NARUC Electric Vehicles State Working Group

EV-RELATED LOAD GROWTH PROJECTIONS

MAY 12, 3:00 - 4:30 PM ET

Welcome

EV SWG Chair

Commissioner Staci Rubin, Massachusetts Department of Public Utilities

EV SWG Vice Chair

Commissioner Milt Doumit, Washington Utilities and Transportation Commission

EV Commission Staff Leads

Benjamin Baker, Maryland Public Service Commission

Steve Olea, Arizona Corporate Commission

NARUC Staff

Margerie Snider

Danielle Sass Byrnett

Agenda

Feel free to enter questions into chat at any time

3:00 PM	**Welcome and Announcements: Commissioner Rubin** • Agenda review
3:10 PM	**Speakers:** • **Greg Mandelman**, Electric Power Engineers • **Arthur Yip**, National Laboratory of the Rockies
4:10 PM	**Member Discussion**
4:30 PM	**Adjourn**

Next EV SWG Meeting:
June 16, 3:00-4:30 pm ET
EV Rate Design

NEW NARUC Professional Development Course: Electric Vehicle Grid Integration and Grid Impacts for State Regulators
May 19-21, 2:00-4:00 pm ET daily. Discounted for NARUC members.

NARUC Summer Policy Summit: Unlocking VGI: A Multi-State Blueprint for (Electric) Vehicle-Grid Integration
Tuesday, July 21 at 11am CT

Today's Speakers

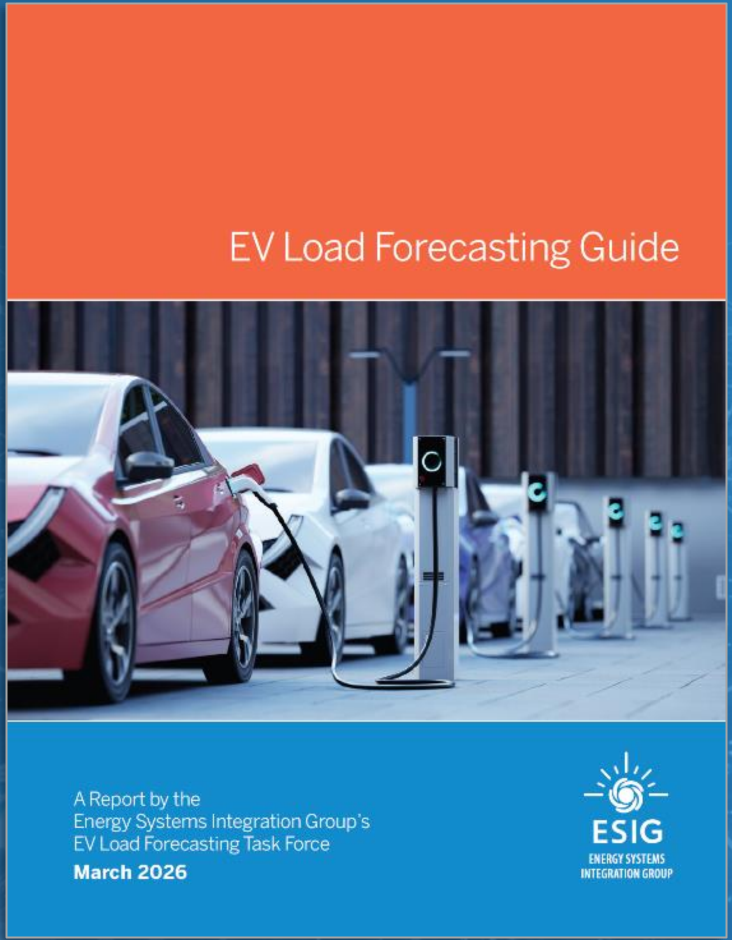
- **Greg Mandelman**, Electric Power Engineers
- **Arthur Yip**, National Laboratory of the Rockies

NARUC EV State Working Group

Energy Systems Integration Group EV Load Forecasting Task Force

EV Load Forecasting Guide

A practical framework for utilities, regulators, and stakeholders



Prepared by Greg Mandelman

May 12, 2026

Director, Analytics & Energy Programs

Electric Power Engineers

Contents

EV Load Forecasting Guide

#	Topic
1	Why This Guide, Why Now
2	What Makes EV Forecasting Different
3	Three Components, One Framework
4	Practical Framework for Forecasting EV Charging Loads
5	Best Practices Across The Forecasting Lifecycle
6	What Regulators Should Take Away

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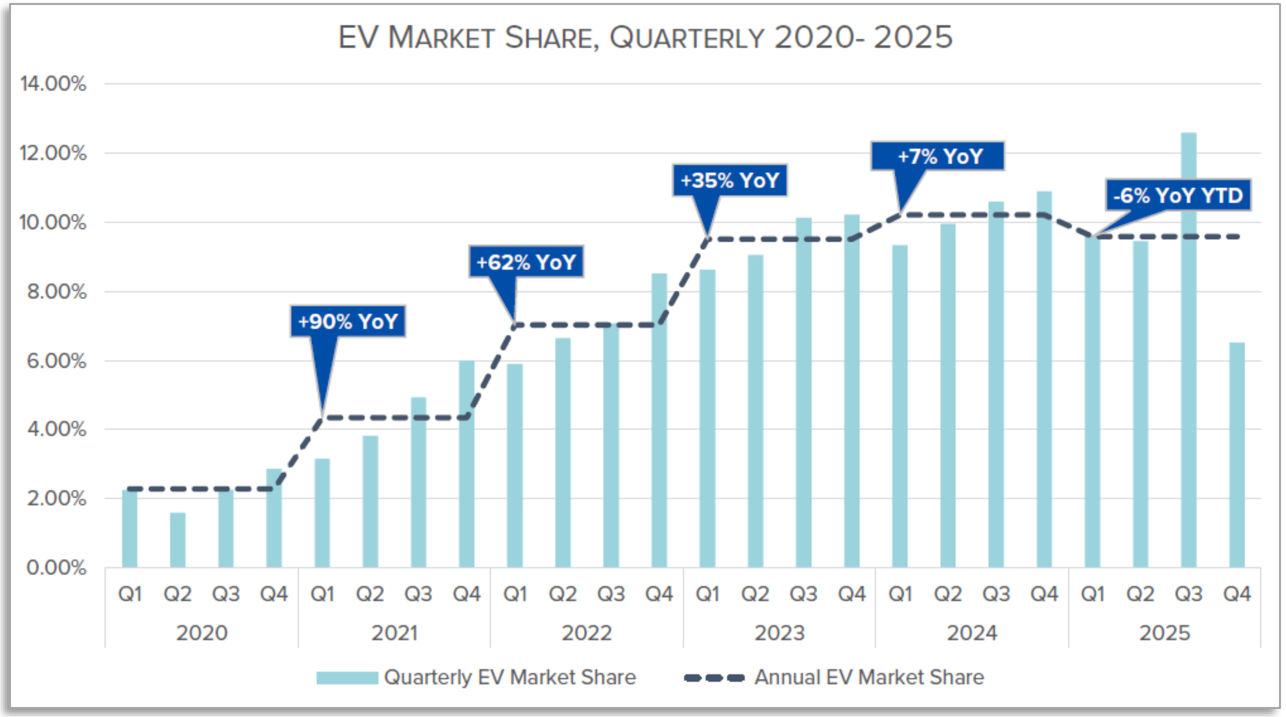
Why This Guide, Why Now

EV loads are materializing faster than planning practices can keep up

- Light-duty vehicle (LDV) market share surged from 2% to over 10% between 2020 and 2024, before moderating to 9.6% in 2025 – 7.3M EVs now on the road
- A single EV can consume nearly half the annual electricity of an average U.S. household
- EV loads are mobile, behavioral heterogenous, and geographically concentrated — traditional econometric models don't handle this well
- Without fit-for-purpose forecasts, utilities risk service delays and inefficient grid investments

US LDV EV Market Share, Year-over-Year Market Share Quarterly 2020-2025



Source: Alliance for Automotive Innovation

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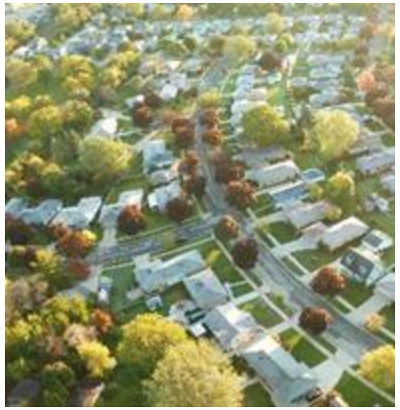
Guide available here

What Makes EV Forecasting Different

EVs introduce complexities that traditional load forecasting doesn’t address



Traditional Loads

- Fixed location
- Predictable patterns
- Weather/economic driven

EV Loads

- Travel & mobility behavior
- Geographically variable
- Concentrated risk

Less predictable adoption patterns — EV adoption is not tightly correlated with premise-level electricity usage

Locational & behavioral uncertainty — EVs are mobile; charging depends on travel needs, convenience, cost, and availability

Concentrated high-impact loads — Fleet depots and DCFC plazas can appear rapidly and overwhelm local distribution

Dynamic technology trajectory — Battery, range, and bidirectional capabilities are moving targets

“Triple mobility” — Vehicles move, owners relocate, vehicles change hands

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Three Components, One Framework

The Guide structures EV load forecasting into three components

1. **EV Adoption Forecasting** — How many EVs, what type, where, and when
2. **EV Charging Infrastructure Forecasting** — What type of charging assets are needed to serve EVs
3. **EV Charging Profiles** — Converting hourly chargers loads into kW demand and kWh load profiles

These components are sequential with iterative feed back affects, such infrastructure availability influencing adoption

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Practical Framework for Forecasting EV Charging Loads

The Guide is organized around supporting three distinct activities

Forecast Scoping

Audience: Utility planners, regulators, stakeholders

Focus: Define objectives, scope, scenarios, assumptions

Forecast Implementation

Audience: Utility analysts, consultants

Focus: Data gathering, modeling, documentation

Forecast Review

Audience: Regulators, intervenors

Focus: Evaluate methodology, reasonableness, fitness for purpose

Regulators play a critical role during Forecast Scoping and Forecast Review

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Best Practices Across The Forecasting Lifecycle

Organized around scoping, implementing, reviewing, and applying EV load forecasts

Scoping
BPs 1–4

Best Practice 1

Define the forecast's **core requirements collaboratively**, including the forecast area, time horizon, and required spatial granularity, to align with its intended purpose.

