Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Energy and Emissions Trade-offs of Electric Vehicle Charging and Vehicle Fuel Consumption in the United States

Mahyar Amirgholy

mahyar.amirgholy@kennesaw.edu

Kennesaw State University

Tanvir Alam Chowdhoury

Kennesaw State University

Laeticia Neno Aloyem

Kennesaw State University

Kleevens Gabriel

Kennesaw State University

Chenyu Wang

Kennesaw State University

Honghui Xu

Kennesaw State University

Article

Keywords:

Posted Date: November 17th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11382228/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Energy and Emissions Trade-offs of Electric Vehicle Charging and Vehicle Fuel Consumption in the United States

Mahyar Amirgholy[1]*, Tanvir Alam Chowdhoury[1], Laeticia Neno Aloyem[2], Kleevens Gabriel[1], Chenyu Wang[2], Honghui Xu[2]

[1] Department of Civil and Environmental Engineering, Kennesaw State University, Georgia, United States, 30060
[2] College of Computing and Software Engineering, Kennesaw State University, Georgia, United States, 30060

* Corresponding author: Mahyar Amirgholy (mahyar.amirgholy@kennesaw.edu)

Abstract

While electric vehicles (EVs) produce no tailpipe emissions, their upstream emissions increase with the growing electricity demand from the power grid for battery charging. This research investigates how the growth in electric vehicle (EV) adoption and travel demand over time affects overall vehicle fuel consumption and emissions, as well as electricity demand for EV battery charging and the resulting upstream emissions from power generation through a predictive analysis across four major U.S. cities: Atlanta, Los Angeles, New York, and Seattle. Our results highlight the trade-off between reductions in vehicle tailpipe emissions from increased EV adoption and the corresponding increases in upstream emissions from EV charging. Although increasing EV adoption generally has a positive impact on reducing vehicle emissions, even after accounting for the upstream emissions from EV battery charging in regions that rely heavily on fossil fuels for power generation, such as Atlanta, Georgia, these environmental benefits are substantially greater in regions where renewable energy contributes a larger share of the electricity mix, such as Seattle, Washington, and Los Angeles, California. The comparison across these U.S. cities highlights the importance of clean electricity generation in maximizing the environmental benefits of transportation electrification.

Introduction

The projected increase in electric vehicle (EV) adoption is expected to substantially reduce air pollutant emissions over the coming years. However, the growing electricity demand for EV battery charging will also increase upstream emissions from the power grid, with the magnitude of the increase depending on the energy mix, power generation technologies, and the efficiency of the transmission and distribution system. Moreover, although EVs produce no tailpipe emissions, emissions from internal combustion engine (ICE) vehicles are expected to increase as traffic congestion worsens due to rising travel demand and vehicle miles traveled. This research presents a predictive analysis of vehicle fuel consumption and emissions as well as EV electricity demand for battery charging and the resulting upstream emissions from power plants under projected increases in EV adoption and travel demand across four major U.S. cities: Atlanta, Georgia; Los Angeles, California; New York, New York; and Seattle, Washington.

Vehicle fuel consumption and air pollutant emissions depend on various factors, including vehicle design, weight, powertrain technology, driving patterns, and kinematic variables. At the microscopic scale, vehicle fuel consumption and emissions can be estimated based on instantaneous vehicle speed, acceleration, and engine power [1-4], while estimation accuracy can be further improved by incorporating vehicle-specific characteristics such as weight, aerodynamics, and powertrain technology [5-7]. Simulation models incorporate vehicle characteristics to estimate second-by-second emissions based on instantaneous vehicle kinematics with a high level of accuracy [8-10]. Incorporating high-resolution location coordinates and telematics data into simulation models can further improve real-world estimation accuracy [11-13]. Nevertheless, the extensive data requirements and high computational demands of microscopic simulation models have been the main limitations to their practical application at large scales.

Alternatively, macroscopic models enable the estimation of aggregated vehicle fuel consumption and emissions at large scales without requiring microscopic details. Instead of detailed vehicle characteristics, macroscopic models use overall vehicle information, including vehicle type, age, and fuel type, to estimate vehicle fuel consumption and emissions based on the average traffic speed, total vehicle miles traveled, and local environmental factors in different regions [14,15]. One prominent example of a macroscopic model is EMFAC (Emission Factors Model), developed by the California Air Resources Board (CARB), which provides a macroscopic framework for estimating emissions from on-road vehicles in California based on traffic data and a set of emission factors for various vehicle classes [16,17]. The U.S. Environmental Protection Agency (EPA) has also developed MOVES (Motor Vehicle Emission Simulator), which enables the estimation of vehicle fuel consumption and emissions per mile traveled for various vehicle classes based on their type, age, and fuel at different traffic speeds [18]. In its recent version, MOVES also features the capability to estimate non-tailpipe emissions from electric vehicles, such as particulate matter (PM) from tires and brakes, as well as the electricity consumption of EVs based on vehicle speed [18,19].

