



Atlanta Energy and Emissions Modeling and Analysis Tool (AEEMAT): Integrating ARC's ABM with EPA's MOVES and NREL's Cambium Leveraging Machine Learning

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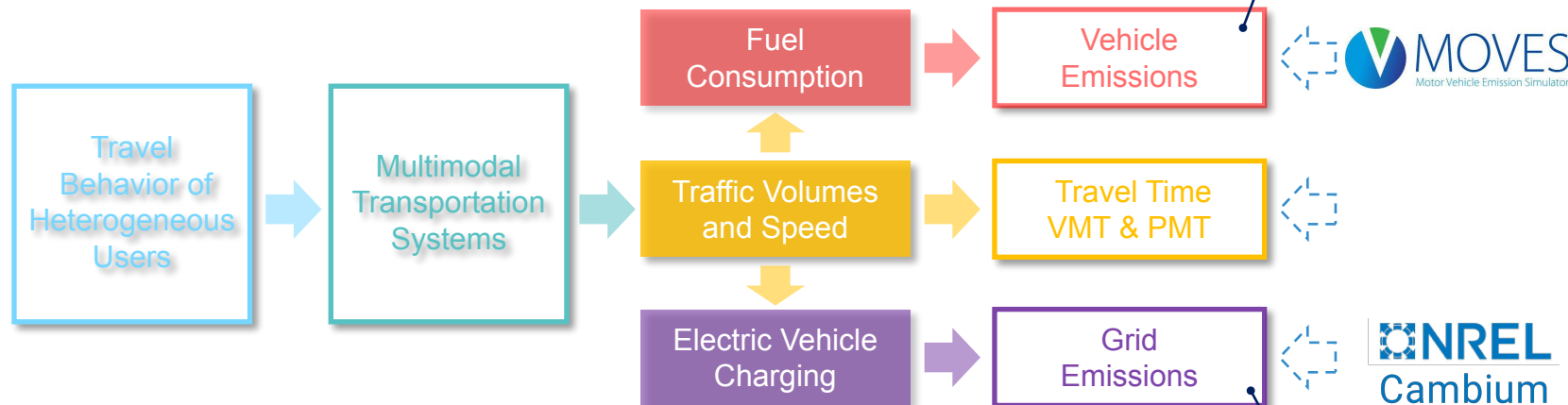
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Air Protection Branch
Georgia Environmental Protection Division

Association of Metropolitan Planning Organizations Conference
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Introduction

Energy and Emission Analysis in Metro Atlanta

Atlanta Regional Commission's (ARC) Activity-Based Model (ABM) enables comprehensive travel demand analysis to support transportation planning for improving mobility, reducing transportation-related emissions, and enhancing quality of life for all residents.



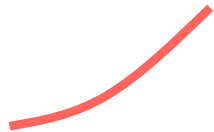
The U.S. Environmental Protection Agency's (EPA) Motor Vehicle Emission Simulator (MOVES) enables accurate estimation of vehicle fuel consumption and emissions, as well as electricity demand for electric vehicle (EV) charging, based on outputs from ARC's ABM.

The National Renewable Energy Laboratory's (NREL) Cambium energy sector simulation model enables accurate prediction of increases in grid emissions, based on MOVES estimations of electricity demand for EV battery charging.

Introduction

Impact of Electric Vehicle Adoption on Fuel Consumption, Electricity Demand, and Resulting Air Pollution Emissions

The growing adoption of electric vehicles (EVs) will gradually reshape overall travel behavior at the regional level and significantly increase electricity demand for battery charging.



Long-Term Projected Rise in EV charging in Georgia (NREL Cambium).

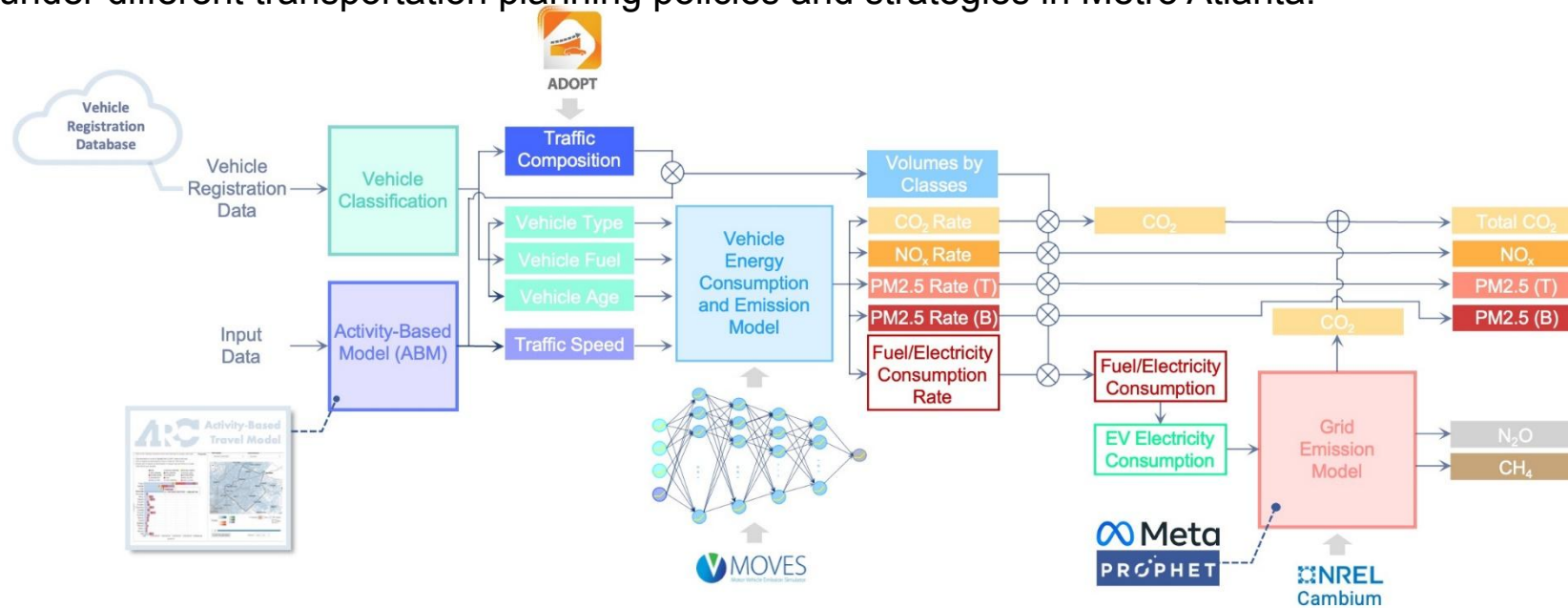


CO₂ Emission Rate of a 2024 Gasoline Passenger Car with Speed in Atlanta, GA (EPA MOVES4).

Objective

Atlanta Energy and Emissions Modeling and Analysis Tool (AEEMAT)

AEEMAT is an integrated machine learning tool for predictive modeling and analysis of fuel consumption and electricity demand for EV battery charging, as well as the resulting air pollutant emissions from various vehicle classes and a mixed-energy power grid under different transportation planning policies and strategies in Metro Atlanta.



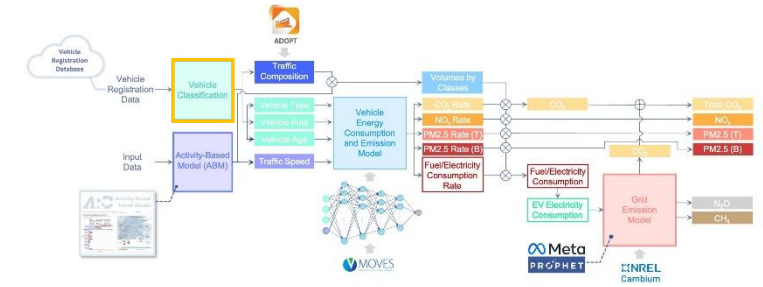
Integrated Architecture and Data Pipeline of the AEEMAT Hybrid Modeling Framework

Integration of ARC's ABM with EPA's MOVES and NREL's Cambium within the AEEMAT framework enables accurate energy and emissions analysis of different transportation planning policies and strategies at the regional level in Metro Atlanta.

