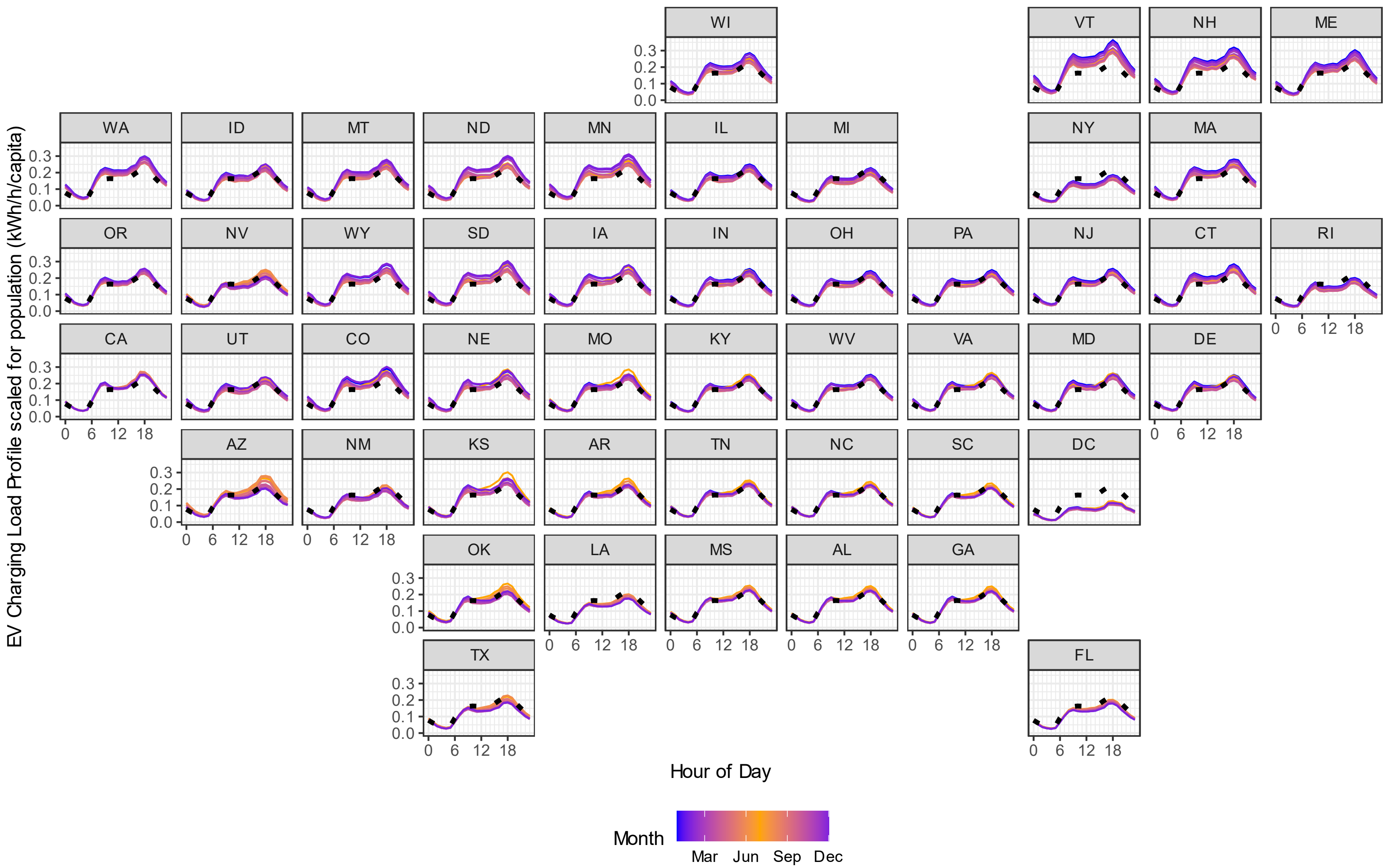

Figure ES-2. State-level per-capita EV charging load profiles for an average weekday for the All EV Sales by 2035 scenario for projected year 2035 under the immediate and ubiquitous charging strategy, for the contiguous United States, with seasonal variation shown by line color (blue for winter and orange for summer) and U.S. annual average in black dashes

Table of Contents

List of Figures

List of Tables

1. Introduction

Vehicle electrification is increasing in speed and scale, with widespread light-duty vehicle electrification moving from a question of "if" to "when" and "where." Vehicle electrification will increase electricity consumption by a substantial but manageable amount, with multiple studies projecting that full electrification of the light-duty vehicle stock would account for 13%–29% of future aggregate U.S. load (Mai et al. 2018; Fox-Penner, Gorman, and Hatch 2018; Milovanoff et al. 2020). However, for energy system planning and design, "*when* and *where* electric vehicle (EV) charging occurs will be as critical as *how much* electricity is needed" (Muratori and Mai 2020), especially in the transitional medium-term horizon.

Significant spatial and temporal heterogeneity in EV loads across the United States is expected due to variations in travel behavior, vehicle ownership preferences (e.g., pickup trucks or cars), and technology adoption. Spatiotemporal differences in EV energy use also arise from weather impacts. For example, the energy used by the same EV to drive a mile can change by up to 50%–100% in very cold temperatures. Overall, these factors combine to result in major spatial and temporal variations in EV electricity demand, which heavily impacts charging needs and implications for the electricity system. In addition, patterns in these factors are expected to change as electrified transportation technologies and infrastructure mature.

Previous literature has clearly illustrated and demonstrated significant spatial and temporal heterogeneity in EV energy use[2] (Tamayao et al. 2015; Yuksel and Michalek 2015; Wu et al. 2019; Miller, Arbabzadeh, and Gençer 2020; Desai et al. 2020; Parker et al. 2021; Yang et al. 2021; Vega-Perkins et al. 2023) due to factors such as temperature, household demographics and travel behavior, and vehicle type. However, most only present data and analysis for representative consumers, vehicles, scenarios, and/or cases—for example, for 16 regions, for four seasons, or for intermediate or representative metrics such as energy or emissions per EV or per mile—rather than projections for absolute values such as total electric load in each county. In addition, most studies focus on annual energy use, typically in connection with calculating economics of adoption or emissions benefit, while some derive hourly energy use patterns from assumed and static timing of charging. None produce hourly charging load data comprehensively for differentiated household types in every U.S. county from bottom-up simulation of heterogeneous household travel demand, vehicle ownership, transportation mode choice, technology adoption, and flexible charging. Additionally, while aggregate charging load impacts at the national level have been produced by top-down approaches, integrated assessment modeling, and other large-scale modeling efforts (e.g., the Energy Information Administration (EIA's) Annual Energy Outlook (AEO) (EIA 2019), National Renewable Energy Laboratory's (NREL's) Electrification Future Study [Mai et al. 2018]), we are unaware of corresponding spatially, demographically, and temporally disaggregated load projections that add up to national totals. The work described in this report enhances the Transportation Energy & Mobility

[2] Most studies have focused on the heterogeneity of emissions and costs associated with EV energy use, because they are also heavily spatially and temporally dependent with when, where, and how the energy is procured and consumed. Many studies have also focused on heterogeneity in both EV and non-EV energy use, affordability, and vulnerability (Zhou, Aeschliman, and Gohlke 2021; Liu and Kontou 2022). Here, we focus on spatially, demographically, and temporally differentiated EV energy consumption and charging loads, and defer to other modeling tools for detailed emissions and cost modeling.

Pathway Options (TEMPO) model to enable and create comprehensive bottom-up projections of highly resolved charging loads from simulation of representative households across the entire United States. The data resolution has been designed to integrate with bulk power system investment and operational models, in addition to enabling detailed analysis of EV charging loads.

This report describes how TEMPO was enhanced to project spatially, demographically, and temporally resolved household EV charging demand in future scenarios. Heterogeneity in many drivers of transportation demand, options, and choice are expected to contribute to heterogeneity in energy use and EV charging load profiles. In the TEMPO model, we disaggregated four major categories of inputs to the county level:

i. Household and demographics data that are most relevant to transportation demand by county, captured by the unique combinations and proportions of TEMPO's 60 household bins in each county. Each bin has unique estimates of trip behavior and mode choice affecting passenger miles traveled and vehicle miles traveled (VMT), vehicle ownership, and preferences such as those related to fuel economy and technology choice.

ii. Vehicle-related data such as stock, fuel type and technology, fuel economy, and vehicle class (e.g., midsize cars, pickup trucks) preferences by county. Each bin and county have unique distributions of these characteristics and attributes that affect vehicle availability, usage decisions, and the energy intensity of vehicle usage.

iii. Vehicle energy efficiency affected by temperature, by county, month, and hour.

iv. Vehicle electrification scenarios based on historical and existing EV adoption by county and future goals.

Table 1 summarizes the subset of TEMPO inputs that were disaggregated in this work. Appendix A and Table A-1 document other TEMPO inputs that were not disaggregated for this project but could be in the future. The methodologies and assumptions used for this enhanced resolution are documented in Sections 2.2–2.5. With these TEMPO enhancements, we are able to simulate highly resolved household travel behavior and EV ownership and use in every county. Then, Section 2.6 discusses how TEMPO was enhanced to simulate week-long trip energy consumption schedules, apply charging strategies, and generate hourly household EV charging load profiles for different scenarios. Finally, Section 3 presents summarized results from all scenarios and then focuses on detailed results from the *All EV Sales by 2035* scenario, demonstrating TEMPO's capabilities in simulating spatially, demographically, and temporally resolved household electric vehicle charging load scenarios for the contiguous United States.

Table 1. TEMPO Data Inputs Disaggregated by County

	TEMPO Data Input	National Model Resolution	Data Source	County-Level Model Resolution	Data Source	Projected Evolution
Household	Household count per TEMPO bin (household income, household composition, and urbanity) [# households/bin]	60 bins, national	National Household Travel Survey (NHTS) (FHWA 2017)	60 bins for each of 3,143 U.S. counties	American Community Survey (ACS)/Public Use Microdata Sample (PUMS) (2019), Claritas (2021)	Annual Energy Outlook (AEO) (2019)
Vehicle	Household vehicle ownership [# vehicles/households]	60 bins, national	NHTS (2017), AEO (2019)	60 bins for each of 3,143 U.S. counties	ACS/PUMS (2019), Polk (2018)	AEO (2019)
	Household vehicle stock, by size class, technology/fuel, and vintage	National	NHTS (2017), AEO (2019)	County-specific (3,143 U.S. counties)	ACS/PUMS (2019), Polk (2018)	AEO (2019)
	Household vehicle size class distributions	60 bins, national	NHTS (2017), AEO (2019)	Bin- (60) and county- (3,143) specific, via county household counts and vehicle ownership	NHTS (2017), Polk (2018)	AEO (2019)
	Household vehicle energy efficiency, by size class and technology/fuel [kWh/mi]	National	AEO (2019), Annual Technology Baseline (ATB) (2020), U.S. Environmental Protection Agency (EPA) (2019)	Bin- (60) and county- (3,143) specific, via county household counts and vehicle ownership	NHTS (2017), ACS/PUMS (2019), Polk (2018), AEO (2019), EPA (2019)	ATB (2020)
		Temporal: annual average		Temporal: Location- (geographic centroid of county population), season- (monthly average), and trip-time- (hour) specific temperature, affecting energy efficiency	Temperature: NWS/MesoWest via ComStock (Liu et al. 2023); Energy efficiency: EVI-Pro (NREL 2016), Yuksel and Michalek (2015), Geotab (2020)	Weather year 2012
Vehicle Electrification	EV sales share, by technology type [EVs/vehicles]	National	Scenario-specific: AEO (2019), Mai et al. (2018) (EFS), Biden (2021)	County-specific (3,143 U.S. counties)	Polk (2021)	CARB (ACC II), anticipated participation from states that currently follow CA ACC I (ZEV) via Section 177 of Clean Air Act, and Biden 2021 goal

2. Methods and Model Development

2.1 TEMPO Overview

TEMPO is a comprehensive transportation demand model that generates long-term scenarios of U.S. mobility energy use and emissions (Muratori, Jadun, et al. 2021). TEMPO fills a critical modeling gap by enabling national assessment of emerging transportation technologies and behaviors and cross-sectoral integrated studies (Muratori et al. 2020). TEMPO models the entire U.S. domestic passenger and freight mobility systems across all travel modes, including walking, biking, public transport, light-duty personal travel, mobility as a service (MaaS), and domestic aviation passenger modes, as well as air, rail, truck, and ship freight modes. However, the scope of this project is limited to household travel demand and household-owned passenger light-duty vehicles.

TEMPO models heterogeneous passenger travel demand by categorizing U.S. households according to socio-demographics and geographic characteristics. For each nationally representative household type, TEMPO estimates household-level, activity-based travel demand and consumer preferences for travel mode, vehicle ownership, vehicle size class, and drivetrain technology. TEMPO then characterizes available options for each trip and household by attributes such as cost and time and system-level variables such as travel mode and infrastructure availability. Then, for samples of representative households, TEMPO simulates decisions regarding trip mode choice, vehicle purchase, technology adoption, and vehicle refueling/charging. The impacts of these simulated decisions are aggregated into vehicle sales, vehicle stock, energy use, and emissions metrics.

TEMPO was originally developed to run at the national and annual level using household, travel, vehicle, and energy data binned by household income, urbanity, and household size, and with no explicit spatial resolution. However, significant variations in factors affecting mobility demand and choices exist across U.S. counties, such as household and vehicle characteristics and consumer preferences. Table 1 reviews how data for these factors were disaggregated and harmonized to enable county-level simulations for the entire United States.

At its core, TEMPO derives nationally representative household-based travel demand and attributes from the 2017 National Household Travel Survey (NHTS) (FHWA 2017). For county-level projections of travel demand, TEMPO leverages the nationally representative household-bin-specific travel behavior derived from NHTS and applies it to every county based on each county's household mix (i.e., the distribution of households in each of the TEMPO household types/bins). This draws from geographically specific data on households from the American Community Survey (ACS) 2014–2018 Public Use Microdata Sample (PUMS) (U.S. Census Bureau 2019) and proprietary Claritas data (Claritas 2021) on urbanicity to capture differences in household attributes, mobility behavior, and technology adoption. The details of this process are described in Section 2.2.

Spatial heterogeneity and differences across counties apply to vehicle-related data as well, with different levels of vehicle stock, vehicle size class, and technology preferences across different counties. Base year (2017) vehicle ownership and stock by household bin and county were drawn from both ACS/PUMS (U.S. Census Bureau 2019) and Polk vehicle registration data (IHS Markit 2018) at the county level instead of the national level. Other vehicle attributes were disaggregated by applying the nationally representative NHTS distributions to the ACS/PUMS household counts for each county. The details of this process are described in Section 2.3.

Temperature affects the energy efficiency of EVs; Section 2.4 addresses how vehicle energy efficiency in TEMPO was adjusted to account for location-specific seasonal temperature. Adoption of EVs significantly varies across the country and over projected years; Section 2.5 discusses one of TEMPO's approaches in determining disaggregated EV adoption for the simulated scenarios in this report. Finally, EV charging occurs at instances throughout days and weeks; Section 2.6 describes the assignment of charging amounts and times for each vehicle and household in each county according to simulated trip schedules, charging constraints, preferences, and behaviors.

2.2 Disaggregating Household Counts for Each TEMPO Household Bin to the County Level

In TEMPO, households are classified along three dimensions: income (low, middle, high), household composition (no driver, single driver, small driver household, large driver household), and urbanity (rural, small town, second city, suburban, urban). NHTS (2017) data were used to develop unique travel demand profiles (trip length, frequency, vehicle occupancy distributions, mode preferences) for each of these 60 bins[3] (Muratori, Jadun, et al. 2021). Figure 1 shows national household counts in each household bin.

[3] TEMPO's 60 household bins arise from the combination of 3 income bins (low, household income <$50,000; middle, $50,000–125,000; high, >$125,000) × 4 household composition bins (No Driver; Driver, Single [1-person household]; Driver, Small [2-person household]; Driver, Large [3+]) × 5 urbanity bins (Urban, Suburban, Second City, Small Town, Rural).

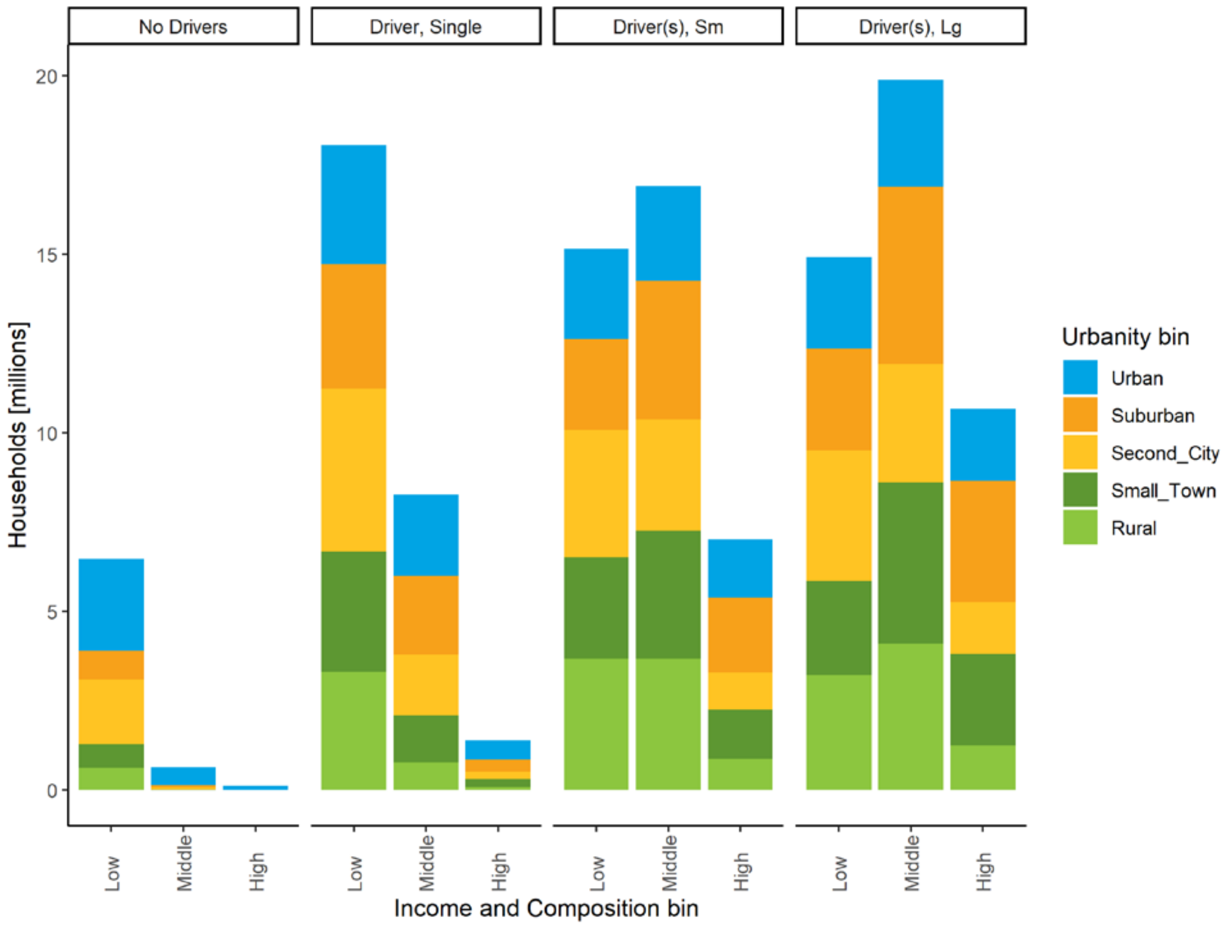

Figure 1. National household counts by TEMPO household bin as of 2017.