Best Practice 2

Specify the **mix of vehicle segments** to be forecast (e.g., light-duty, fleet, off-road) based on their potential grid impact and relevance to the forecast area.

Best Practice 3

Explore the use of **multiple scenarios** to investigate a range of plausible futures by varying assumptions about technologies, market conditions, consumer behaviors, and policies.

Best Practice 4

Engage **stakeholders early and consistently** to shape scenarios, define assumptions, and build trust in the forecast results.

Adoption
BPs 5–8

Best Practice 5

Use **comprehensive and clearly documented inputs** for adoption for each adoption scenario included in the forecast, and identify how inputs apply to each vehicle duty

Best Practice 6

Model the adoption of both **personally owned and fleet-owned vehicles**, recognizing that fleets prioritize total cost of ownership and operational needs while consumers are influenced by a broader set of factors.

Best Practice 7

Select adoption forecasting models and approaches (e.g., consumer preference, propensity, diffusion) that are **fit-for-purpose** based on data availability and desired granularity.

Best Practice 8

Calibrate and **validate** adoption models against historical registration data, and **benchmark** results against reputable third-party forecasts to ensure credibility.

Infrastructure
BPs 9–11

Best Practice 9

Base infrastructure forecasts on the outputs of the EV adoption forecast, including vehicle counts, characteristics, and spatial distribution.

Best Practice 10

Ground infrastructure assumptions in **empirical data** where possible, including real-world charging behavior, travel patterns and observed charger utilization rates.

Best Practice 11

Select **infrastructure forecasting methods** (e.g., needs-based simulation, EV-to-charger ratios) that are appropriate for the required level of detail, from high-level estimates to specific siting analysis.

Charging
BPs 12–14

Best Practice 12

Integrate vehicle, infrastructure, and grid data— including vehicle miles traveled, dwell times, charger power levels, and baseline grid conditions—to create **detailed load profiles**.

Best Practice 13

Model multiple charging scenarios to quantify a range of estimates for grid impacts of different behaviors, including unmanaged charging and various smart charging or demand response strategies.

Best Practice 14

Calibrate charging profiles by benchmarking against real-world metered data from sources like utility advanced metering infrastructure, charging network operators, or pilot programs.

Implementing the Forecast

Reviewing
BPs 15–17

Best Practice 15

Ensure forecast **transparency** through comprehensive and accessible documentation of all data sources, assumptions, methodologies, and calculations.

Best Practice 16

Evaluate the forecast for **reasonableness and analytical robustness** by benchmarking against other forecasts (such as past forecasts, state agency forecasts, or forecasts by other parties) and conducting sensitivity analyses on key variables (e.g., baseline EV stock, fuel price projections, technology cost curves).

Best Practice 17

Confirm the forecast is fit-for-purpose by ensuring its outputs (e.g., granularity, time horizon) are relevant and clear for their intended use in planning or regulatory proceedings.

Application
BPs 18–20

Best Practice 18

Use the forecast as a tool to **inform actionable grid planning**, including identifying the need for targeted infrastructure upgrades and evaluating the potential of load management to mitigate costs.

Best Practice 19

Foster **coordination and data sharing** among all planning stakeholders—including utilities, regulators, other agencies, and other parties—to align assumptions and create more cohesive forecasts.

Best Practice 20

Incorporate **emerging technologies and modeling advances** into long-term scenarios to ensure forecasts remain forward-looking and account for potential market shifts like vehicle-to-grid (V2G) or ultra-fast charging.

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Implementing the Forecast

Takeaways for Regulators

Key Themes and accompanying best practices

Theme	Best Practices	Description
Scenario Analysis	BP 3, 13, 16	A single point forecast is insufficient; use confidence bands around adoption and charging assumptions
Transparency	BP 1, 5, 10, 12, 15	Documented data sources, assumptions, methodologies, and calculations
Calibration	BP 8, 14, 16	Benchmarking against historical registration data and reputable third-party forecasts
Fitness-for-Purpose Alignment	BP 1, 7, 17	Forecast outputs match planning use (distribution vs bulk system vs rate design)
Cross-Agency Coordination	BP 1, 19	Align utility, DOT, and energy office assumptions

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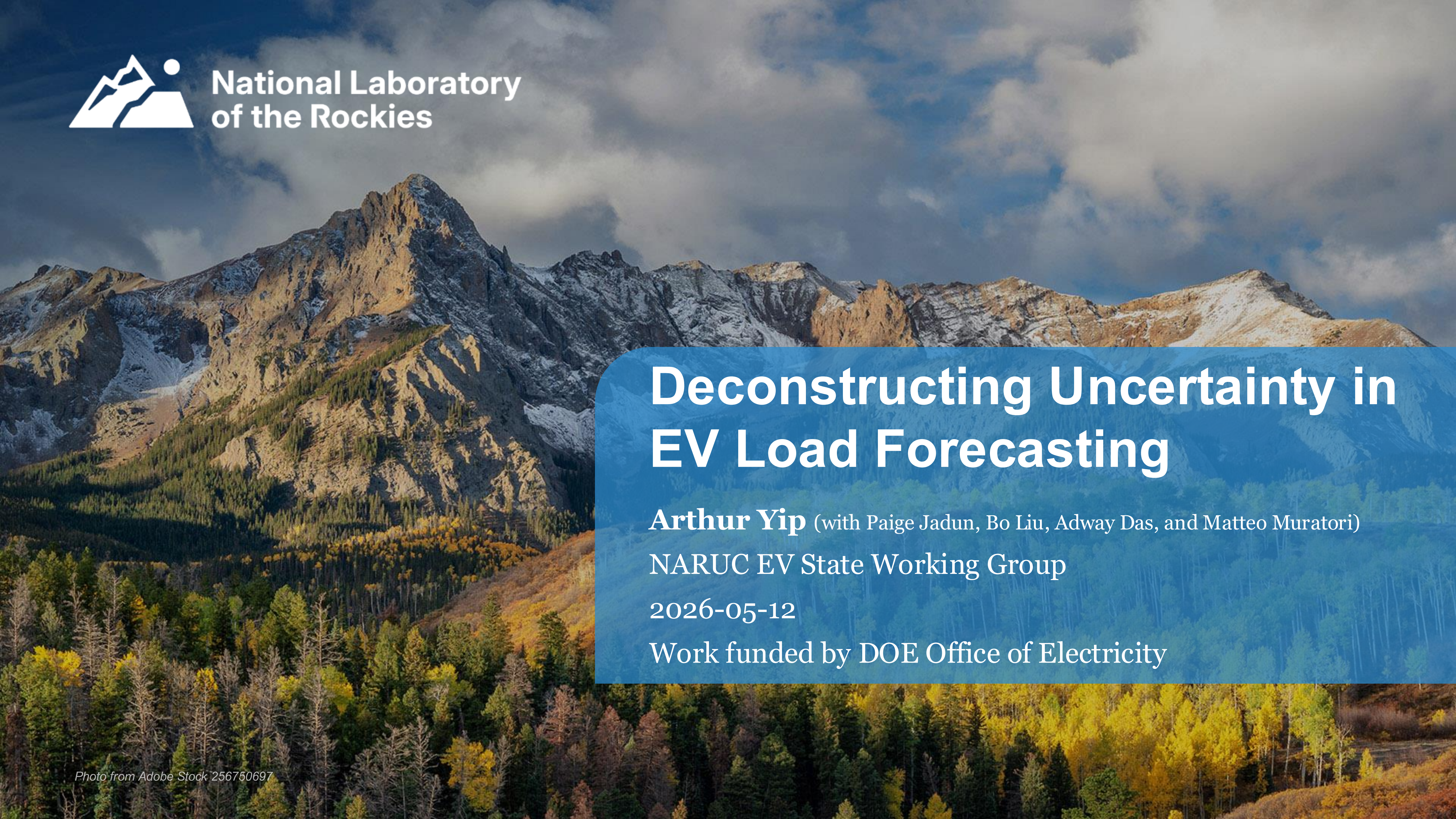
Speaker Q & A

- **Greg Mandelman**, Electric Power Engineers



National Laboratory of the Rockies

Deconstructing Uncertainty in EV Load Forecasting

Arthur Yip (with Paige Jadun, Bo Liu, Adway Das, and Matteo Muratori)

NARUC EV State Working Group

2026-05-12

Work funded by DOE Office of Electricity

Photo from Adobe Stock 256750697

While increased transport electrification is largely expected, load impacts are highly uncertain

How much, where, and when EV load will appear depends on many factors

Example factors of uncertainty

Grid
- Electricity rates/prices
- TOU rate designs
- Response to TOU rates
- Grid capacity

EV adoption is large source of load uncertainty, with many factors listed here impacting adoption (e.g., cost, model availability, etc.)

Charging infrastructure
- Availability
- Speed of deployment
- Perception & preferences
- Charging behavior/ utilization

Managed Charging
- Cost & availability
- Reliability & flexibility
- Preferences/perception
- Operation/dispatch

Vehicle technology
- Battery/vehicle costs
- EV performance/efficiency
- Range/battery size
- Battery degradation
- Competing technologies (ICEV & conventional fuel costs; FCEV & H2 costs)

Consumer choice
- Preferences/perception
- Size class preference
- Values of EVs for resiliency

Vehicle market
- Make & model availability
- Used vehicle market
- EV marketing
- Supply chain
- Fleet ownership/charging business model

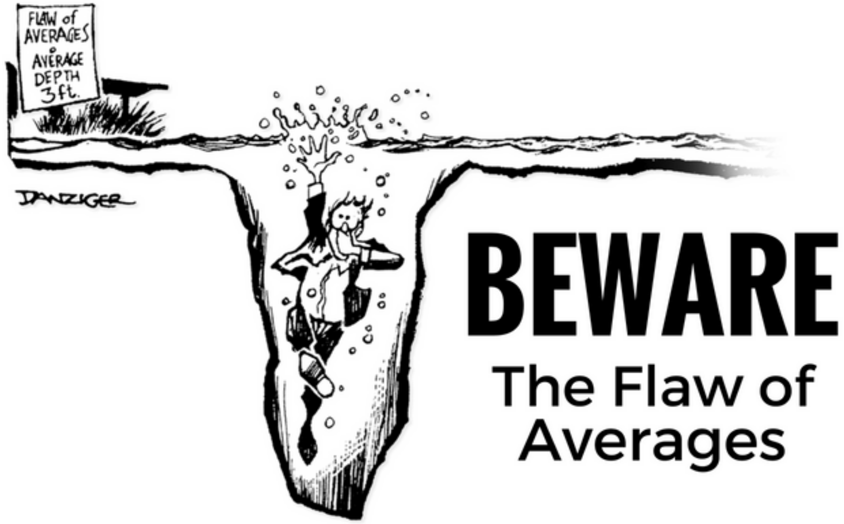
Policy
- ZEV mandates
- ICEV bans
- Tax credits/rebates

