Predictive Analysis of Greenhouse Gas Emissions from Electric Vehicle Charging in the United States

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Abstract

Electric vehicles (EVs) produce significantly fewer emissions compared to traditional vehicles running on fossil fuels. However, the increase in electrical energy consumption of EVs from the power grid—driven by rising adoption and higher vehicle miles traveled due to lower travel and maintenance costs— leads to higher greenhouse gas emissions from power plants. This research presents a predictive analysis of greenhouse gas emissions from the power generation mix at the state level in the United States as energy consumption by EVs from the grid increases, under various projections of technology costs, fuel prices, demand growth, and electricity sector policies. The predictive analysis of greenhouse gas emissions resulting from EV charging is performed using a machine learning model developed on the Meta Prophet platform, enabling the precise capture of temporal patterns and seasonality. Trained with simulation results from the Cambium model, developed by the National Renewable Energy Laboratory (NREL), our machine learning model provides accurate and continuous predictions of CO_2, N_2O, and CH_4 emission rates from EV charging over the coming months and years under eight power generation planning scenarios, outlining different projections for costs, prices, demand, and policy outcomes. We apply our machine learning model to analyze the emissions of CO_2, N_2O, and CH_4 from power generation resulting from increased EV charging in California, Georgia, New York, and Washington. Our analysis reveals that, without significant changes to current electricity sector policies, by 2030, CO_2 emissions from power plants due to EV charging in California, Georgia, New York, and Washington will increase by 83.79%, 18.15%, 42.22%, and 35.23%, N_2O by 64.40%, -20.69%, 10.54%, and -2.70%, and CH_4 by 56.90%, 21.56%, 31.17%, and 22.58%, respectively, driven by a projected 150%, 162%, 170%, and 168% rise in energy consumption of EVs from the grid.

Keywords: electric vehicles; grid emissions; machine learning; NREL Cambium; greenhouse gas; renewable energy; electricity sector policies

1 Introduction

While electric vehicles (EVs) produce significantly fewer emissions compared to conventional vehicles running on fossil fuels, the increased electrical energy consumption required to charge EVs from the grid leads to higher greenhouse gas emissions from power plants. The lower cost of electricity compared to gasoline and the reduced maintenance costs of EVs, coupled with the convenience of driving thanks to advanced driver assistance technologies, encourage users to travel more and further. With the rapid increase in EV adoption, which is expected to accelerate in the coming years due to incentivizing transportation decarbonization policies implemented at the state and national levels (US DOT, 2022; US DOE, 2023), the total vehicle miles traveled (VMT) by EVs is projected to significantly rise. The subsequent increase in electrical energy consumption for charging EV batteries will result in higher greenhouse gas emissions from power plants, depending on the power generation technology, distribution network efficiency, load temporal distribution load temporal distribution, and the energy mix of the grid in different states. This research addresses the challenge of predicting the rise in greenhouse gas emissions from power plants due to the increased energy consumption of EVs on a large scale using a machine learning approach.

The increasing energy consumption for EV battery charging is placing escalating pressure on the electrical grid, particularly during peak demand periods. Detailed simulations of urban EV charging behavior reveal significant spikes

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in electricity demand during evening hours, underscoring the urgent need for advanced demand-side management strategies to prevent grid overload (Harris and Webber, 2014; Arias et al., 2017; Wang and Infield, 2018; Xiang et al., 2019; Guo et al., 2022). Regional analyses of EV energy consumption also highlight the stress on grids in densely populated areas, where higher concentrations of EVs necessitate the implementation of smart grid technologies to effectively balance supply and demand (Xu et al., 2018; Jia et al., 2020; Jonas and Macht, 2024). Therefore, strategic placement of charging stations plays a critical role in alleviating local grid pressures and enhancing energy efficiency, particularly in urban environments (Sadeghi-Barzani et al., 2014; Ahmad et al., 2022; Powell et al, 2022a; Li et al., 2024). Comparisons between urban and rural areas show that urban grids, with their higher EV density, face more immediate challenges, requiring targeted infrastructure improvements. In contrast, rural areas, while currently less impacted, may face future challenges as EV adoption increases. The deployment of decentralized renewable energy systems, such as small-scale wind or solar farms, could provide rural areas with a sustainable source of energy for EV charging, reducing the need for extensive grid expansions (Shepero et al., 2020; McKinney et al., 2023). Longitudinal analyses of EV adoption trends project significant increases in electricity consumption, underscoring the urgent need for scalable grid infrastructure to support such growth (Ul-Haq et al., 2018; Kapustin and Grushevenko., 2020; Powell et al, 2022b; Li and Jenn, 2024; Kamis and Abraham, 2024). On a national scale, integrating renewable energy sources is critical in mitigating the additional load from EVs, emphasizing the synergistic potential between widespread EV adoption and clean energy policies. The integration of renewable energy systems with EV charging infrastructure, particularly through smart charging strategies, can significantly mitigate greenhouse gas emissions from power plants as the energy consumption of EVs from the power grid increases. (Cheng et al., 2018; Lee and Hur, 2019; Shi et al., 2020; Esmaeili et al., 2022).

Greenhouse gas emissions from power plants, driven by the energy consumption of EVs from the grid, are heavily influenced by the electricity generation mix. In regions where fossil fuels dominate the grid, the expected reduction in greenhouse gas emissions from EVs may be minimal or even negative compared to conventional vehicles running on fossil fuels. In fact, in areas heavily reliant on coal-fired power plants, the life-cycle greenhouse gas emissions from EVs can exceed those of internal combustion engine vehicles due to the high carbon intensity of electricity generation (Hawkins et al., 2013; Faria et al., 2013; Woo et al., 2017). Conversely, in regions where renewable energy constitutes a significant portion of the electricity mix, EVs can markedly reduce greenhouse gas emissions (Holdway et al., 2010; Hu et al., 2016; Bastida-Molina et al., 2020). The timing of EV charging is also crucial, as grid emissions intensity varies throughout the day. Charging during off-peak hours, when renewable energy generation is higher, can further diminish emissions (Jochem et al., 2015; Rangaraju et al., 2015; Fernández 2018). Therefore, implementing smart charging strategies that align EV charging with periods of low grid emissions can substantially reduce the carbon footprint of electric vehicles (Casals et al., 2016; Filote et al., 2020). The widespread adoption of EVs could act as a catalyst for improvements in the electricity grid, potentially accelerating the transition to cleaner energy sources (Onn et al., 2018). However, to accurately assess the energy and environmental impacts of increasing EV adoption, it is critical to analyze greenhouse gas emissions from power plants resulting from EV charging across various scenarios that project technology costs, fuel prices, demand growth, and electricity sector policies.

This research presents a predictive analysis of greenhouse gas emissions from the power generation mix at the state level with the increase in energy consumption of EVs from the grid in the United States. The predictive analysis of greenhouse gas emissions resulting from EV charging is performed using a machine learning model developed on the Meta Prophet platform, accurately capturing temporal patterns and seasonality. Greenhouse gas emissions from power plants due to the energy consumption of EVs for battery charging are influenced by several critical factors, including power generation technology, distribution network efficiency, load temporal distribution, and the energy mix of the grid. We accurately capture the impact of these factors on greenhouse gas emissions from EV charging by training the proposed machine learning model using simulation results from the Cambium model, developed by the National Renewable Energy Laboratory (NREL). The Cambium model projects evolution of power generation and distribution systems, providing a robust framework for simulating the operations of the electric sector across the United States. Trained with simulation results from the Cambium model, our machine learning model enables accurate and continuous predictions of carbon dioxide (CO_2), nitrous oxides (N_2O), and methane (CH_4) emissions from EV charging over the coming months and years. To provide a comprehensive predictive analysis of greenhouse gas emissions resulting from EV charging, we train the model using eight power generation planning scenarios, each outlining different projections of technology costs, fuel prices, demand growth, and electricity sector policies. We

then apply our machine learning model to analyze the emissions of CO_2, N_2O, and CH_4 from power generation resulting from increased EV charging in California, Georgia, New York, and Washington. Our analysis reveals that, without significant changes to current electricity sector policies, by 2030, CO_2 emissions from power plants due to EV charging in California, Georgia, New York, and Washington will increase by 83.79%, 18.15%, 42.22%, and 35.23%, N_2O by 64.40%, -20.69%, 10.54%, and -2.70%, and CH_4 by 56.90%, 21.56%, 31.17%, and 22.58%, respectively, driven by a projected 150%, 162%, 170%, and 168% rise in energy consumption of EVs from the grid.