Data from NHTS (2017). Each colored segment represents one of 60 TEMPO household bins.

A number of households are sampled to represent each bin in TEMPO simulations and then weighted by the number of households in that bin divided by the number of samples to produce nationally representative results, leveraging unique travel behavior and patterns estimated for each household bin based on NHTS households. For example, in TEMPO, No Driver households have very different travel behavior than other types of households and are weighted according to their counts, reflecting their prevalence in the United States.

To estimate household counts by TEMPO household bin (three-way joint distributions) for every county, two-way joint income and composition household counts at the census tract level were constructed via iterative proportional fitting (IPF) using data from ACS5 (2014–2018)[4] supplemented by PUMS data,[5] building on methodology used in the Low-Income Energy

[4] Because the NHTS (2017) data were collected between 2016 and 2017, the time frame of the ACS5 2014–2018 data set is the closest match, though data for some census areas in this data set will be from 2014 and others will be from 2018, creating some inherent mismatches to the NHTS data.

[5] The ACS5 data are used to inform the 1D distributions of households in each income and composition bin at the tract level, while PUMS data informs the 2D distribution of households in each income and composition bin at the PUMA level. These are combined using IPF with ACS5 data as enforced marginal totals and PUMS microdata as seed data.

Affordability Data (LEAD) Tool (Ma et al. 2019). The third dimension (i.e., urbanity) was then added based on data at the census block group level from Claritas, a firm specializing in marketing and customer segmentation that provided the same definitions for the NHTS. Figure 2 summarizes the distribution of urbanicity across the United States.

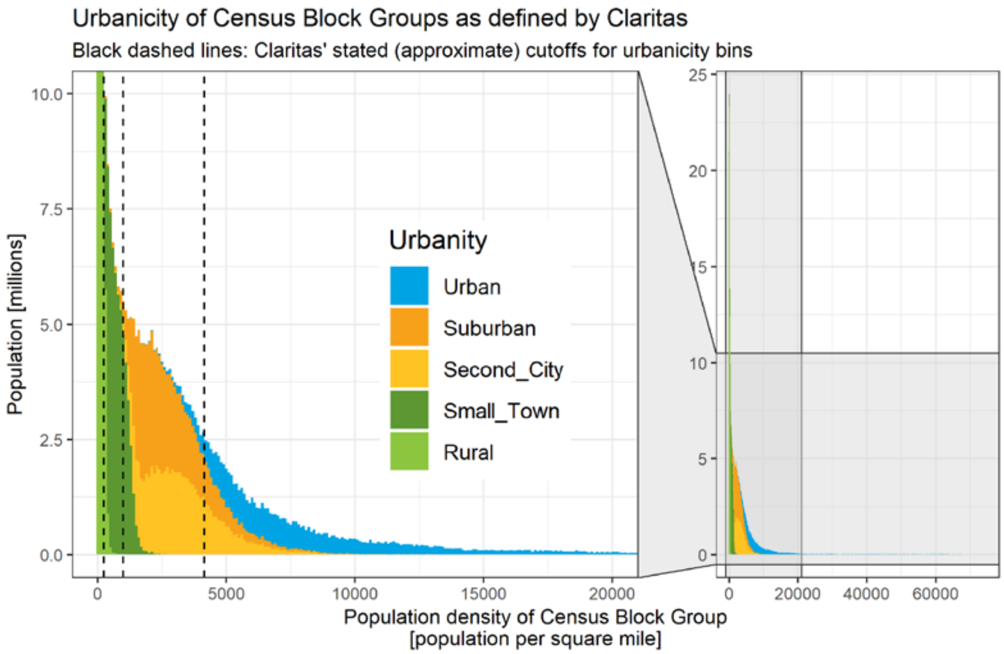

Figure 2. Summary of Claritas urbanicity data plotted against raw population density (population per square mile).

The black dashed lines are Claritas' publicly stated approximate cutoffs for urbanicity bins. The proprietary Claritas definitions include manual assignment based on other factors such as geographic contiguity, particularly to distinguish between "suburban" and "second city," which had the same population density cutoffs but were determined based on neighbors and access.[6]

These urbanicity data were aggregated to produce urbanity distributions within each census tract and then combined with the tract-level income and composition data and further aggregated to generate joint distributions[7] of households in every bin for every county.

To illustrate the variety of household counts in different U.S. counties, Figure 3 and Figure 4 show the resulting household counts for selected counties, and Figure 5 maps out the heterogeneity across the contiguous United States. For those familiar with U.S. geography, the trends seen in the figures likely confirm expectations. The sheer amount of heterogeneity seen across these transportation-relevant characteristics suggests that most county-level TEMPO results are unlikely to resemble the national averages given by the national-scale TEMPO model. Furthermore, even counties that are nominally similar (like all-urban New York and San Francisco) have different breakdowns in terms of income and number of drivers, as well as characteristics of the mobility systems and travel options (e.g., public transit speed and

[6] Attempts at replicating Claritas' definitions based on ACS population density data and GIS analysis were blocked by proprietary definitions, a lack of transparent methodology, and a lack of validation data. Assignment of urbanity based solely on publicly available data was generally valid but noticeably different in inspected areas.
[7] Also known as cross-tabulation by multiple variables.

availability) that differentiate TEMPO's findings in terms of vehicle adoption, trip modalities, and energy use (with the caveat that public transit availability inputs in TEMPO have not yet been made more geographically specific than urbanity).

This derived set of household data is used as the 2017 baseline for TEMPO and scaled to match the NHTS and U.S. Energy Information Administration (EIA) national totals. TEMPO then uses national household[8] growth projections from EIA AEO and applies them uniformly to every county and bin. This means that TEMPO does not project growth in household counts differently for different household bins or counties and does not project changes to the distribution of household income, sizes, or urbanicity in individual counties over time. For example, TEMPO does not currently account for population migration between counties or from/to the United States; changing demographics such as rising or falling real incomes by county; changes in household sizes, drivers, or ages differing by county; or urbanization or densification.

[8] A potential future source of population data and projections is LandScan, which may help improve the resolution of population projections across the United States. While changes in demographics within each county may not be captured by LandScan if the data are not demographically distinguished, changes in U.S. demographics overall may be captured if LandScan projects higher population increases in areas of certain demographics—for example, in urban areas or richer areas, thereby representing more urban households in the future or more households being higher income in the future. We stress that this would likely only capture part of the actual demographic trend because the household bin distributions remain fixed at the county and national levels and we do not have comprehensive projections how these distributions will shift in the future, particularly at the necessary geographic resolution.

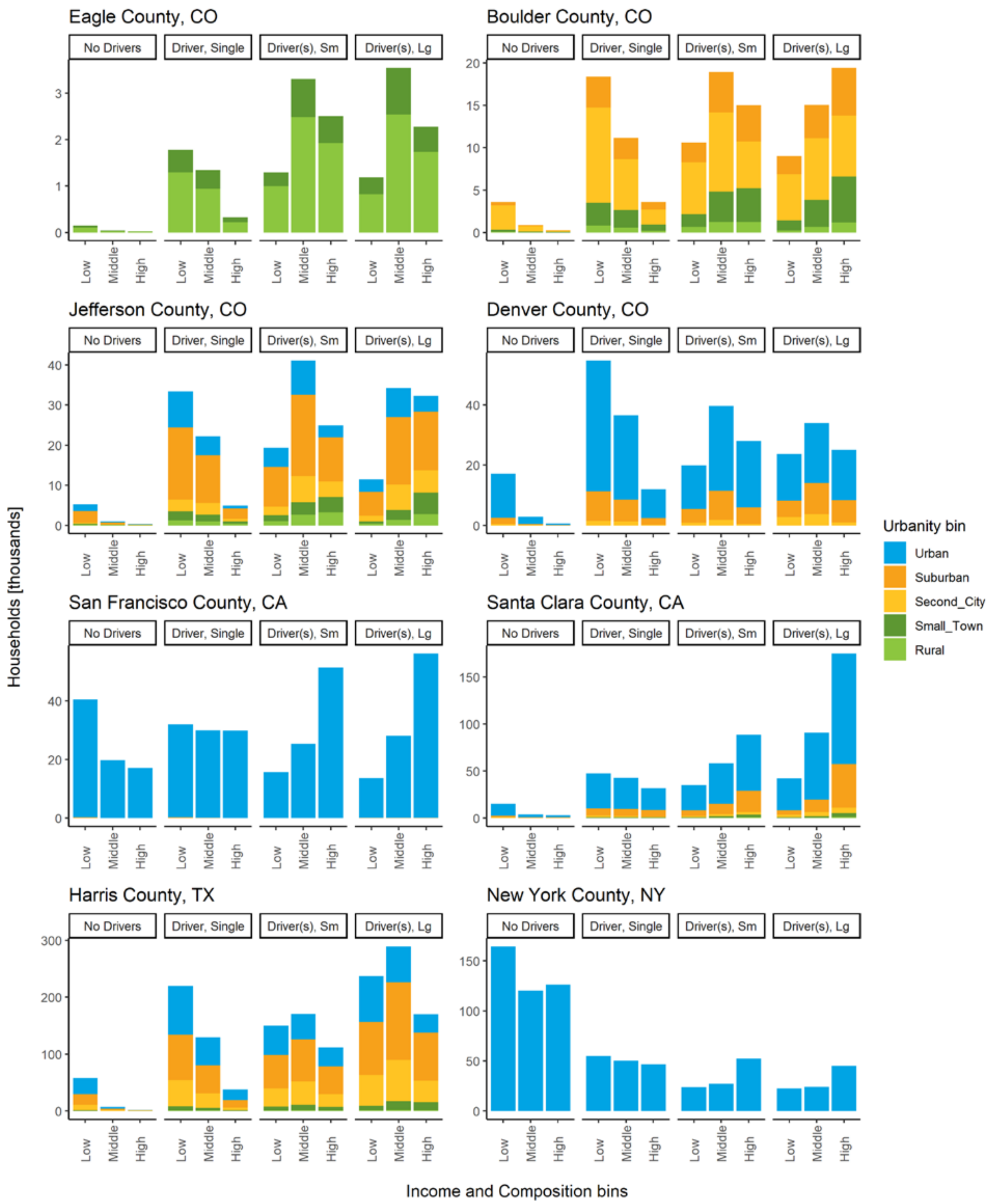

Figure 3. Household counts by TEMPO household bin for selected U.S. counties as of 2017.

Data derived from ACS/PUMS (2018). Every county is represented by a unique mix of household counts in each of the 60 TEMPO household bins. TEMPO samples from each bin in every county, allowing the model to consider both household-bin-specific and county-specific factors affecting trips and choices.

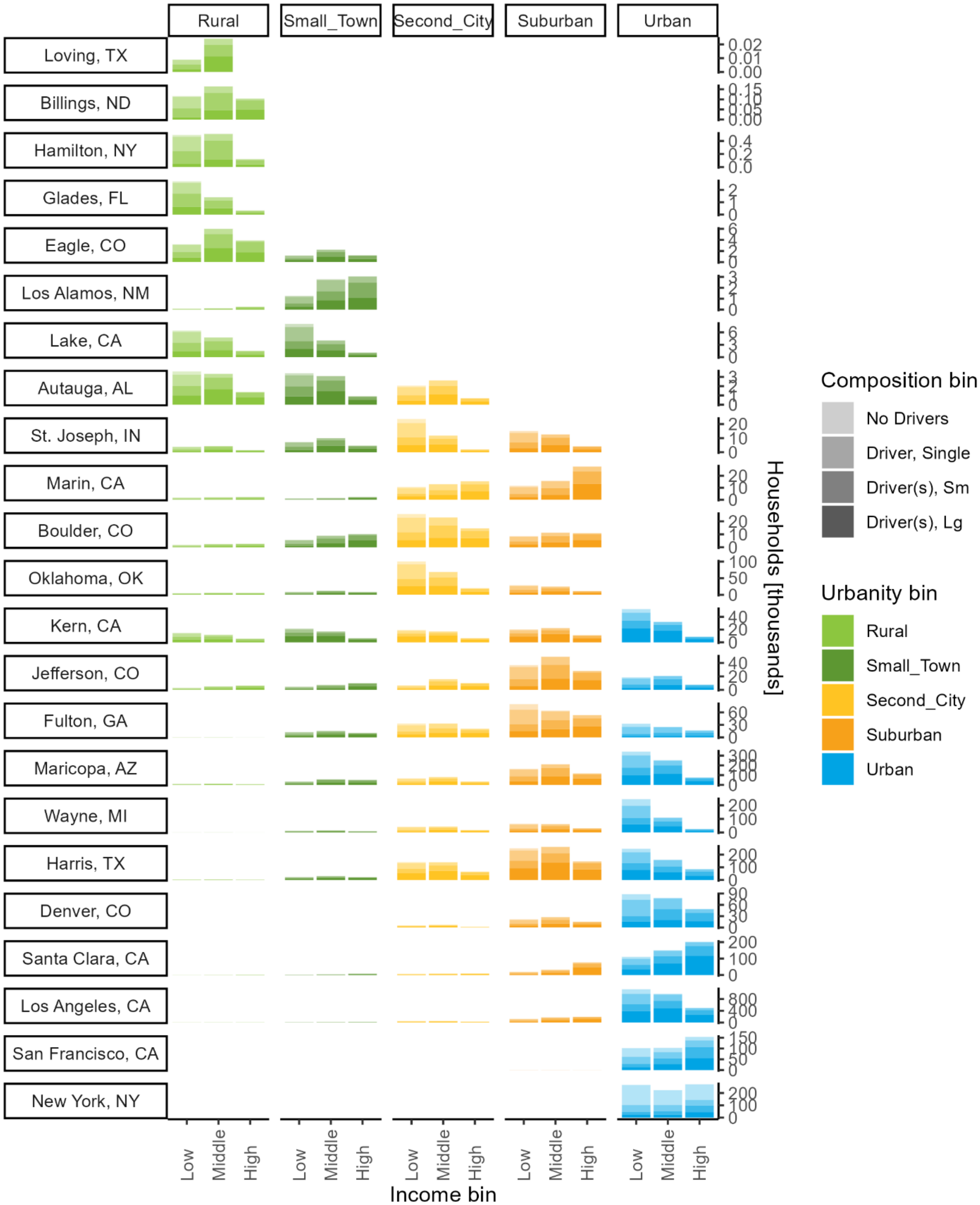

Figure 4. Household counts by TEMPO household bin for selected U.S. counties, ordered by population density, as of 2017.

Data derived from ACS/PUMS (2018). Every county is represented by a unique mix of household counts in each of the 60 TEMPO household bins. TEMPO samples from each bin in every county, allowing the model to consider both household-bin-specific and county-specific factors affecting trips and choices.

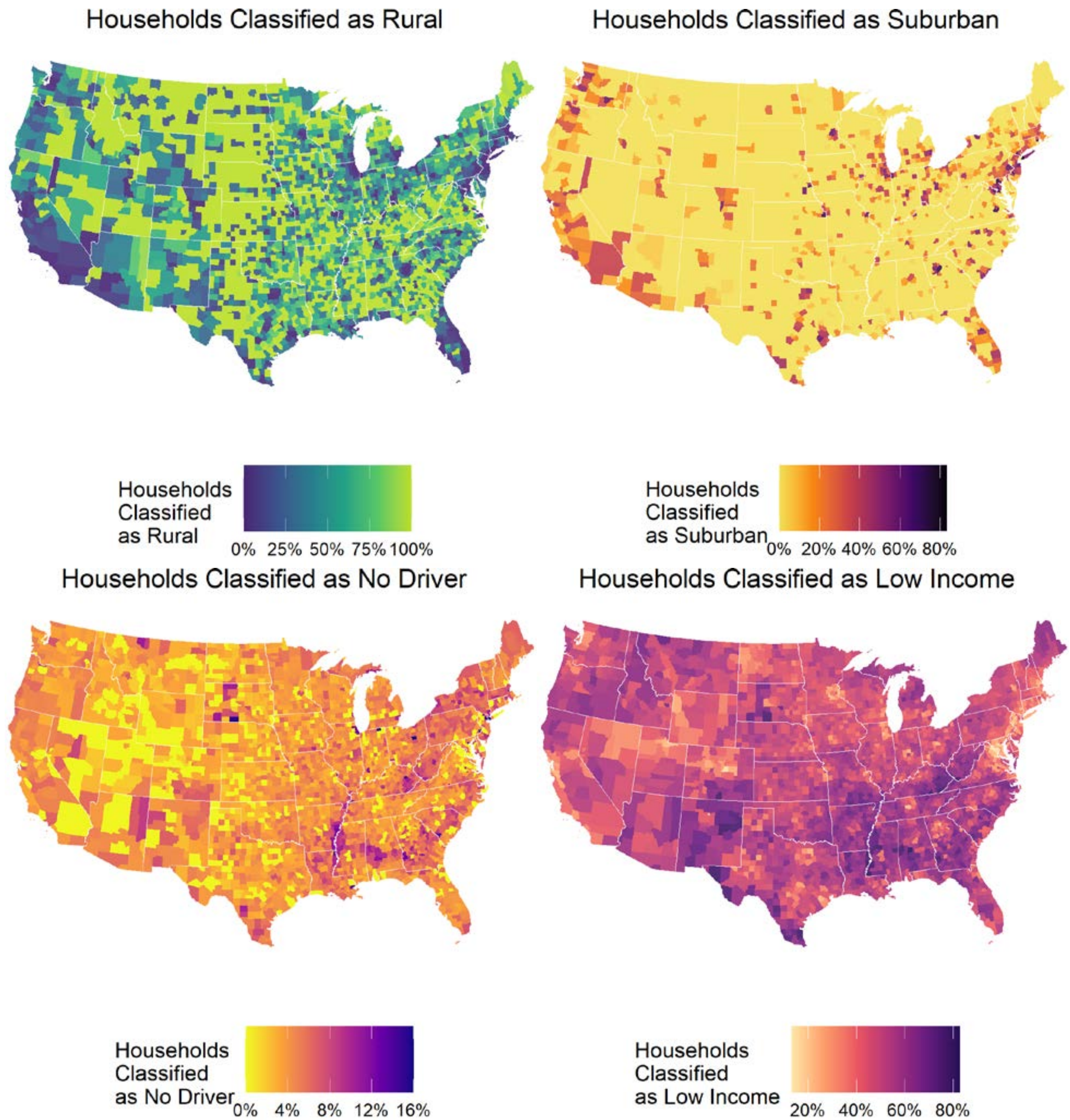

Figure 5. Proportions of households in selected urbanity, household composition, and income bins in each county in the United States as of 2017 (TEMPO baseline calibration year).