Although EVs eliminate tailpipe emission, the electricity required for battery charging results in upstream indirect emissions from power plants. The magnitude of these emissions depends primarily on the electricity generation mix. In regions where fossil fuels dominate electricity generation, the EV charging emissions can be substantial even relative to ICE vehicles. In areas heavily reliant on coal-fired power plants, the life-cycle greenhouse gas emissions of EVs may exceed those of ICE vehicles because of the high carbon intensity of electricity generation [20-22]. In contrast, in regions where renewable energy constitutes a significant share of the electricity mix, EVs can substantially reduce greenhouse gas emissions [23-25]. The timing of EV charging also plays a critical role, as the carbon intensity of electricity generation varies throughout the day. Charging during off-peak periods, when renewable energy

generation is more abundant, can further reduce upstream emissions [26-28]. Therefore, smart charging strategies that align EV charging with periods of low grid carbon intensity can significantly enhance the environmental benefits of transportation electrification [29,30]. Moreover, widespread EV adoption could stimulate investments in cleaner electricity generation and grid modernization, thereby accelerating the transition toward a lower-carbon power system [31]. Hence, comprehensive assessment of the energy and environmental impacts of increasing EV adoption and vehicle miles traveled requires accounting not only for reductions in tailpipe emissions but also for the growing electricity demand for EV charging and the resulting upstream emissions from power plants.

This research provides a predictive analysis of vehicle fuel consumption and emissions, as well as the electricity demand of EVs for battery charging and the resulting emissions from power plants under projected increases in travel demand and EV adoption across four major U.S. cities: Atlanta (GA), Los Angeles (CA), New York (NY), and Seattle (WA). Traffic composition is estimated using vehicle registration data to classify vehicles based on their type, fuel, and age, while traffic dynamics are predicted under the projected increase in travel demand using a macroscopic traffic model at the regional scale. Vehicle fuel consumption, EV electricity demand, and tailpipe emissions of CO_2, NO_x, and PM2.5 from tires and brakes are then estimated based on the projected traffic composition, EV adoption, and predicted traffic speeds and volumes at the regional scale using a machine learning model trained on MOVES simulation data. Having estimated the electricity demand of EVs for battery charging from the power grid, the resulting increase in emissions from power plants is also estimated using a machine learning model trained on simulation data from Cambium, developed by the National Renewable Energy Laboratory (NREL), which simulates energy sector emissions by accounting for regional power generation technologies, distribution network efficiency, temporal load distribution, and the electricity generation mix of the grid.

Our results provide a predictive analysis of increases in vehicle fuel consumption and tailpipe emissions of CO_2 and NO_x, and PM2.5 emissions from tires and brakes, as well as EV electricity demand for battery charging and the resulting upstream emissions of CO_2, N_2O, and CH_4 from power plants under projected increases in travel demand and EV adoption through 2030. The predictive analysis incorporates lower and upper bounds for the projected increases in travel demand and EV adoption over the coming years to account for projection uncertainty. The impacts of increasing travel demand and EV adoption are also investigated more broadly through a comprehensive sensitivity analysis independent of specific future projections. To this end, we provide a comprehensive analysis of CO_2, NO_x, and PM2.5 emissions from tires and brakes, as well as the increase in EV electricity demand for battery charging and the resulting CO_2, N_2O, and CH_4 emissions from EV charging under traffic volume increases ranging from 0% to 10% and EV penetration rates in the additional traffic ranging from 0% to 100%. We leverage these results to demonstrate how much the EV penetration rate in mixed traffic must increase to entirely prevent or partially mitigate the increase in CO_2 and NO_x emissions associated with increasing traffic volumes over time. However, the combined increase in travel demand and EV penetration has a synergistic negative impact on PM2.5 emissions from tires to the relatively higher weight of electric vehicles particularly in road networks such as New York. Furthermore, as EV electricity demand increases with higher traffic volumes and EV penetration rates, the resulting CO_2, N_2O, and CH_4 emissions from EV charging increase substantially under the mid-case scenario (i.e., no fundamental changes in energy sector policies compared to 2025), highlighting the importance of cleaner electricity generation for maximizing the environmental benefits of transportation electrification.

Results

This research provides a predictive analysis of fuel consumption of different vehicle types and the resulting vehicle emissions, as well as the electricity demand for EV charging and the resulting emissions from the power grid, with a focus on four major U.S. cities: Atlanta, Los Angeles, New York, and Seattle. **Figure 1** presents the downtown regions considered in this study for each of these cities.