2 EV Charging Emission Model

Greenhouse gas emissions from EV charging exhibit temporal patterns and seasonality due to fluctuations in energy demand and seasonal shifts in the energy mix, particularly in the availability of renewable energy. To accurately capture these dynamics in predicting greenhouse gas emissions from EV charging, we develop a machine learning model on the Meta Prophet platform, enabling the precise capture of temporal patterns and seasonality. The machine learning model is trained using simulation results from the Cambium model, with parameters fine-tuned for optimal performance. Once fully trained, the model delivers accurate and continuous predictions of CO_2, N2O, and CH_4 grid emission rates (i.e., the additional emissions from power plants per 1 MWh increase in EV charging from the grid) through 2050. By bypassing the need for running complex simulations, the proposed machine learning model facilitates the prediction of greenhouse gas emissions from increased EV charging, under various projections of technology costs, fuel prices, demand growth, and electricity sector policies.

Machine Learning Approach

We develop our EV charging emission prediction model on the platform of the Prophet model. The Prophet model, developed by Meta, is a powerful tool designed for time series forecasting that has gained widespread use due to its flexibility and robustness. Prophet is particularly adept at handling time series data that exhibit strong temporal patterns, seasonal effects, missing data, and outliers (Taylor and Letham, 2018). The additive structure of the Prophet model allows for the precise capture of non-linear trends, along with monthly and yearly temporal and seasonal greenhouse gas emission patterns, including holiday season effects. We employ the Prophet platform to present our EV charging emission model as follows:

$$e_k(t) = e_k^{NP}(t) + e_k^{P}(t) + e_k^{R}(t) + \varepsilon_{k,t}, \tag{1}$$

where $e_k(t)$ is the time series of the emission rate of type $k \in \{\mathrm{CO_2}, \mathrm{N_2O}, \mathrm{CH_4}\}$, $e_k^{NP}(t)$ represents the trend component capturing non-periodic changes in the time series of the emission rate of type k, $e_k^{P}(t)$ is the seasonal component, which captures periodic variations in the time series of the emission rate of type k, $e_k^{R}(t)$ incorporates the recurring patterns such as of holiday seasons, and $\varepsilon_{k,t}$ denotes the error term representing any idiosyncratic changes not captured by the non-periodic, periodic, recurring elements of the model. We capture non-periodic trends in greenhouse gas emission rates from EV charging using a precise linear structure that allows for capturing multiple phases of non-linear growth or decline, as well as abrupt shifts in the emission rate time series:

$$e_k^{NP}(t) = (\beta + I(t)^T \delta_\beta)t + (\alpha + I(t)^T \delta_\alpha), \tag{2}$$

where β denotes the growth rate, α is the offset parameter, $I(t)$ is an indicator function for change points, and δ_α and δ_β are offset adjustments and rate adjustments, respectively, at the change points. We also capture periodic trends in EV charging emission rates using Fourier series:

$$e_k^{P}(t) = \sum_{i=1}^{N} \left(a_i \cos\frac{2\pi i t}{P} + b_i \sin\frac{2\pi i t}{P} \right), \tag{3}$$

where P is the period (365.25 for the yearly period), N is the number of Fourier terms, and a_i and b_i are the Fourier coefficients that control the amplitude and phase of the periodic trends at frequency i. We also capture the recurring patterns in the EV charging emission rate that do not necessarily follow a regular periodicity over time:

$$e_k^R(t) = \sum_{i=1}^{M} \gamma_i \chi_i(t), \tag{4}$$

where $\chi_i(t)$ is an indicator function for the i-th recurrence, and γ_i is the impact of the i-th recurrence out of M. In the proposed formulation of the EV charging emission prediction model, unsystematic errors are assumed to follow a normal distribution for each emission type k, $\varepsilon_{k,t} \sim \mathcal{N}(0, \sigma_k^2)$.

The proposed machine learning approach, developed on the Prophet platform, is particularly effective for predicting EV charging emission rates over time, thanks to key features aligned with the characteristics of the training data and forecasting requirements. In the context of predicting EV charging emission rates, we encounter gaps in the training data for multiple years in between the years for which the average emission rates are available for all 12 months (i.e., 2024, 2026, 2028, 2030, 2035, 2040, 2045, 2050). The proposed machine learning approach is capable of handling such gaps effectively without requiring the imputation of missing values. Its robustness to missing data ensures that the prediction remain accurate and reliable, making it ideal for our dataset where training data is not available for all consecutive years.

The rates of greenhouse gas emissions from power plants due to EV charging exhibit strong periodic patterns, driven by variations in the energy mix and demand across different months and seasons. The Fourier series-based approach in the proposed machine learning model effectively captures these periodic fluctuations. The model's piecewise linear component also enables tracking long-term trends in power plant emissions over extended periods. Moreover, the model incorporates a weighting mechanism for recurring patterns, allowing it to capture irregularities such as holiday seasons. Leveraging these features, the proposed machine learning approach is both computationally efficient and scalable, enabling precise predictions of grid emissions as EV energy consumption rises for planning and policy-making analysis. The model's additive framework simplifies computation, enabling quick adjustments and iterations, while ensuring consistent predictions over time, effectively capturing long-term trends, periodic patterns, and recurring irregularities that impact greenhouse gas emissions from power plants due to EV battery charging from the grid.

Training Data

To provide accurate predictions of power plant emission rates through 2050, we train our machine learning model using results from Cambium, an advanced simulation tool developed by NREL. Cambium projects the evolution of power generation and distribution systems, offering a robust framework for simulating the operations of the U.S. electric sector. The Cambium model draws on data from the Regional Energy Deployment System (ReEDS) and PLEXOS, a sophisticated, high-performance tool for energy system simulation, to model both operational dynamics and the long-term evolution of the electric grid under various scenarios (Gagnon et al., 2024). ReEDS is a least-cost optimization model that projects the structural changes in the electric sector, considering factors such as fuel costs, technology costs, and policies. It determines the optimal mix of generation and transmission assets to minimize system costs. PLEXOS, on the other hand, simulates operations of the electric sector based on the ReEDS projections, capturing the dynamic and operational aspects of the grid. The integration of these two models allows Cambium to provide a comprehensive view of future electricity systems.

The Cambium model enables the simulation of operations and the evolution of the electric sector, allowing for the estimation of emissions rates for CO_2 (kg/MWh), N_2O (g/MWh), CH_4 (g/MWh) from EV charging across the United States under various scenarios projecting technology costs, fuel prices, demand growth, and electricity sector policies. In this research, we utilize Cambium simulation results to train the machine learning model for eight scenarios, each centered around the median values of key input variables, including technology costs, fuel prices, demand growth, and current electricity sector policies, as detailed below (Gagnon et al., 2024):

1. *Mid-case:* This scenario represents central estimates for key inputs such as technology costs, fuel prices, and demand growth, with no inclusion of nascent technologies. It assumes electric sector policies as they existed in September 2023

2. *Low Renewable Energy and Battery Costs:* This scenario mirrors the assumptions of the Mid-case but assumes lower costs and greater performance improvements for renewable energy and batteries.

3. *High Renewable Energy and Battery Costs:* Similar to the Mid-case scenario, but with higher costs and less significant performance improvements for renewable energy and batteries.

4. *High Demand Growth:* This scenario also uses the same base assumptions as the Mid-case but assumes a higher average annual demand growth rate of 2.8% from 2024 to 2050, consistent with a trajectory towards 100% economy-wide decarbonization.

5. *Low Natural Gas Prices:* This scenario is consistent with the Mid-case assumptions but assumes lower natural gas prices.

6. *High Natural Gas Prices:* This scenario follows the same base assumptions as the Mid-case but assumes higher natural gas prices.

7. *95% Decarbonization by 2050:* Building on the Mid-case scenario, this assumes the inclusion of nascent technologies and enforces a national decarbonization constraint, progressively reducing net electricity sector emissions to 5% of 2005 levels by 2050.

8. *100% Decarbonization by 2035*: Similar to the 95% Decarbonization scenario, but with a more aggressive target of achieving net-zero emissions by 2035 through the inclusion of nascent technologies and a linear reduction to zero emissions.

The simulation results from the Cambium model enable effective training of the proposed machine learning model across various scenarios, each capturing different projections for technology costs, fuel prices, demand growth, and electricity sector policies. Cambium's comprehensive simulation framework provides precise estimates of emission rates by accounting for power generation mixes and grid operations across the United States. By leveraging Cambium's projections, the machine learning model delivers accurate predictions of greenhouse gas emissions from EV charging under diverse policy and economic conditions, ensuring robustness and reliability in forecasting emission trends and their dependency on shifting technological and market dynamics.