Environment/ Macro
- Temperature
- Extreme weather events
- Urban planning/design
- Household demographics

Transportation system
- Telework/virtual travel
- Travel behavior
- Emerging modes & AVs
- Freight logistics
- Transit services
- Fleet makeup & locations

Yip et al. Forthcoming

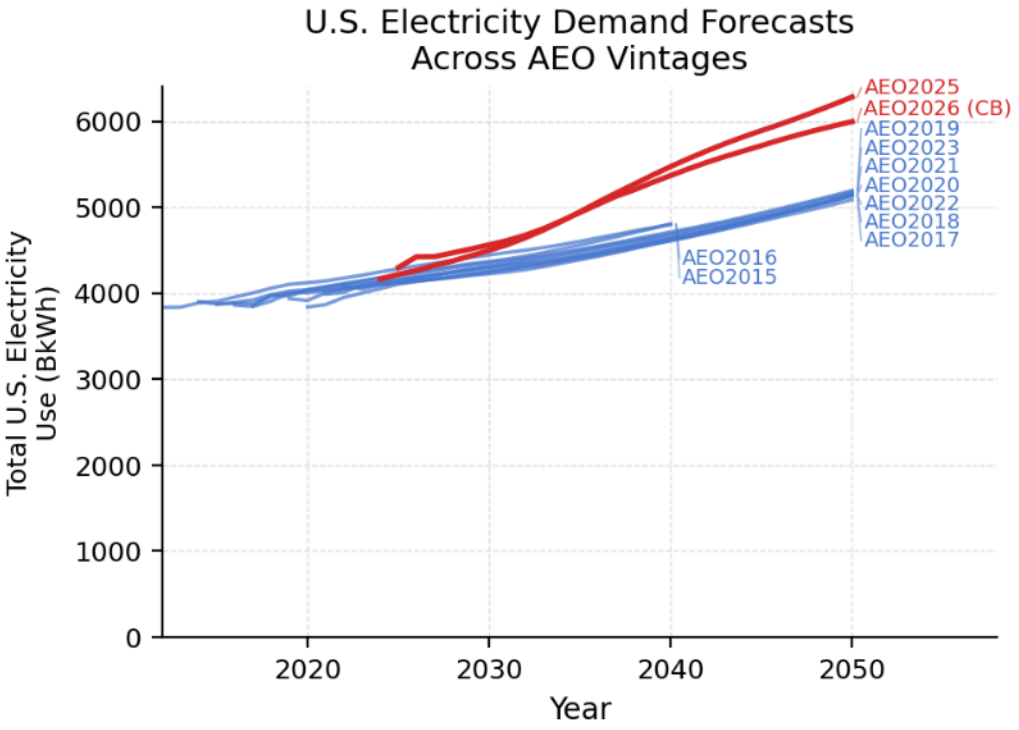
National-level or average assumptions will miss local impacts (regional and temporal) of particular concern to planners



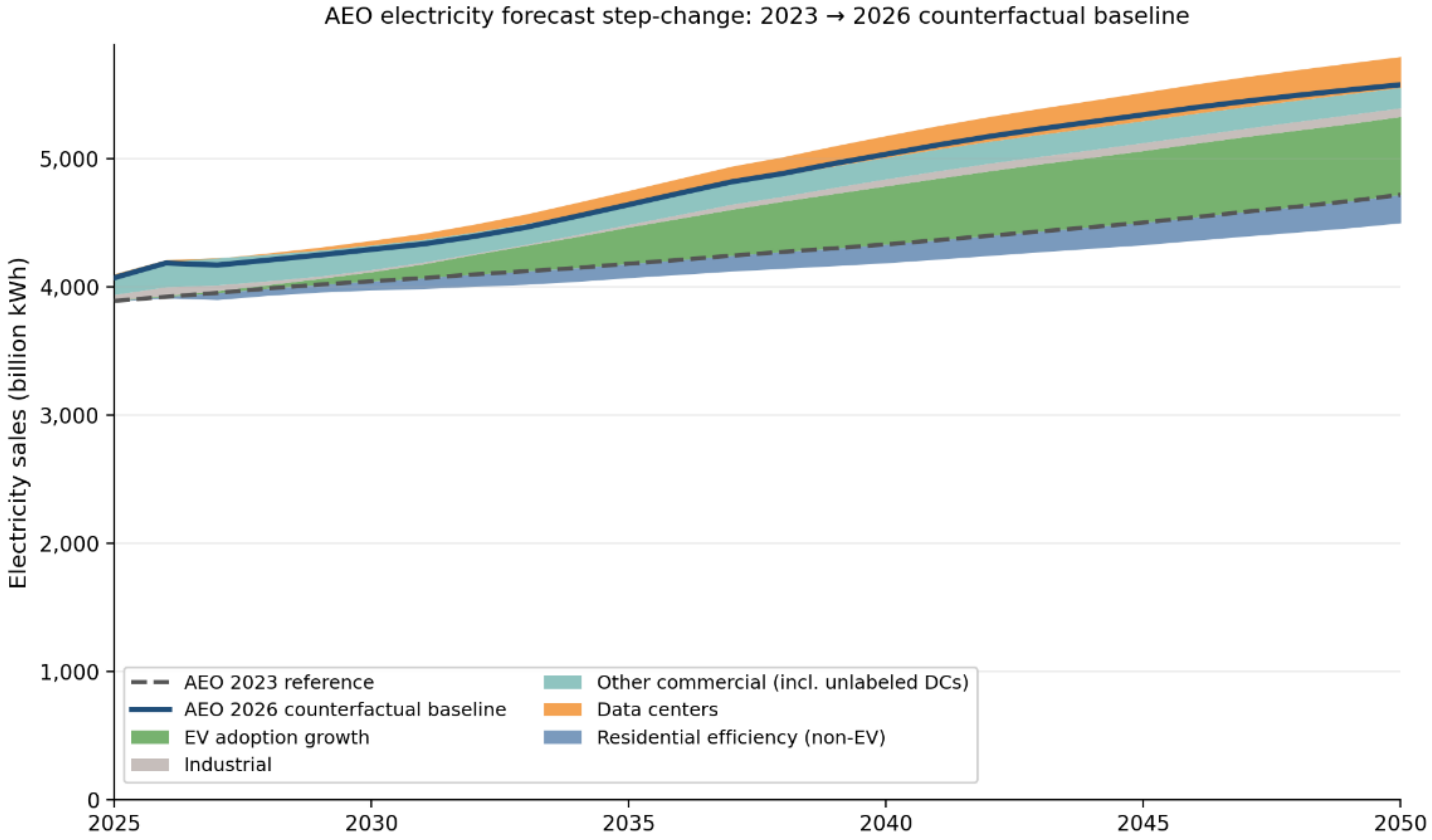
Savage, Sam L. The flaw of averages: why we underestimate risk in the face of uncertainty. John Wiley & Sons, Inc., 2012

Understanding sources of load uncertainty and considering for local factors can help create more robust forecasts

EVs are still the largest expected source of long-term load growth



AEO2026 = Counterfactual Baseline. No AEO2024 published.



Source: NLR (Chernyahovskiy) analysis of EIA data

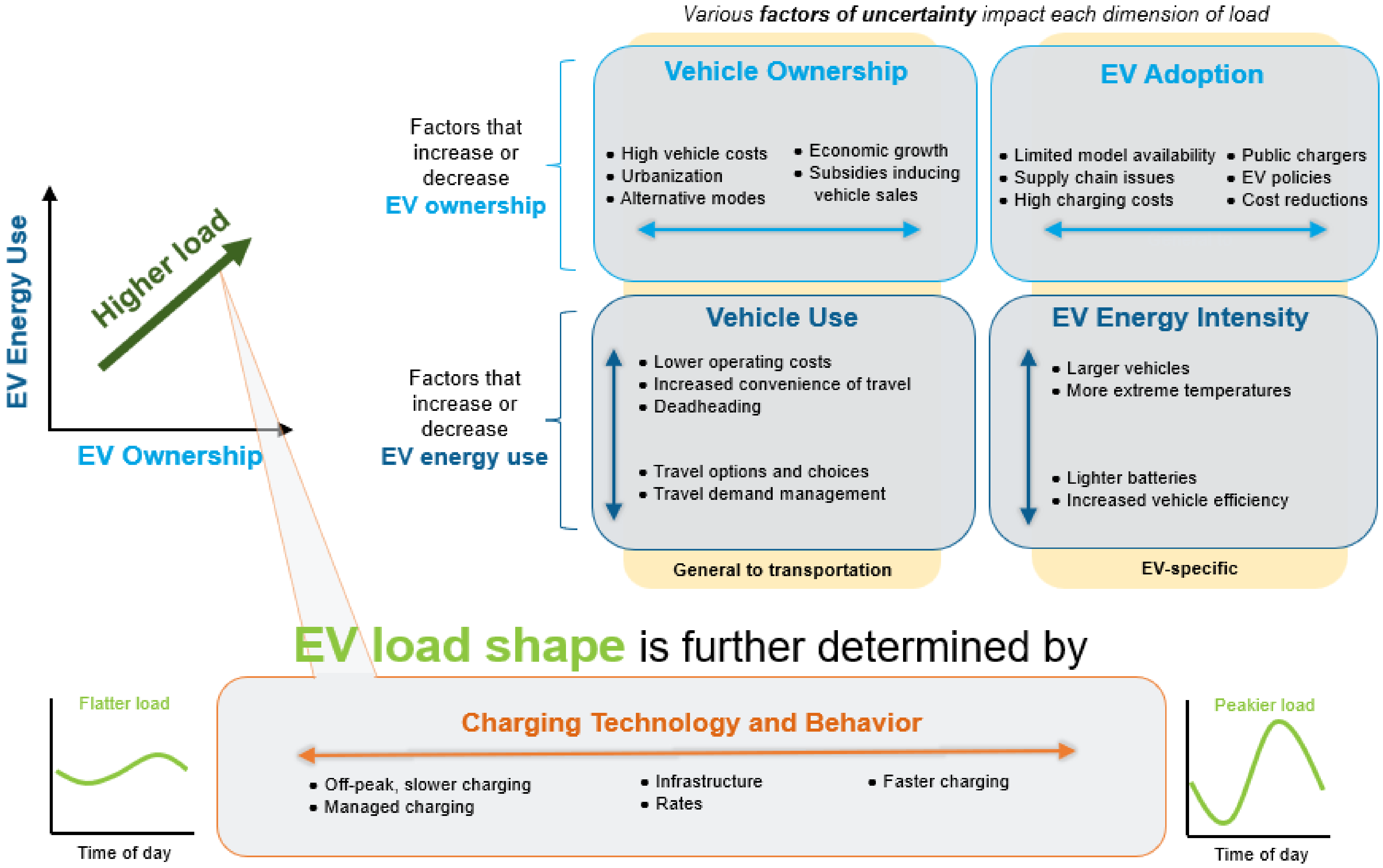
We deconstruct EV load into dimensions and drivers

- **Adoption & ownership**: how many EVs and of what kind?
- **Vehicle use & travel behavior**: how many electric miles traveled?
- **Energy intensity:** how much energy is consumed per unit of travel?
- **Charging behavior & technology**: when, where, and how will EVs charge?