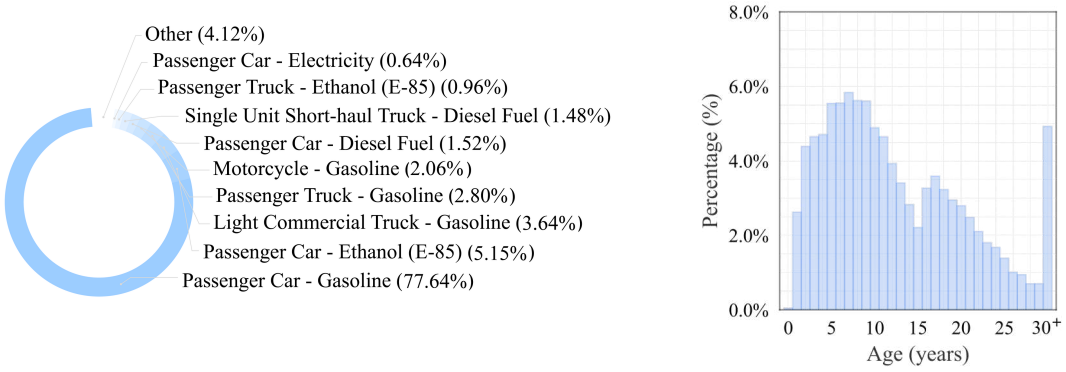
(a) Atlanta **(b) Los Angeles**

(c) New York **(d) Seattle**

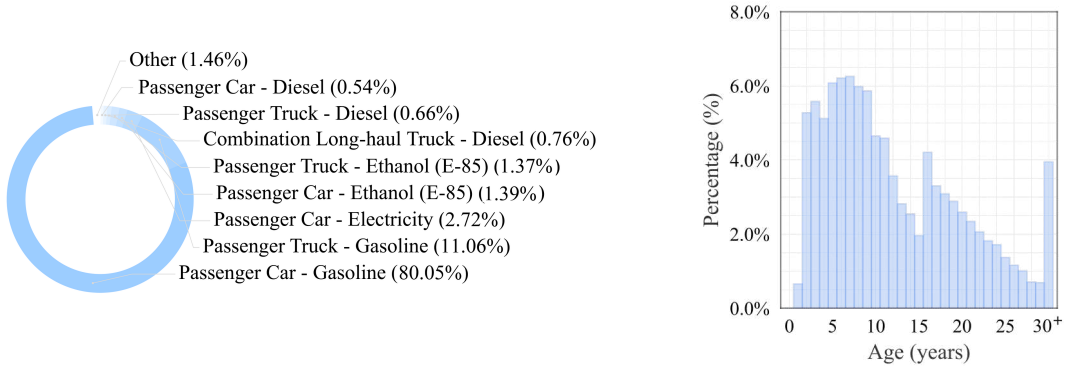
Figure 1. Downtown Study Regions in Atlanta, Los Angeles, New York, and Seattle. The New York study region has the highest population density, reflecting the compact and highly urbanized structure of the city, whereas Atlanta has the lowest population density and a comparatively less dense road network. Los Angeles and Seattle have intermediate population densities and relatively dense, grid-oriented street networks. These differences in urban form, population concentration, and network structure provide geographically diverse settings for evaluating traffic dynamics, vehicle energy consumption, and emissions.

Vehicle Classification Based on Registration Data

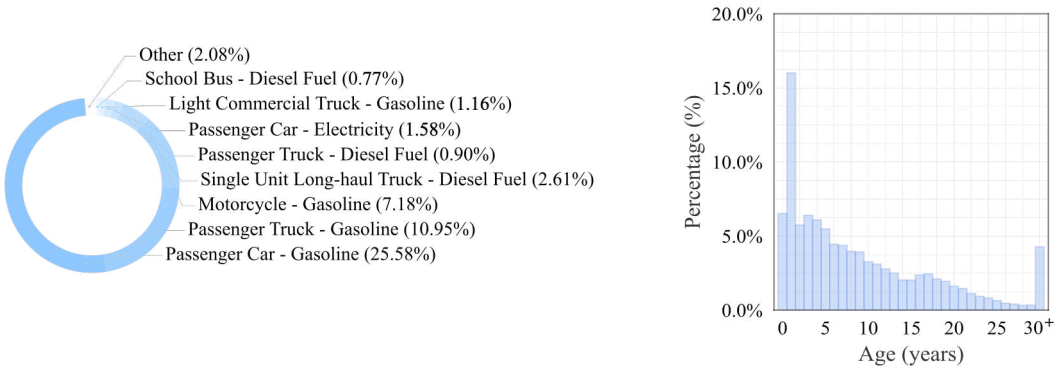
Accurate analysis of vehicle fuel consumption and emissions, as well as the electricity demand of EVs, requires accurate estimation of mixed-traffic composition. We use vehicle registration data from the Georgia Department of Driver Services, California Department of Motor Vehicles, New York Department of Motor Vehicles, and Washington Department of Licensing to classify vehicles based on their fuel type (compressed natural gas (CNG), diesel fuel, electricity, ethanol (E-85), and gasoline), vehicle type (combination long-haul truck, combination short-haul truck, light commercial truck, motorhome [recreational vehicle], motorcycle, other buses, passenger truck, passenger car, refuse truck, school bus, single-unit long-haul truck, single-unit short-haul truck, and transit bus), and age (1 to 30 years), consistent with the MOVES vehicle classification structure. After removing classes with no registration records (for example, a 25-year-old electric school bus that does not exist in practice) the number of active vehicle classes remains above 300. The ring charts in **Figure 2a-d** present the overall composition of mixed traffic based on vehicle type and fuel in Georgia, California, New York, and Washington. The overall age distributions of vehicles in these states are also presented in the histograms in **Figure 2a-d.**