Model Training

We train our machine learning model using simulation results from the Cambium model to provide accurate and continuous predictions of CO_2, N_2O, and CH_4 emission rates from EV charging through 2050 in California, Georgia, New York, and Washington. Given the intermittent nature of the simulation data, we normalize the training dataset to ensure consistency and accuracy in the predictive model. Normalization scales the data to a uniform range without distorting the inherent differences, which is essential for effective model training. Normalization standardizes the emission rates, minimizing disparities due to varying magnitudes and ensuring the dataset is cohesive. The resulting standardized training dataset, which includes normalized emission rates across the specified months and years, establishes a reliable foundation for accurate long-term predictions.

With the normalized data in place, we configure and train our machine learning model, designed to handle time series data with periodic, non-periodic, and irregular patterns, as well as missing values, making it a powerful tool for predictive analysis. The proposed model is trained using the normalized emission rates of CO_2, N_2O, and CH_4, incorporating monthly variations across different years. The training process involves fitting the model to capture long-term trends, periodic patterns, and recurring irregularities in the data, ensuring accurate predictions of emission rates. Throughout the training, the model parameters are carefully tuned to align with the normalized dataset. Tab. 1 summarizes the RMSE, MAE, MAPE, and R^2 performance metrics for predicting CO_2, N_2O, and CH_4emission rates

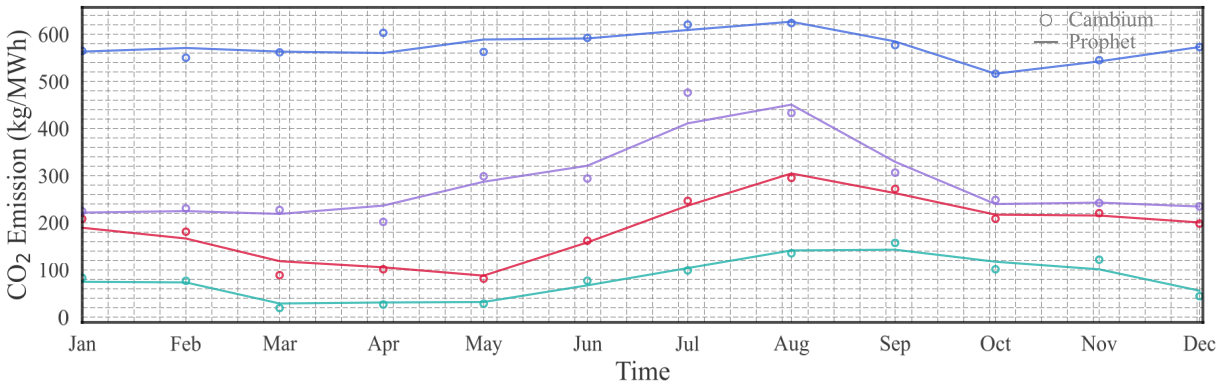
in California, Georgia, New York, and Washington under eight scenarios, each reflecting different projections for technology costs, fuel prices, demand growth, and electricity sector policies. These metrics highlight the high accuracy and robustness of our machine learning model in estimating power plant emission rates across various scenarios.

Tab. 1. Performance Metrics of the Machine Learning Model

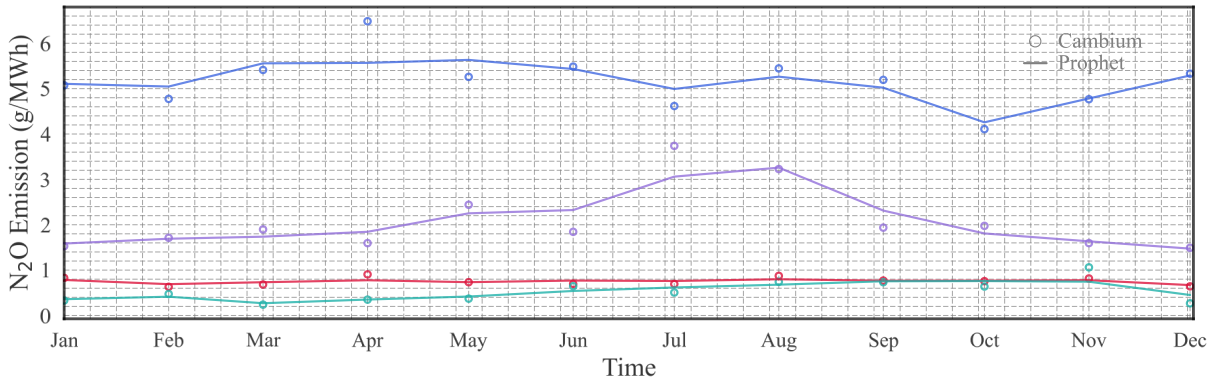
	Scenario	Meta Prophet Emission Model											
		CO_2				N_2O				CH_4			
		RMSE	MAE	MAPE	R^2	RMSE	MAE	MAPE	R^2	RMSE	MAE	MAPE	R^2
California	Scenario 1	8.43	5.86	35.53	0.989	0.038	0.027	22.87	0.982	71.71	50.11	67.52	0.986
	Scenario 2	7.15	5.04	44.86	0.991	0.063	0.044	38.35	0.959	59.36	41.88	63.59	0.988
	Scenario 3	5.13	3.66	41.98	0.995	0.026	0.019	15.40	0.988	44.76	31.24	95.64	0.993
	Scenario 4	4.93	3.71	35.93	0.996	0.066	0.039	25.36	0.953	96.78	65.52	189.5	0.976
	Scenario 5	12.99	8.29	80.76	0.976	0.056	0.035	21.49	0.959	97.01	65.72	194.7	0.976
	Scenario 6	5.19	3.88	21.62	0.996	0.066	0.049	58.01	0.970	47.71	33.74	56.09	0.993
	Scenario 7	7.94	6.03	53.34	0.991	0.052	0.039	44.70	0.974	74.45	56.26	32.50	0.983
	Scenario 8	14.43	5.57	5.51	0.969	0.110	0.045	8.43	0.901	105.1	39.75	6.39	0.968
Georgia	Scenario 1	11.23	7.70	4.99	0.996	0.188	0.131	13.30	0.987	39.07	27.10	3.21	0.998
	Scenario 2	12.20	9.49	7.72	0.994	0.239	0.181	17.82	0.975	36.54	27.94	4.92	0.998
	Scenario 3	9.46	7.16	5.26	0.996	0.207	0.158	19.20	0.987	43.21	32.42	4.12	0.995
	Scenario 4	11.04	8.47	4.39	0.993	0.223	0.166	13.53	0.973	30.75	23.47	2.48	0.998
	Scenario 5	20.95	17.54	12.64	0.972	0.445	0.341	25.81	0.856	43.99	32.71	6.08	0.997
	Scenario 6	13.79	10.51	6.38	0.993	0.247	0.183	17.64	0.976	42.81	31.74	3.61	0.997
	Scenario 7	14.71	11.90	15.46	0.995	0.314	0.231	39.08	0.977	65.90	52.95	10.28	0.995
	Scenario 8	13.41	6.28	3.51	0.995	0.231	0.104	9.13	0.975	68.01	31.09	2.89	0.996
New York	Scenario 1	13.05	5.81	2.80	0.988	0.138	0.062	5.32	0.975	33.46	16.32	1.71	0.996
	Scenario 2	13.29	6.94	3.75	0.989	0.140	0.068	6.94	0.977	38.53	21.10	2.56	0.995
	Scenario 3	13.02	6.36	3.46	0.989	0.114	0.060	6.01	0.984	43.74	20.08	2.25	0.994
	Scenario 4	15.11	6.68	3.24	0.983	0.152	0.064	5.43	0.961	32.88	17.19	2.10	0.997
	Scenario 5	10.90	4.99	2.73	0.989	0.073	0.033	2.95	0.984	43.36	23.18	2.85	0.995
	Scenario 6	12.55	5.93	2.70	0.991	0.129	0.061	4.83	0.983	30.93	15.45	1.89	0.997
	Scenario 7	11.28	6.11	3.71	0.990	0.144	0.076	7.02	0.974	29.76	16.11	2.13	0.996
	Scenario 8	11.94	5.32	3.49	0.988	0.122	0.054	6.61	0.976	47.79	19.96	2.71	0.991
Washington	Scenario 1	5.75	4.04	15.59	0.967	0.063	0.041	29.97	0.901	39.53	27.23	19.09	0.965
	Scenario 2	4.84	3.60	17.46	0.978	0.039	0.026	25.09	0.960	34.85	26.01	20.90	0.976
	Scenario 3	5.34	4.13	22.41	0.981	0.031	0.025	24.72	0.970	38.58	27.98	31.80	0.982
	Scenario 4	6.77	4.89	22.69	0.983	0.058	0.038	28.74	0.966	51.88	36.82	45.20	0.979
	Scenario 5	8.53	5.54	26.22	0.956	0.105	0.063	49.37	0.813	52.51	34.55	28.45	0.968
	Scenario 6	6.45	5.01	17.43	0.993	0.062	0.042	32.93	0.988	57.24	41.51	23.85	0.986
	Scenario 7	7.50	5.34	18.26	0.989	0.124	0.074	48.01	0.946	63.36	45.36	15.42	0.979
	Scenario 8	10.00	4.14	7.30	0.952	0.096	0.041	13.92	0.902	59.85	24.46	7.15	0.957

Once trained, the Prophet model provides accurate predictions of the temporal dynamics of emission rates throughout the study period, extending through 2050. The proposed model provides a comprehensive view of projected emission rates, effectively capturing both long-term trends and short-term seasonal variations. The model's robustness in handling missing data ensures that any gaps in the historical training dataset do not compromise the accuracy of the predictions. By bypassing the need for complex simulation models, this machine learning approach facilitates the predictive analysis of greenhouse gas emissions from power plants due to EV charging, accounting for various projections of technology costs, fuel prices, demand growth, and electricity sector policies.