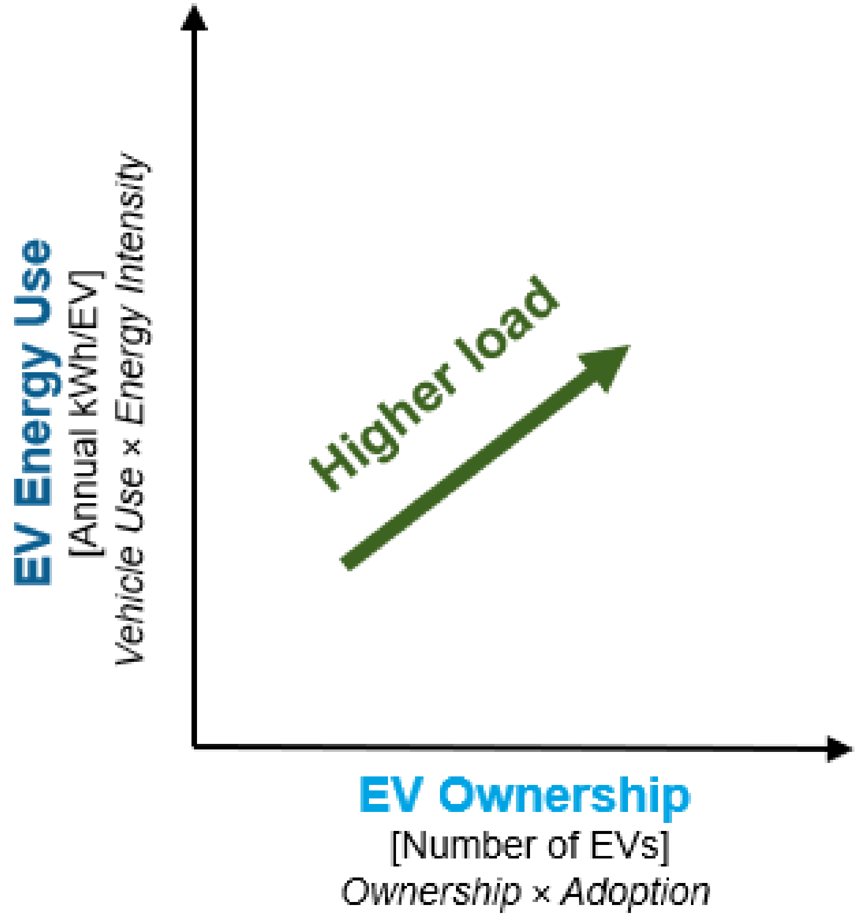
All subject to **inherent heterogeneity** (*i.e.*, regional and temporal variations) and **forecast uncertainty** (*i.e.*, uncertainty of the future)

How much load, **when,** and **where?**

Annual EV load is determined by EV ownership and EV energy use



We decompose EV load into a Kaya-style identity equation



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

= **EV Ownership** [Number of EVs] *Ownership × Adoption* × **EV Energy Use** [Annual kWh/EV] *Vehicle Use × Energy Intensity*

$$= [vehicles] \times \left[\frac{EVs}{vehicles}\right] \times \left[\frac{mi/yr}{EV}\right] \times \left[\frac{kWh}{mi}\right]$$

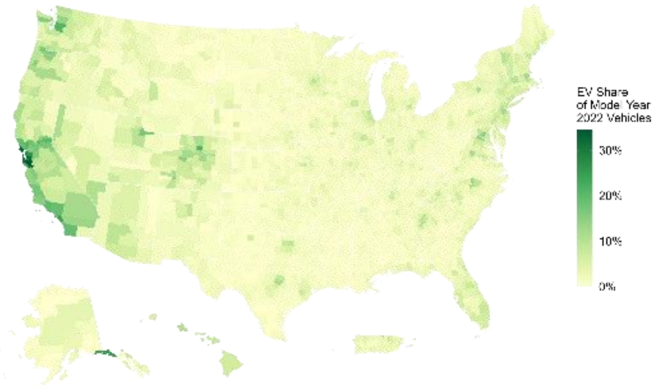
$$[vehicles] \leftarrow f\left(\begin{array}{c} income, \\ geography, \\ \dots \end{array}\right) \qquad \left[\frac{EVs}{vehicles}\right] \leftarrow f\left(\begin{array}{c} EV\ sales\ share, \\ new\ vehicle\ sales, \\ vehicle\ survival, \\ \dots \end{array}\right)$$

$$\left[\frac{mi/yr}{EV}\right] \leftarrow f\left(\begin{array}{c} urbanicity, \\ household \\ vehicle\ mix, \\ mode\ shares, \\ eVMT\ effects, \\ \dots \end{array}\right) \qquad \left[\frac{kWh}{mi}\right] \leftarrow f\left(\begin{array}{c} vehicle\ size, \\ EV\ efficiency, \\ weather, \\ driving\ style, \\ \dots \end{array}\right)$$

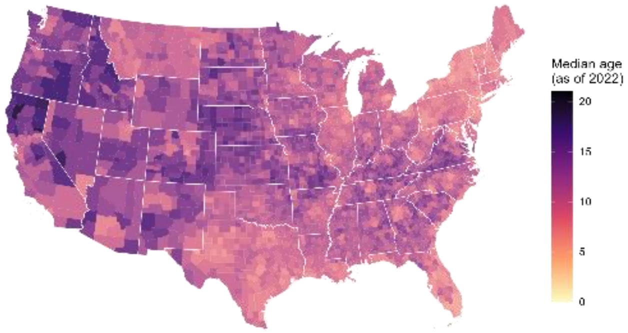
Uncertainty stems from regional and temporal variation, and future developments in technology and policy