Approach

Vehicle Classification

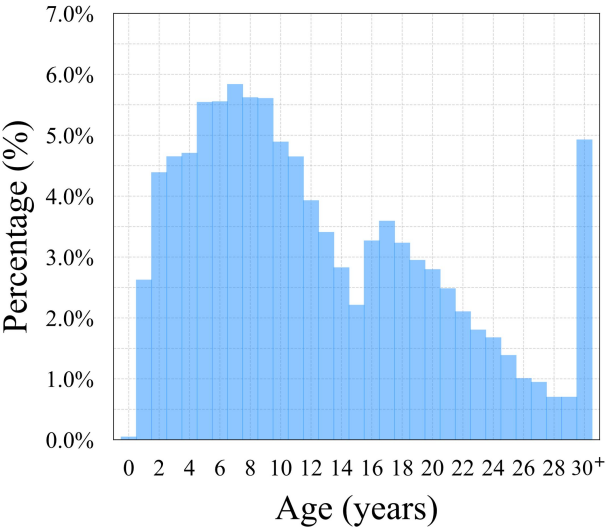
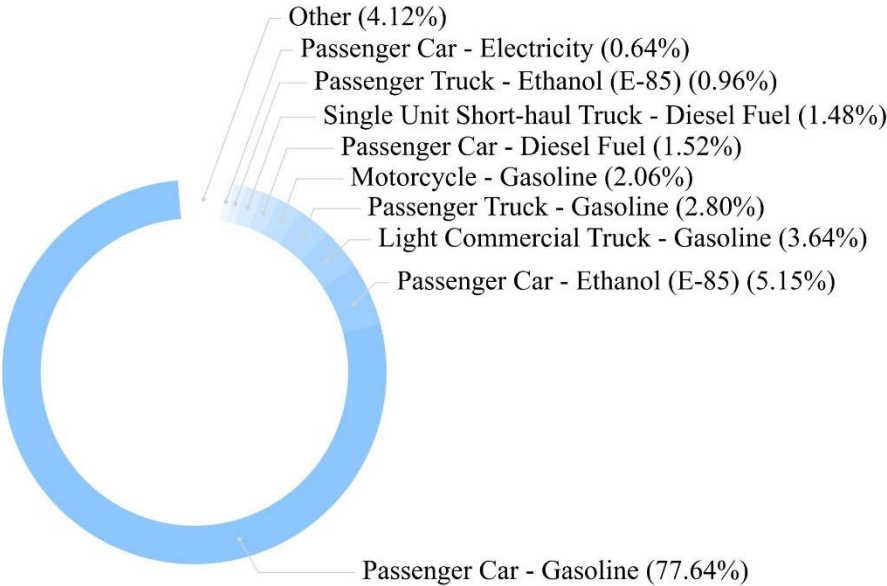
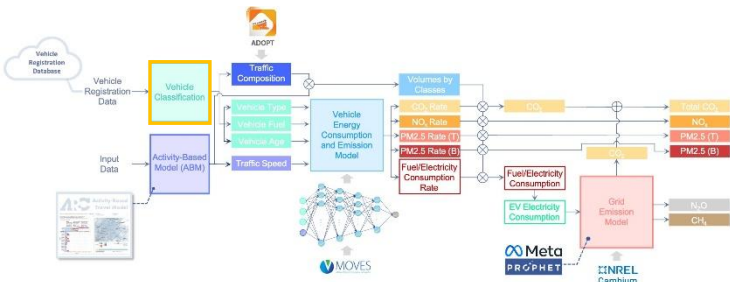
Georgia vehicle registration data is used to classify the fleet by type, fuel, and age, consistent with the vehicle classification framework of EPA's MOtor Vehicle Emission Simulator (MOVES).



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Vehicle Classification

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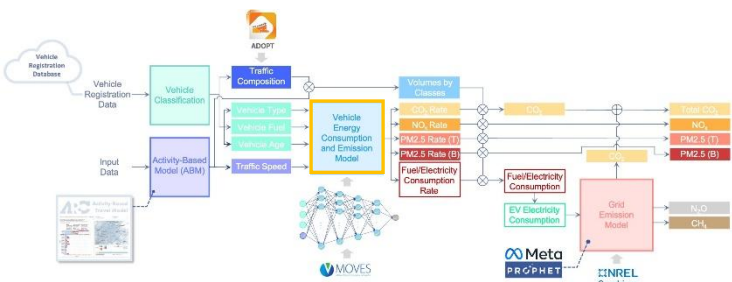


Distribution of Vehicles Based on Their Type, Fuel, and Age in Georgia

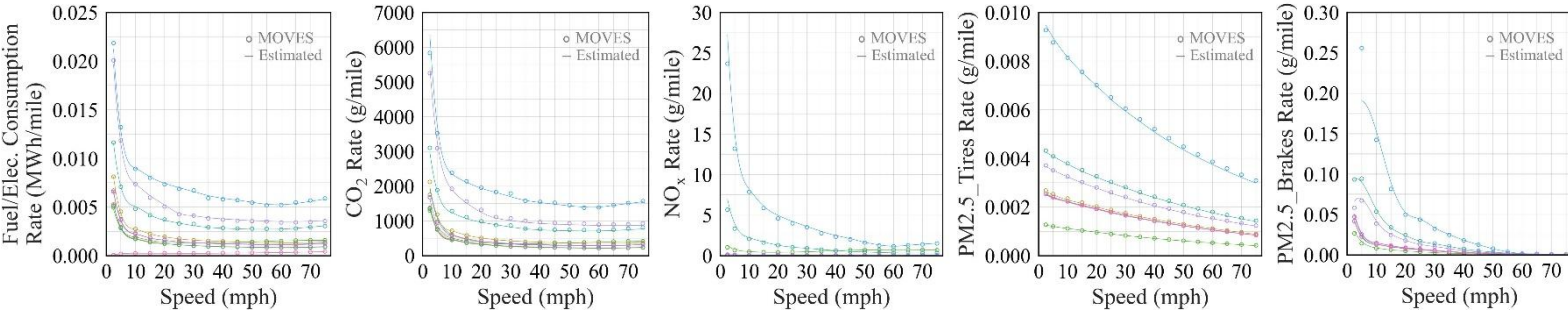
Approach

Deep Learning for Energy and Emissions Analysis of Heterogenous Traffic

Fuel consumption and electricity demand for EV charging, along with the resulting emissions, are estimated based on traffic speed dynamics by accounting for vehicle type, fuel, and age, using a feed-forward neural network model trained on EPA MOVES simulation data.

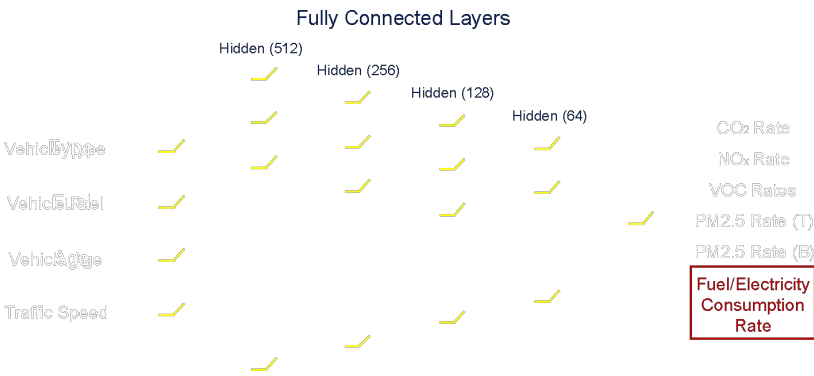


City	Vehicle Energy Consumption and Emission Estimation Model															
	Energy Consumption				CO ₂				NO _x				PM2.5_Brakes			
	RMSE	MAE	MAPE	R ²	RMSE	MAE	MAPE	R ²	RMSE	MAE	MAPE	R ²	RMSE	MAE	MAPE	R ²
Atlanta	0.054	0.03	0.252	0.997	0.063	0.04	0.26	0.996	0.039	0.025	0.083	0.999	0.064	0.025	0.168	0.996