Fig. 1a-d illustrate the predicted additional emissions of CO_2, N_2O, and CH_4 per 1 MWh of EV charging from the grid under the mid-case scenario through 2025 in California, Georgia, New York, and Washington. As shown in Fig. 1a, CO_2 emission rates peak during winter (January to March) due to increased reliance on fossil fuels for heating, particularly in Georgia. In spring (April to June), emissions decline as renewable energy generation ramps up, especially in Washington and California. A significant rise in CO_2 emissions occurs in summer (July to September), notably in California and New York, where natural gas plants ramp up to meet cooling demand. Georgia's CO_2 emissions remain relatively stable throughout the year, with no significant summer spike, reflecting its consistent reliance on fossil fuels, while Washington experiences only a minor increase in summer emissions due to its reliance on hydropower. By fall (October to December), emissions decrease again as demand subsides, with Washington maintaining the lowest emissions year-round due to its renewable energy mix. As shown in Fig. 1b, Georgia has the highest N_2O emission rates, peaking in May and August, due to its year-round reliance on fossil fuels and increased generation during periods of higher demand. New York shows a moderate rise in N_2O emissions during the summer months (June to September), driven by increased electricity demand and reliance on fossil fuels to supplement renewable energy. California and Washington maintain relatively low N_2O emissions throughout the year, benefiting from their significant use of renewable energy sources like solar and hydropower, with some seasonal variation. As shown in Fig. 1c, Georgia consistently records the highest CH_4 emissions throughout the year due to its continuous reliance on natural gas and coal. California and New York show sharp increases in CH_4 emissions during the summer months (July to September), driven by increased cooling demand that necessitates higher natural gas plant output. Washington, once again, records the lowest CH_4 emissions year-round, thanks to its substantial use of hydropower.



(a) CO_2



(b) N2O

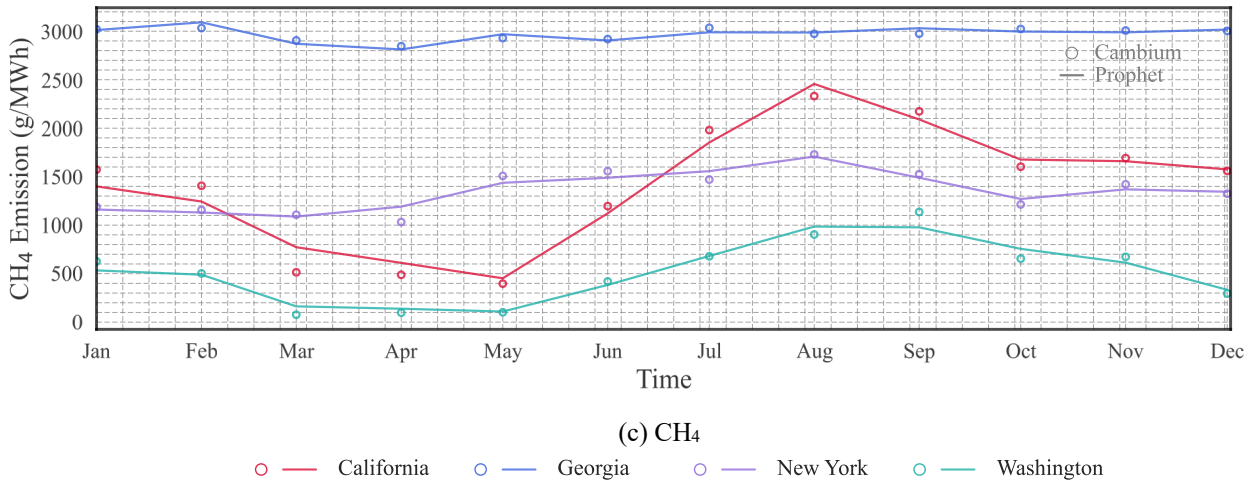


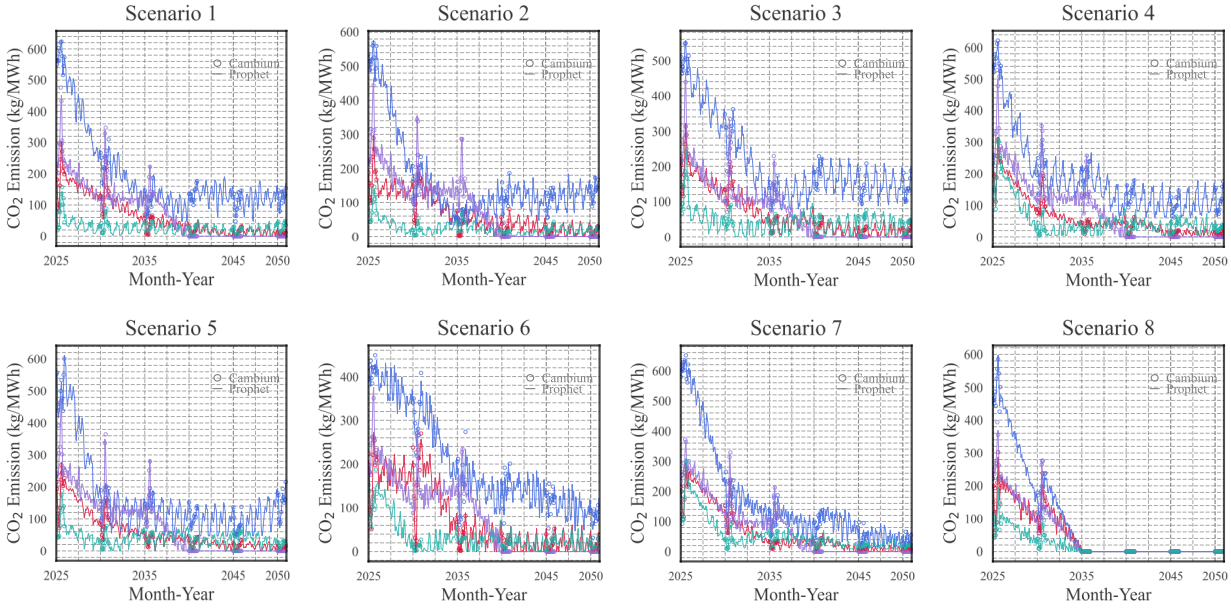
Fig. 1. Prediction of Power Plant CO_2, N_2O and CH_4 Emission Rates Through 2025

FIGURE 2a-c depict the projected CO_2, N_2O, and CH_4 emission rates under eight power generation planning scenarios, each reflecting different projections for costs, prices, demand growth, and policy outcomes through 2050. In FIGURE 2a, CO_2 emission rates decline steadily across all scenarios from 2020 to around 2035, though the pace and trajectory of reduction vary based on projections of renewable energy deployment and fossil fuel phase-outs. Scenarios 7 and 8, which feature more aggressive renewable integration and stronger policy support, demonstrate faster declines, particularly in California and Washington, where hydropower and solar energy are dominant. Georgia, with its heavier reliance on fossil fuels, shows slower reductions in emissions across all scenarios. Notably, Scenarios 1–6 project a rise in CO_2 emission rates after 2030, more pronounced in Georgia and, to a lesser extent, in California and Washington, due to increasing energy demand, slower renewable deployment, and a partial return to fossil-based generation to meet peak demand[2]. In contrast, New York achieves near-zero emission rates by 2040 in all scenarios, driven by large-scale renewable energy adoption and a complete phase-out of fossil fuel generation.