Many counties exclusively contain rural-classified households. Most counties have very few households with no drivers. Many counties across the United States have large proportions of households classified as low-income.

The household data derived from ACS/PUMS using IPF were validated by comparing aggregate results to the NHTS and AEO data, checking the national totals first, then by household dimension, and then by each bin. Figure 6 shows minor discrepancies in totals between data sources, which we concluded to fall within a reasonable margin of error due to definitions, such as driver status, year of survey, and inherent uncertainty from survey results.

Figure 6. Total number of U.S. households across each of TEMPO's three household bin dimensions, with comparison between TEMPO national distributions (red, data from NHTS) and TEMPO county distributions (blue, data based on ACS/PUMS/Claritas), aggregated to the national level.

2.3 Disaggregating Vehicle-Related Data

Besides household composition variability, there are also significant county-level differences in vehicle ownership and vehicle class preferences. At the national level, TEMPO uses NHTS (2017), Polk (IHS Markit 2018), AEO (EIA 2019),[9] and ATB (NREL 2020) for base year (2017) data on light-duty vehicle ownership, stock, and attributes (fuel/technology type, size class, and energy efficiency). Future projections for these data are also taken from the same sources to

[9] In addition, AEO reports composite test cycle fuel economy in mpg-equivalent—i.e., the ratings in the EPA Fuel Economy Guide, but calculates actual energy use accounting for on-road actual use with degradation factors. Details in EPA 420-R-06-017. In this work, the energy adjustment due to temperature incorporates both a temperature dependency and a real-world efficiency adjustment relative to the EPA rating.

create a reference scenario and scenarios with different technology costs and fuel prices. Additional scenarios are created by exogenously changing parameters related to energy efficiency and sales shares by technology. Analysis of these different possible futures demonstrates the relationship between key input variables and outcomes in terms of mobility, energy use, costs, and emissions.

To create county-level TEMPO, we estimated household-bin- and county-specific discrete distributions of vehicle ownership from the ACS/PUMS-derived vehicle ownership data. This allows for better county specificity and larger sample sizes than applying NHTS bin-specific distributions.[10] While this shifts the data source for vehicle ownership from NHTS, a transportation-focused survey, to ACS, a broader demographics survey, we found that the overall mean vehicle ownership based on ACS was aligned with that from NHTS. However, in both the aggregated NHTS national total and ACS county totals (survey data), vehicle counts were on average about 11% lower than those in AEO and Polk vehicle registration data,[11] potentially reflecting survey bias or some mismatch in definitions of household vehicles. TEMPO addresses this by scaling its ACS-derived vehicle ownership discrete distributions (shifting of means) to match[12] AEO/Polk vehicle count totals in each county for 2017 (the TEMPO calibration year). Finally, projections to 2050 were created by scaling these disaggregated vehicle ownership distributions based on the EIA AEO trend in vehicle ownership.[13]

Vehicle size class and energy efficiency distributions were also disaggregated into county- and household-bin-specific distributions. We applied NHTS (national) size class distributions to ACS (county) household counts to maintain household bin integrity and consistency so that appropriate travel behaviors were matched with their likely vehicle owners and vehicle attributes. Although using detailed Polk registration data about vehicles would result in better county specificity (with directly observed county-specific data providing greater fidelity), it requires assumptions that enforce all types of households in a county having the same county-specific distribution of vehicles, which could assign the wrong types of vehicles to many

[10] An alternative simpler approach that would maintain household bin specificity and national model alignment would be to apply the NHTS (national) bin-specific vehicle ownership distributions to the ACS-derived county-level household bin counts. However, this would likely cause some loss of county-specific variation that is not explained by TEMPO's household bin classification.
[11] Total 2017 registered non-fleet light-duty vehicles from Polk: 238 million, compared to total 2017 household-owned vehicles derived from ACS: 212 million.
[12] We also find several small outlier counties with very high (up to 9) and very low (0.5) registered vehicles per household based on Polk data, which likely reflect anomalies or quirks in registration behavior or data issues. We re-estimate the vehicle counts and distributions for these outlier counties based on that expected from NHTS and ACS data.
[13] AEO's projection of vehicle ownership is roughly a constant 0.8 vehicles per capita for 2017–2050.

households.[14] Further disaggregation of size classification and energy efficiency is limited by data availability.[15]

We then created projections to 2050 for vehicle size class and fuel economy by scaling these disaggregated starting points using the national projected trends in size from EIA AEO (EIA 2019) and projected trends in fuel economy from NREL's Annual Technology Baseline (ATB) Mid and Advanced trajectories (NREL 2020). Similar to the projections for household data, the projections for vehicle data were scaled uniformly. These attributes are disaggregated and calibrated to the heterogeneity observed in 2017, and then their values are projected forward uniformly by the national trend from EIA AEO and NREL ATB.[16] For example, EIA projects a continued national shift away from compact cars toward SUVs. TEMPO builds on the existing distribution in preferences seen across individual household bins and counties and projects a nation-wide shift in vehicle size preference from compact cars toward SUVs for every household bin and county.[17] In both EFS and All EV Sales by 2035 scenarios, vehicle energy efficiency are based on the NREL ATB 2020 Advanced trajectories.[18] In addition, vehicle energy efficiency is further adjusted from rated values according to temperature, as described in the next chapter.

Figure 7 and Figure 8 show the disaggregated vehicle data based on the aforementioned methods for 2017 and reflect the heterogeneity in vehicle ownership and size classes across the United States represented in TEMPO.

---

[14] Polk ZIP code/county-level data about size class distributions and make-model information that can be associated with EPA-based fuel economy statistics could be used for county-specific detail, but household bin information would be lost because the vehicle characteristics would be applied uniformly to the mix of household bins in the county. The trade-off considered is whether county disaggregation or household-bin disaggregation captures the heterogeneity in household vehicle characteristics and attributes.
[15] For example, we use EIA AEO's estimated real-world energy efficiency performance adjusted from test cycle results, but this varies in reality according to finer heterogeneity in driving and road conditions, road grade, and city/highway driving. These conditions can be expected to differ by urbanity and county, but is not captured in this work.
[16] That is, we do not project that certain household bins, counties, or vehicle types will change in vehicle ownership levels, vehicle size preferences, or vehicle fuel economy differently than others.
[17] Building on this example: Some household bins and counties already have few compact cars and many SUVs. The national trends in vehicle size class preferences are uniformly applied as rates of change so that the aggregated projections of all households and counties align with the national projection. This results in maintained growth in relative SUV share in these household bins and counties, as opposed to an alternative assumption where there is potential saturation in these bins and counties and relatively more growth in other bins and counties.
[18] However, note that the original EFS study used projections from Jadun et al. (2017) and Moawad et al. (2016), reflecting lower EV energy efficiencies (and resulting in higher load per EV-mile) than was simulated in TEMPO, even in the "EFS" scenario. See Scenario Results Summary section for discussion of impact on results.

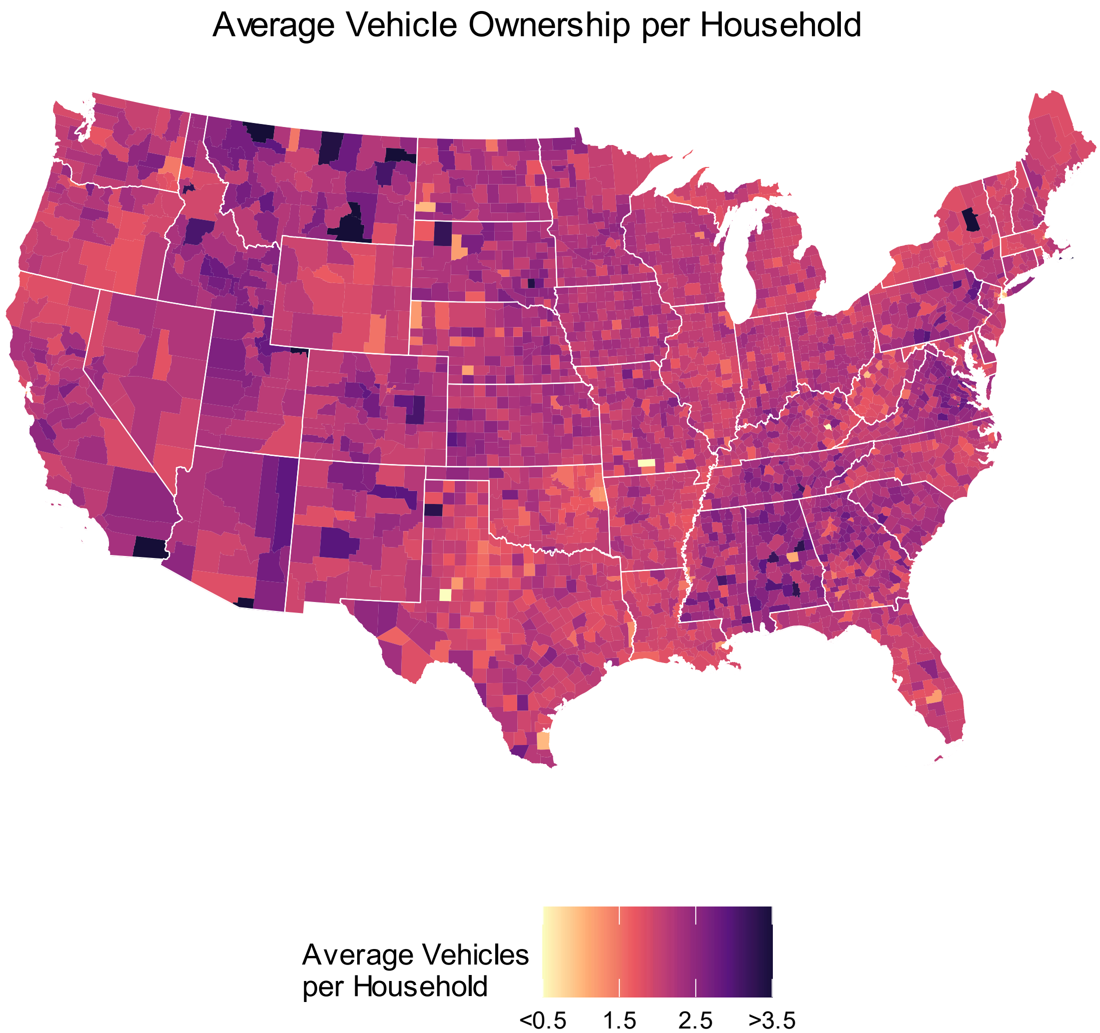

Figure 7. Average vehicle ownership per household by U.S. county as of 2017, based on ACS/PUMS household microdata and Polk registration data

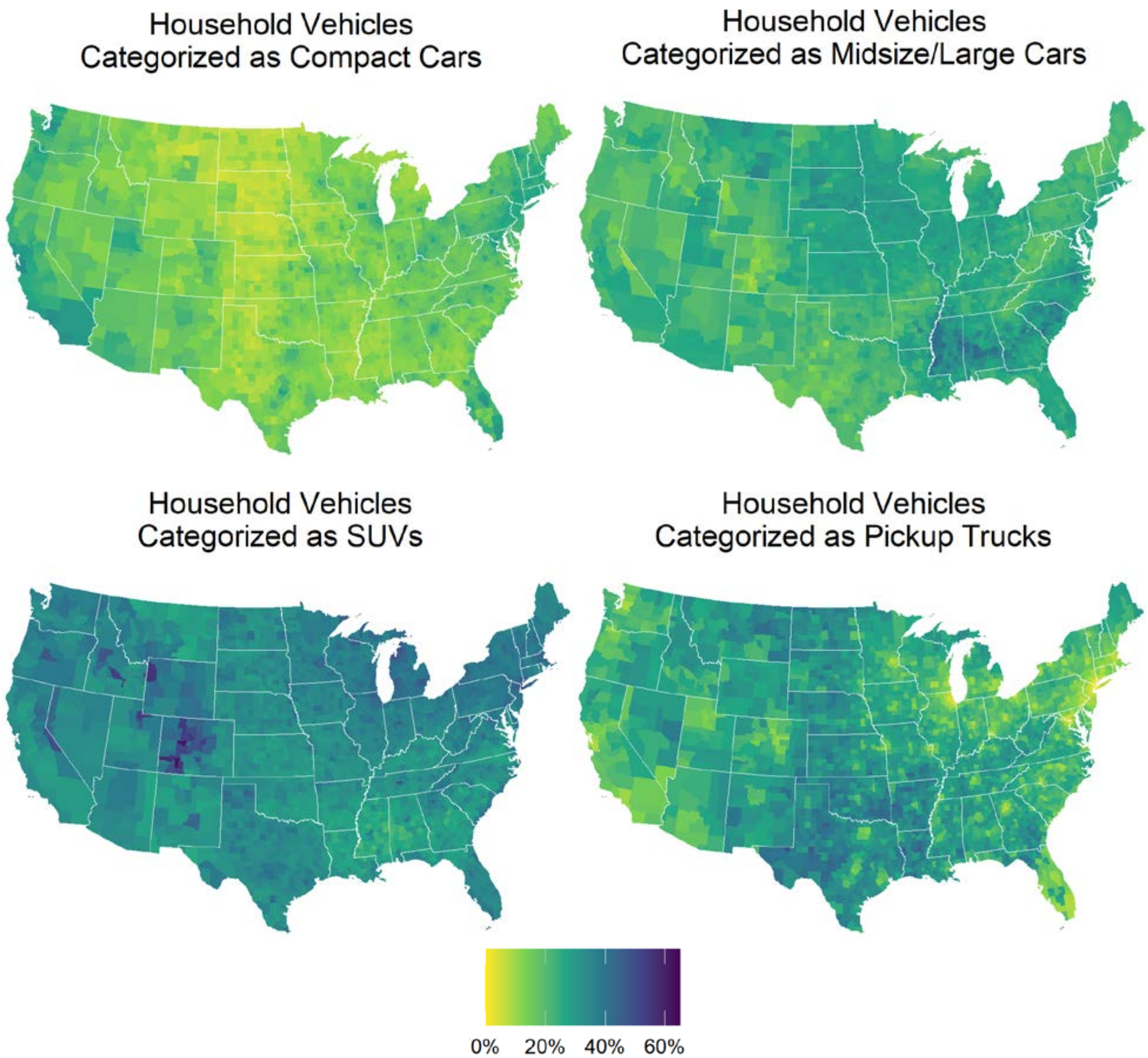

Figure 8. Proportions of vehicle size class across U.S. counties in 2017 based on Polk registration data.

Consumers in different areas of the United States have adopted vehicles of different sizes. TEMPO uses these data to set the baseline for county-specific vehicle size class distributions, which enables projection of consumer preferences based on existing heterogeneity in size class preferences. Vehicle size class mix affects county-specific vehicle electrification rates and vehicle energy use.

2.4 Accounting for the Effect of Temperature on EV Loads

Vehicle energy use depends on ambient temperature because of impacts on heating and cooling energy use and equipment performance (Miller, Arbabzadeh, and Gençer 2020; NREL 2016; Yuksel and Michalek 2015). EVs are disproportionately affected by temperature compared to conventional internal combustion engine vehicles, due to the sensitivity of batteries and direct-current fast charging (DCFC) chargers to temperature, lack of engine waste heat to reuse for cabin heating, and the relative efficiency of the electric drivetrain, which magnifies the heating and cooling load portion of total vehicle energy consumption. For example, the energy used by the same EV to drive a mile can change by up to 50% at temperature extrema (NREL 2016; Geotab 2020), heavily impacting vehicle range, charging needs and resulting loads, cost of driving, and consumer experience. This means using national annual average fuel economy and energy efficiency metrics can obscure variation in vehicle energy use in different locations and at different times of day and seasons of the year, which is of particular interest to the NREL demand-side grid (dsgrid) project and for grid planning and operational studies more broadly. Therefore, in addition to disaggregating TEMPO inputs spatially by county, TEMPO was modified to capture region- and season-specific effects on vehicle energy use and charging.

TEMPO adjusts vehicle energy efficiency and DCFC charger efficiency as a function of ambient temperature based on vehicle test data (Yuksel and Michalek 2015; NREL 2016)[19] and DCFC charger test data (INL 2016) reflecting energy use under different temperature conditions. These data and relationships are consistent with those used in EVI-Pro (NREL 2016) and have been validated against recent 2020 data from Geotab[20] (Geotab 2020). Summaries of these relationships are shown in Figure 9 through Figure 11.

[19] In the *National Economic Value Assessment of Plug-In Electric Vehicles* (NREL 2016), temperature-based EV energy consumption adjustment was based on Yuksel and Michalek (2015)'s fit to FleetCarma/Geotab data shown as "CMU Leaf Fit" and on NREL-collected data on a Ford Fusion.