- Passenger Car - Gasoline
- Passenger Car - Ethanol (E-85)
- Light Commercial Truck - Gasoline
- Passenger Truck - Gasoline
- Motorcycle - Gasoline
- Passenger Car - Diesel Fuel
- Single Unit Short-haul Truck - Diesel Fuel
- Passenger Truck - Ethanol (E-85)
- Combination Long-haul Truck - Diesel Fuel
- Single Unit Short-haul Truck - Gasoline
- Light Commercial Truck - Ethanol (E-85)
- Passenger Car - Electricity

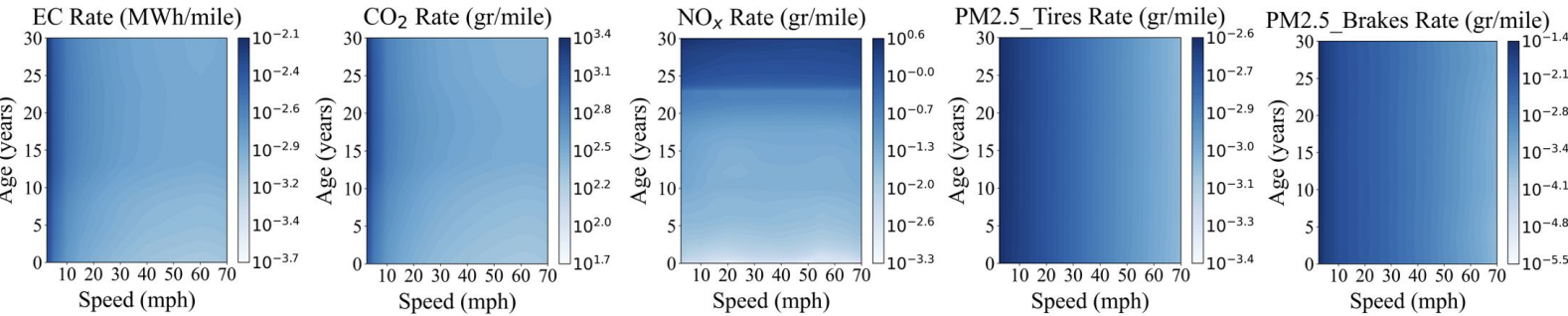
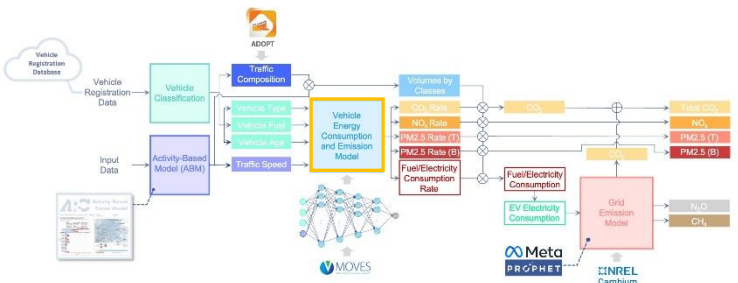
Estimated Electricity/Fuel Consumption and Emission Rates for a Representative Subset of 2024 Vehicles in Atlanta



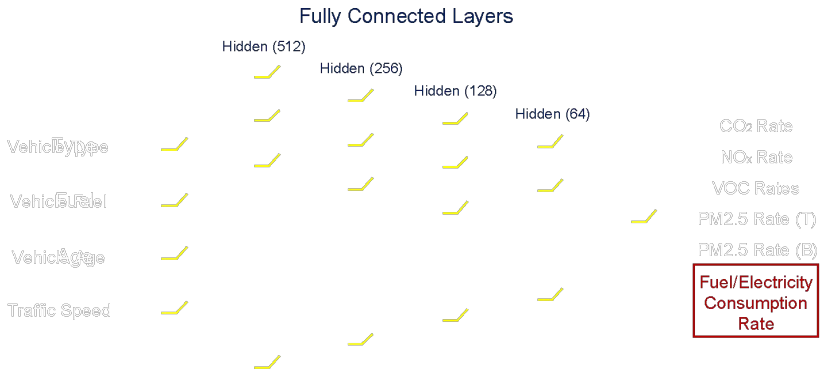
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Fuel Consumption and Air Pollutant Emission Rates of a Passenger-Gas Vehicle by Speed and Age in 2025 in Atlanta.

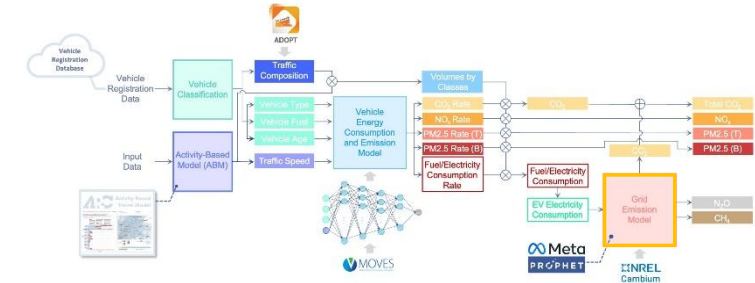


Approach

Machine Learning for Predictive Modeling of Grid Emissions from EV Charging

Grid emissions from EV charging are estimated using a machine learning model developed on Meta's Prophet platform and trained with simulation data from NREL's Cambium model.

Scenarios Projecting Technology Costs, Fuel Prices, Demand Growth, and Electricity Sector Policies



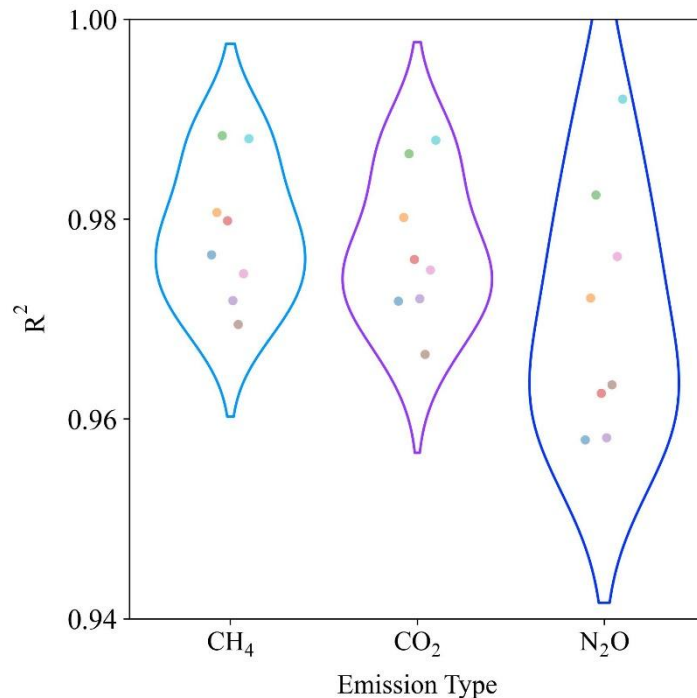
1. **Mid-case Scenario:** This scenario represents central estimates for fundamental inputs, including technology costs, fuel prices, and overall demand growth. It specifically assumes electric sector policies as they were in place during August 2024.
2. **Low Renewable Energy and Battery Costs:** This scenario mirrors the foundational assumptions of the Mid-case but posits a future where renewable energy and battery costs are considerably lower than central estimates.
3. **High Renewable Energy and Battery Costs:** Similar to the Mid-case scenario, this projection assumes the same core assumptions but forecasts a future where renewable energy and battery costs are notably higher.
4. **High Demand Growth:** This scenario also utilizes the same base assumptions as the Mid-case, yet it anticipates a significantly higher average annual demand growth rate of 2.8% from 2022 through 2050, contrasting with the 1.8% in the base assumptions.
5. **Low Natural Gas Prices:** This scenario maintains consistency with the Mid-case assumptions but projects a future where natural gas prices are assumed to be lower.
6. **High Natural Gas Prices:** This scenario follows the same foundational assumptions as the Mid-case but anticipates a future where natural gas prices are assumed to be higher.
7. **Low Renewable Energy and Battery Costs with High Natural Gas Prices:** Building upon the base assumptions of the first scenario, this scenario combines the assumption of lower renewable energy and battery costs with higher natural gas prices.
8. **High Renewable Energy and Battery Costs with Low Natural Gas Prices:** This scenario also uses the same base assumptions as the first scenario, but it specifically combines higher renewable energy and battery costs with lower natural gas prices.