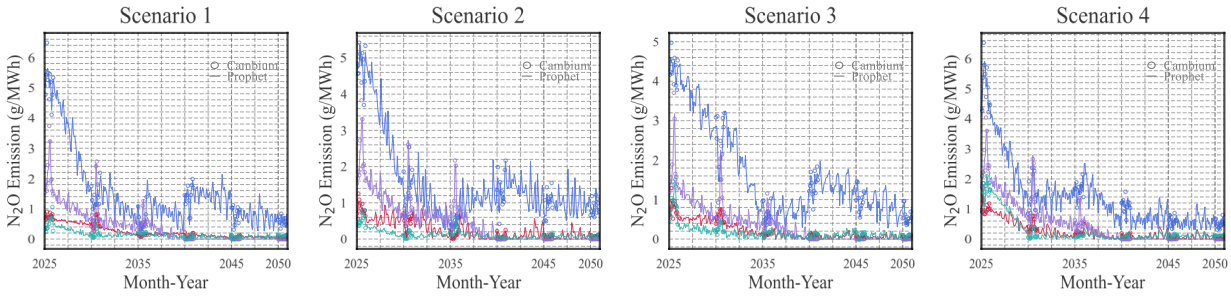
As shown in Fig. 2b, in all scenarios, there is a marked decline in N_2O emission rates from 2025 to 2040, driven by the transition from fossil fuels to renewable energy. The rate of reduction varies across scenarios, with more aggressive policy interventions and faster adoption of renewables leading to steeper declines, particularly in California, New York, and Washington, where renewable energy plays a significant role. In contrast, Georgia, which remains heavily reliant on fossil fuels, sees slower reductions after 2030 due to increasing energy demand and delayed renewable integration, worsened by the expiration of the IRA's financial incentives. By 2040, all states except Georgia achieve near-zero N_2O emissions, as the phase-out of natural gas and accelerated renewable energy deployment enable near-total decarbonization.

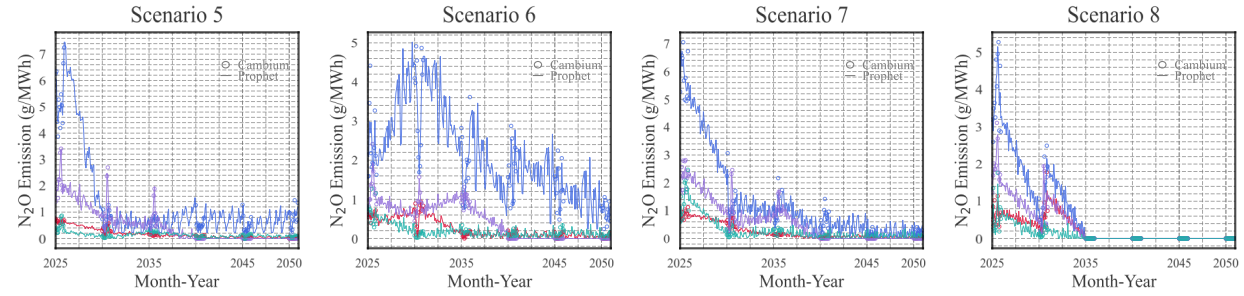
[2] The expiration of tax credits provided by the Inflation Reduction Act (IRA) for renewable energy projects is expected to have a significant adverse impact on CO_2, N_2O, and CH_4 emissions from power generation. The IRA's financial incentives have been crucial in accelerating the deployment of renewable energy technologies, driving down emissions of air pollutants. However, these incentives are set to phase out by 2032, or once the U.S. electricity sector achieves a 75% reduction in greenhouse gas emissions from 2022 levels. As these financial supports taper off, the pace of renewable energy deployment is projected to slow, while electricity demand is expected to continue rising, driven largely by the electrification of transportation and heating sectors. This mismatch between growing demand and slower renewable energy growth will likely result in increased reliance on fossil fuel power plants, particularly natural gas, to meet peak demand, leading to a rebound in CO_2, N_2O, and CH_4 emissions. The continued operation of natural gas plants, due to the inability of renewable energy to scale quickly enough after the expiration of the IRA's clean energy provisions, is projected to result in a substantial increase in air pollutant emissions.

Fig. 2c plots the decline in CH_4 emission rates across all scenarios between 2025 and 2035, though the pace of reduction varies by state and scenario. In California and Washington, CH_4 emissions drop sharply, driven by early and widespread adoption of renewable energy sources like solar and hydropower, which rapidly displace natural gas as a primary energy source. Georgia, however, experiences a more gradual reduction in CH_4 emissions due to its continued reliance on fossil fuels and slower integration of renewable energy. Notably, in Scenarios 1–6, CH_4 emissions are projected to rise after 2030, particularly in Georgia and, to a lesser extent, in California and Washington. This increase is attributed to rising energy demand, coupled with slower renewable energy deployment and a partial return to fossil fuel generation to meet peak demand following the expiration of the IRA's clean energy provisions. New York, meanwhile, sees moderate reductions in CH_4 emissions, benefiting from a balanced energy mix of renewables and natural gas, though it lags behind Washington's swift transition to hydropower. By 2040, New York surpasses Washington and achieves near-zero CH_4emissions in most scenarios, while Georgia continues to exhibit higher CH4 emission rates due to its reliance on natural gas for peak demand.