[20] Geotab (2020) describes their data sample as "5.2 million trips taken by 4,200 EVs representing 102 different make/model/year combinations from model years 2010–2019". Geotab's data disclaimer: "Temperature-range curve is derived by Geotab from >4000 connected light duty EVs. Rated range refers to EPA 5-cycle test. This data is subject to change as additional data is collected and analyzed. Please refer to Geotab.com for the most up-to-date tools and analysis. v.1.0 May 2020"

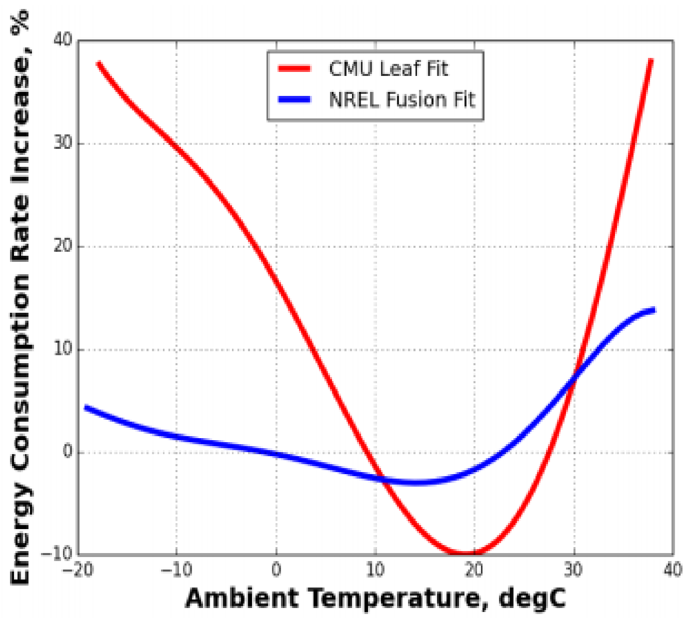

Figure 9. Battery-electric vehicle (BEV) ("CMU Leaf") and internal combustion engine vehicle ("NREL Fusion") energy efficiency adjustment for different ambient temperatures based on NREL 2016, Yuksel and Michalek 2015, and Fleetcarma (Geotab) 2014 data

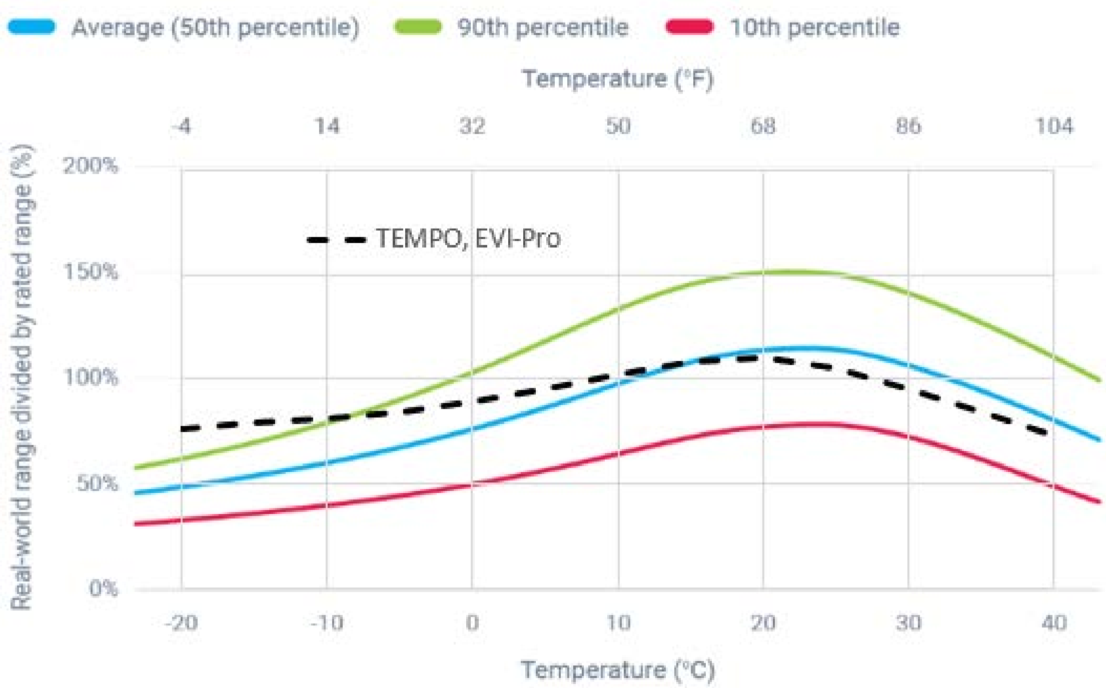

Figure 10. BEV energy efficiency adjustment in TEMPO and EVI-Pro (black dashes) compared to Geotab (2020) data (colored lines for average, 90th, and 10th percentiles) [21]

[21] We note that the current TEMPO and EVI-Pro BEV energy efficiency adjustment (black dashes) deviates from the median (50th percentile) of the Geotab (2020) data (blue line), especially at lower temperatures, and therefore underestimates energy consumption at these low temperatures. In upcoming model releases, we plan to recalibrate

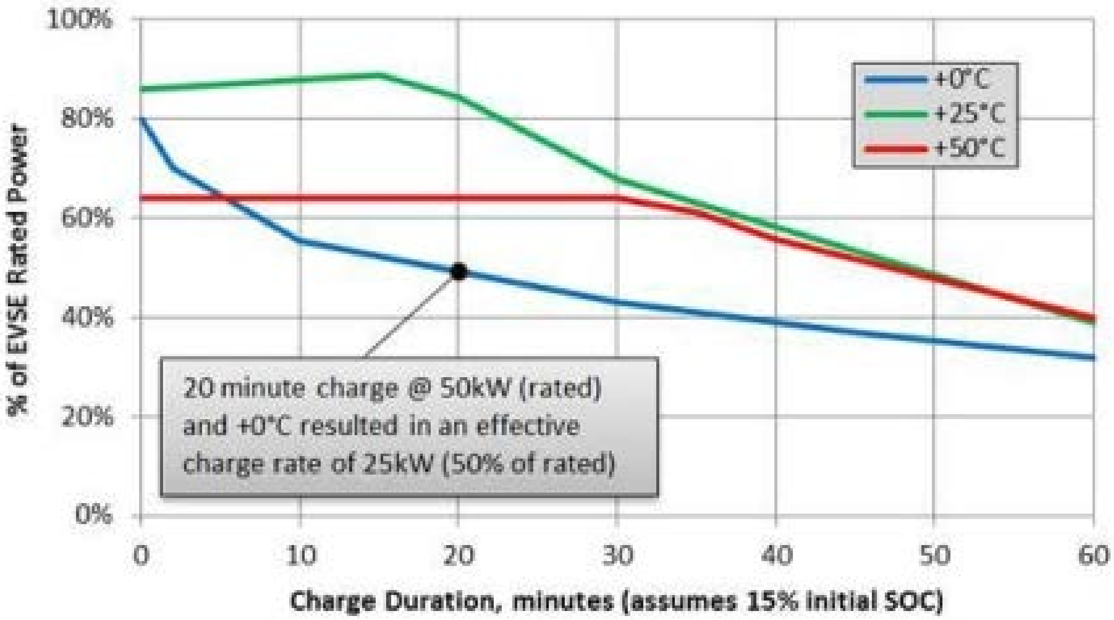

Figure 11. Effective DCFC charger efficiency for three different ambient temperatures.

Source: INL 2016

For consistency with dsgrid and other participating models (ResStock and ComStock), we use exogenous county-specific data for a specific weather year, 2012, from MesoWest/National Weather Service weather station aggregates collected by the ComStock team (Liu et al. 2023). From these data, TEMPO extracts a snapshot of average ambient temperatures for each hour of the day for every month and county for the 2012 weather year. For each trip or charging event, TEMPO calculates and applies an adjustment to vehicle and charger energy consumption according to this temperature at the time of day (hour), month, and county (weather station closest to county population centroid) of the event. This directly increases (or reduces) the electric load from charging EVs at these locations and times. While EV adoption and use decisions may also be indirectly affected by temperature impacts, TEMPO currently only considers the direct impact of temperature on EV load via adjusted energy intensity. Figure 12 shows ambient temperatures across the United States at two example points in time and their associated adjustment to energy consumption.

these adjustments to reflect the best available information on BEV performance in low-temperature conditions. However, recent and rapid technological changes in reconfigured and improved air conditioning/heat pump systems in new EVs are expected to mitigate some of the additional energy use at temperature extrema.

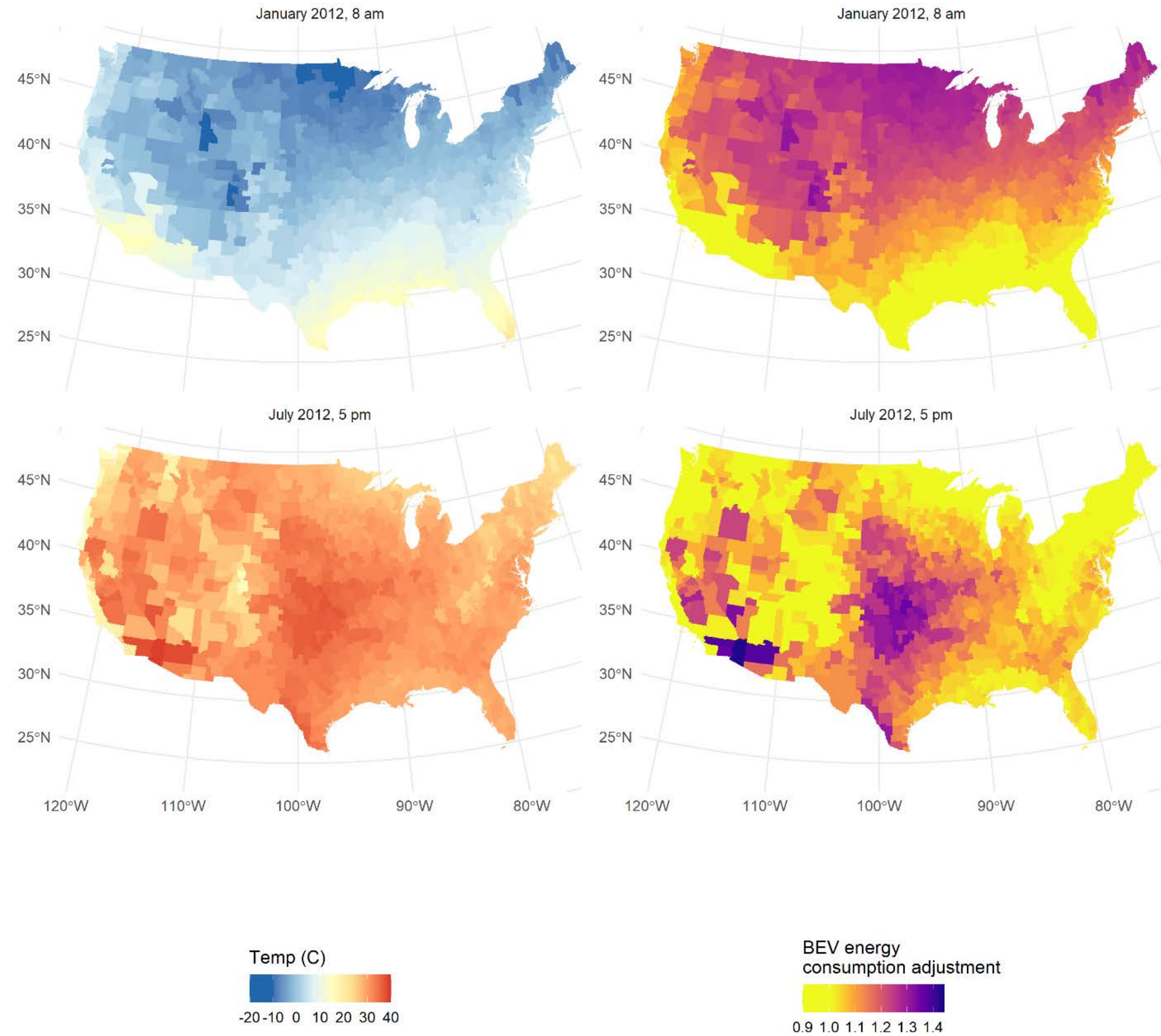

Figure 12. Ambient temperatures (left) and impact on BEV energy consumption (right) across the United States for January 2012, 8 a.m., and July 2012, 5 p.m., reflective of spatial, temporal, and seasonal variation in weather conditions.

Data from Liu et al. 2023.

To further demonstrate the range and variation in energy efficiency adjustment due to temperature, Figure 13 shows this simulated adjustment factor for each month and weather station location in the United States. The national median trend (black line in Figure 13) has EV energy consumption per mile at its highest in the winter, lowest in the spring and fall shoulder seasons, and around or just higher than the EPA rating during the summer months. However, each U.S. county has its own weather patterns, and “average” or “median” weather can therefore be misleading. Following the colored lines for four selected locations in the United States, we see very different EV energy consumption patterns. A location such as Minneapolis-St. Paul (blue line) can be considered to have similar temperature impacts on EV energy consumption as predicted by the U.S. median (black line), with higher energy use in winter months and slightly higher than rated energy use in the summer too. However, this is only one type of weather pattern in the United States; in a location such as Sacramento (yellow line), we see larger summer and smaller winter peaks, while in a location such as Phoenix (orange line), we see very large increases in energy consumption during summer months and no increases in the winter. In a location such as Los Angeles (green line), we see a year-round EV energy consumption below the EPA-rated value due to milder weather conditions compared to those in the EPA test cycles. These distinct variations in weather patterns and their impact on energy use are incorporated into TEMPO's county-level simulation results.

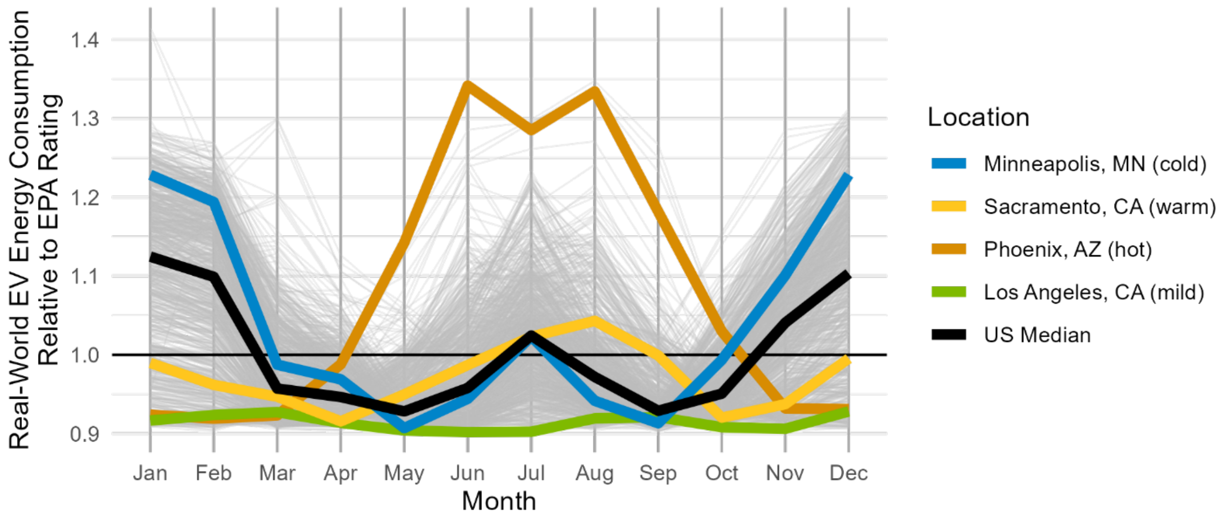

Figure 13. Adjustments to EV energy consumption in TEMPO based on weather year 2012 temperatures.

The data for all 975 U.S. weather stations used in this study (from Liu et al. 2023) are shown in grey. The national median pattern is shown in black. Lines for four selected locations (colored lines) demonstrate distinct seasonal patterns, which are used to adjust EV energy consumption with location specificity.

2.5 Developing Vehicle Electrification Scenarios

The future is already here; it's just not very evenly distributed.

– William Gibson

TEMPO has the capability to project vehicle electrification endogenously using a utility-based technology choice logit algorithm (Muratori, Jadun, et al. 2021), or to apply sales shares based on exogenously defined scenarios. Exogenous sales shares are uniformly applied to all vehicle size classes.[22] For this report, we simulated three exogenous passenger light-duty EV adoption scenarios, shown in Figure 14:

A. *AEO Reference Case*, with EV adoption aligned with the Reference Case in the 2018 EIA Annual Energy Outlook (AEO) (EIA 2019), which was used to calibrate the TEMPO model.

B. *EFS High Electrification*, with EV adoption in line with the High Electrification scenario in the NREL Electrification Futures Studies (EFS) (Mai et al. 2018).

C. *All EV Sales by 2035*, assuming U.S.-average EV sales reaching 50% in 2030 and 100% in 2035, in line with various announced targets.