NREL
Cambium

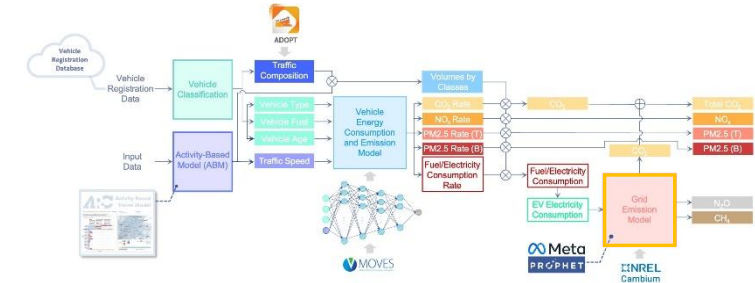
Approach

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R² performance metric of the grid emission model



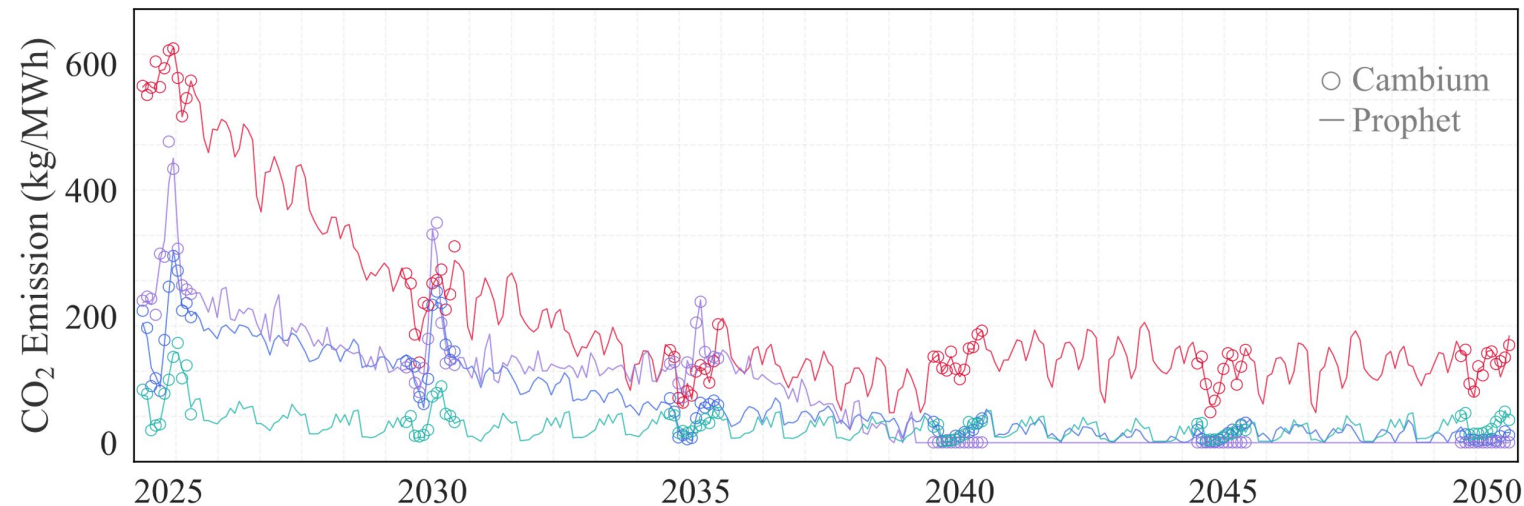
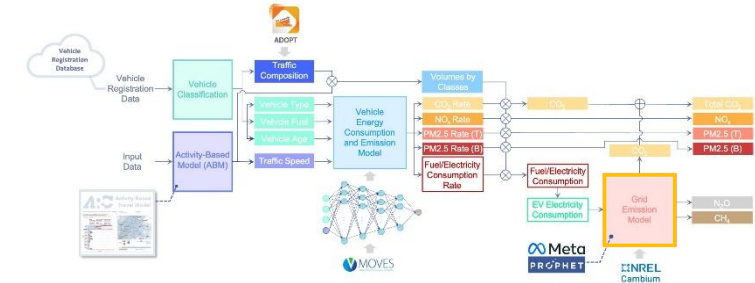
NREL
Cambium

- Mid-case Scenario
- Low Renewable Energy and Battery Costs
- High Renewable Energy and Battery Costs
- High Demand Growth
- Low Natural Gas Prices
- High Natural Gas Prices
- Low Renewable Energy and Battery Costs with High Natural Gas Prices
- High Renewable Energy and Battery Costs with Low Natural Gas Prices

Approach

Machine Learning for Predictive Modeling of Grid Emissions from EV Charging

Grid emissions from EV charging are estimated using a machine learning model developed on Meta's Prophet platform and trained with simulation data from NREL's Cambium model.



Projected CO₂ Grid Emission Rates from EV Charging Through 2050 in California, Georgia, New York, and Washington (Mid-case Scenario)

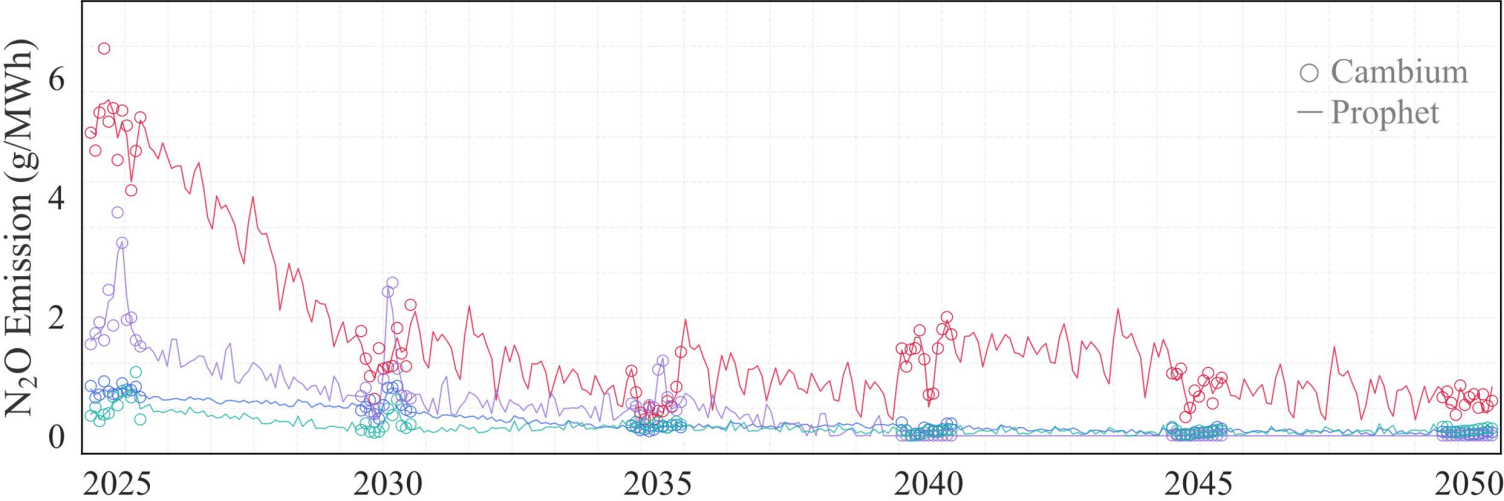
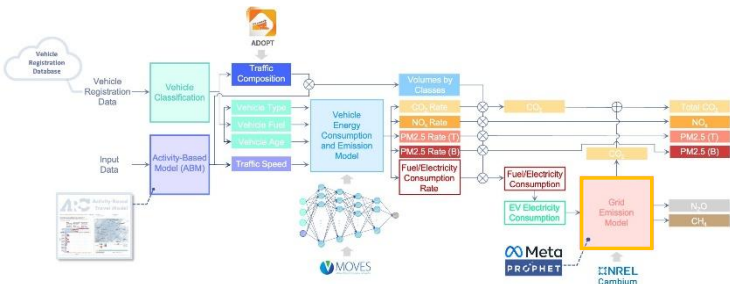


- — California
- — Georgia
- — New York
- — Washington

Approach

Machine Learning for Predictive Modeling of Grid Emissions from EV Charging

Grid emissions from EV charging are estimated using a machine learning model developed on Meta’s Prophet platform and trained with simulation data from NREL’s Cambium model.