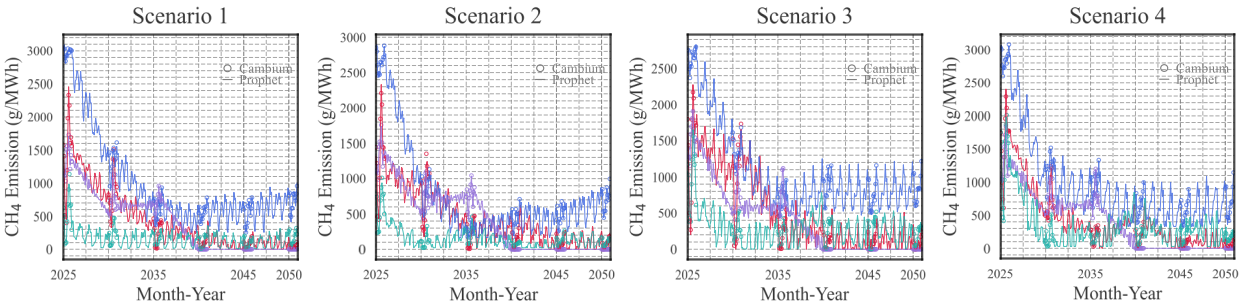


(a) CO_2





(b) N_2O



(c) CH_4

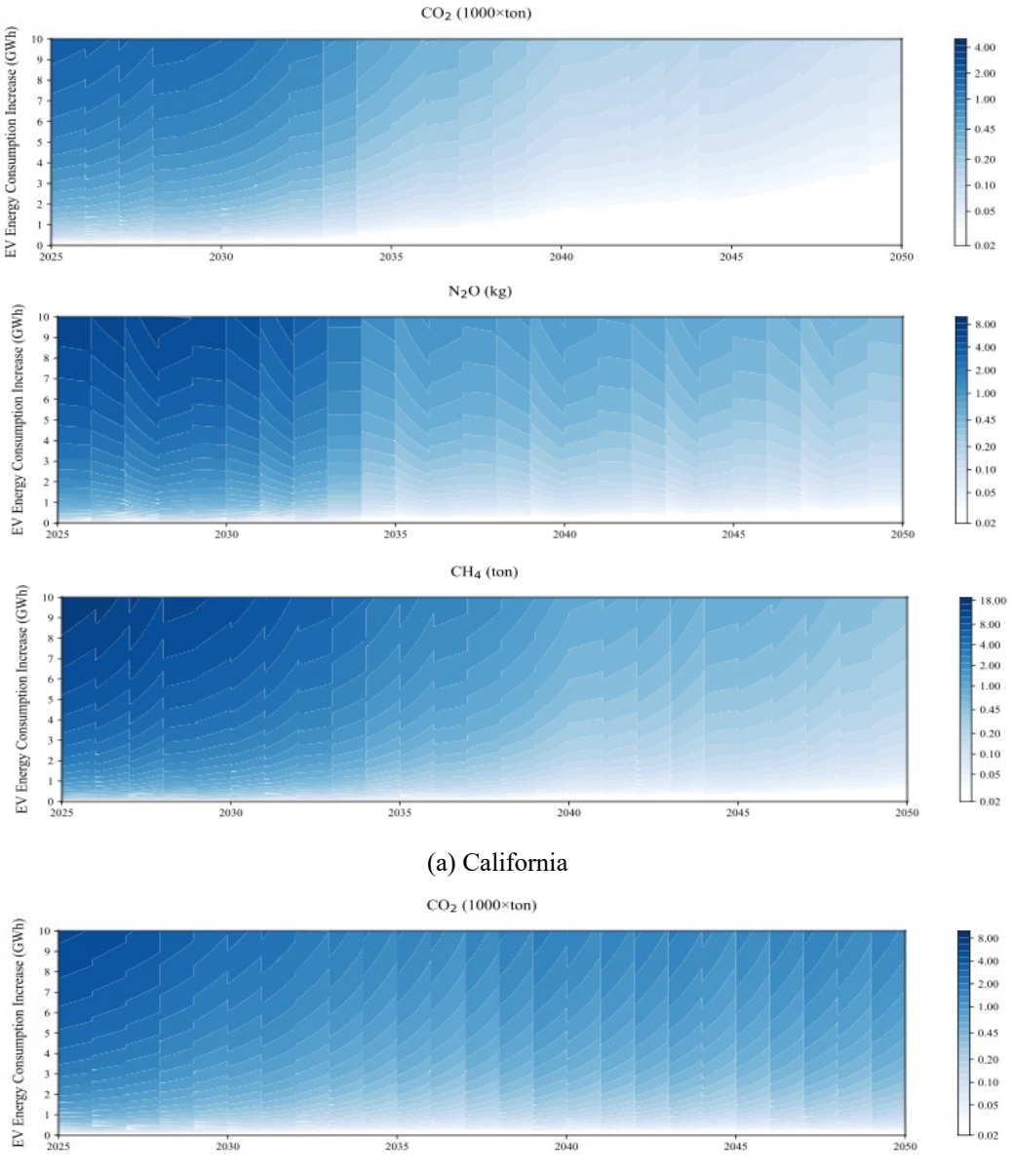
California Georgia New York Washington

FIGURE 2. Prediction of Power Plant CO_2, CH_4, and N_2O Emission Rates through 2050

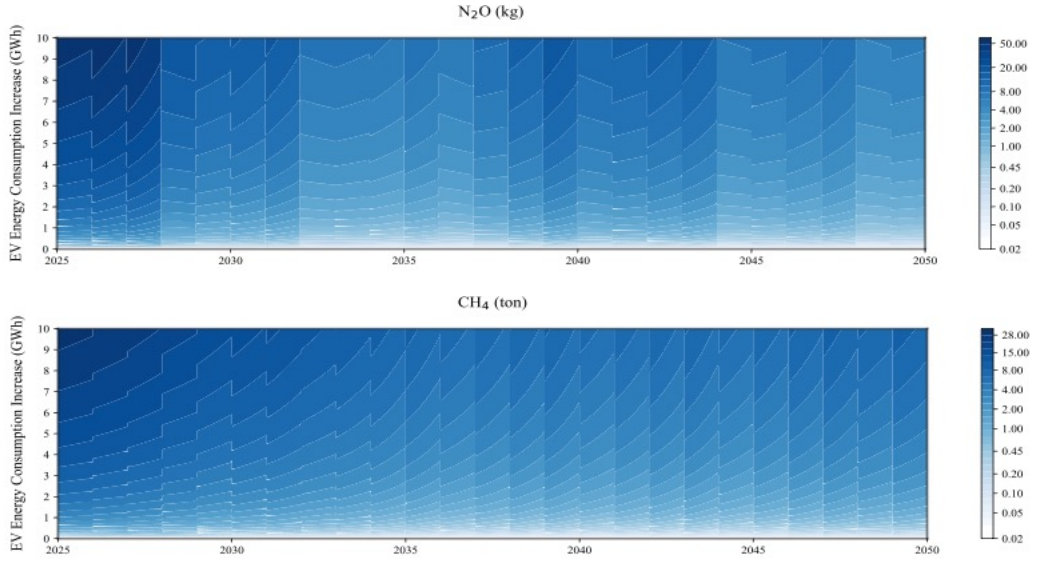
3 Predicting Greenhouse Gas Emission from EV Charging

The electric energy consumption of EVs from the power grid to charge their batteries results in increased greenhouse gas emissions from power plants, influenced by factors such as power plant technology, distribution network efficiency, load temporal distribution, and the energy mix of the grid. The proposed machine learning approach allows for accurate estimation of greenhouse gas emissions from power plants as EV energy consumption rises under various projections of technology costs, fuel prices, demand growth, and electricity sector policies. Fig. 3a-d plot the increase in emissions of CO_2, N_2O, and CH_4 due to the electrical energy consumption of EVs from the power grid under the Mid-case Scenario (Scenario 1) through 2050 in California, Georgia, New York, and Washington.

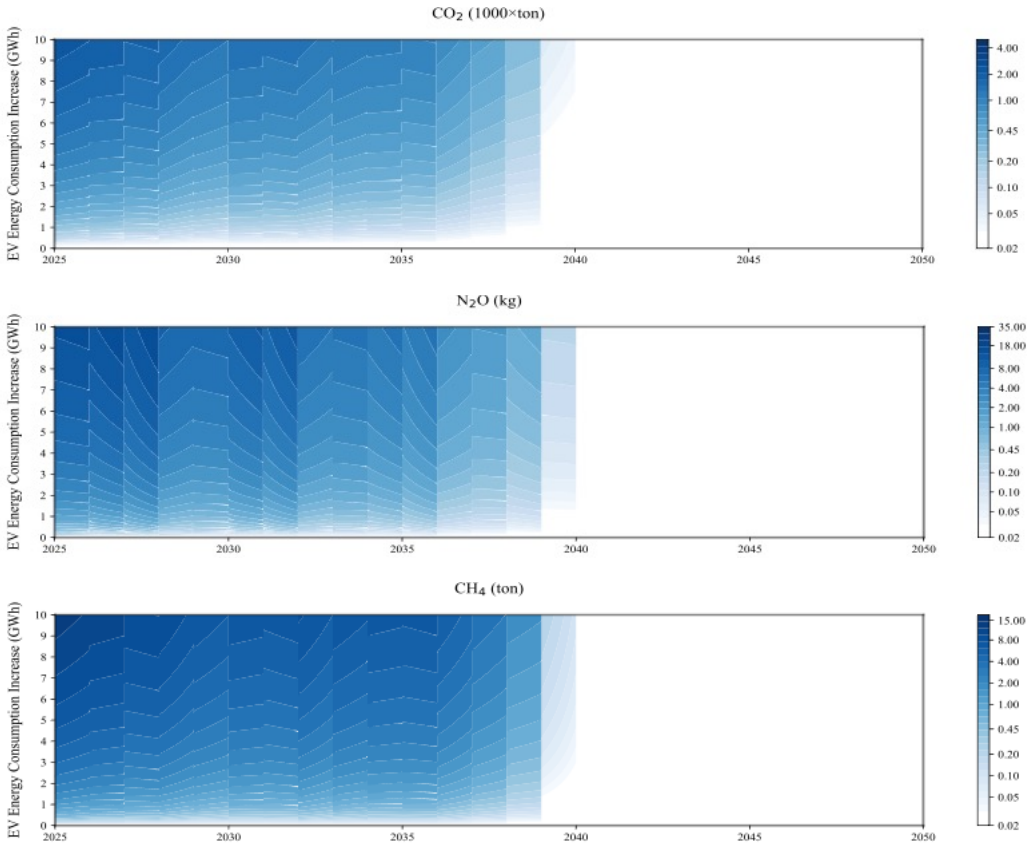
In California and Washington, the increase in CO_2, N_2O, and CH_4 emissions is relatively moderate, largely due to their significant reliance on renewable energy sources like solar and hydropower, which substantially reduce the need for natural gas and limit related emissions. California's early adoption of solar energy and Washington's vast hydropower capacity allow both states to meet the growing demand for EV charging with minimal dependence on fossil fuels. In contrast, Georgia, with its continued reliance on fossil fuels, particularly natural gas and coal, experiences the sharpest increases in CO_2, N_2O, and CH_4 emissions, reflecting the higher emissions intensity per unit of electricity generated, especially during periods of peak demand. New York exhibits a more moderate increase in emissions across all three pollutants, though these emissions drop sharply by 2040 as the state accelerates its transition from natural gas to offshore wind, nuclear, and other renewable energy sources.