Inherent Heterogeneity

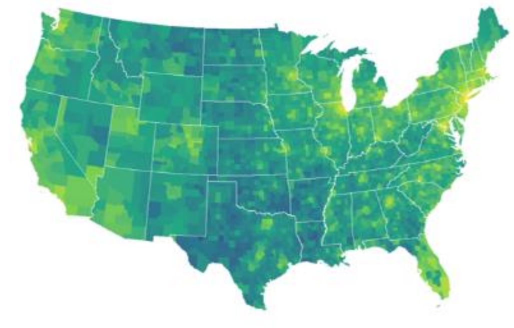
EV Market Share By County



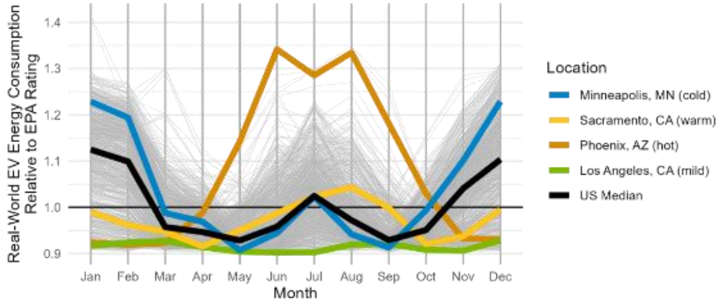
Median Age of Vehicles



Household Vehicles Categorized as Pickup Trucks

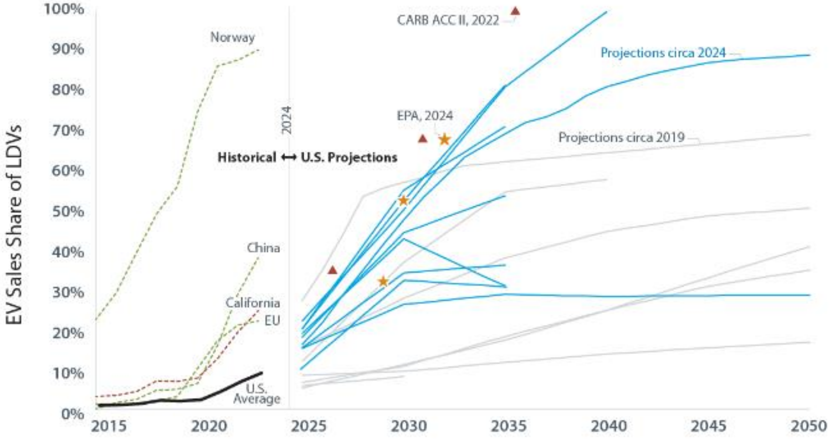


EV Energy Consumption by Month and Location



Forecast Uncertainty

EV Adoption Projections

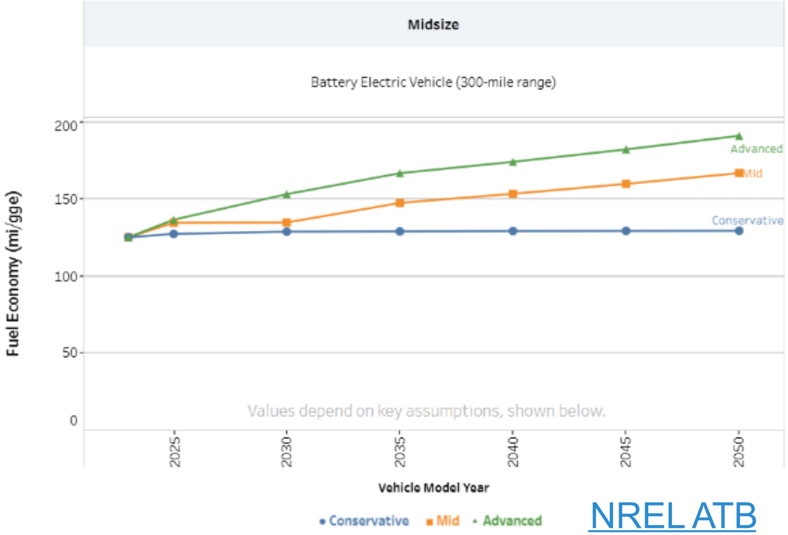


Muratori et al. 2025

EVSE buildout

Rates, Behavioral response

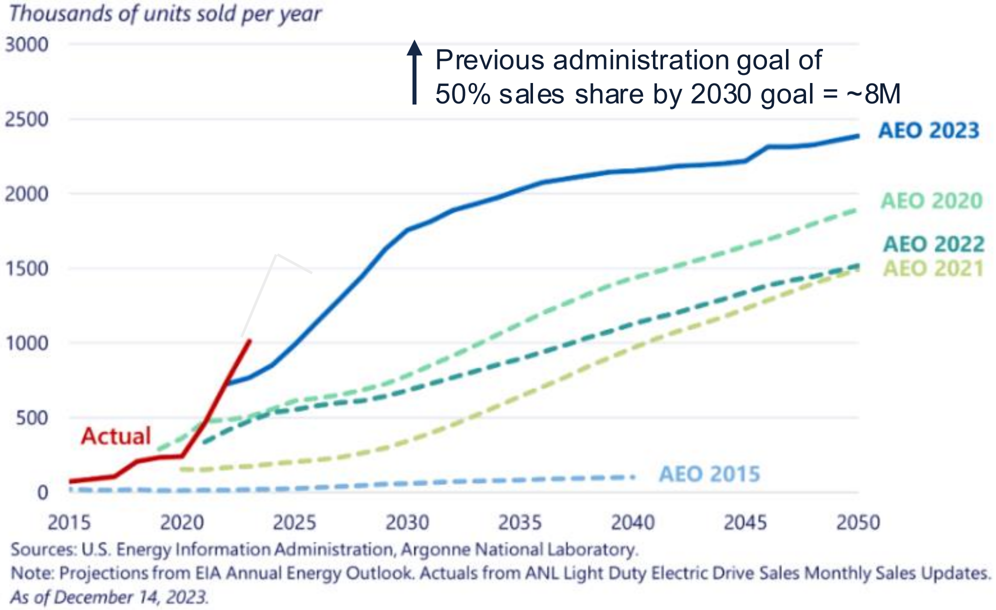
EV Efficiency Projections

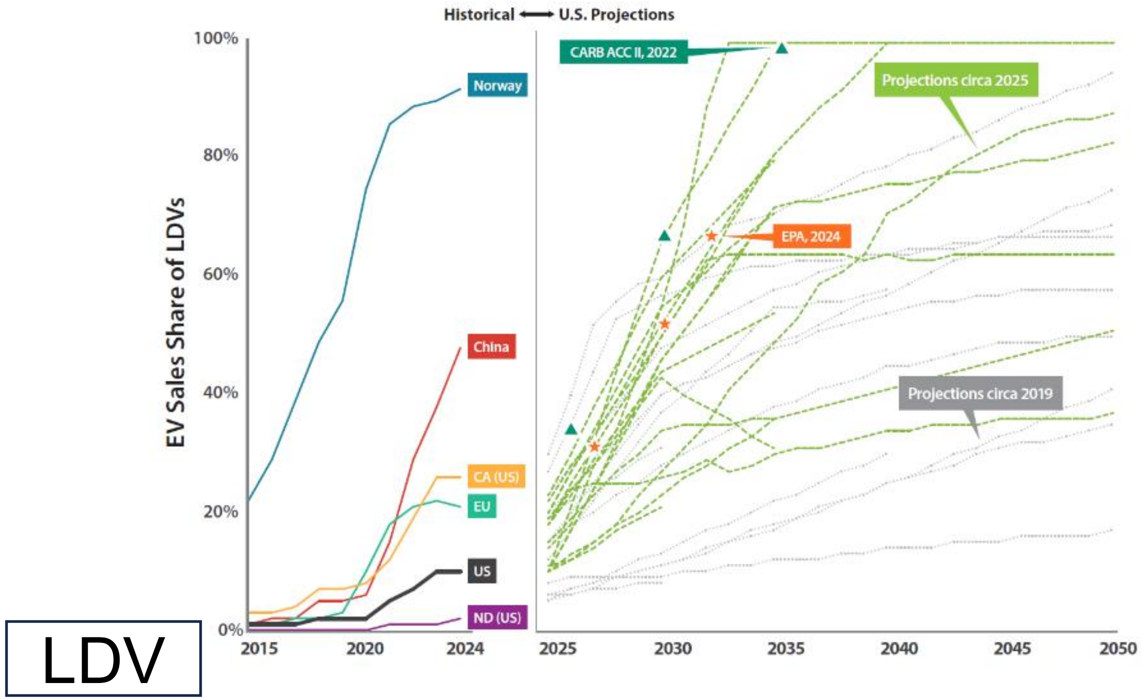


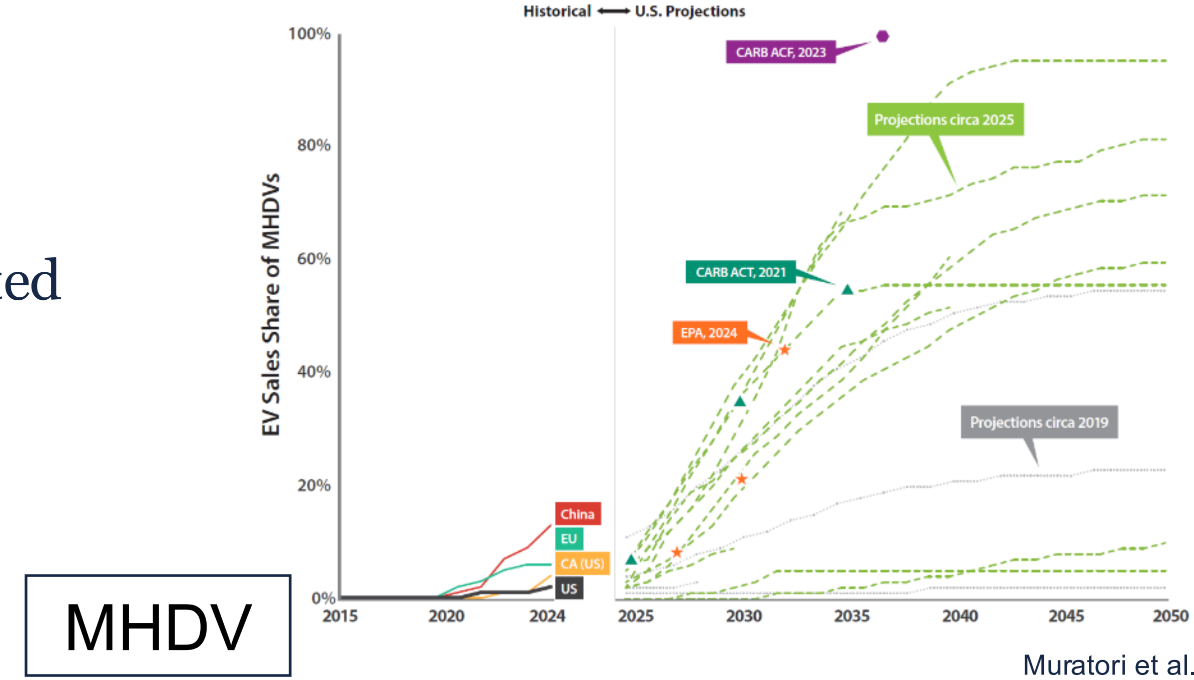
NREL ATB

Source for figures: Yip et al. (2023) Highly Resolved Projections of Passenger Electric Vehicle Charging Loads for the Contiguous United States

EV Adoption







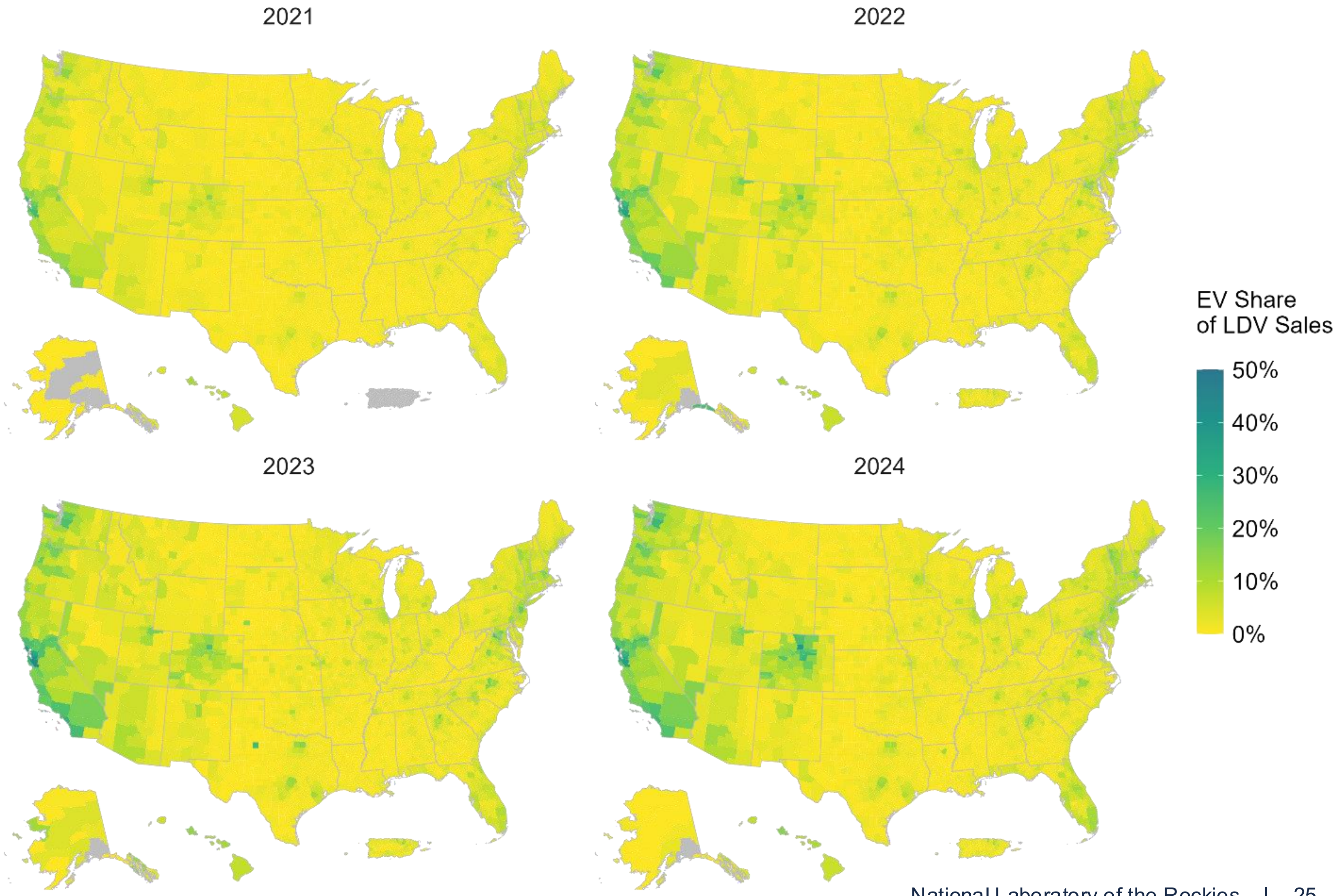
- Many historic projections have underestimated rate of growth (predicting adoption is difficult!)
- Even within an adoption goals (*e.g.*, meeting state regulations/targets), **uncertainty remains in other dimensions**