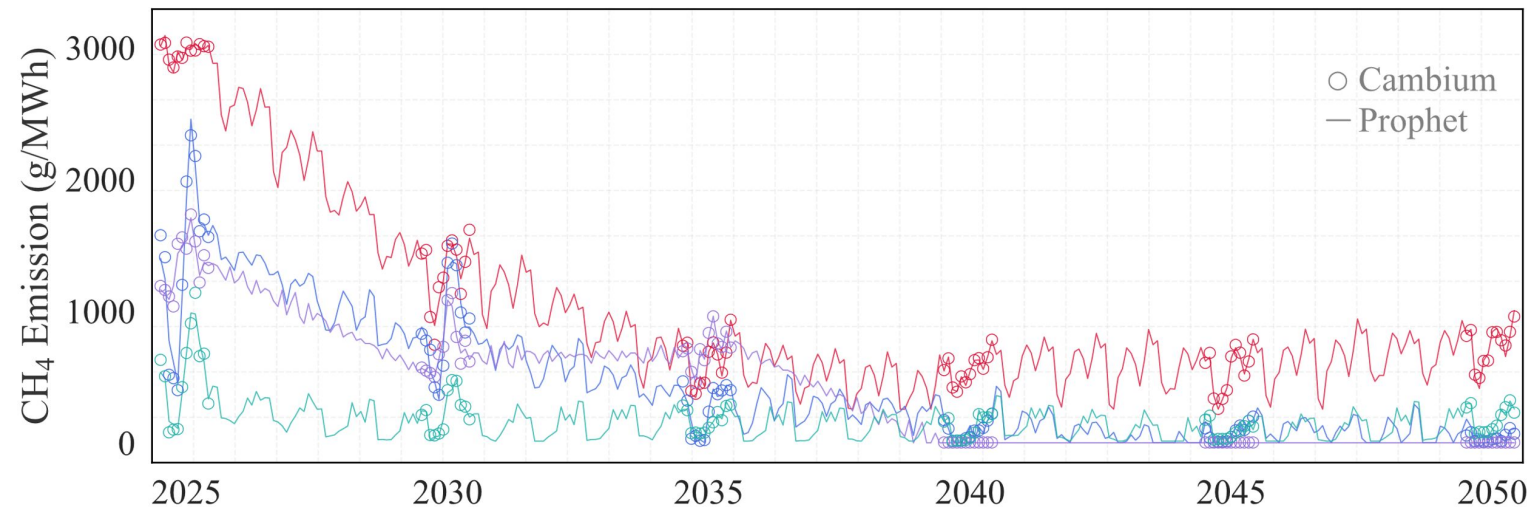
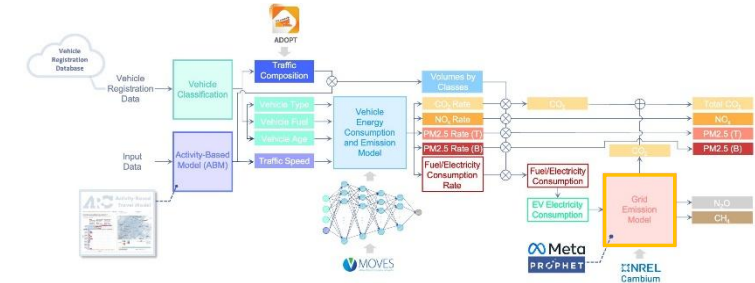
- — California
- — Georgia
- — New York
- — Washington

Projected N₂O Grid Emission Rates from EV Charging Through 2050 in California, Georgia, New York, and Washington (Mid-case Scenario)

Approach

Machine Learning for Predictive Modeling of Grid Emissions from EV Charging

Grid emissions from EV charging are estimated using a machine learning model developed on Meta's Prophet platform and trained with simulation data from NREL's Cambium model.



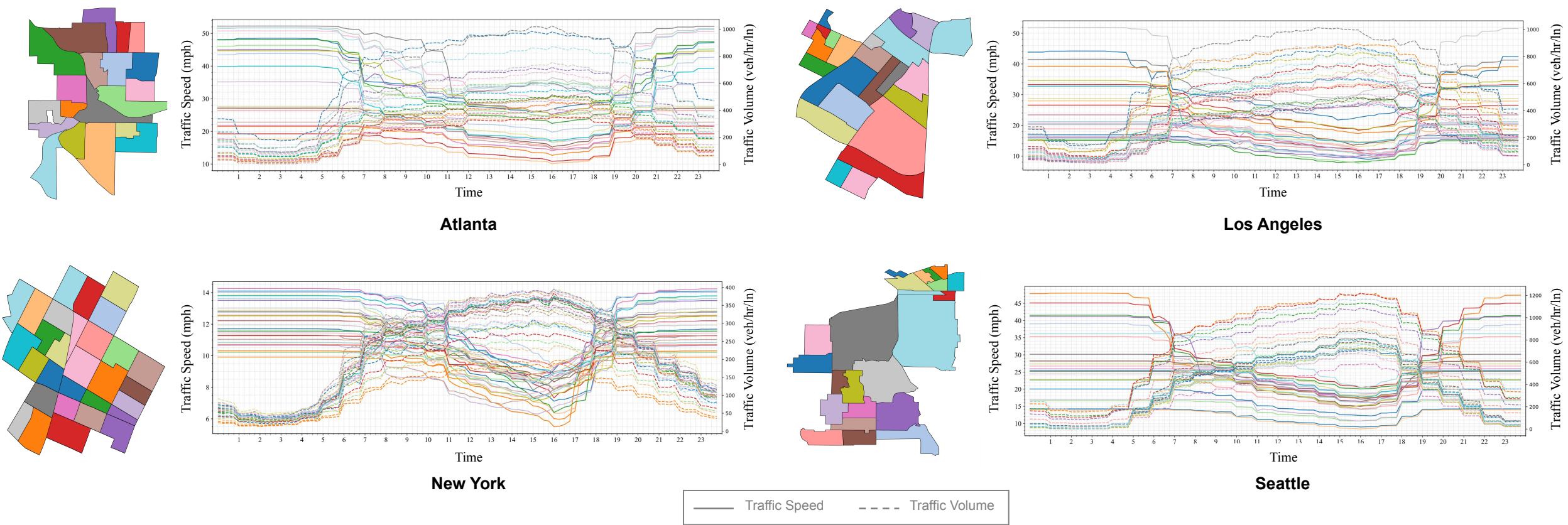
Projected CH₄ Grid Emission Rates from EV Charging Through 2050 in California, Georgia, New York, and Washington (Mid-case Scenario)



- — California
- — Georgia
- — New York
- — Washington

Case Study: Atlanta, Los Angeles, New York, and Seattle

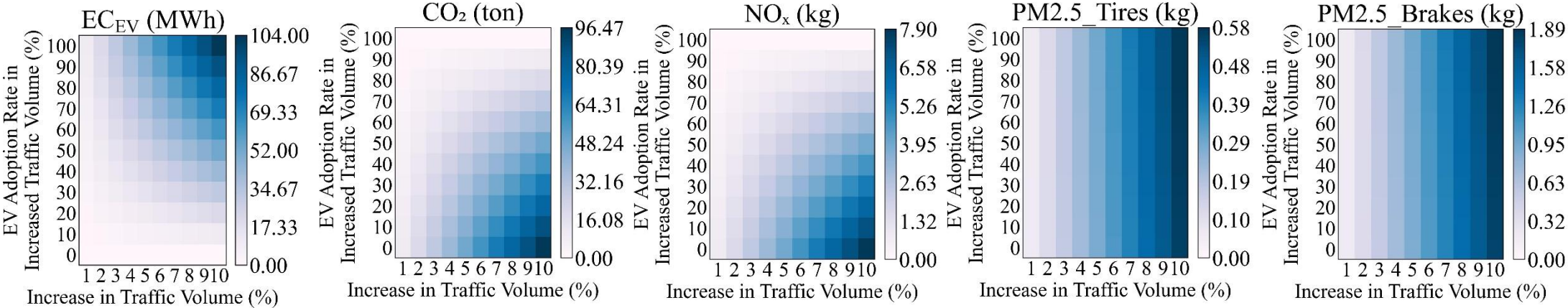
Traffic Data:



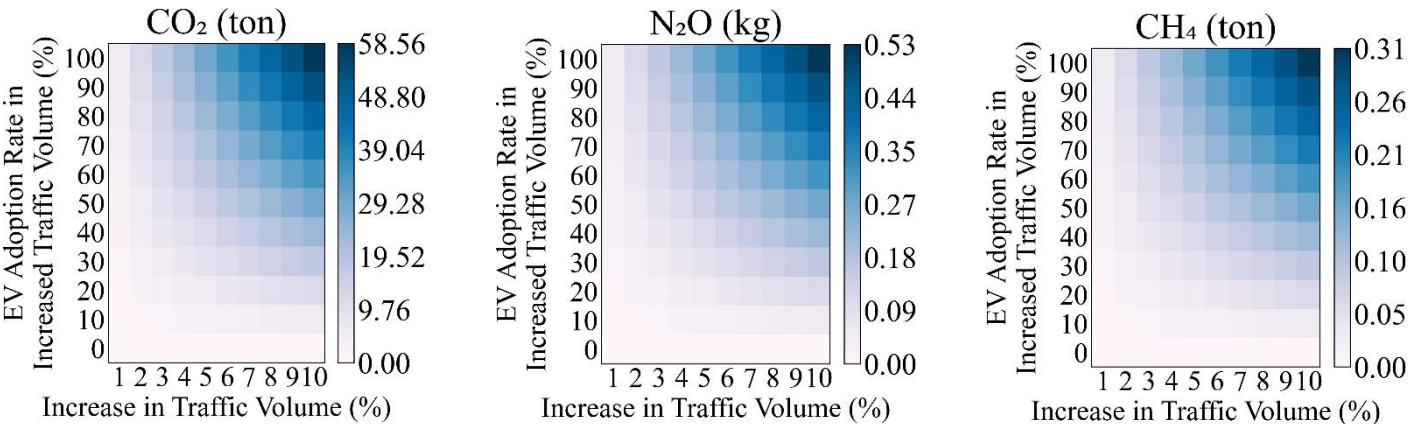
Average Workday Daily Traffic Speed and Volume Profiles for September, October, and November 2024 in Atlanta, Los Angeles, New York, and Seattle

Case Study: Atlanta, Los Angeles, New York, and Seattle

Energy and Emissions Analysis: Atlanta



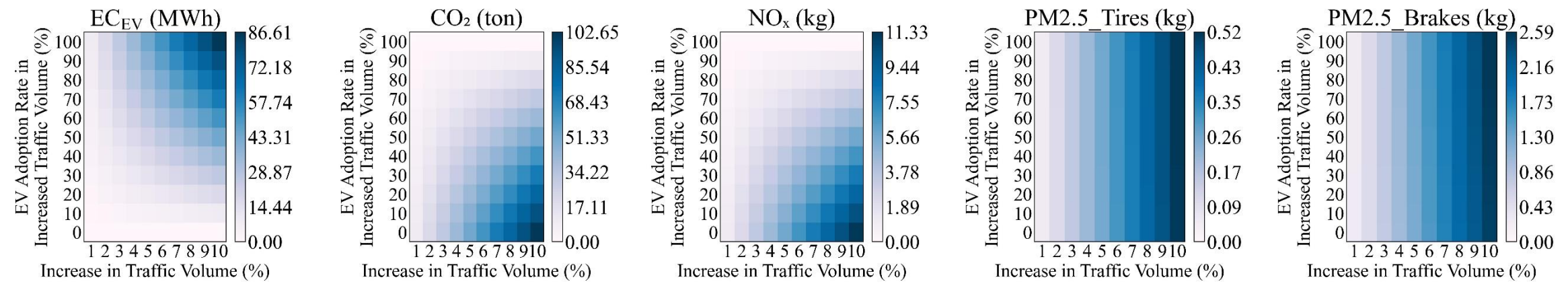
Daily EV Charging Demand and Vehicle Emissions by Traffic Volume and EV Adoption in Atlanta



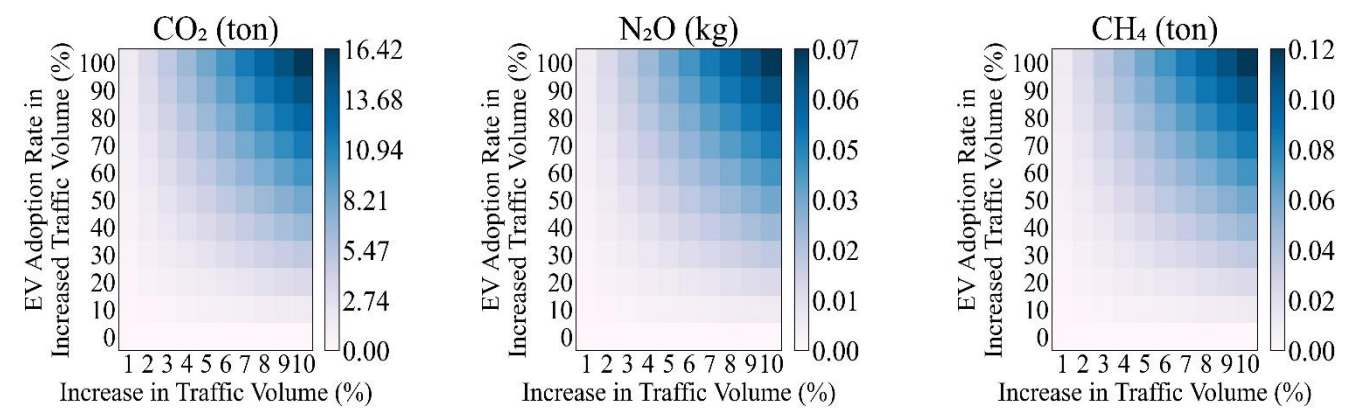
Daily Grid Emissions from EV Charging by Traffic Volume and EV Adoption in Atlanta

Case Study: Atlanta, Los Angeles, New York, and Seattle

Energy and Emissions Analysis: Los Angeles



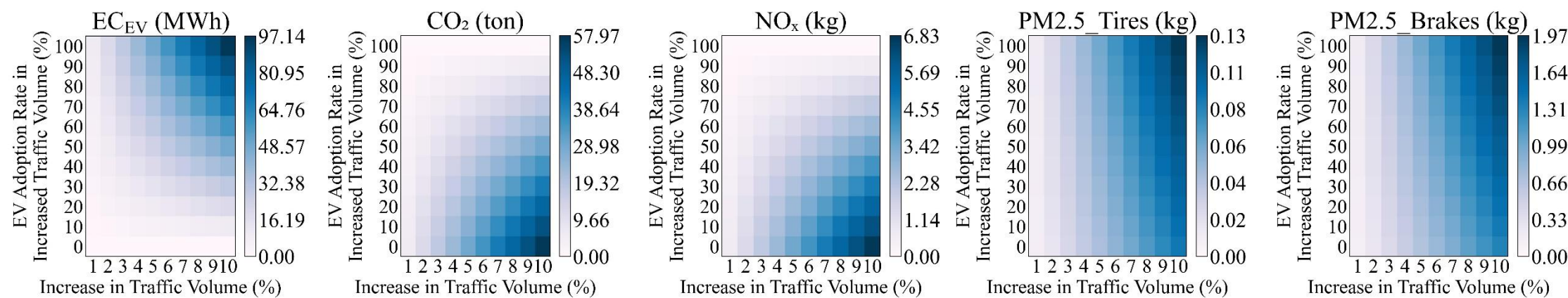
Daily EV Charging Demand and Vehicle Emissions by Traffic Volume and EV Adoption in Los Angeles