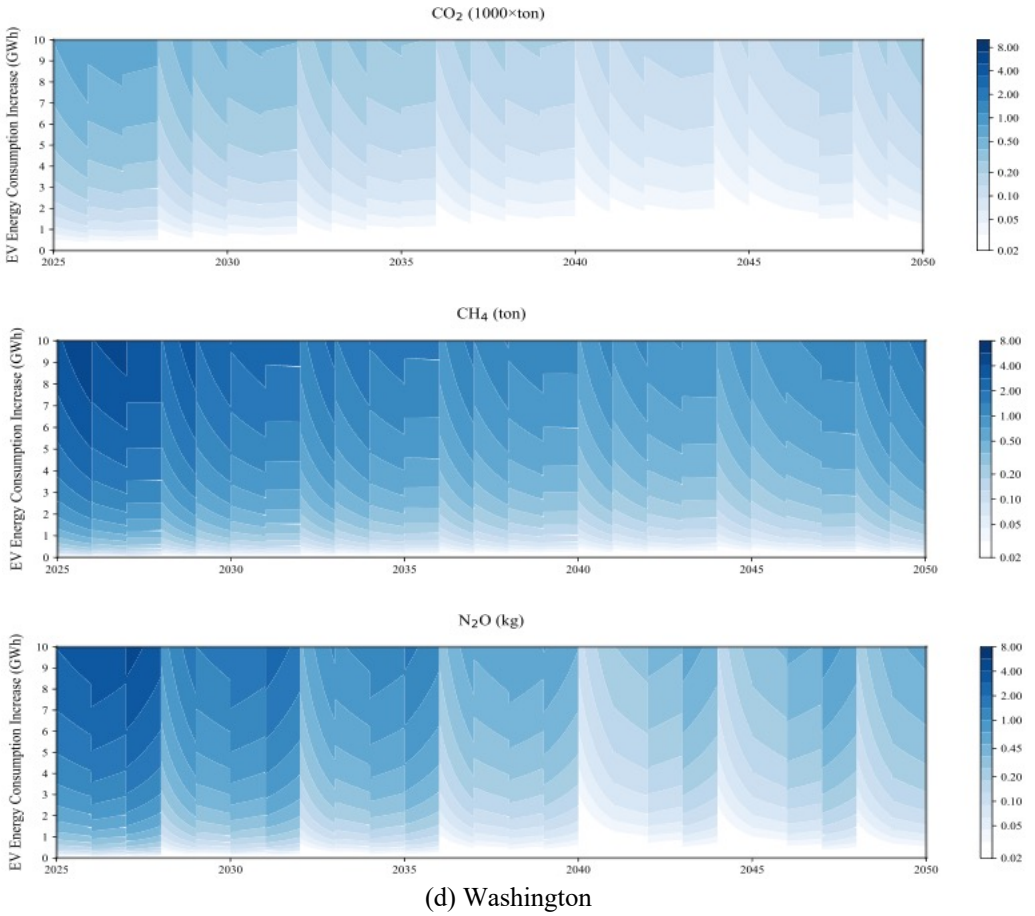
(a) California



(b) Georgia



(c) New York



(d) Washington

Fig. 3. Prediction of Power Plant CO_2, CH_4, and N_2O Emissions with Increased Energy Consumption of EVs from Power Plants – Mid-case Scenario

To accurately forecast the increase in greenhouse gas emissions from power plants due to EV charging in the coming years, we estimate the rise in energy consumption from the grid based on projected EV adoption rates and total VMT. Fig. 4 plots the projected relative increase in EV adoption compared to 2024 through 2030 in California, Georgia, New York, and Washington (US DOE, 2024a). These projections are based on several key factors, including historical EV registration trends, the expansion of charging infrastructure, and state-level policies aimed at promoting electrification. These projections also account for the development of public and private charging networks, alongside incentives such as rebates and stricter emissions standards designed to accelerate EV adoption.

The increase in electrical energy consumption for charging EV batteries is then estimated based on an average energy consumption rate of 0.34 kWh/mile (US DOE, 2024b) and the monthly EV traveled distances of 1,000 miles in California, 917 miles in Georgia, 750 miles in New York, and 875 miles in Washington (US DOT, 2024). Fig. 5 presents the projected increase in electricity consumption for EV charging, along with the lower and upper bounds, across California, Georgia, New York, and Washington from 2025 to 2030. California is expected to see the highest increase in demand, driven by its more significant rise in EV adoption and higher average vehicle miles traveled, while Georgia, New York, and Washington follow similar upward trends at slightly lower levels.

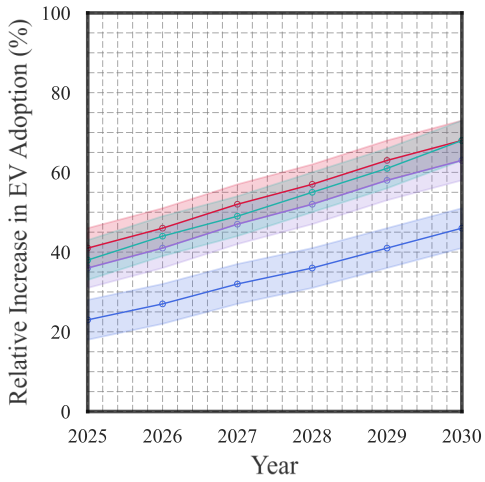


FIGURE 4. Projected Relative Increase in EV Adoption Compared to 2024 Through 2030

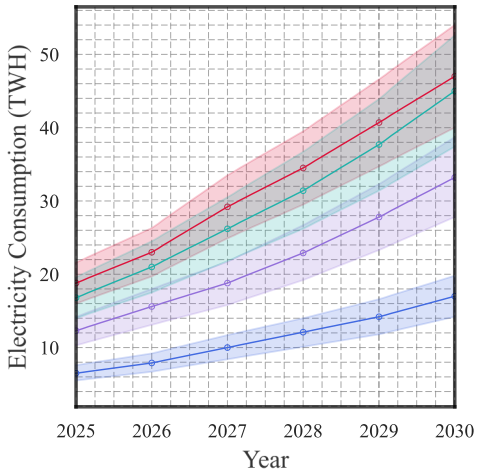
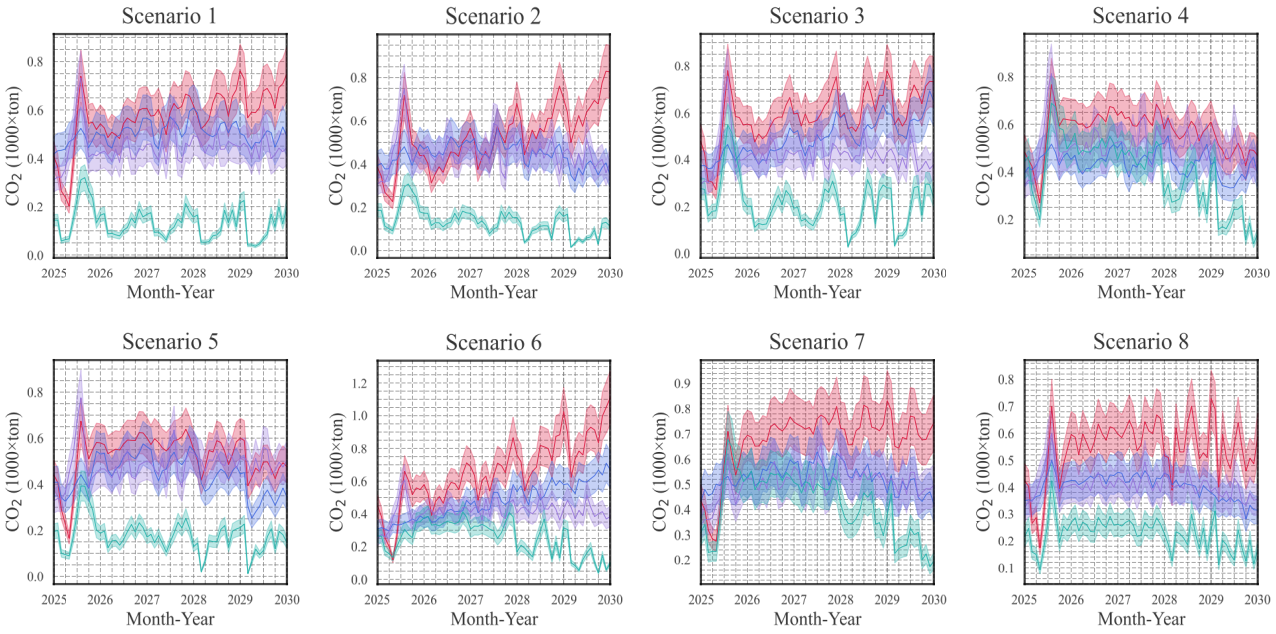