Muratori et al. 2025

EV adoption varies by region

“The future is already here; it’s just not very evenly distributed.”
– William Gibson

Understanding local EV market maturity can help inform near-term adoption;
Applicability to longer-term estimates should be carefully considered

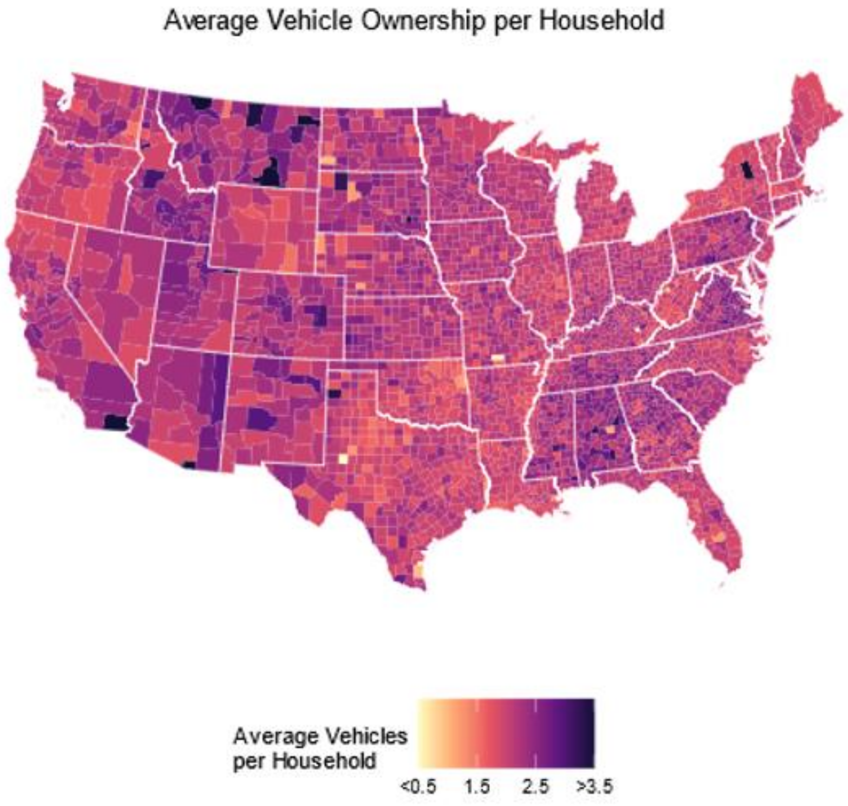


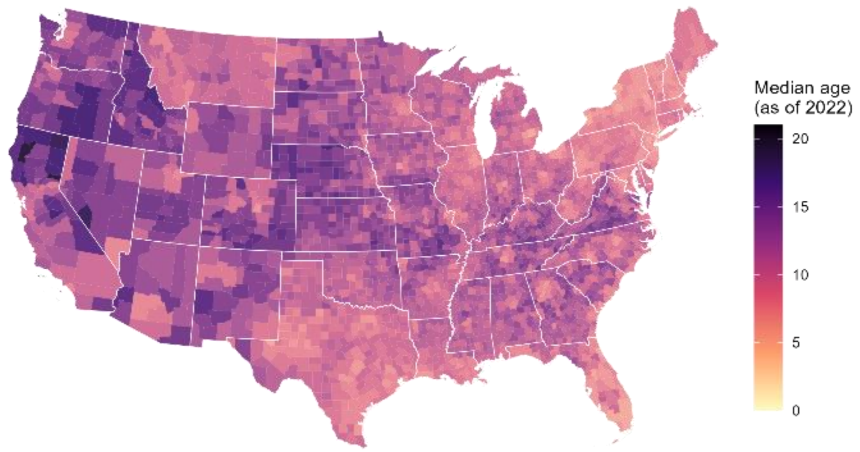
Source: Yip et al. (2023); Muratori et al. (2025)

Vehicle Ownership

- Vehicle sales do not equal vehicle stock
- Regional vehicle ownership trends may dictate how fast electrification will happen
  - Regions with slower stock turnover may take longer to electrify
- Used vehicle markets will also impact diffusion (EV dynamics still uncertain)

Considering local characteristics of total vehicle sales and vehicle age can improve accuracy of vehicle stock projections





Vehicle use and travel behavior

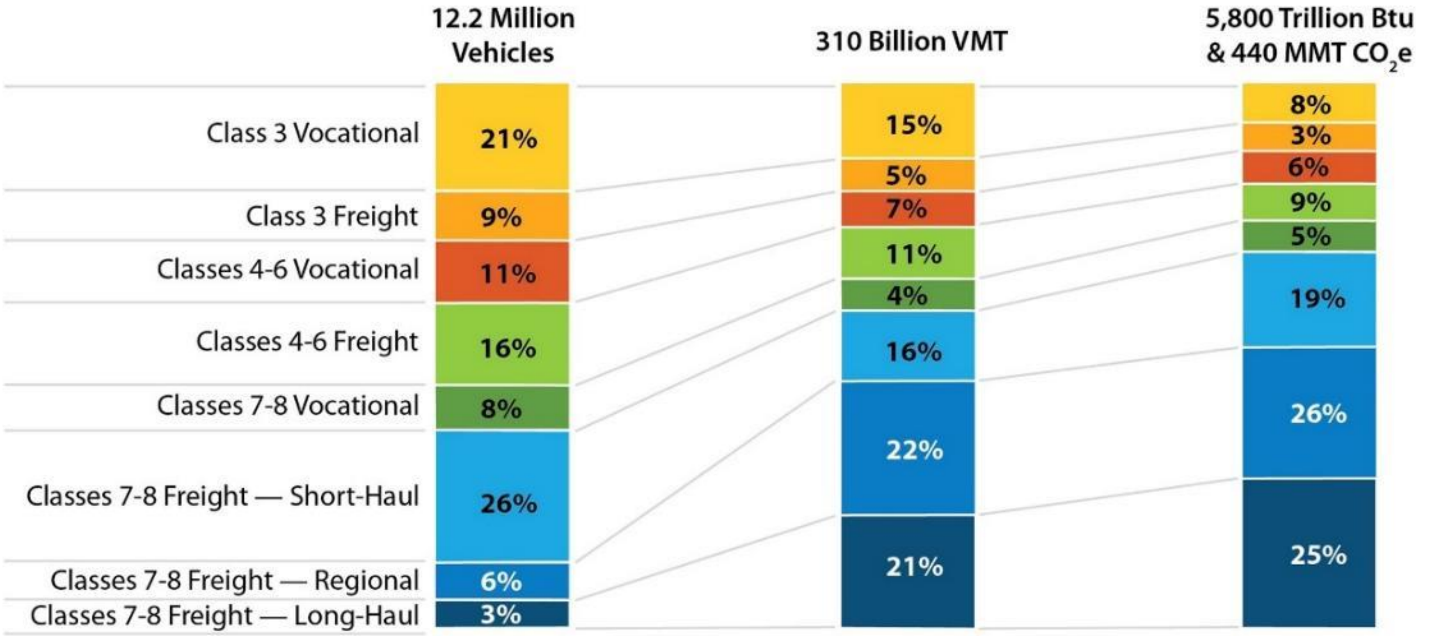
- **Vehicle miles traveled (VMT) varies by geography**, impacted by
  - Demographics
  - Urban design
  - Access to public transit
  - Vehicle ownership
  - And more
- Near-term uncertainty in **e-VMT**, likely dependent on past/current technology and customer profile
- Overall travel may be impacted in the mid- to long-term by
  - **New technologies and business models** (e.g., autonomous vehicles, ride-hailing)
  - **Strategies** aimed at reducing VMT (*e.g.*, public transit, urban planning, congestion pricing)

Regional VMT characteristics should be considered; sensitivity analysis of VMT informed by transportation studies can help capture uncertainty in longer term load scenarios

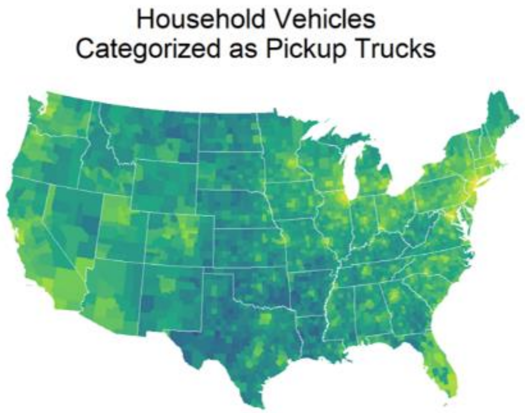
Energy intensity

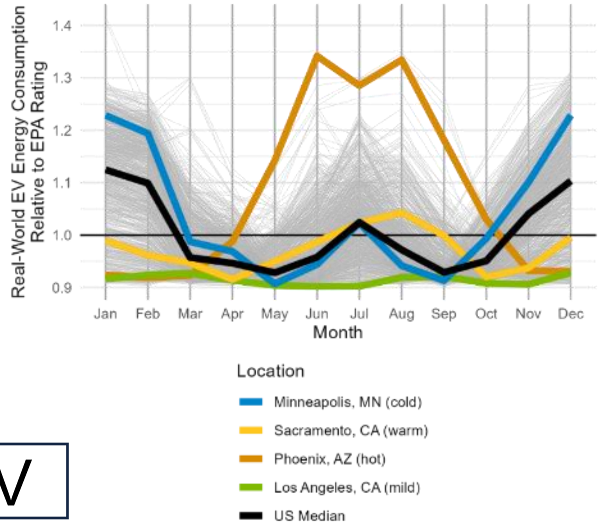
- Energy intensity is impacted by regional factors including
  - Vehicle size
  - Temperature
  - Road grade
  - Drive style
  - And more
- Vehicle efficiency advancements achieved through vehicle R&D also plays a large role