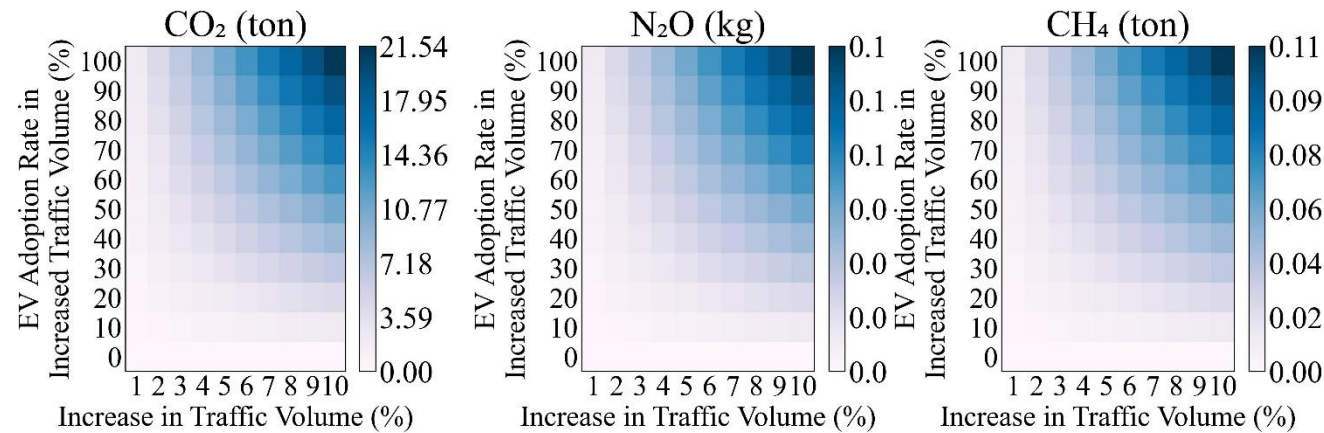
Daily Grid Emissions from EV Charging by Traffic Volume and EV Adoption in Los Angeles

Case Study: Atlanta, Los Angeles, New York, and Seattle

Energy and Emissions Analysis: New York



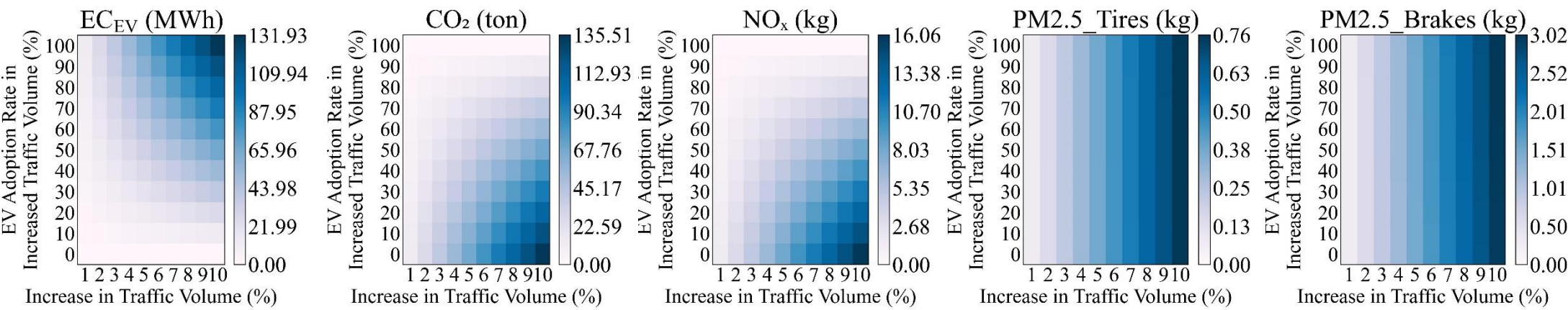
Daily EV Charging Demand and Vehicle Emissions by Traffic Volume and EV Adoption in New York



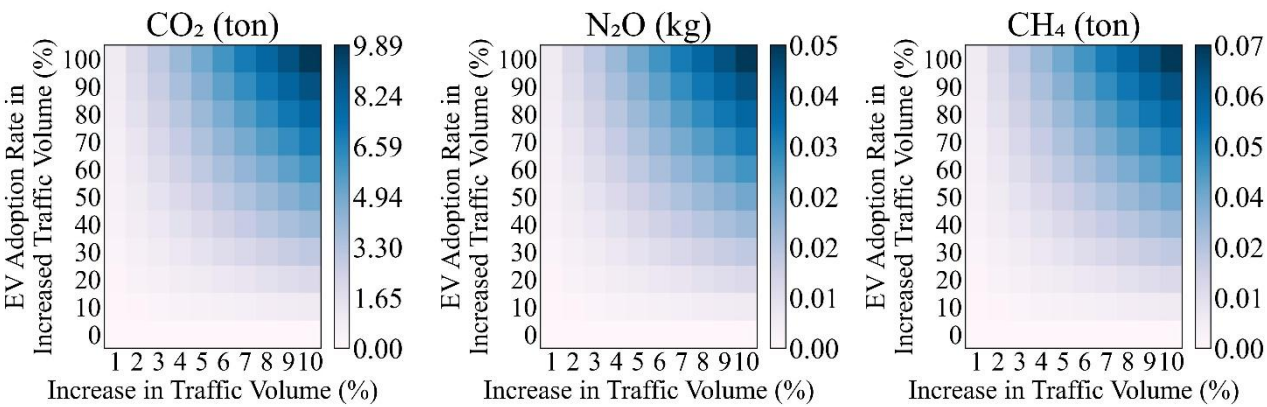
Daily Grid Emissions from EV Charging by Traffic Volume and EV Adoption in New York

Case Study: Atlanta, Los Angeles, New York, and Seattle

Energy and Emissions Analysis: Seattle



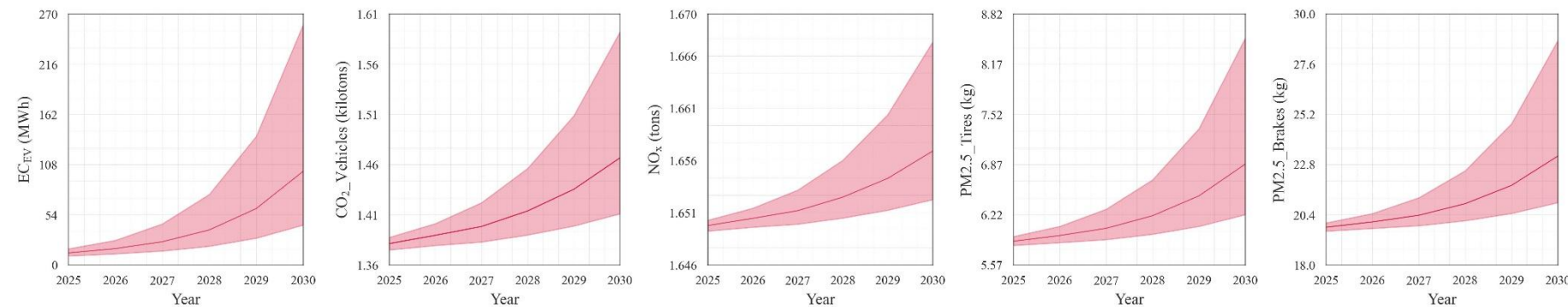
Daily EV Charging Demand and Vehicle Emissions by Traffic Volume and EV Adoption in Seattle



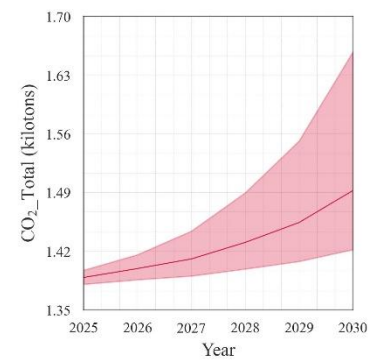
Daily Grid Emissions from EV Charging by Traffic Volume and EV Adoption in Seattle