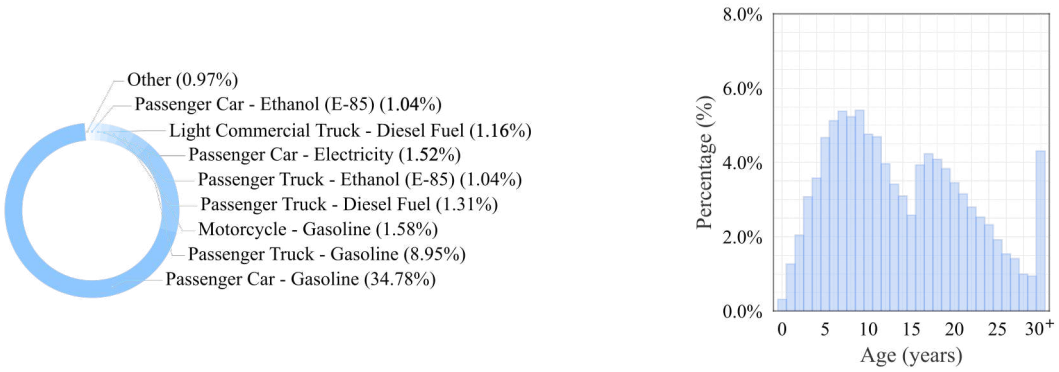
(a) Georgia



(b) California



(c) New York

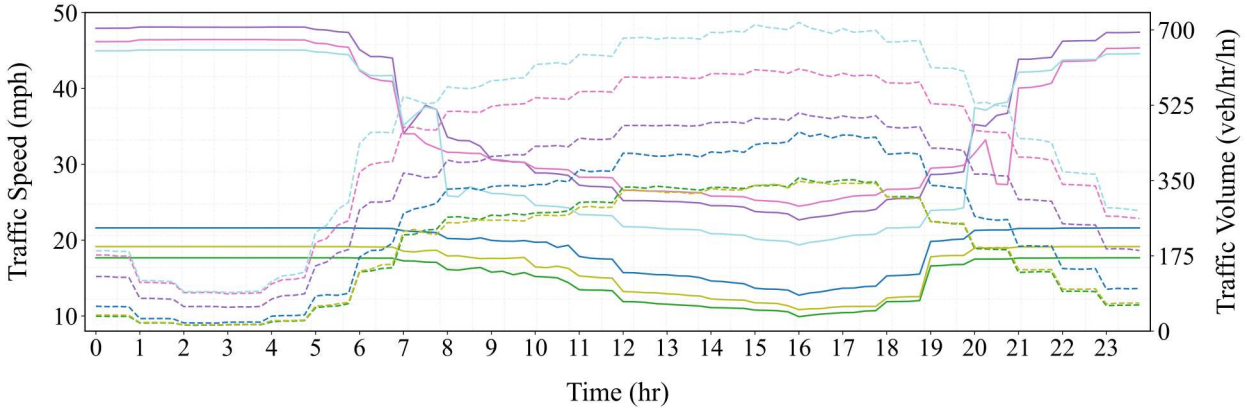


(d) Washington

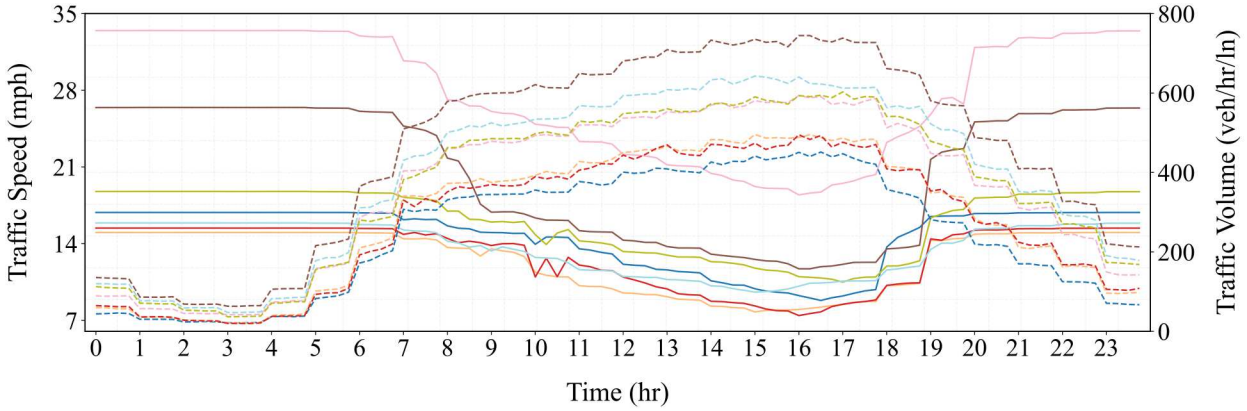
Figure 2. Distribution of Vehicles Based on Their Type, Fuel, and Age in Georgia, California, New York, and Washington. Gasoline passenger cars dominate the vehicle fleet in all four states, accounting for 77.64% in Georgia, 80.05% in California, 51.15% in New York, and 69.57% in Washington. New York has the most diverse fleet composition, with comparatively large shares of gasoline passenger trucks (21.89%) and motorcycles (14.35%), whereas Georgia has a relatively high share of E-85 passenger cars (5.15%). Electric passenger cars still represent a small proportion of registered vehicles, ranging from 0.64% in Georgia to 2.72% in California. The age distributions in Georgia, California, and Washington generally peak among vehicles approximately 5-10 years old, whereas New York has a notably larger share of newer vehicles and a more gradual decline with vehicle age. All four states also contain a noticeable proportion of vehicles aged 30 years or older.

Traffic Dynamics Estimation

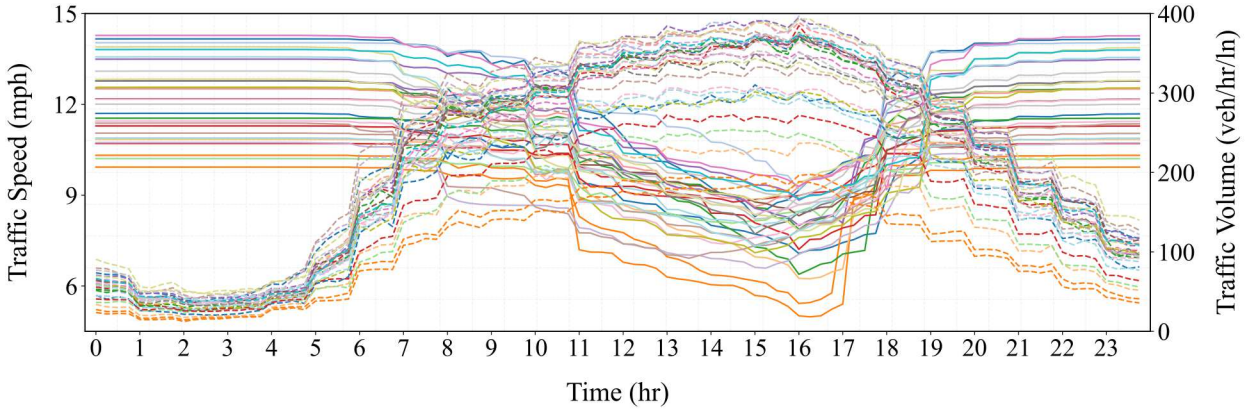
The energy consumption and emissions of vehicles vary with traffic volume and speed over time. To provide an accurate energy and emissions analysis, we capture traffic dynamics in Atlanta, Los Angeles, New York, and Seattle at the regional scale using a macroscopic traffic model, as described in detail in **Supplementary Note 1**. Traffic volumes are estimated over 15-minute time intervals at the regional level, as presented in **Figure 1**, using a machine learning approach and a fusion of vehicle probe and road sensor data. We estimate traffic speed profiles under projected increases in traffic volumes over time using the macroscopic traffic model calibrated for each study region in downtown Atlanta, Los Angeles, New York, and Seattle, as presented in **Figure 1**. **Figure 3a-d** presents the estimated traffic speed and volume profiles for an average workday during September–November 2024 in downtown Atlanta, Los Angeles, New York, and Seattle. As shown, traffic speeds decrease substantially as traffic volumes increase during the day and begin to return toward free-flow conditions as traffic volumes decline in the evening. Speeds remain close to free-flow levels during the night and early morning until traffic volumes begin to increase again.