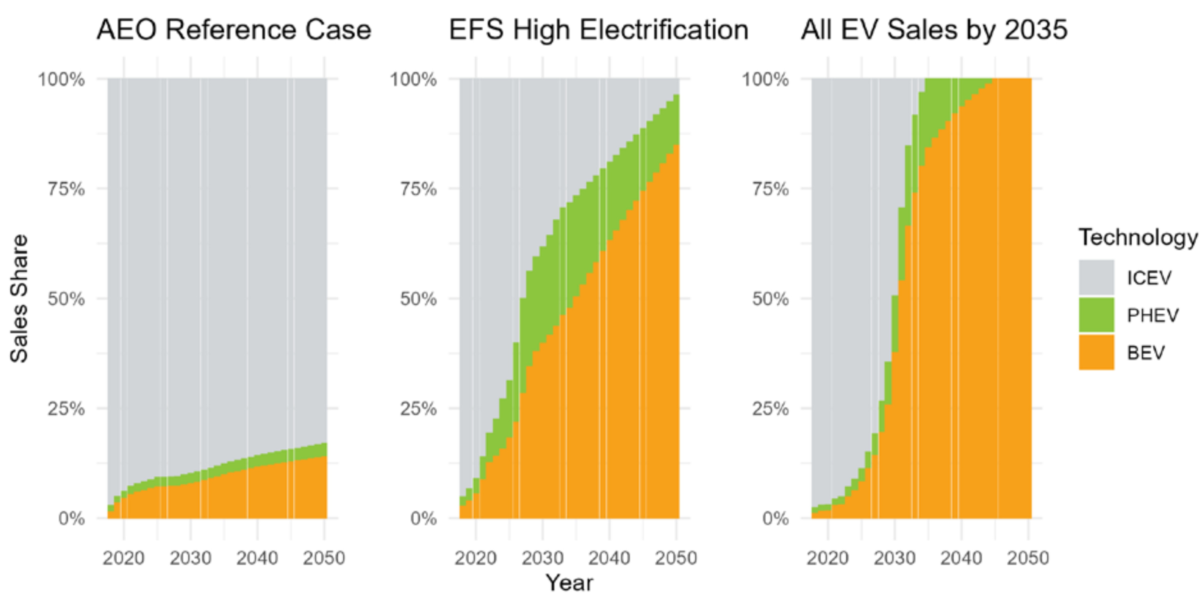

Figure 14. Projected national technology sales shares for each EV adoption scenario

In the AEO Reference Case scenario, mobility evolution and technology adoption were calibrated to align with the EIA AEO 2018 Reference Case. The EIA AEO Reference Case is a baseline projection that assumes no new policies and static technology, reflecting "business-as-usual" conditions that should not be mistaken for a scenario representative of what is likely to happen in the future (EIA 2019). In the EFS High Electrification scenario, EV adoption results from "a combination of technology advancements, policy support, and consumer enthusiasm that

[22] We note that as of 2023, EVs still do not yet exist in every vehicle size class and segment, but also note rapid growth in EV model options in recent years, globally and in the United States.

enables transformational change in electrification" in line with that assumed in the NREL EFS (Mai et al. 2018) High Electrification scenario. This is characterized by advanced EV cost and performance improvements and strong EV policies. The High Electrification county-specific projections represent pathways and outcomes consistent with the national EFS scenario rather than precise projections of the future for each county. In the All EV Sales by 2035 scenario, national EV adoption reaches 50% in 2030, aligned with the national goal announced in a 2021 Biden Administration Executive Order,[23] and 100% by 2035, a target roughly aligned with announced commitments of several major automakers and "ICE Phase-Out" targets of sub-national governments and global coalitions, including the 2035 timeline set in the zero-emission vehicle (ZEV) state mandates regulating manufacturer fleet composition in California and several other U.S. states that have announced they will follow with the same ambition (New York, Washington, Massachusetts, Oregon, and Vermont).[24] In this scenario, plug-in hybrid electric vehicles (PHEVs) are assumed to be 20%–30% of the total EV sales share in the 2025–2035 transition time frame before tapering off to 0% by 2045, based on expert opinion and latest trends in BEV technology, infrastructure, and policies.

While exogenous scenarios and projections are defined at the national level, EV sales and stock data disaggregated to the county level are only available for historical data. In other words, the national-level scenarios do not project where EV sales may be lower or higher than the national average in future years. We disaggregate projected EV adoption by county by anchoring each county's EV sales share for the base year to county-level vehicle registration data from Polk in the base year[25] and then applying the exogenously defined national-level growth rate trends uniformly across all counties. This approach captures the current heterogeneity in EV adoption observed across U.S. counties and extends this into the future, assuming similar positioning of counties in terms of EV adoption either leading or lagging the national average growth trend. Counties in states with ZEV regulations aligned with California[26] are also assumed to lead the national average growth trend (i.e., grow faster and earlier than the national average).

[23] "50% clean car sales by 2030" https://www.whitehouse.gov/briefing-room/statements-releases/2021/08/05/fact-sheet-president-biden-announces-steps-to-drive-american-leadership-forward-on-clean-cars-and-trucks/

[24] Section 177 of the Clean Air Act allows other states to adopt California's vehicle emissions standards. As of 2023, five states (Washington, Massachusetts, New York, Oregon, and Vermont) have adopted standards equivalent to the most recent (finalized in 2022) California Air Resources Board Advanced Clean Cars II (ACC II) program, which will require manufacturers to sell 100% ZEV by 2035. https://cleantechnica.com/2022/12/23/canada-joins-california-oregon-washington-vermont-in-clean-transportation-push/. In addition, internationally, countries such as Canada (2035), the UK (2035), Norway (2025), France (2040), Netherlands (2030), and Austria (2030) have announced 100% ZEV targets, either via fleet composition regulation and credit compliance or GHG standards. https://theicct.org/phase-out-map-ldv/.

[25] While TEMPO's base simulation year is 2017, it is possible and useful for exogenous EV sales share projections to be anchored and calibrated to the most recent EV sales data (e.g., 2022). We expect to regularly update these scenarios of EV sales, given the rapid pace of change in EV adoption across the United States.

26 As of 2023, states that have joined California in its Low-Emission Vehicle (LEV) and ACC I ZEV program were Connecticut, Maine, Maryland, Massachusetts, New Jersey, New York, Oregon, Rhode Island, and Vermont. Several other states (Colorado, Minnesota, Nevada, Virginia, and New Mexico) have legislated or previously indicated political intentions to join in future years. Delaware, Pennsylvania, and Washington, D.C., have so far followed the California LEV standards but not the ZEV program. Roughly, these states account for 20%–40% of the U.S. new vehicle sales market. https://ww2.arb.ca.gov/sites/default/files/2022-05/%C2%A7177_states_05132022_NADA_sales_r2_ac.pdf, https://www.c2es.org/document/us-state-clean-vehicle-

Figure 15 show the result of the disaggregation of exogenously specified national sales shares into county-level sales shares in each of the three scenarios. In every scenario, by 2022, many counties, particularly in states with ZEV regulations, had EV sales shares well over the national average of 7%. Although in the AEO scenario, electrification is slow on average (2% to 15% by 2050), some counties reach 70% EV sales share by 2050, while others stay near zero, reflecting high heterogeneity in counties. Similarly, in the EFS and All EV Sales by 2035 scenarios, some counties reach 90%+ EV sales shares in 2030, though the national average is only at about 50%–60%. Figure 16 focuses on the disaggregated exogenous sales shares for the All EV Sales by 2035 scenario, showing them on a choropleth of the United States. We can see that current and near-term (2025) EV sales shares are highly heterogeneous across the United States, with much higher sales in ZEV states, and that future 2030 EV sales shares, when the national average hits the 50% goal in the Biden administration executive order, would be temporarily concentrated in counties with projected leads in sales share while other counties stay lagged in EV sales, potentially due to infrastructure, behavioral, cultural, and/or political reasons. However, because this scenario follows a path of national sales being 100% EV by 2035, every county is specified to reach 100% by 2035 in this scenario, thereby projecting no heterogeneity in sales shares by 2035.

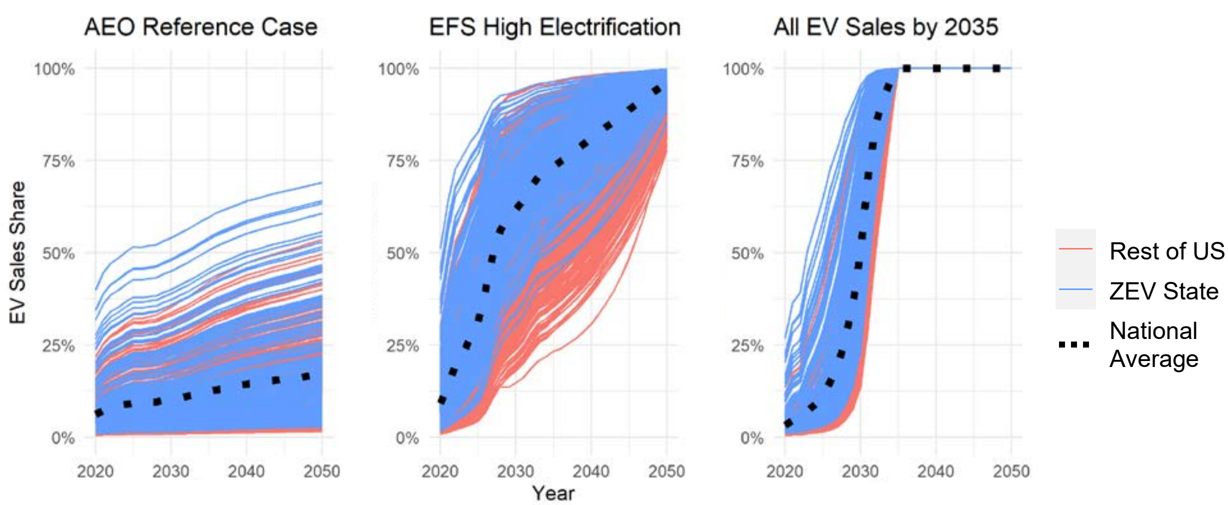

Figure 15. Projected ZEV sales shares for all counties (each colored line) in the United States for three TEMPO vehicle electrification scenarios.

Line colors indicate whether the county is in a state with ZEV mandates that regulate fleet composition. Dashed black lines represent the exogenously specified national projections to which the county-level sales shares average.

policies-and-incentives/. O'Dea, J., State adoption of clean vehicle standards (updated May 6, 2022). Online at: https://docs.google.com/spreadsheets/d/1ihjIzOGLb7cfrvblaNwC74sfFC-LBC26HWDWovgFGuw/edit#gid=0

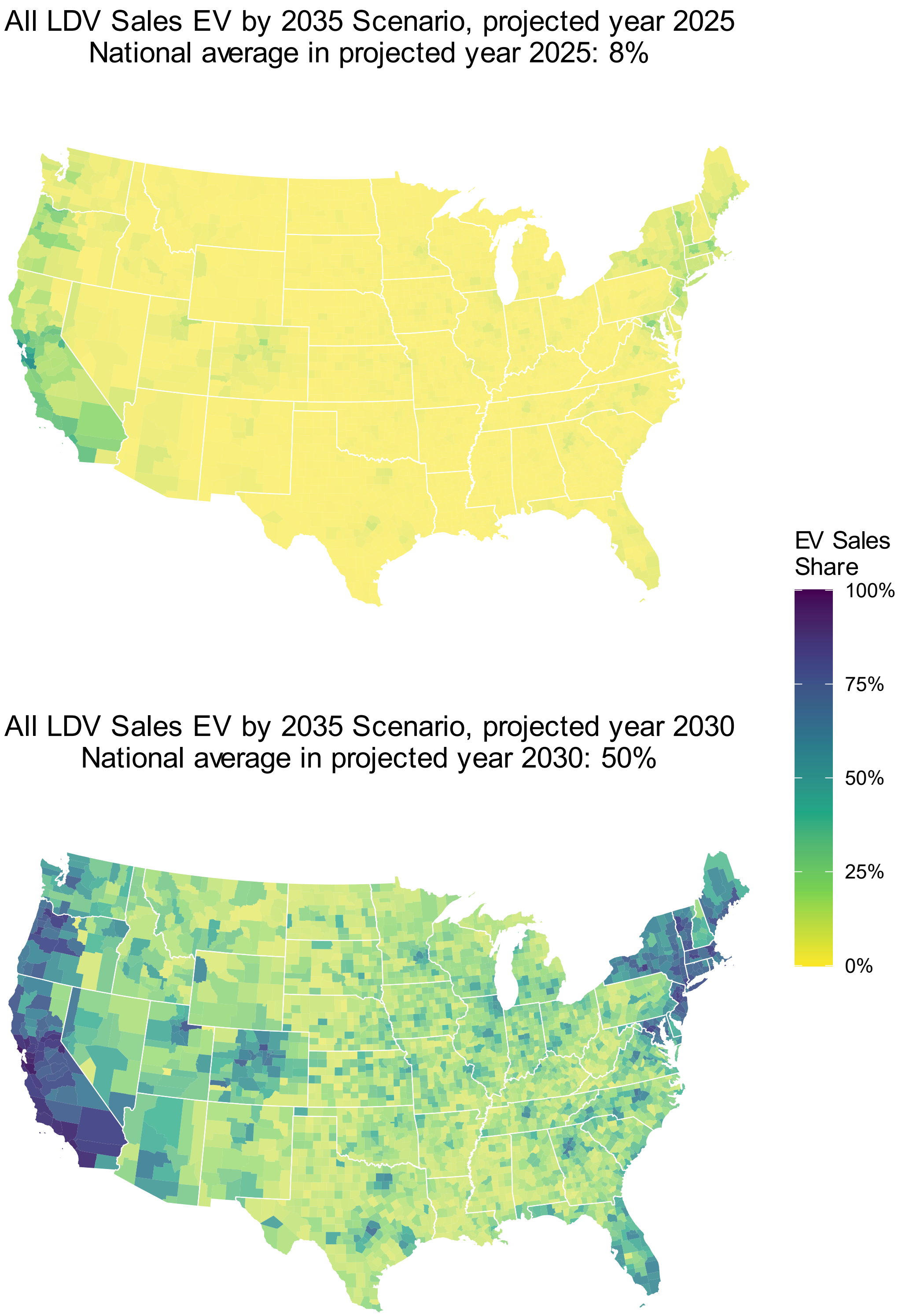

Figure 16. TEMPO's projected ZEV sales shares in 2025 and 2030 for all counties in the contiguous United States in the All EV Sales by 2035 scenario.

2.6 Simulating Week-long Hourly EV Charging Profiles

TEMPO was previously limited to simulating estimates of annual energy consumption. We enhanced TEMPO to generate household EV charging load profiles for each county, based on an aggregation of individually simulated households, vehicles, and trips. Appendix B shows further detail on how simulated data are processed, from TEMPO's individual household-level trips to EV consumption profiles, EV charging schedules, and the county-level load profile data for dsgrid.[27]

TEMPO first simulates a household's mobility needs, then their intra-household and travel mode choice given their available options (vehicle and mode availability), and then the associated energy use from each trip. For the simulation of temporally resolved charging load profiles, we extract the trips that use household EVs and compile week-long hourly trip schedules for each EV by building from weekday/weekend and time-specific travel distributions derived from NHTS. We start each week on a Monday and simulate 12 week-long travel profiles for each year, one representative week per month of the specified weather year, to represent seasonal impacts.[28]

Then, TEMPO converts these week-long EV trip schedules into envelopes of minimum and maximum battery energy required to fulfill that demand. The envelope of each representative vehicle is a feasible space for charging behavior, given the state of charge that resulted from prior consumption and charging, plus energy needs for upcoming trips. This is illustrated in Figure 17, where the top two charts represent TEMPO's simulated vehicle and energy use, and the bottom chart shows the resulting feasible charging envelope.

TEMPO generates an "immediate" charging profile (also called "as soon as possible"), which is the upper bound of the charging envelope, outlined in red in Figure 17. Each vehicle charges as soon as plugged in until fully recharged or taken on another trip. Under "immediate" charging scenarios, the charging profile closely follows the vehicles' energy consumption profile as EV batteries are charged at the first available charging opportunity. This means drivers in TEMPO do not consider any factors, such as electricity prices or charger convenience, that could influence their charge timing. In this report, drivers and vehicles in TEMPO are also assumed to have ubiquitous access to charging whenever a trip is not in progress, though TEMPO can incorporate spatially and temporally disaggregated charging availability to better reflect realistic charging access. The current "immediate + ubiquitous" charging strategy provides a simple approximation reflecting an easily imagined behavioral pattern in which drivers plug in their EV whenever they have ended a trip and there is an EV charger at all parking locations. It is a worst-case scenario from a demand-side flexibility perspective: EVs do not provide any flexibility, and drivers, only considering mobility needs, aim to maintain as high as possible battery state of charge at all times (thus minimizing any possible range anxiety). This also represents a minimal assumption on charging behavior, one that may be loosely supported by anecdotal information on BEV "charging anxiety" and doesn't require any supply-side information on electricity prices or other demand response programs that are used to influence consumer behavior and choices. The lower bound of the charging envelope, outlined in green in the bottom chart of Figure 17,

[27] Footnote 37 and the dsgrid documentation https://dsgrid.github.io/dsgrid/data_format.html discuss the data format of representative weeks for each season, which are then extrapolated to 8760 profiles either in TEMPO or dsgrid.
[28] As opposed to following the actual date-specific hourly weather conditions of the weather year.

corresponds to a “delayed” or “as late as possible” charging strategy where the EV is plugged in as late and rarely as possible. While there is no behavioral evidence for the realism of such a strategy, pairing it with the “immediate” profile can provide bounds on flexibility that EV charging can provide to the power system while still meeting all mobility needs.

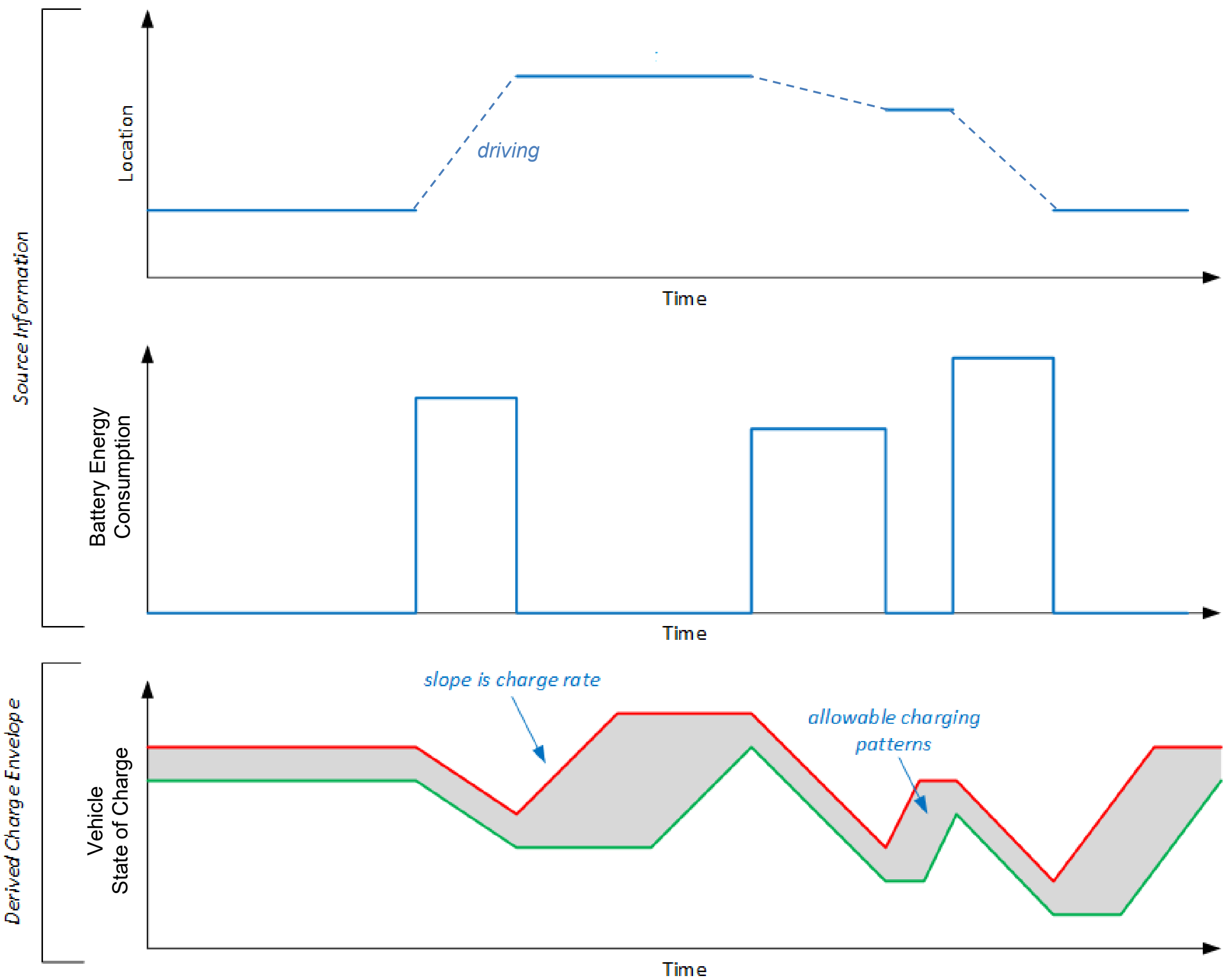

Figure 17. EV charging envelopes characterize the charging opportunities that are consistent with vehicles’ consumption patterns, charging opportunities, and technological capabilities.