Case Study: Atlanta

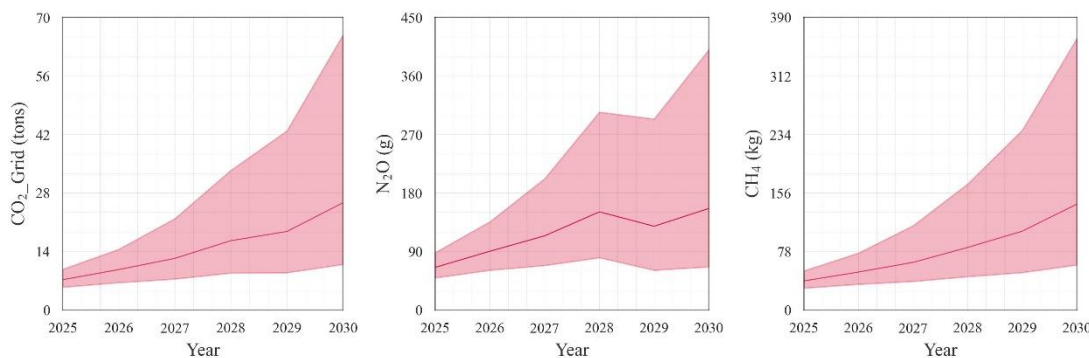
Energy and Emission Analysis (Mid-case Scenario):



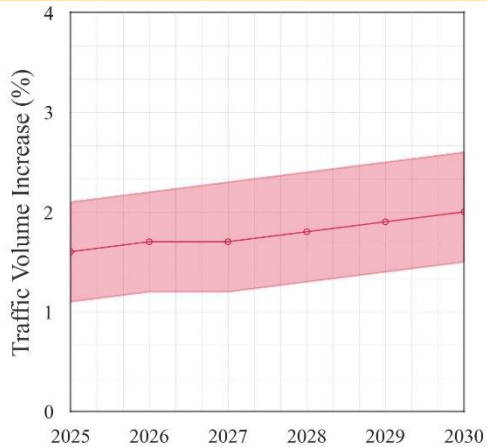
Projected Daily EV Electricity Demand and Vehicle Emissions in Atlanta



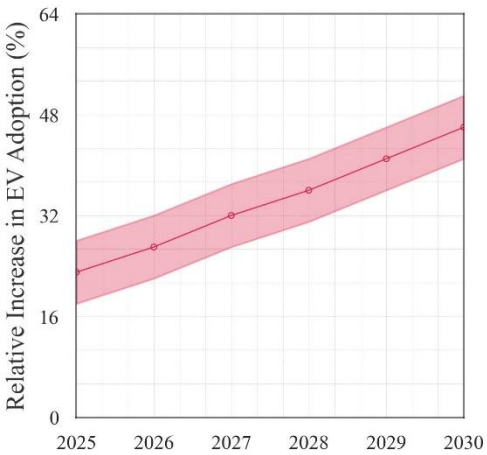
Projected Daily Transportation-Related CO₂ Emissions in Atlanta



Projected Daily Grid Emissions from EV Charging in Atlanta



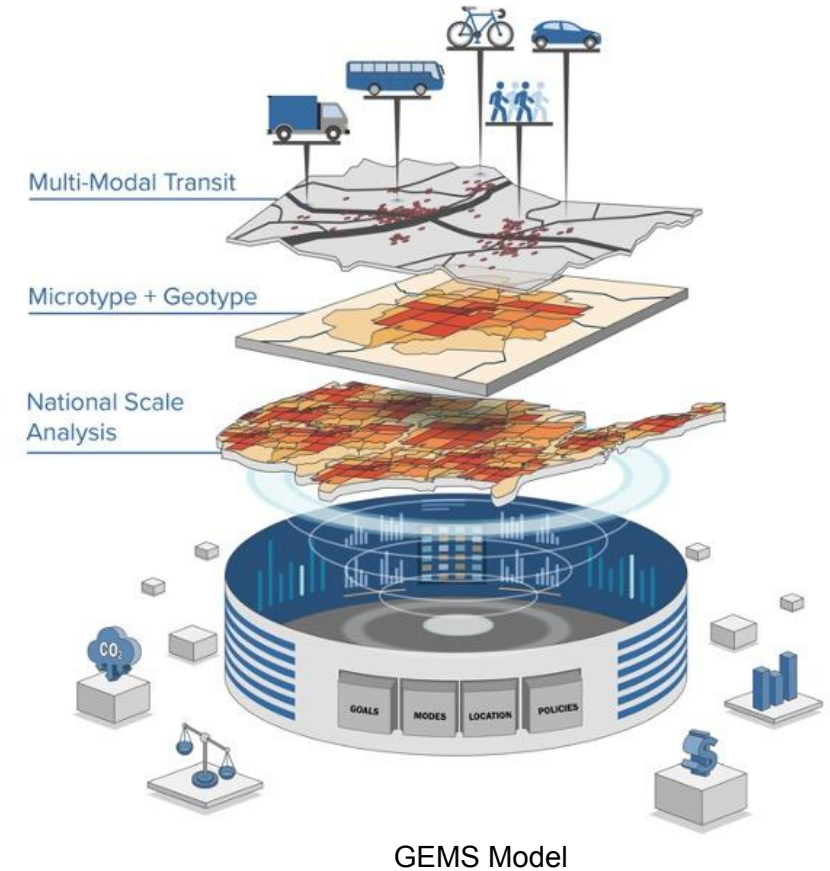
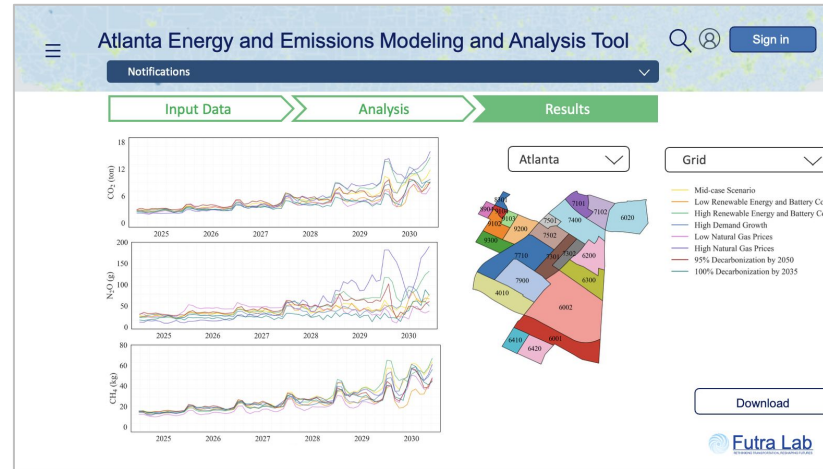
Projected Increase in the Traffic Volumes Compared to 2024 Through 2030



Relative Increase in EV Adoption Compared to 2024 Through 2030

Next Steps

- ❑ Update models using new releases of vehicle registration data, EPA's MOVES, and NREL's Cambium.
- ❑ Develop the user interface fully integrated with ARC's Activity-Based Model (ABM), including ARC's ActivitySim model (atlregional/arc-activitysim ARC ActivitySim implementation).
- ❑ Integrate AEEMAT into Atlanta's Digital Twin Model, which is currently under development at the KSU Center for Interactive Media (CIM).
- ❑ Explore integration opportunities with other regional models, as well as the



Highlights

- Comprehensive energy and emissions analysis of transportation planning strategies and policies at the regional scale requires the integration of travel demand models with EPA's MOVES and NREL's Cambium.
- **AEEMAT** leverages an integrated machine learning model, trained on EPA's MOVES and NREL's Cambium simulation data and linked with ARC's ABM, to provide accurate predictive analysis of vehicle fuel consumption, EV electricity demand, and the resulting emissions from both vehicles and the power grid under various transportation planning, EV adoption, and energy sector development scenarios.
- The integrated machine learning framework of AEEMAT facilitates energy and emissions analysis of transportation policies without the need for repeated simulation runs, analysis, and calculations, which are often time-consuming and costly.
- The proposed integrated machine learning model also has the potential to be integrated with other regional and national travel demand models for energy and emissions analysis at large scales.

We Love Feedback!

Questions/Comments

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