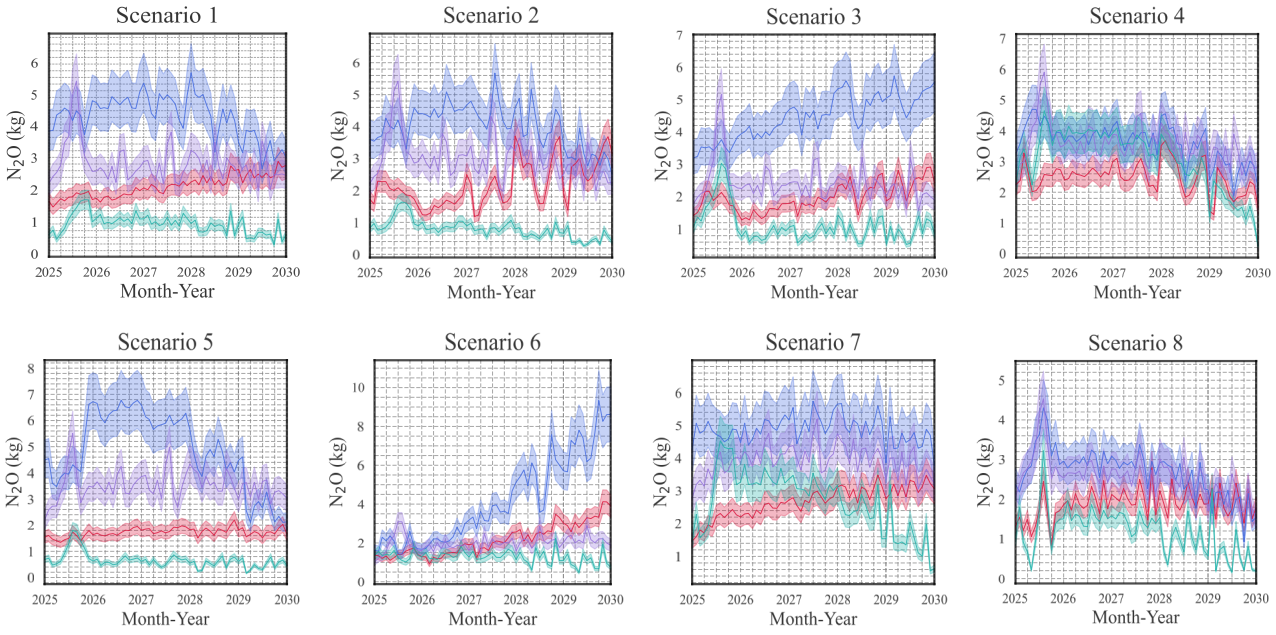
FIGURE 5. Projected Increase in EV Charging Through 2030

Utilizing our machine learning model, developed on the Prophet platform and trained with data from Cambium, we estimate the increase in greenhouse gas emissions corresponding to the projected rise in EV charging from the grid. Fig. 6a-c plots the projected increases in CO_2, N_2O, and CH_4 emissions due to the rise in EV charging through 2030, under eight scenarios that account for various projections of technology costs, fuel prices, demand growth, and electricity sector policies. The projected increases in CO_2, N_2O, and CH_4 emissions resulting from rising EV charging demand show significant variation across scenarios and among the states of California, Georgia, New York, and Washington. In California, emissions of all three pollutants are expected to rise moderately despite substantial EV charging demand, owing to the state's cleaner energy mix dominated by solar and wind. The smallest increases are observed in Scenarios 4, 6, and 8, where aggressive renewable energy adoption mitigates emissions. Georgia, in contrast, is expected to experience the steepest increases in CO_2, N_2O, and CH_4 emissions due to its heavy reliance on natural gas and coal for electricity generation. The largest emission growth in Georgia occurs in Scenarios 3, 5, and 7, where renewable energy integration lags. New York is projected to see moderate increases in emissions across most scenarios but achieves significant reductions by 2030 in Scenarios 4, 6, and 8 as offshore wind and nuclear power replace natural gas in its energy mix. Washington, with its hydropower-dominated grid, is expected to consistently maintain the lowest emissions across all pollutants and scenarios, with minimal increases despite rising EV charging demand. The expected increases in CO_2, N_2O, and CH_4 emissions highlight the role of natural gas in driving CH_4 emissions and the combustion of fossil fuels in contributing to CO_2 and N_2O emissions. These results underscore the pivotal importance of state-specific energy mixes and the pace of renewable energy deployment in mitigating the emissions impact of EV charging demand, emphasizing the critical need for proactive policy measures to accelerate renewable adoption.

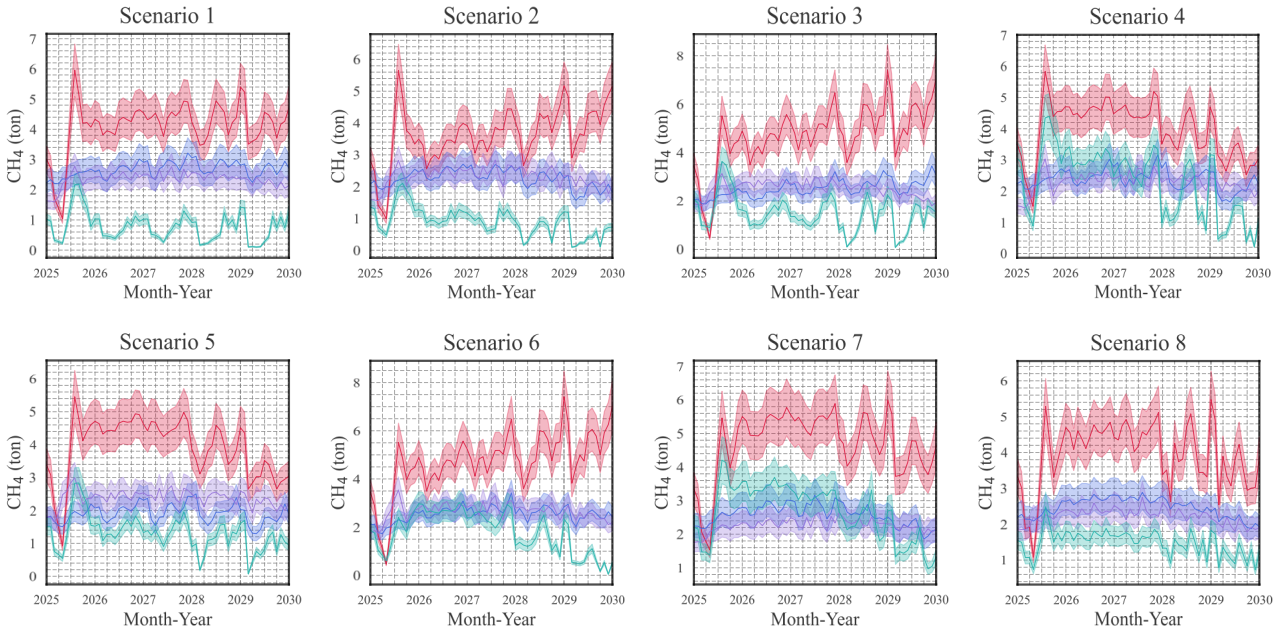
The model results indicate an increase of 83.79%, 18.15%, 42.22%, and 35.23% in emissions of CO_2, 64.40%, -20.69%, 10.54%, and -2.70% in emissions of N_2O, and 56.90%, 21.56%, 31.17%, and 22.58% in emissions of CH_4 from power plants with the projected increase of 150%, 162%, 170%, and 168% in energy consumption of EVs from the grid to in California, Georgia, New York, and Washington, respectively, by 2030 in the mid-case scenario.


Scenario 1
Scenario 2
Scenario 3
Scenario 4
Scenario 5
Scenario 6
Scenario 7
Scenario 8
CO2 (1000×ton)
Month-Year
2025
2026
2027
2028
2029
2030

(a) CO_2


Scenario 1
Scenario 2
Scenario 3
Scenario 4
Scenario 5
Scenario 6
Scenario 7
Scenario 8
N2O (kg)
Month-Year
2025
2026
2027
2028
2029
2030

(b) N_2O



(c) CH_4

California Georgia New York Washington

Fig. 6. Prediction of Power Plant CO2, CH4, and N2O Emissions Through 2030

Conclusion

The increase in electrical energy consumption of EVs from power grids with the rise in their adoption and VMT, is expected to ironically elevate greenhouse gas emissions from power plants in the coming years in the absence of substantial clean energy upgrades. This research leverages machine learning for predicting greenhouse gas emissions from power plants due to rise in the electrical energy consumption of EVs from the grid over the coming years. To this end, we have developed a large-scale emission model based on the Meta Prophet platform, which is specifically designed to capture temporal patterns and seasonality, especially when there are gaps in the training data. Our model is trained using the NREL Cambium database, allowing it to accurately predict the increase in CO_2, CH_4, and N_2O emissions from power plants in response to the escalating energy consumption of EVs for charging their batteries in California, Georgia, New York, and Washington, under eight distinct pricing, taxation, and development scenarios. By bypassing the need for running complex simulation models, the proposed machine learning model facilitates predicting the increase in greenhouse gas emissions from power plants due to the rise in electrical energy consumption from EVs. The model results indicate that the projected increase in energy consumption of EVs leads to an increase of 83.79%, 18.15%, 42.22%, and 35.23% in emissions of CO_2, 64.40%, -20.69%, 10.54%, and -2.70% in emissions of N_2O, and 150%, 162%, 170%, and 168% in emissions of CH_4 from power plants in California, Georgia, New York, and Washington by 2030 with no substantial changes in electricity sector policies from their status as of September 2023.

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