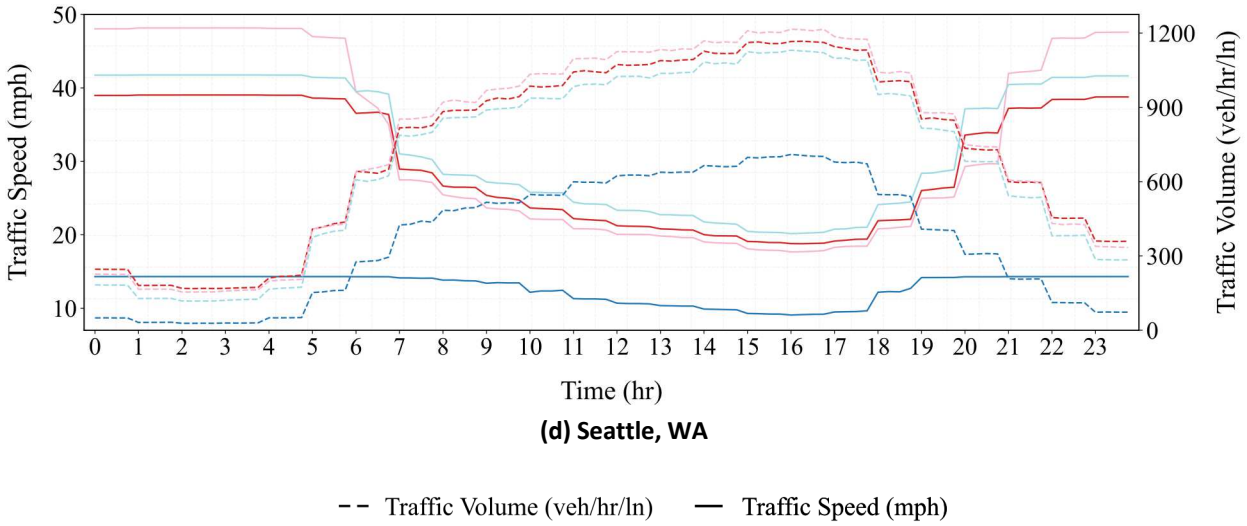
(a) Atlanta, GA



(b) Los Angeles, CA



(c) New York, NY

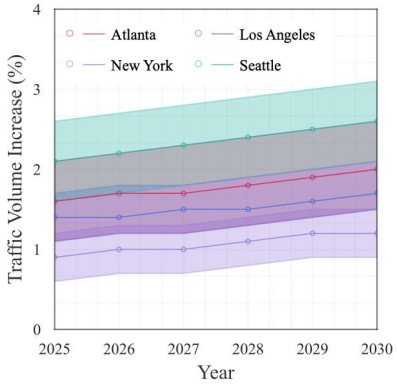


(d) Seattle, WA

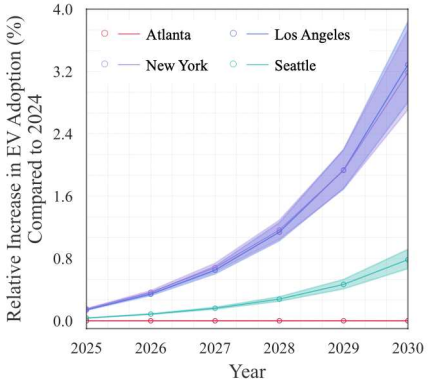
Figure 3. Traffic Speed and Volume Profiles on an Average Weekday During September–November 2024 in Downtown Atlanta, Los Angeles, New York, and Seattle. The solid and dashed lines represent traffic speed and volume, respectively, and are color-coded by subregion according to **Figure 1**. Across all four cities, traffic volumes begin to increase during the morning period, remain elevated throughout much of the day, and decline during the evening. Traffic speeds generally decrease as traffic volumes increase because higher demand leads to greater congestion, and they recover toward free-flow conditions as traffic volumes decline. The profiles also show substantial variation among subregions and cities, with New York exhibiting the lowest daytime speeds, while Atlanta and Seattle show more pronounced differences between nighttime free-flow speeds and congested daytime conditions.

Predictive Analysis of Vehicle Fuel Consumption and Emissions

Fuel consumption and the resulting emissions of different vehicle classes in mixed traffic can be accurately predicted based on regional traffic-speed dynamics under projected increases in traffic volume and EV adoption over time. **Figure 4a** presents the projected increase in total traffic volumes, along with the corresponding lower and upper bounds, in Atlanta, Los Angeles, New York, and Seattle through 2030 [32]. The projected increase in EV adoption through 2030 is also shown in **Figure 4b** [33]. There are various influencing factors are incorporated into these projections, including historical EV registration trends, vehicle fleet turnover, total ownership costs, economic and population growth, and changes in travel demand. These projections also account for anticipated advancements in battery technologies and charging infrastructure, as well as the effects of federal and state policies on future EV market adoption.