The charging envelopes are bounded in red and green, red being the “immediate” or “as soon as possible” charging strategy and green being the hypothetical “delayed” or “as late as possible” charging strategy. These strategies also reflect EV batteries being charged to their maximum and minimum state of charge, respectively (maximum due to physical and technological constraints, and minimum due to energy needed to support travel demand).

TEMPO has the ability to generate any charging pattern within this feasible envelope for each sampled EV. Other patterns worth exploring in further studies include those that are optimal for time-of-use electricity rates and those with centralized or semi-centralized managed charging that provide grid services by scheduling the charging (and potentially discharging) of many EVs. Determining actual or optimal charging loads within this envelope requires co-simulating transportation and power systems, as was done in Hale et al. (2022), where TEMPO was further developed to estimate EV charging patterns within the feasible envelope for the purposes of maximizing value to the bulk power system.

Under the immediate charging strategy, charging rates and sessions are bounded by trip energy demands, vehicle battery capacities, and charger capacities. TEMPO currently distinguishes two types of charging according to charging location: regular charging, which includes residential/workplace/commercial,[29] and public DCFC. Both types of charging are further differentiated by power level: Level 1 (L1) or Level 2 (L2) for regular charging, and 50 kW or 150 kW for public DCFC (Table 2).

While assumed ubiquitous here, limited charging infrastructure availability and charging power levels specific to locations and times would impact the feasible envelope by limiting the ability of EVs to charge where and when there are fewer chargers available than EVs that could plug in. Future charging patterns could reflect trade-offs between overnight charging at home, if available, and opportunity charging at workplaces or public locations. Other considerations related to charging include range anxiety, responsiveness to prices and participation in demand response programs, and ability and willingness to change parking behavior to access charging.

Finally, one significant limitation of the current TEMPO modeling is that all charging loads are assumed to be associated with the household's home county. While residential charging can be safely associated with the household's home county, some workplaces and/or charging during long road trips may be associated with neighboring or farther counties, particularly those containing major travel corridors. However, in the immediate and ubiquitous charging scenarios considered in this report, most of the charging load is done at local residential, workplace, and destination chargers, and all opportunities for charging are used immediately (so even for road trips, EVs typically start off fully charged from the previous charging session). Therefore, the amount of misallocated charging load here in this current work is limited. This issue should be revisited in future work and scenarios where there is more public charging away from home.

Table 2. Charger Assumptions Used in TEMPO for dsgrid Scenarios

Charger Type	Detail	Maximum Charge Rate
Regular charging	Includes residential, workplace, and public commercial/community	95% at 7.2 kW (L2) 5% at 1.4 kW (L1)
Public DCFC	Used when trips exceed vehicle range	75% at 50 kW 25% 150 kW

[29] TEMPO currently does not geolocate driving or resting events and therefore does not distinguish between residential, workplace, or public charging, with the exception of trips that exceed the electric range of a vehicle, which necessitate a charging stop that is assumed to be at a public DCFC station. Simulating trip purpose or origin/destination types, possibly informed by NHTS, would allow TEMPO to model more specific charging availability and infrastructure needs.

3. Results: Charging Load Scenarios

In this section we provide a high-level summary of the three projections created for this report (Section 3.1) and then demonstrate the spatial and temporal heterogeneity in those data by focusing on the All EV Sales by 2035 scenario (Section 3.2).

In general, projecting future EV charging loads is a complex task fraught with many uncertainties. A real-world charging profile depends on vehicle characteristics (e.g., energy efficiency), travel behavior (e.g., amount of travel, timing, and duration of trips), usage details (e.g., outdoor temperature, driving styles), infrastructure availability (e.g., location and types of chargers), policy (e.g., electricity tariffs, charger-specific rates, demand response programs), and charging behavior (e.g., preferences and decisions made around when and where to charge). Because the EV market is currently very small, undergoing rapid technological change, and heavily concentrated in limited consumer segments, empirical data are scarce, and in any case are not necessarily appropriate for long-term extrapolation. As such, we have simulated feasible, rather than likely, charging loads as part of possible scenarios to illustrate plausible outcomes, but these should not be viewed as definitive assessments of future loads associated with EV charging.

3.1 Scenario Result Summary

Because TEMPO is nationally comprehensive and simulates representative households and their trips and EVs for every county over representative days, weeks, seasons, and future years, TEMPO can produce projections of aggregate U.S. load by summing up all the results. This is shown in Figure 18 with total annual energy (TWh/yr) over the projected years and scenarios, and peak hourly demand (GWh/h)[30] for each month, selected year, and scenario. In the All LDV Sales EV by 2035 scenario, the electric load from household-owned EVs reaches 930 TWh/yr. This is somewhat higher than the 750 TWh/yr in the EFS scenario here, primarily due to a faster acceleration and higher proportion of EV sales over the medium term, reaching 100% by 2035 (compared to EFS, which projects EVs reaching approximately 65% of light-duty vehicles by 2035 and reaching 95% only by 2050). In addition, projections of EV energy efficiency have changed significantly since the EFS project, with 20-40% less energy used per mile in 2050 than in the original EFS modeling inputs, resulting in lower load due to LDV electrification, in both scenarios here[31], compared to the original EFS scenario results. The 930 TWh/yr load in 2050 in the All LDV Sales EV by 2035 scenario would be approximately 19% of future load[32], which remains within the range of previous estimates (13-29%) of electric load from full LDV electrification, as discussed in the Introduction.

[30] Hourly load (e.g., in GWh/h) is the finest temporal resolution predicted by TEMPO. The power draw during times within an hour could be higher in terms of instantaneous demand—e.g., in instantaneous gigawatts (GW) measured over seconds or minutes—but the hourly load is the total electricity demanded in the specified hour. Peak hourly load refers to the highest hourly load over all hours of the specified months and years.
[31] Results here reflect a TEMPO scenario with EV adoption in line with the EFS High Electrification scenario, but with EV energy efficiency inputs updated since EFS.
[32] Assuming 930 TWh/yr is the only addition to current load

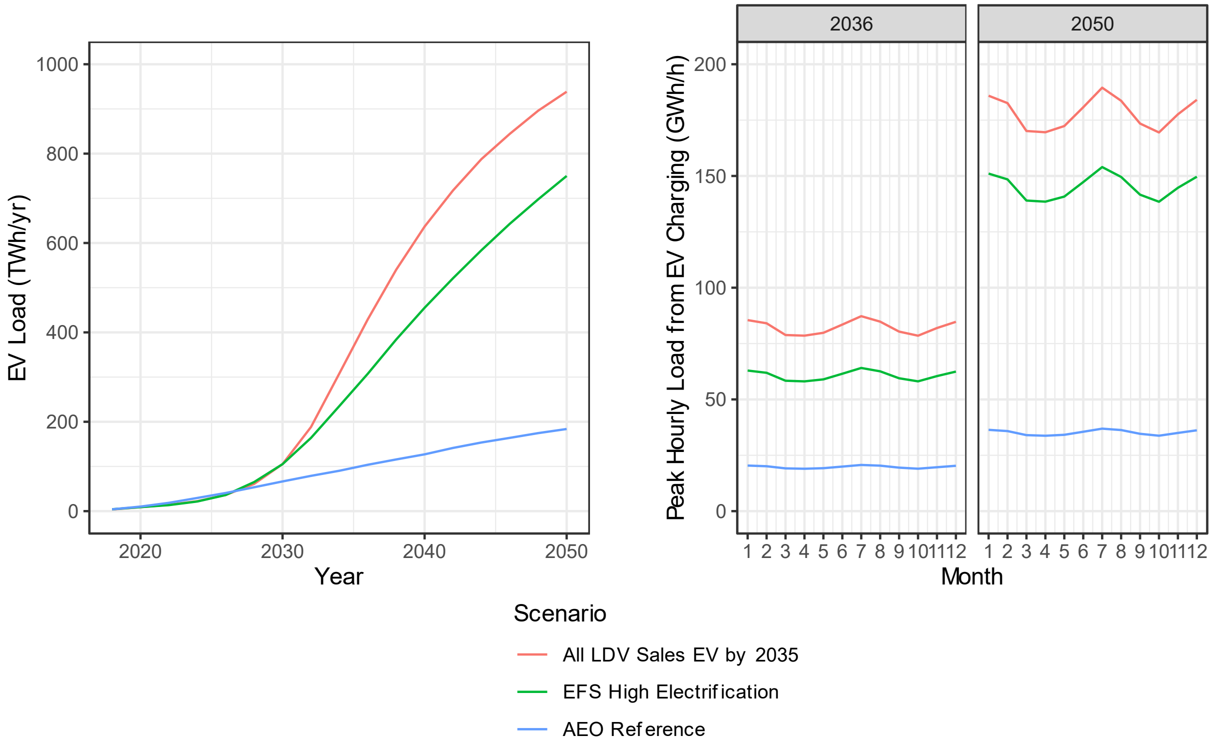

Figure 18. Aggregate U.S. annual and peak hourly EV load under three scenarios

3.2 Spatial and Temporal Heterogeneity in EV Load

We now focus on showing the simulated results of the All EV Sales by 2035 scenario. First, we show the aggregate U.S. charging load profile for average weekdays for every month of the year in Figure 19. Weekday EV charging load under ubiquitous and immediate charging behavior assumptions has a diurnal pattern with a morning and afternoon peak when substantial numbers of vehicles end their trips and start charging. We find aggregate U.S. EV charging load reaches peak hourly loads[33] of 82 GWh/h in 2036 and 181 GWh/h in 2050 during a weekday evening hour[34] in the coldest winter and hottest summer months (dark purple and bright orange lines, respectively, in Figure 19). Aggregate U.S. EV charging load is generally larger in winter months because vehicular heating loads add to vehicle energy consumption; however, vehicular cooling loads in the peak afternoon hours in the summer[35] appear to be comparable in magnitude to heating loads in those hours. Morning peaks are higher in the winter than in the summer. Load grows from 2036 to 2050 primarily due to large increases in EV adoption and continued growth in vehicle size, vehicle ownership, and population, but the growth is mitigated by improved energy efficiency. In this specified scenario and charging strategy, other factors such as

[33] Hourly load (e.g., in GWh/h) is the finest temporal resolution predicted by TEMPO. The power draw during times within an hour could be higher in terms of instantaneous demand (e.g., in GW), but the hourly load is the total electricity demanded in the specified hour. Peak hourly load refers to the highest hourly load over all hours of the specified months and years.
[34] TEMPO develops trip and charging schedules in local time, which means the timing of loads across the United States depends on location. The aggregate U.S. loads presented here have been aggregated with time offset to Central Time. Similarly, in dsgrid, loads are spatiotemporally specified so that time zone can be considered.
[35] Note that TEMPO does not currently consider any seasonal variation in travel or trip behavior.

evolution in charging power, vehicle ownership, travel demand, and mode choice contribute relatively little to changes in load.

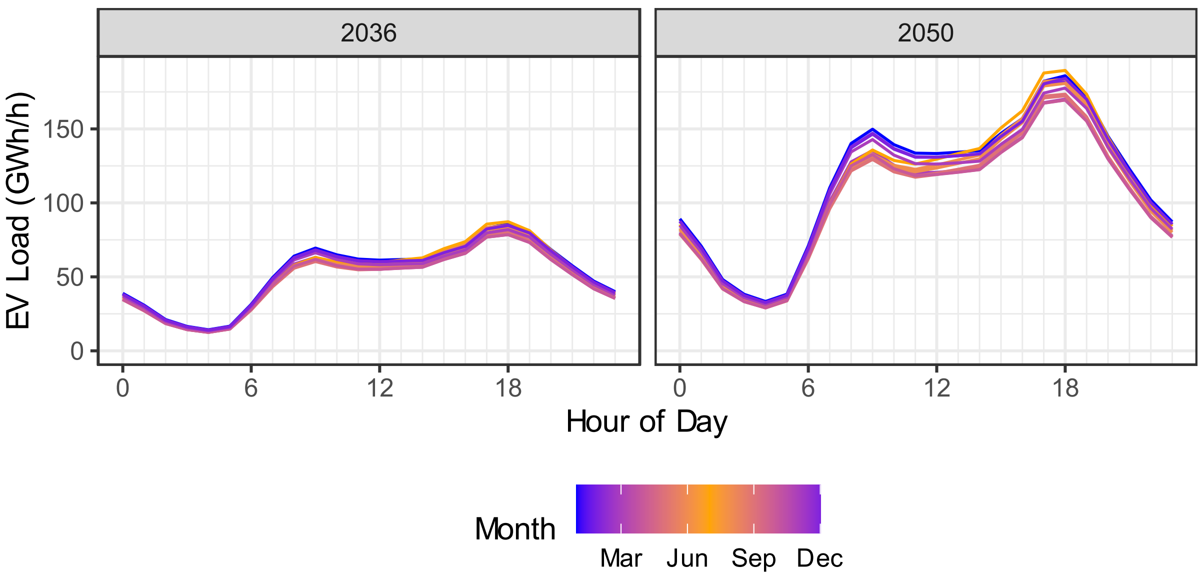

Figure 19. Aggregate U.S. EV charging load profile for an average weekday for the All EV Sales by 2035 scenario for projected years 2036 and 2050 under the immediate and ubiquitous charging strategy, with seasonal variation shown by line color (blue for winter, orange for summer)

The spatial and temporal resolution enabled by county-level TEMPO provides data for county-level hourly load profiles. To illustrate the importance of modeling the heterogeneity of charging load across the United States, we present the projected 2036 EV charging load profiles at the state level for the contiguous United States in Figure 20 and for eight example counties in Figure 21.

The spatial heterogeneity in EV load profiles shown in Figure 20 and Figure 21 arises from a combination of many factors in TEMPO. Setting aside the inherent differences in population or household count between counties, the county-specific charging load on a total, per-capita, or per-household basis first depends on factors such as vehicle ownership [vehicles/household] and EV adoption levels [% EV], and these factors vary based on the disaggregated household and county characteristics and available travel options simulated in TEMPO. These determine the number of EVs or EV/capita in a county. Then, the scaled charging load per EV depends on vehicle use [VMT/EV],[36] which varies by household urbanity/income/size and travel options;

[36] TEMPO does not make explicit assumptions about VMT per vehicle or household; rather, TEMPO preserves travel needs and demand (as estimated from NHTS) and simulates the adoption and use of new options, assuming new options do not induce behavioral changes. TEMPO does simulate households with different VMT, thereby allowing for self-selection of households with lower or higher VMT into EV adoption. TEMPO also simulates households with a portfolio of vehicles, allowing for shifts in VMT within the household set. TEMPO projections so far have not resulted in significant differences in "eVMT" compared to VMT of conventional vehicles. While recent studies have found low eVMT based on early (2014–2017) California EV adopters and their residential meter data (Burlig et al. 2021) and from limited EV data from the 2017 NHTS, more recent data reflecting modern EV capabilities and ranges show that future eVMT is not expected to necessarily differ significantly from typical or average VMT. We also note that projections of possible futures to 2050 require extrapolation beyond inputs based on existing adopters and behaviors.

vehicle and charger energy efficiency [kWh/mi], which varies by vehicle size and type (dependent on county and household); weather (varies by county, time, and season); and charger type. These factors and their spatial heterogeneity combine to form the spatial patterns of EV load shown in Figure 20 and Figure 21. Mathematically, we can decompose EV load into these factors with a modified Kaya-style identity:

$$Annual\ EV\ load\ \left[\frac{kWh}{yr * capita}\right]$$

$$= Vehicle\ ownership\ \left[\frac{vehicles}{capita}\right] * EV\ share\ \left[\frac{EVs}{vehicles}\right] * Annual\ VMT\ \left[\frac{mi/yr}{EV}\right] * EV\ energy\ intensity\ \left[\frac{kWh}{mi}\right]$$

This formulation can reveal how the variation in factors dependent on geography and scenario impacts total EV load and it is being used in ongoing TEMPO work to analyze the inherent heterogeneity and uncertainty in EV load across the United States and in future scenarios.