MHDV



Local data on vehicle characteristics/operations and temperature can refine energy intensity estimates; future vehicle technology assumptions should be informed by robust sources





LDV

Source for both figures: [Yip et al. (2023) Highly Resolved Projections of Passenger Electric Vehicle Charging Loads for the Contiguous United States]

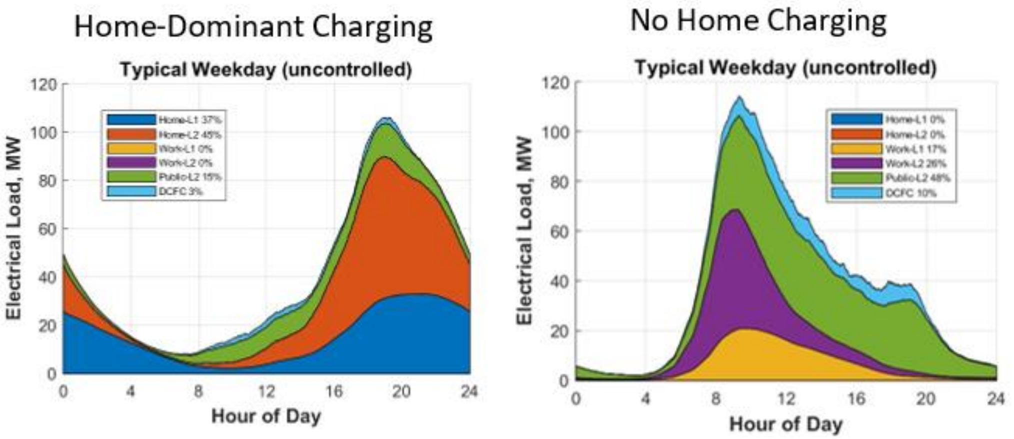
Charging behavior and technology

- EV load shape is impacted by
  - Charging infrastructure availability (and dependence on building stock types)
  - Charging power/technology
  - Charging preferences and behavior

- Current trends may not reflect future conditions (location and power levels)

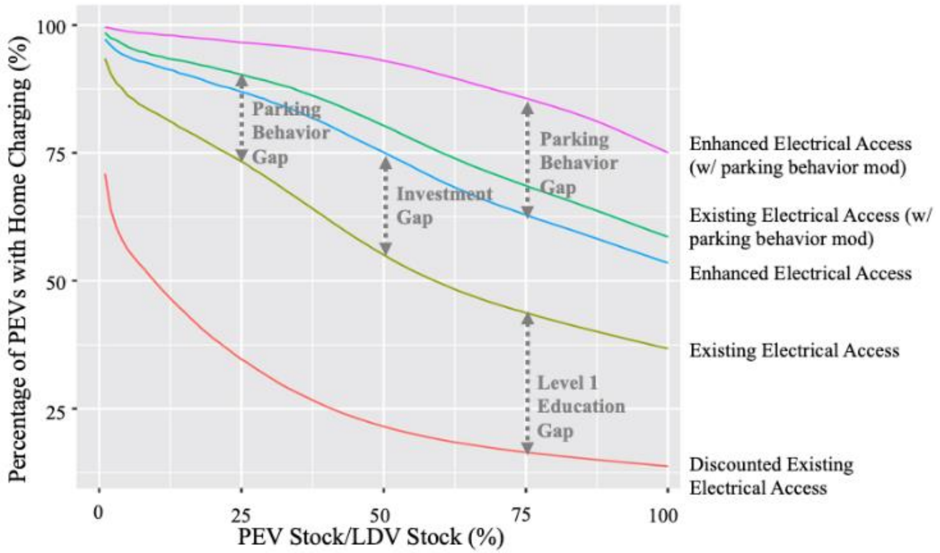
Consideration of potential for evolving load profiles can inform more robust forecasts/sensitivities

Load shapes differ by charging situation



NREL EVI-Pro Model: https://www.nrel.gov/transportation/evi-pro.html

Charging access will vary with higher EV penetrations

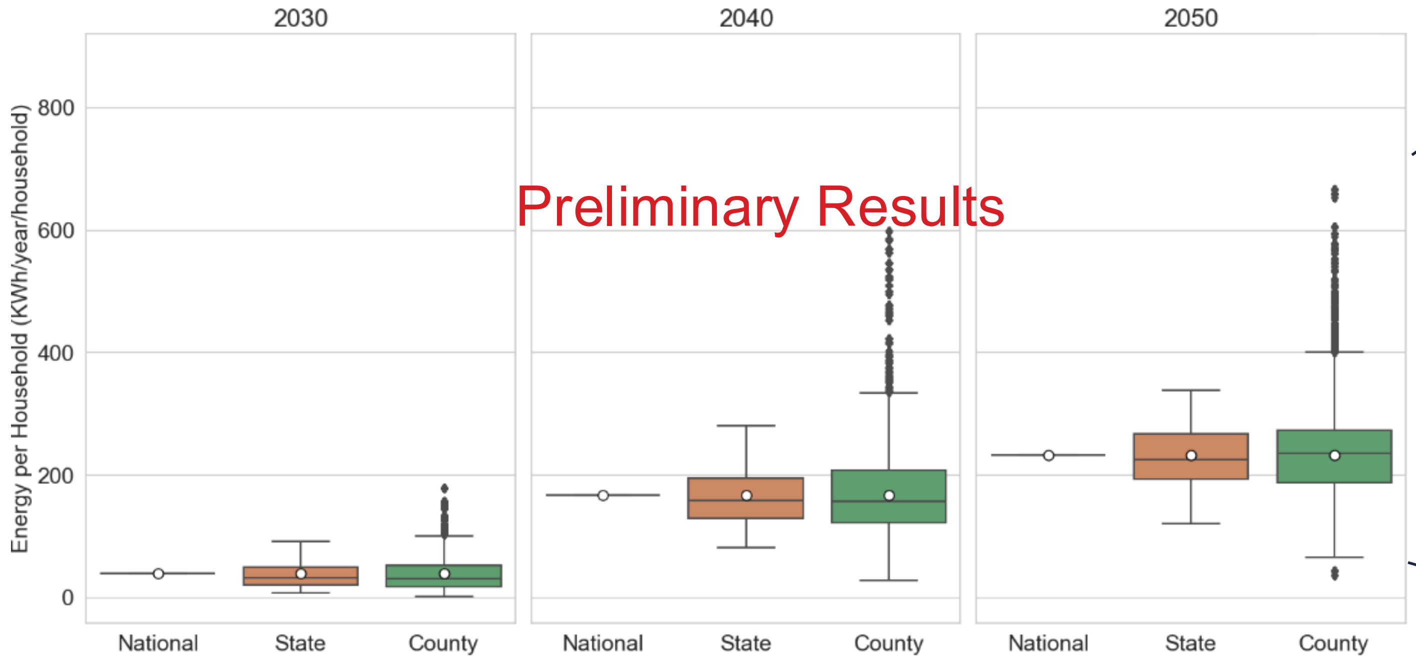


[Ge et al. 2021](Ge et al. 2021).

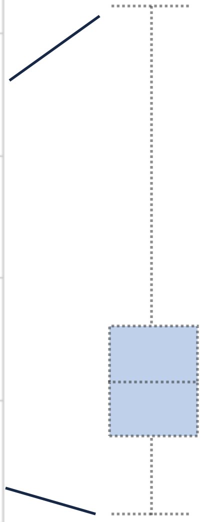
Regional and Temporal Uncertainty

- Projecting load at a high level of resolution is hard!
- Extreme uncertainty is expected in how individual households, businesses, and fleets will electrify and how they will charge

Modeled energy use per household at various regional aggregations



Source: preliminary results informed by [DECARB analysis]



Higher resolution (*e.g.*, census tract, neighborhood) estimates likely subject to even more variability

Solutions to cope with uncertainty should allow for regional flexibility (*e.g.*, make ready program, line extension policy)