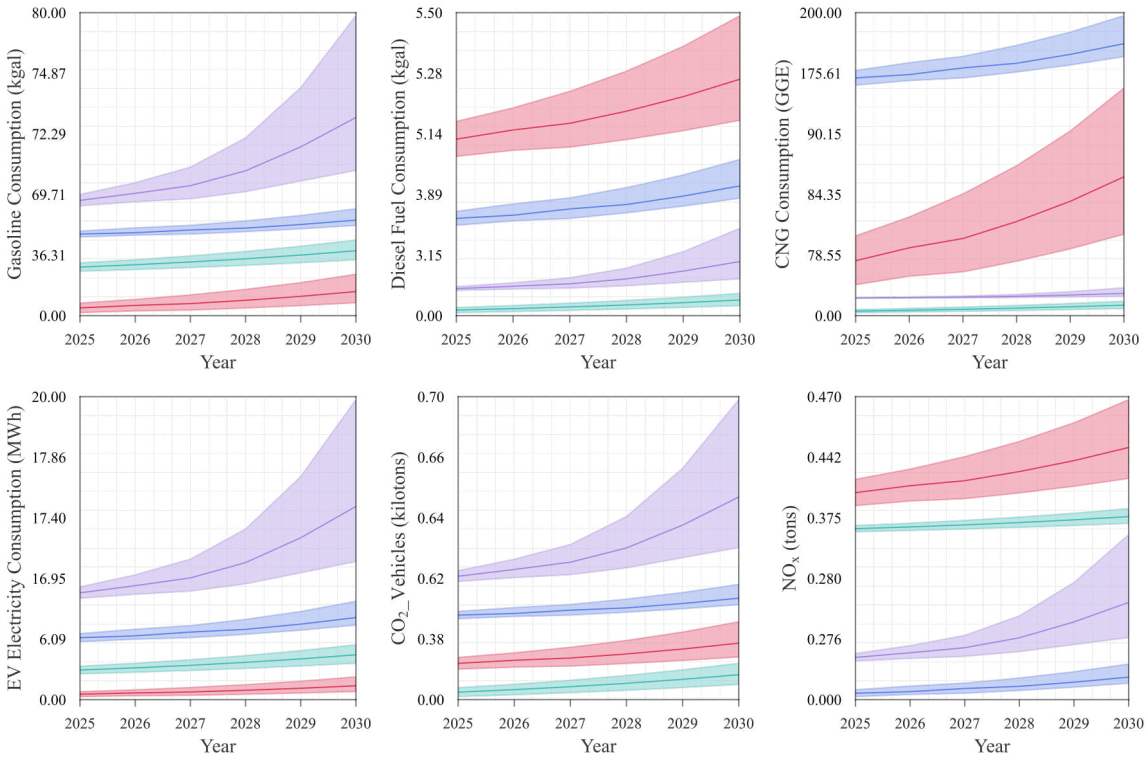
(a) Projected Increase in the Traffic Volumes Compared to 2024



(b) Projected Increase in EV Adoption Compared to 2024

Figure 4. Projected Increases in Traffic Volume and EV Adoption Relative to 2024 in Atlanta, Los Angeles, New York, and Seattle. Traffic volumes are projected to increase gradually through 2030 in all four cities, with Seattle showing the largest increase, followed by Los Angeles, Atlanta, and New York. The shaded areas represent the corresponding lower and upper projection bounds. EV adoption is also projected to increase most rapidly in Los Angeles and New York, with Los Angeles reaching a slightly higher level by 2030, while Seattle shows a more moderate increase and Atlanta remains nearly unchanged relative to 2024. The widening shaded bands represent the lower and upper bounds of the 95% confidence intervals and indicate increasing uncertainty in the longer-term projections.

Figure 5 shows the projected changes in daily gasoline, diesel, and CNG consumption, EV electricity consumption, and vehicle emissions of CO_2, NO_x, and PM2.5 from tires and brakes under increasing EV adoption and traffic volumes in downtown Atlanta, Los Angeles, New York, and Seattle. Fuel and electricity consumption and all emission types generally increase through 2030, although the magnitude of growth varies across cities because of differences in traffic demand, traffic composition, traffic dynamics, and projected EV adoption. New York has the highest gasoline and EV electricity consumption, as well as the highest vehicle CO_2 emissions, which is consistent with its high traffic volumes, dense road network, large share of gasoline-powered vehicles, and lower traffic speeds due to heavier congestion. Atlanta has the highest diesel consumption and NO_x emissions, reflecting the presence of diesel trucks and heavy traffic congestion, which increase combustion-related emissions. Los Angeles has the highest CNG consumption due to the substantial presence of CNG heavy-duty vehicle fleets in California and also the highest PM2.5 emissions from tires because of its relatively large share of passenger trucks and the resulting contribution of heavier vehicles to tire wear. New York has the highest PM2.5 emissions from brakes, consistent with frequent braking and stop-and-go traffic in highly congested urban networks. Seattle generally has moderate fuel consumption and emission levels across the indicators. The widening shaded bands represent the lower and upper bounds of the 95% confidence intervals and indicate increasing uncertainty in the longer-term projections.