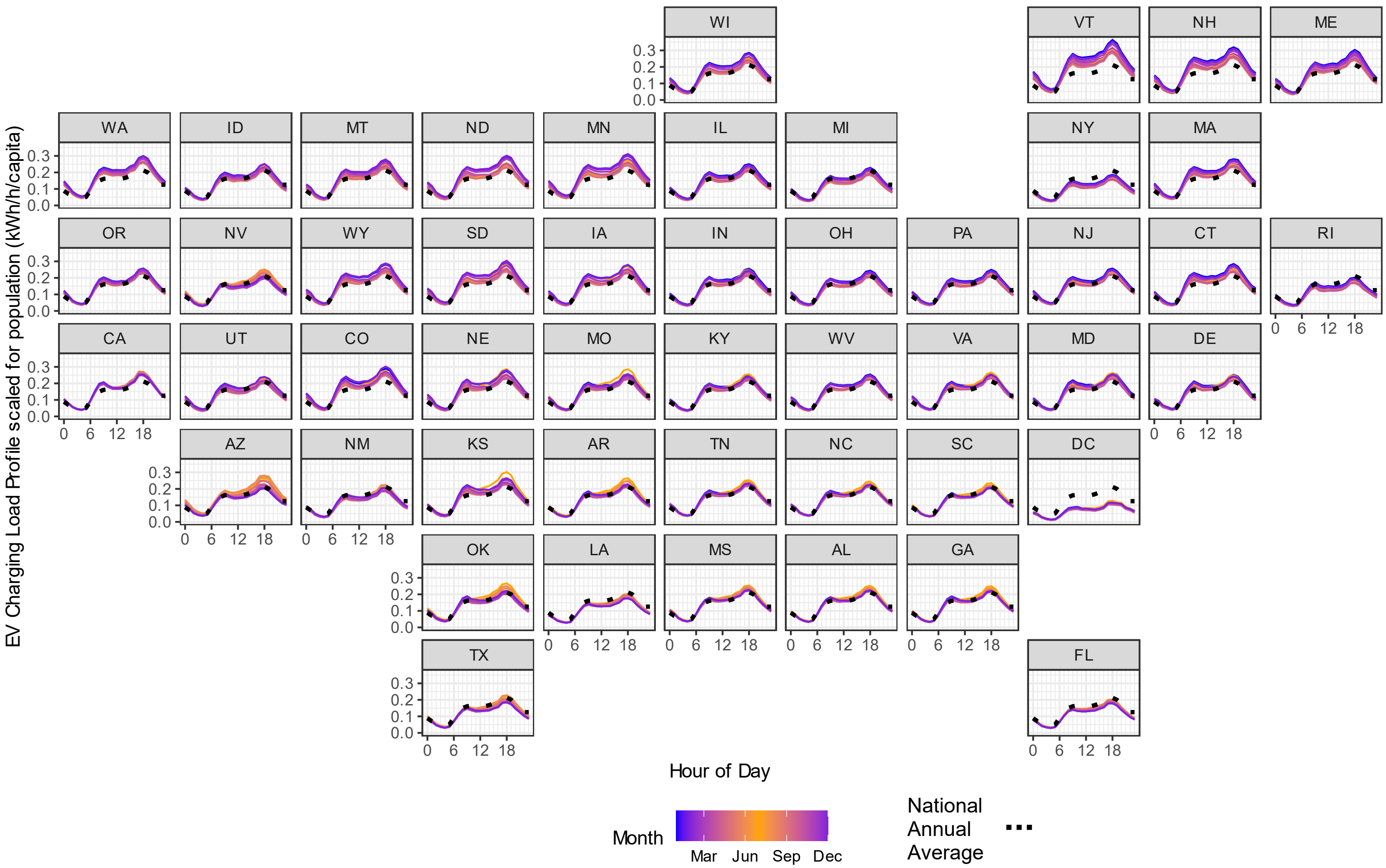

Figure 20. State-level per-capita EV charging load profiles for an average weekday for the All EV Sales by 2035 scenario for projected year 2036 under the immediate and ubiquitous charging strategy, for the contiguous United States, with seasonal variation shown by line color (blue for winter, orange for summer) and U.S. annual average in black dashes.

The EV load profile variation simulated in TEMPO for this report and the dsgrid project arises from a combination of differences in EV adoption, VMT, vehicle size, and climatic impacts on EV efficiency. Northern states with higher rurality and states with higher EV adoption tend to have larger loads.

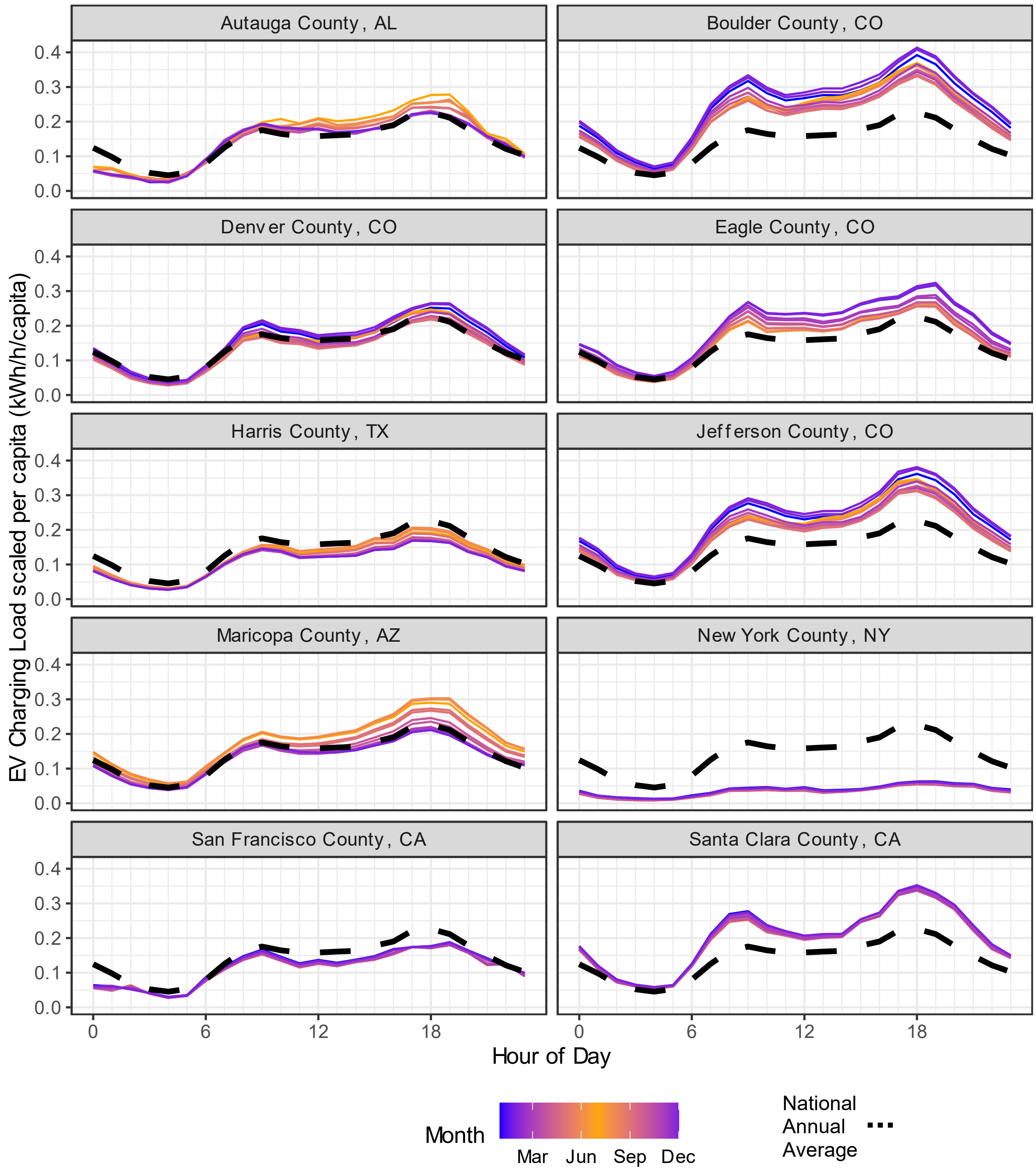

Figure 21. County-level per-capita EV charging load profiles for an average weekday for the All EV Sales by 2035 scenario for projected year 2036 under the immediate and ubiquitous charging strategy, with seasonal variation in color (blue for winter, orange for summer) and U.S. annual average in black dashes.

The load profile variation simulated in TEMPO for this report and the dsgrid project arise from a combination of differences in EV adoption, VMT, vehicle size, and climatic impacts on EV efficiency. The urbanity and density of a county heavily impacts vehicle ownership and use, with New York (containing Manhattan) being a special case. Certain counties such as Santa Clara (containing San Jose and Silicon Valley) also have particularly high EV adoption.

Of note in Figure 21, lower vehicle ownership and use in highly urban counties such as New York County, New York (Manhattan), and San Francisco County, California, reduce their vehicles per capita and VMT per EV, explaining their relatively lower charging load per capita. Higher EV adoption levels in certain states such as California increase their EV share and EV per capita. VMT per mi tends to be larger in rural areas, correlated with larger vehicles, and areas with more temperature extrema.

While differences in household mixes and demographics modeled in TEMPO can explain part of the difference in EV load, county-specific factors enabled by this work can help produce load simulations with better locational specificity. For example, Jefferson County, Colorado, and Harris County, Texas, have relatively similar household mixes, as shown from the demographics example in Figure 5, resulting in similarities in simulated transportation demand and vehicle preferences. However, county-specific factors such as EV adoption, vehicle size mix, and temperature effects further differentiate the EV energy usage and load profile in these two counties in TEMPO's county-level simulations beyond household bin mix, as can be seen in the middle panels of Figure 21.

4. Conclusions

This report documents enhancements made to the TEMPO model to project spatially and temporally resolved national-scale passenger EV charging load profiles and summarizes three scenarios and corresponding data sets created for the NREL dsgrid project. In brief, TEMPO was enhanced from a national and annual model focused on aggregate energy demand to include county-level projections of household EV hourly charging load profiles, accounting for heterogeneity in consumers, travel, and temperature affecting EV energy demand. In alignment with NREL's forward-looking grid modeling, three scenarios for EV adoption covering 2020–2050 were created: *AEO Reference Case*, *EFS High Electrification*, and *All EV Sales by 2035*, and associated data sets have been included in dsgrid for public use.

Overall, TEMPO was already a projection model that coupled known relationships between demographics, urbanity, mobility demand, transportation mode selection, and vehicle types to travel patterns and population projections to create realistic scenarios of transportation energy use for the United States. However, geographically resolved hourly charging profiles are required to support large-scale capacity expansion (investment) and production cost (operational) modeling of bulk power systems. In this work, we enhanced TEMPO to capture the distribution of each county's population across TEMPO's native 60 household bin resolution, which captures urbanity and sociodemographic variables; determined vehicle ownership, attribute, and type preferences by county; and used 2012 weather data for 975 locations to capture the impact of outdoor temperature on vehicle energy efficiency. We also developed county-disaggregated EV adoption scenarios and simple algorithms to simulate representative week-long EV trip and charging schedules based on heuristics and assumed charging behavior and infrastructure availability.

Future EV charging load profiles are highly uncertain. TEMPO attempts to model realistic mobility demands and transportation mode and technology choices given configurable sets of inputs; brackets large uncertainties through the creation of scenarios; and conducts sensitivity, benchmarking, and validation analyses so its results can be understood in context, used for cross-sectoral analyses, and continuously improved. Extending TEMPO to produce county-level, hourly charging profiles introduces even more uncertainties—for example, future demographic composition and urbanity levels, charging infrastructure build-out, and charging behavior, all of which could develop and change differently in different counties over time. In this work we make basic assumptions along all of these dimensions: Urbanity of counties is held constant, and demographic distributions are held constant while population grows according to national trends. In these scenarios, we make the simplifying assumption that all EVs plug in as soon as they park and charge (immediate and ubiquitous charging), until their batteries are full or they depart on their next trip, whichever comes first (uncoordinated charging). We also assume all charging is associated with the household's home county.

As described in Section 2.6, TEMPO can simulate EV charging flexibility with bounded envelopes in which EV charging can be managed to meet all mobility requirements. However, determining actual or optimal charging loads within this envelope requires co-simulating transportation and power systems, as was done in Hale et al. (2022), where TEMPO was further developed to estimate EV charging patterns within the feasible envelope for the purposes of maximizing value to the bulk power system.

There is significant work ongoing and more work possible (especially coupled with realistic charging infrastructure scenarios) to explore different EV charging behaviors and the nexus between transportation electrification and electricity systems transformation, including coordination with the grid to provide value to the power system via demand response; scheduled, managed, or opportunistic charging; vehicle-to-grid (V2G) services; or direct use of vehicle batteries to power loads (V2X) (Hoehne and Chester 2016; Anwar et al. 2021).

Given this project's limited scope and simplifying assumptions, future work could include:

- Incorporation of detailed baseline and projected variation in residential and public parking and EV charger infrastructure availability, by county and household bin.
- Consideration of trip purpose and expected origins/destinations, by hour, to improve representation of charging availability, options, behavior, and appropriate charging load assignment (i.e., for counties with significant public charging of vehicles from other counties).
- Consideration of short- and long-term travel flexibility and changes in EV usage enabled by new technologies, behaviors, business models, and policies such as telecommuting, ride-hailing, micromobility, e-commerce, and vehicle automation.
- Developing advanced charging strategies and decisions informed by spatiotemporal-specific electricity supply and prices.
- Improved resolution of charging efficiency, dependent on charging location, type, power/speed, and behavior.
- Enhancement of the representation of county-level vehicle stock and sales, with consideration of vehicle age, used vehicles, and county-specific sales, survival/retirement, and vehicle transfers.
- Research to determine the appropriate temporal resolution for capturing weather and seasonal impacts and longer-term impacts of climate change on both energy efficiency and travel behavior.
- Subsequent support for multiple weather year and typical meteorological year scenarios.
- Development and validation of spatially and temporally resolved policies, regulations, infrastructure, and prices affecting EV adoption and use.
- Incorporation of county-level population projections and/or more detailed demographic and urbanity projections.
- Extension to charging loads from electrification of:
  - Non-household light-duty vehicles (e.g., taxi, ride-hailing, mobility-as-a-service fleets).
  - Light-, medium-, and heavy-duty vehicles used for non-household/passenger purposes, e.g., freight, service, vocational, work.
  - Other vehicles and travel modes such as buses, transit, micromobility, rail, maritime, aviation, and off-road vehicles (e.g., construction, agriculture, mining).
- Extension to quantify indirect transport electrification electricity needs (i.e., electricity consumed to produce hydrogen and other transportation fuels) and their temporal flexibility.
- Inclusion of other metrics such as activity/service, vehicle sales/stock, costs, emissions, and energy demand (not only electricity) projections in the data transferred to and published in

dsgrid, which would be helpful in producing normalized metrics and/or in the evaluation of remaining electrification potential.

- Research to compare simulated results against real-world observed EV loads—e.g., Burlig et al. (2021), Qiu et al. (2022)—and validate behavioral assumptions and load impacts affecting spatial and temporal patterns, such as rebound and response to pricing.
- Research to compare simulated results against results from other models—e.g., NREL's EVI-Pro (NREL 2016); Miller, Arbabzadeh, and Gençer (2020).
- Validation via comparison of intermediate results such as heterogeneous VMT and fuel economy (mpg)—e.g., BTS (2021), Zhou et al. (2021).

Table A-1 also discusses some of the limitations and potential enhancements of TEMPO's current representation of households, vehicles, infrastructure, economics, and travel behavior.

Limitations stated, this work developed three scenarios of annual hourly load projections for household EV charging for all counties in the contiguous United States projected through 2050. We believe this is a first-of-its-kind data set, the value of which is evident when we observe just how heterogenous EV adoption, use, and charging is in the simulation results. The spatial and temporal heterogeneity in the projections emerges from coupling the on-the-ground heterogeneity of today in urbanity, household composition, vehicle preferences, and weather, with the TEMPO projections of mobility need, transportation mode choice, and vehicle choice. The result is data and supporting modeling tools that can be used today to inform location-specific grid planning and operational models, as well as comprehensive, scenario-spanning, and internally consistent projections of EV adoption, use, and charging load.

5. References

Anwar, Muhammad, Matteo Muratori, Paige Jadun, Elaine Hale, Brian Bush, Paul Denholm, Ookie Ma, and Kara Podkaminer. 2022. "Assessing the Value of Electric Vehicle Managed Charging: A Review of Methodologies and Results." *Energy and Environmental Science* 15 (2): 466–98. https://doi.org/10.1039/d1ee02206g.

Borlaug, Brennan, Jacob Holden, Eric F. Wood, Byung Ho Lee, Justin Fink, Scott Agnew, and Jason Lustbader. 2020. "Estimating Region-Specific Fuel Economy in the United States from Real-World Driving Cycles." *Transportation Research Part D: Transport and Environment* 86 (September): 102448. https://doi.org/10.1016/j.trd.2020.102448.

Bureau of Transportation Statistics (BTS). 2021. Local Area Transportation Characteristics for Households (LATCH) https://www.bts.gov/latch.

Burlig, Fiona, James Bushnell, David Rapson, and Catherine Wolfram. 2021. "Low Energy: Estimating Electric Vehicle Electricity Use." *AEA Papers and Proceedings* 111 (February): 430–35. https://doi.org/10.1257/pandp.20211088.

Claritas. 2021. "Consumer & Business Data." https://claritas.com/data/.

Desai, Ranjit C., Roger Chen, Eric Hittinger, and Eric Williams. 2020. "Heterogeneity in Economic and Carbon Benefits of Electric Technology Vehicles in the US." *Environmental Science & Technology* 54 (2): 1136–46. https://doi.org/10.1021/acs.est.9b02874.

Federal Highway Administration (FHWA). 2017. "2017 National Household Travel Survey." U.S. Department of Transportation. http://nhts.ornl.gov.

Fox-Penner, Peter, Will Gorman, and Jennifer Hatch. 2018. "Long-term U.S transportation electricity use considering the effect of autonomous-vehicles: Estimates & policy observations." *Energy Policy* 122: 203–213. https://doi.org/10.1016/j.enpol.2018.07.033.

Ge, Y., C. Simeone, A. Duvall, and E. Wood. 2021. *There's No Place Like Home: Residential Parking, Electrical Access, and Implications for the Future of Electric Vehicle Charging Infrastructure*. Golden, CO: National Renewable Energy Laboratory. NREL/TP-5400-81065. https://www.nrel.gov/docs/fy22osti/81065.pdf.

Geotab, 2020. Real-world range vs. rated range. https://www.geotab.com/blog/ev-range/.

Gohlke, David. 2021. Comparison of gasoline prices between EIA, GasBuddy, and OPIS. Poster at Transportation Research Board Annual Meeting.

Hale, Elaine, Luke Lavin, Arthur Yip, Brady Cowiestoll, Jiazi Zhang, Paige Jadun, and Matteo Muratori. 2022. *Electric Vehicle Managed Charging: Forward-Looking Estimates of Bulk Power System Value*. Golden, CO: National Renewable Energy Laboratory. NREL/TP-6A40-83404. https://doi.org/10.2172/1890139.

Hoehne, C., and M. Chester. 2016. "Optimizing plug-in electric vehicle and vehicle-to-grid charge scheduling to minimize carbon emissions." *Energy* 115 (1): 646–657. https://doi.org/10.1016/j.energy.2016.09.057.