Expected uncertainty varies by dimension and forecast horizon

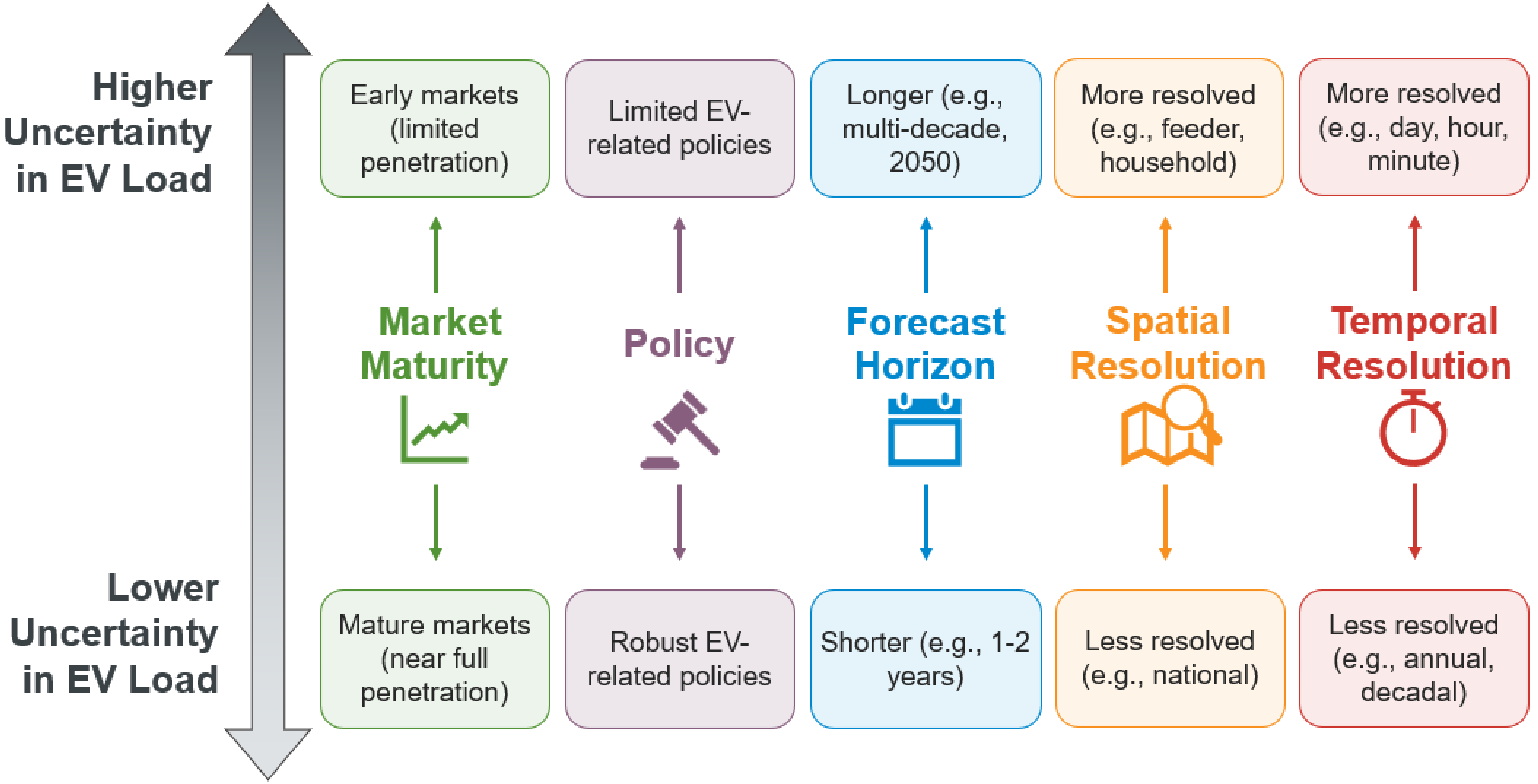
	Uncertainty in Near/Midterm Forecast	Uncertainty in Long-Term Forecast	
LD EV Adoption	High	Mid	Significant heterogeneity in adoption that may reduce over time as markets evolve and with presence of policy/regulatory support
MHD EV Adoption	High	High	Early adoption limited to selected applications (e.g., buses, delivery vans) and limited vehicle supply. Future areas of success remain unclear due to technology competition (e.g., FCEVs, biofuels) and/or potential electrification challenges across diverse applications.
LDV Charging	Low	Mid	Growing uncertainty from potential changes in future charging preferences and behaviors compared to current adopters, especially as those without home charging purchase more EVs
MHD Charging	High	High	High uncertainty given limited deployment to inform expected behaviors and diversity of MHD use cases; uncertainty will likely reduce over time as markets evolve and more information becomes available
EV Efficiency	Low	High	Growing uncertainty in technological progress and how vehicle characteristics may evolve to meet market preferences (e.g., demand for larger vehicles or higher power/acceleration)
Travel Behavior	Low	Mid	Growing uncertainty due to potential for disruptions (e.g., telework, autonomous vehicles, ecommerce) and/or shifts driven by demand management (e.g., mode shifting, changes in urban planning)
Vehicle Ownership	Low	Mid	Growing uncertainty driven by longer-run transitions and/or emerging technologies which may impact ownership (e.g., economic growth, logistics, ride-hailing, mode shifting, etc.)

High Significant heterogeneity, which may/may not persist; high forecast uncertainty driven by tech. advancement and/or potential disruptions

Mid Moderate heterogeneity, but well supported by data; moderate potential for change and/or disruptive shifts

Low Inherent heterogeneity well understood, with current trends likely representative of future behavior; or high regulatory certainty

General Trends in the Context of Mid- to Long-Term EV Load Forecasting



Roles and Responsibilities in EV Load Forecasting

Researcher
Develops foundational methods, data, analysis for forecasts

- **Improve modeling capabilities** to reflect greater spatial/temporal resolution and **make tools/data available**
- **Increase transparency** of assumptions for EV load dimensions to facilitate knowledge share
- **Recognize uncertainty in analysis results** based on potential ranges of input assumptions, external factors, and model representation

Grid Planner
Develops load forecasts for grid planning, investment decisions, etc.

- Utilize **multidisciplinary collaboration** and/or research to consider **key dimensions of EV load**
- **Use localized, real-world data to reflect heterogeneity** in travel, vehicle ownership, market maturity, adoption propensity, etc.
- **Consider applicability of current trends/heterogeneity to future scenarios**; historical data might not reflect future expected conditions
- **Increase transparency** of key assumptions to build confidence and facilitate conversations

Regulator
Provides oversight to ensure reliability, security, etc.

- **Leverage forecasts that transparently account for uncertainty** to enable long-term deployment
- **Understand and encourage knowledge share of best practices** in representing uncertainty in EV load forecasting methods as source of comparison

Policymaker
Makes policy or key decisions impacting power grid or transport sectors

- **Clarify jurisdictional ambitions for EV markets** through goals, policies, or programs aimed at EV adoption, thus reducing risk of investing in supporting infrastructure
- **Design and implement practices that allow for flexibility** to cope with regional and temporal uncertainty in where or when EV load might occur (e.g., make ready program, line extension policy)

Understand dimensions of EV load and key sources of uncertainty
to facilitate more robust decision-making at all levels

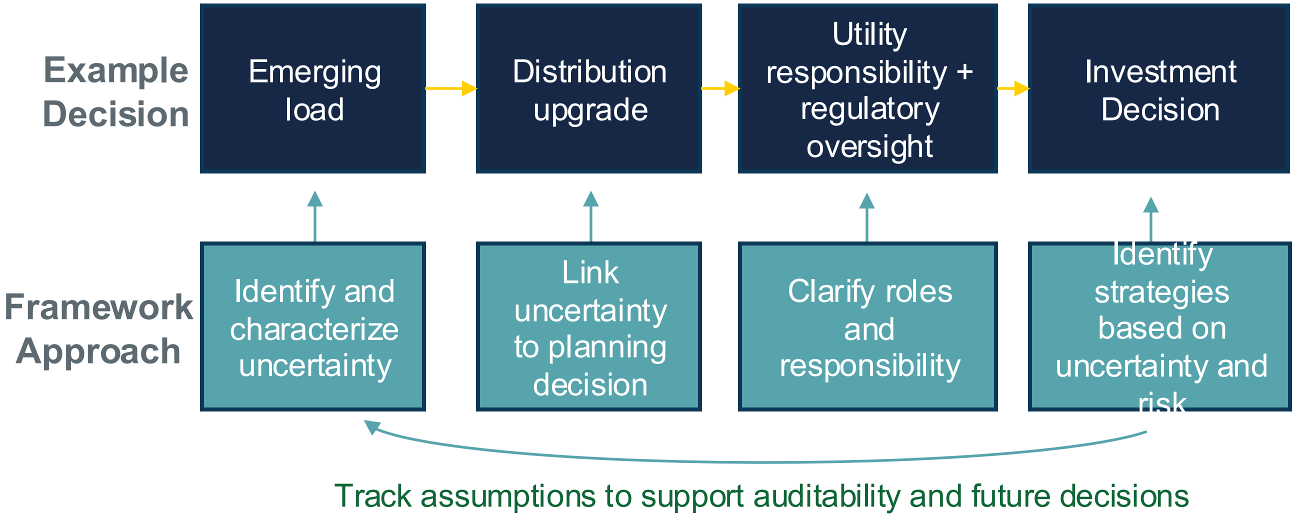
Next Phase: Advancing the State of the Art

Current state of the art

- Existing grid planning approaches address uncertainty through forecasting, scenario analysis, and probabilistic modeling
- There is no consistent process to link uncertainty to planning decisions or assign responsibility across stakeholders (beyond the utility)

Project Approach

- Previous work focused on decomposing uncertainty in EV load and clarifying stakeholder roles and responsibility
- This project aims to move beyond EV load to develop a general, decision-centered framework that
  - **identifies and characterizes uncertainty**
  - **links uncertainty to specific planning decisions**
  - **clarifies stakeholder roles and responsibilities**
  - **identifies response strategies and decision pathways**
  - **enables traceability and feedback across the decision lifecycle**
- The framework is designed to
  - **complement** existing modeling tools
  - **be adaptable** across different regulatory environments
  - **support practical use** in planning and regulatory processes



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Applying Uncertainty Framework in Distribution Grid Planning Decisions

Framework Approach

- Characterize Uncertainty
- Link to Decisions & Clarify Roles
- Define Strategies
- Enable Feedback & Auditability

Illustrative Framework Application to Decision Lifecycle

Frame the Use Case

Context
Where & when
(utility/ regulator setting)

Planning Stage
Forecast → needs → alternatives → review

Why it Matters
Reliability, affordability, resilience, equity

Assess Uncertainty

Characterization
What is unknown or variables?

Data Needs
What information is required?

Planning Methods
Scenarios, forecasts, etc.

Decision & Governance

Planning Decision
(e.g., upgrade, defer, rate design)

Roles & Accountability
Who decides? Who bears risk?

Response Strategy
Build, stage, defer, monitor, flexible options

Track, Learn, Improve

Feedback & Auditability
Track assumptions & outcomes

Continuous Learning
Update decisions and planning inputs

Feedback

Increased **transparency**, **auditability**, and **confidence**

Clarification of Next Phase Objectives

- **What this project IS:**
  - A **structured, decision-oriented framework** to help stakeholders navigate uncertainty in grid planning
  - A framework that operates primarily **between analysis and decision-making**, structuring how uncertainty is interpreted, acted upon, and learned from
  - A process to support **transparent, defensible, and confidence-based decisions** under uncertainty
  - A guide to **clarify stakeholder roles and shared responsibility** across utilities, regulators, policymakers, and other actors

- **What this project IS NOT:**
  - **Not a replacement for modeling** — it complements existing tools by improving how results are interpreted and used in decisions
  - **Not duplicative of risk or scenario frameworks** — it focuses on how results are used in decisions and addresses uncertainty before it can be fully quantified as risk
  - **Not a prescriptive or one-size-fits-all solution** — it provides a flexible, adaptable structure across planning contexts
  - **Not an exhaustive catalog of uncertainties** — it is a focused, practical framework, initially applied to high-impact use cases

Q&A

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Speaker Q & A

- **Greg Mandelman**, Electric Power Engineers
- **Arthur Yip**, National Laboratory of the Rockies

Member Discussion Questions

1. Has your state started to include EV loads into load forecasting analysis?
2. If so:
   A. What challenges have you faced?
   B. Which of the best practices have you adopted?
3. If not, what concerns or ideas do you have about including EV loads into forecasting analysis?

Next EV SWG Meetings & Events

Virtual: EV Rate Design:
June 16, 3:00-4:30 pm ET

In Person at Summer Policy Summit:
Unlocking VGI: A Multi-State Blueprint for (Electric) Vehicle-Grid Integration on July 21

NEW NARUC Professional Development Course: Electric Vehicle Grid Integration and Grid Impacts for State Regulators
May 19-21, 2:00-4:00 pm ET daily.
Discounted for NARUC members.

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