Idaho National Laboratory (INL). 2016. "2013 Nissan Leaf BEV – VINs 0545, 0646, 7885 & 9270: Advanced Vehicle Testing –DC Fast Charging at Temperature Test Results." Idaho Falls, ID: INL. https://avt.inl.gov/sites/default/files/pdf/fsev/2013LeafDCFCAtTempBOT.pdf.

IHS Markit (Polk). 2018. "Automotive Products & Solutions." https://ihsmarkit.com/industry/automotive.html#products.

Jadun, Paige, Colin McMillan, Daniel Steinberg, Matteo Muratori, Laura Vimmerstedt, and Trieu Mai. 2017. *Electrification Futures Study: End-Use Electric Technology Cost and Performance Projections through 2050*. Golden, CO: National Renewable Energy Laboratory. NREL/TP-6A20-70485. https://www.nrel.gov/docs/fy18osti/70485.pdf.

Liu, Lixi, Carlo Bianchi, Anthony Fontanini, Elaine Hale, Ry Horsey, Amy LeBar, Andrew Parker, Janet Reyna, and Noah Sandoval. 2023. *Highly Resolved Reference Projections of Building Energy Use for the Contiguous United States: Building Sector Energy Baselines, Projection Methods, and Results.* Golden, CO: National Renewable Energy Laboratory. NREL/TP-5500-84471. Forthcoming. Data accessed via https://github.com/NREL/comstock-weather.

Liu, Shanshan, and Eleftheria Kontou. 2022. "Quantifying Transportation Energy Vulnerability and Its Spatial Patterns in the United States." *Sustainable Cities and Society* 82 (March): 103805. https://doi.org/10.1016/j.scs.2022.103805.

Ma, Ookie, Krystal Laymon, Megan Day, Ricardo Oliveira, Jon Weers, and Aaron Vimont. 2019. *Low-Income Energy Affordability Data (LEAD) Tool Methodology*. Golden, CO: National Renewable Energy Laboratory. NREL/TP-6A20-74249. https://www.nrel.gov/docs/fy19osti/74249.pdf.

Mai, T. T., P. Jadun, J. S. Logan, C. A. McMillan, M. Muratori, D. C. Steinberg, L. J. Vimmerstedt, B. Haley, R. Jones, and B. Nelson. 2018. *Electrification Futures Study: Scenarios of Electric Technology Adoption and Power Consumption for the United States*. Golden, CO: National Renewable Energy Laboratory. NREL/TP-6A20-71500. https://doi.org/10.2172/1459351.

Moniot, Matthew, Jason Lustbader, Eric F. Wood, Byung Ho Lee, Justin Fink, and Scott Agnew. 2021. "A Framework for Characterizing the Ambient Conditions Experienced by Light Duty Vehicles in the United States." *International Journal of Sustainable Transportation* 16 (2): 137–51. https://doi.org/10.1080/15568318.2020.1849470.

Miller, I., M. Arbabzadeh, and E. Gençer. 2020. "Hourly Power Grid Variations, Electric Vehicle Charging Patterns, and Operating Emissions." *Environmental Science & Technology* 54 (24): 16071–16085. https://doi.org/10.1021/acs.est.0c02312.

Milovanoff, Alexandre, I. Daniel Posen, and Heather L. MacLean. 2020. "Electrification of Light-Duty Vehicle Fleet Alone Will Not Meet Mitigation Targets." *Nature Climate Change* 10 (12): 1102–7. https://doi.org/10.1038/s41558-020-00921-7.

Moawad, Ayman, Namdoo Kim, Neeraj Shidore, and Aymeric Rousseau. 2016. "Assessment of Vehicle Sizing, Energy Consumption and Cost Through Large Scale Simulation of Advanced Vehicle Technologies." Argonne National Laboratory. ANL/ESD-15/28 126422 https://doi.org/10.2172/1245199.

Muratori, M., and T. Mai. 2020. "The shape of electrified transportation." *Environmental Research Letters* 16 (1): 011003. https://doi.org/10.1088/1748-9326/abcb38.

Muratori, M., M. Alexander, D. Arent, M. Bazilian, P. Cazzola, E. M. Dede, J. Farrell, et al. 2021. "The Rise of Electric Vehicles—2020 Status and Future Expectations." *Progress in Energy* 3 (2): 022002. https://doi.org/10.1088/2516-1083/abe0ad.

Muratori, M., P. Jadun, B. Bush, C. Hoehne, L. Vimmerstedt, A. Yip, J. Gonder, E. Winkler, C. Gearhart, and D. Arent. 2021. "Exploring the Future Energy-Mobility Nexus: The Transportation Energy & Mobility Pathway Options (TEMPO) Model." *Transportation Research Part D: Transport and Environment* 98: 102967. https://doi.org/10.1016/j.trd.2021.102967.

Muratori, M., P. Jadun, B. Bush, D. Bielen, L. Vimmerstedt, J. Gonder, C. Gearhart, and D. Arent. 2020. "Future integrated mobility-energy systems: A modeling perspective." *Renewable and Sustainable Energy Reviews* 119: 109541. https://doi.org/10.1016/j.rser.2019.109541.

National Renewable Energy Laboratory (NREL). 2016. *National Economic Value Assessment of Plug-In Electric Vehicles, Volume I*. Golden, CO: National Renewable Energy Laboratory. NREL/TP-5400-66980. https://www.nrel.gov/docs/fy17osti/66980.pdf.

———. 2020. "2020 Annual Technology Baseline." https://atb.nrel.gov/.

———. 2022. "U.S. Utility Rate Database." OpenEI. Accessed 9 Sept. 2022. https://apps.openei.org/USURDB/.

Parker, Nathan, Hanna L. Breetz, Deborah Salon, Matthew Conway, Jeffrey J. Williams, and Maxx Patterson. 2021. "Who Saves Money Buying Electric Vehicles? Heterogeneity in Total Cost of Ownership." *Transportation Research Part D-Transport and Environment* 96 (July): 102893. https://doi.org/10.1016/j.trd.2021.102893.

Qiu, Y. L., Y. D. Wang, H. Iseki, X. Shen, B. Xing, and H. Zhang. 2022. "Empirical grid impact of in-home electric vehicle charging differs from predictions." *Resource and Energy Economics* 67: 101275. https://www.sciencedirect.com/science/article/pii/S0928765521000609.

Tamayao, Mili-Ann M., Constantine Samaras, Chris Hendrickson, and James R. Chelikowsky. 2015. "Regional Variability and Uncertainty of Electric Vehicle Life Cycle CO_2 Emissions across the United States.” *Environmental Science & Technology* 49 (14): 8844–55. https://doi.org/10.1021/acs.est.5b00815.

U.S. Census Bureau. 2019. “2014-2018 American Community Survey Public Use Microdata Samples.” https://www.census.gov/programs-surveys/acs/technical-documentation/table-and-geography-changes/2018/5-year.html.

U.S. Energy Information Administration (EIA). 2019. *Annual Energy Outlook 2019 with projections to 2050*. Washington, D.C.: EIA. https://www.eia.gov/outlooks/archive/aeo19/pdf/aeo2019.pdf.

Vega-Perkins, Jesse, Joshua P. Newell, and Gregory A. Keoleian. 2023. “Mapping Electric Vehicle Impacts: Greenhouse Gas Emissions, Fuel Costs, and Energy Justice in the United States.” *Environmental Research Letters* 18 (1): 014027. https://doi.org/10.1088/1748-9326/aca4e6.

Wu, D., F. Guo, F. R. Field, R. D. De Kleine, H. C. Kim, T. J. Wallington, and R. E. Kirchain. 2019. “Regional Heterogeneity in the Emissions Benefits of Electrified and Lightweighted Light-Duty Vehicles.” *Environmental Science & Technology* 53: 10560–10570. https://doi.org/10.1021/acs.est.9b00648.

Yang, Fan, Yuanyuan Xie, Yelin Deng, and Chris Yuan. 2021. “Temporal Environmental and Economic Performance of Electric Vehicle and Conventional Vehicle: A Comparative Study on Their US Operations.” *Resources, Conservation, and Recycling* 169 (June): 105311. https://doi.org/10.1016/j.resconrec.2020.105311.

Yuksel T., and J. J. Michalek. 2015. “Effects of regional temperature on electric vehicle efficiency, range, and emissions in the United States.” *Environmental Science & Technology* 49: 3974–3980. https://doi.org/10.1021/es505621s.

Yuksel, Tugce, Mili-Ann M. Tamayao, Chris Hendrickson, James R. Chelikowsky, and Constantine Samaras. 2016. “Effect of Regional Grid Mix, Driving Patterns and Climate on the Comparative Carbon Footprint of Gasoline and Plug-in Electric Vehicles in the United States.” *Environmental Research Letters* 11 (4): 044007. https://doi.org/10.1088/1748-9326/11/4/044007.

Zhou, Y., S. Aeschliman, and D. Gohlke. 2021. “Household Transportation Energy Affordability by Region and Socioeconomic Factors.” *Transportation Research Record* 2675 (10): 81–95. https://doi.org/10.1177/03611981211010186.

Appendix A. Disaggregation and Enhancement of TEMPO Inputs Possible in Future Work

Table A-1. TEMPO Data Inputs That Could Be Further Explicitly Spatially Disaggregated or May Benefit From Further Enhanced Representation

	TEMPO Data Input	Model Resolution	Potential Enhancements, Disaggregation, and Data Sources
Household	Household counts	60 bins for each of 3,143 U.S. counties	Enhancements of projections of migration, urbanization, household size, and driver licensing are possible. Potential data from LandScan.
Vehicle	Vehicle stock by age/vintage, and survival/retirement schedule	National	Endogenous vehicle ownership and household-level vehicle dropping is a work in progress. County-level preferences for "age" (i.e., used vehicles) can be inferred from Polk/Experian vehicle registration data. County-level vehicle survival may vary due to regional factors such as salt, heat on battery degradation, VMT; vehicle factors such as ownership, maintenance, vehicle quality; and demographic factors such as income-based preferences. County-level stock and regional survival, paired with a representation of used vehicle transfers, could better represent vehicle stock and sales, but remains a work in progress.
	Vehicle energy efficiency	Differentiated by size class and weather	Further disaggregation of vehicle energy use possible to distinguish preferences for vehicle luxury/sport/efficiency, vintage specificity, and driving type by urbanity. More detailed and alternative weather data could further inform vehicle energy use, such as location- and season-specific road conditions (Moniot et al. 2021; Borlaug et al. 2020)
Infrastructure	EV charging availability (by charger type/ location type and by time)	Urbanity-specific (5)	In current scenarios and data for dsgrid, ubiquitous L1 and L2 charging and ubiquitous DCFC availability (only used for trips that exceed range) were assumed. County-specific residential charging availability data available from Ge et al. (2021). County-specific estimates of public charging are available from the Alternative Fuels Data Center (AFDC), EVI-X, early National Electric Vehicle Infrastructure (NEVI) plans, and are in development. Time-specific trip purpose and locational data available from NHTS (2017). To inform how much charging load should be assigned within or to neighboring or farther counties, the U.S. Department of Transportation Highway Performance Monitoring System could be used to

	TEMPO Data Input	Model Resolution	Potential Enhancements, Disaggregation, and Data Sources
			approximate travel activity within/across counties and the likely location of public charging. EVI-X/EVI-RoadTrip may also be helpful. In addition to charging availability, further detail on charging efficiencies by charging speed/type, location, and behavior may become important with more variations on charging scenarios.
	Public transit availability (by mode and by time)	Urbanity-specific (5)	In current scenarios and data for dsgrid, calibrated to NHTS and/or assumed. Data available from BTS and NTD, but difficult to disaggregate comprehensively for 3,143 counties.
	Mobility as a service (MaaS) and micromobility availability (by mode)	Urbanity-specific (5)	In current scenarios and data for dsgrid, calibrated to NHTS and/or assumed.
Economic	Energy prices	National, by scenario	Although most demand (e.g., trip frequency and length) is configured to be price-inelastic in TEMPO, structural differences in regional prices could drive differences in behavior and choices. Spatially differentiated gasoline and diesel prices (e.g., with impact of differences in fuel taxes and refining capacity) available from EIA, GasBuddy, OPIS (Gohlke 2021). Spatially differentiated and temporally specific (e.g., time-of-use or hourly prices) electricity rates available by utility region in URDB (NREL 2022) or from samples and/or historical wholesale market prices. General projections available from ATB (NREL 2020) and/or NREL Standard Scenarios. Vehicle charging costs, especially for future medium-/heavy-duty vehicle charging, are dependent on equipment/infrastructure costs, charging situation/type, charge management, capacity utilization, and public investment.
	Technology (vehicle) costs	National, by scenario	AEO, ATB, U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Vehicle Technologies Office targets. Dealer incentives, marketing, specialized offerings can differ by location, but data would be difficult to collect and integrate.
	Prices affected by taxes, subsidies, incentives, and regulations	National, by scenario	Can be modeled as adjustments to prices. Scenarios do not explicitly include ZEV and CAFE/GHG regulations requiring manufacturer fleet-level credit compliance, state and local subsidies, and Inflation Reduction Act provisions for clean vehicles, clean commercial vehicles, used clean vehicles, clean electricity, clean hydrogen, clean fuels, advanced energy, and advanced manufacturing. Data available

	TEMPO Data Input	Model Resolution	Potential Enhancements, Disaggregation, and Data Sources
			from sources such as AFDC, Dsire, Atlas Public Policy EV Hub. However, the exogenous vehicle electrification scenarios in this report are qualitatively informed by these programs and their incentives and ambition.
Travel Behavior	Cost and time elasticities and preferences for technologies/fuels and modes	Bin- (60) and county- (3,143) specific, via county household counts	Currently based on literature and/or fitted and calibrated with NHTS and AEO and/or with scenario-based assumptions.
		Temporal: Non-time-varying	
	Trip/travel patterns: trip counts, trip lengths, vehicle occupancies	Bin- (60) and county- (3,143) specific, via county household counts	Currently, distributions fitted to NHTS (2017) trip data, with scaling to match aggregate AEO/BTS estimates. Adjustments for seasonal/holiday travel could be based on Highway Performance Monitoring System data, if warranted.
		Temporal: 10 periods/day, weekday/weekend	
	VMT by age and position in household	N/A	Data available from NHTS (2017). Model representation in development.
System	Travel time intensities (by mode)	Urbanity	NHTS, BTS. Localized estimates of congestion could be incorporated, if warranted. (could affect energy use, mode choice)
	Emission intensities (by fuel)	National	GREET, EPA (could affect energy taxes/prices, regulations, affecting vehicle technology or mode choice)
	Non-household passenger light-duty vehicle attributes (cost/ time intensities, stock/fuel economy, occupancies)	National	Calibrated to NHTS/assumed

Appendix B. TEMPO-dsgrid Linkage

Table B-1 shows the structure and format of TEMPO's intermediate data files generated in the process of simulating charging profiles, and the final data set compiled and submitted to dsgrid.

While the provided load data are aggregates of individual households and vehicle loads, the metadata provided allows for a disaggregation of vehicle size class (compact car, midsize/large car, SUV, pickup), vehicle technology type (PHEV25, PHEV50, BEV100, or BEV300), and household type (vehicle energy use associated with households in each of TEMPO's 60 household bins). This results in 2,016 data points[37] per charger type (2) for each simulated household type (up to 60), vehicle technology type (4), vehicle size class (4), county (3,143), model year (30), and scenario (3). Thus, the total number of simulated data points is 1.095 trillion, although many values are efficiently stored zeros.

Table B-1. Structure and Format of TEMPO Intermediate and Output Data Files for dsgrid

	TEMPO			**dsgrid**	
File name	**household-trips.csv** [a]	**household-ev-profile.csv** [b]	**household-ev-charging.csv** [c]	**lookup.parquet** [d]	**data.parquet** [e]
Content	Trips	Consumption	Charging	Metadata	Load data
Parquet Data ID				√	√
Scenario	√	√	√	√	
Region (county)	√	√	√	√	
Model Year	√	√	√	√	
Weather Year	2012 only				
Month			√		√
TEMPO Time Period/Weekday	√				
Hour of Week		√	√		
Hour [of Day]					√
Day [of Week]					√
Household Composition Bin	√	√	√	Compiled in new "Subsector" variable	
Household Income Bin	√	√	√		
Urbanity Bin	√	√	√		
Vehicle Technology	√	√	√		
Vehicle Class	√	√	√		

[37] 2016 data points, from 12 representative weeks of a year × 7 days of week × 24 hours of day, as opposed to 8,760 or 8,783 data points for every hour in a year. Because TEMPO only simulates representative weeks and seasonal impacts (rather than following every hour in a specific weather year), this data format minimizes unnecessary data duplication and avoids false precision in the TEMPO data submitted to dsgrid.

	TEMPO			dsgrid	
File name	**household-trips.csv** [a]	**household-ev-profile.csv** [b]	**household-ev-charging.csv** [c]	**lookup.parquet** [d]	**data.parquet** [e]
Fuel	√	Electricity only			
Mode	√	Household passenger ("personal") light-duty vehicle only			
Household ID	√	√	√		
Vehicle ID	√	√	√		
Weighting Factor	√	√	√		
Trip Distance	√	√			
Trip/Charge Duration	√	√	√		
Trip Energy Consumed	√	√	√		
Charger Energy Delivered			√		
Charging Type/Power			√		
Load: L1&L2 [kWh]					√
Load: DCFC [kWh]					√

[a] Trip schedules for individual representative EVs from TEMPO simulations.

[b] Week-long energy consumption profiles of when and how much energy each EV consumes when driving.

[c] Week-long charging profiles of when and how much each EV accumulates energy from charging and what charger type was used.

[d] Aggregate charging load metadata "lookup" file identifying the household and vehicle type (subsector) and specific sample.

[e] Aggregate charging load data, reflecting the hourly electricity demand of each household type and vehicle type (subsector) for each county (based on weighted sums of week-long profiles and with seasonal adjustment based on month and temperature).

At this time, only the charging load data and metadata are being directly submitted to dsgrid. However, dsgrid has been designed to eventually enable submission of other metrics, which could include data describing activity, service, stock, costs, energy demand, and emissions, such as trips or miles traveled time series, vehicle counts, energy consumption (other than electricity) time series, and/or emissions data, which—along with the differentiation across household types, vehicle types, and geographies—would support output of a variety of normalized metrics at a variety of geographic, temporal, and sub-sectoral resolutions. This would also be important for evaluation of remaining electrification potential.