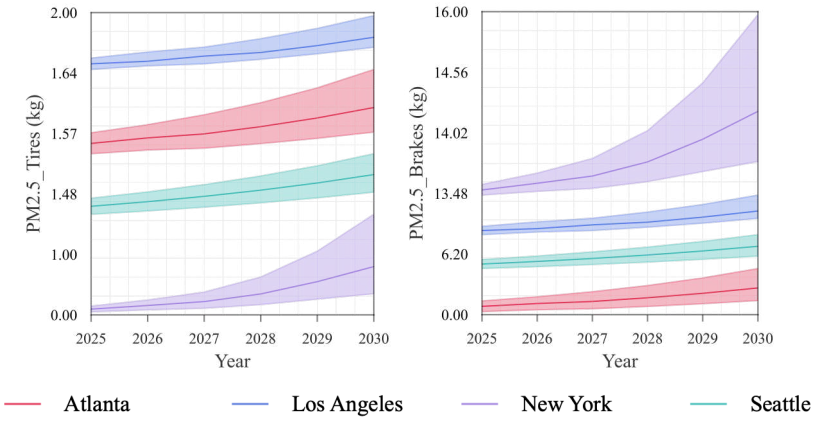


Figure 5. Predictive Analysis of Daily Vehicle Fuel Consumption and Air Pollutant Emissions Under Projected Increases in Travel Demand and EV Adoption in Atlanta, Los Angeles, New York, and Seattle. New York has the highest gasoline consumption and EV electricity demand due to the high traffic volumes within a dense urban network. Atlanta has the highest diesel consumption due to the larger penetration rate of diesel vehicles in traffic, particularly heavy-duty vehicle classes, while Los Angeles has the highest CNG consumption due to the greater presence of CNG heavy-duty vehicles. Vehicle CO_2 and NO_x emissions generally increase over time, with New York and Atlanta exhibiting the highest levels, respectively, due to differences in traffic composition and dynamics. PM2.5 emissions from tires and brakes also increase across all cities, with Los Angeles showing the highest tire emissions due to its larger share of passenger trucks, and New York showing the highest brake emissions due to frequent braking and stop-and-go traffic patterns in dense urban networks. The shaded areas represent the lower and upper bounds of the 95% confidence intervals, indicating increasing uncertainty in the longer-term projections.

Predictive Analysis of Grid Emissions Resulting from EV Charging

While EVs do not produce tailpipe emissions, their electricity demand for battery charging results in indirect upstream emissions from the power grid, which increase with rising EV adoption and total vehicle miles traveled over time. To accurately capture the air pollution impacts associated with accelerating EV adoption and increasing vehicle miles traveled, it is necessary to account for these indirect emissions from EV charging. The emissions resulting from EV charging depend on a broad range of influential factors, including power generation technologies, distribution network efficiency, temporal load distribution, and the energy mix of the grid. Having estimated EV electricity demand for battery charging based on EV penetration in mixed traffic and traffic dynamics, as well as the dynamic estimation of power grid emission rates (i.e., the additional air pollutant emissions from power plants associated with a 1 MWh increase in electricity consumption from the grid), we provide a predictive analysis of grid emissions resulting from EV charging by accounting for energy mix, technology costs, fuel prices, demand growth, and electricity sector policies. **Figure 6** presents the predicted daily emissions of CO_2, CH_4, and N_2O resulting from EV charging in Atlanta, Los Angeles, New York, and Seattle under the mid-case energy-sector scenario defined by the National Renewable Energy Laboratory (NREL). This scenario assumes moderate renewable energy and battery technology costs, natural gas price projections [34], and an average annual electricity demand growth of 1.8% from 2024 to 2050, reaching 6,509 TWh/year by 2050 (see [35] for further analysis details).

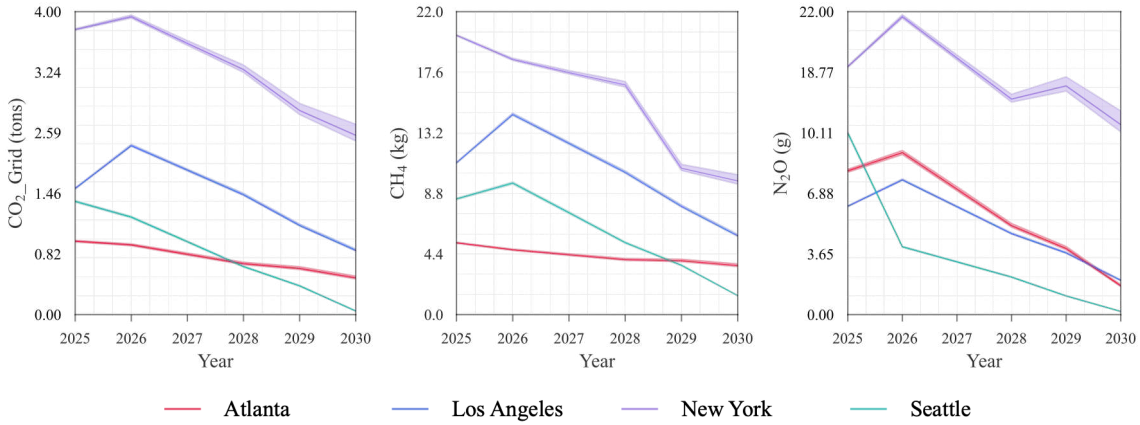
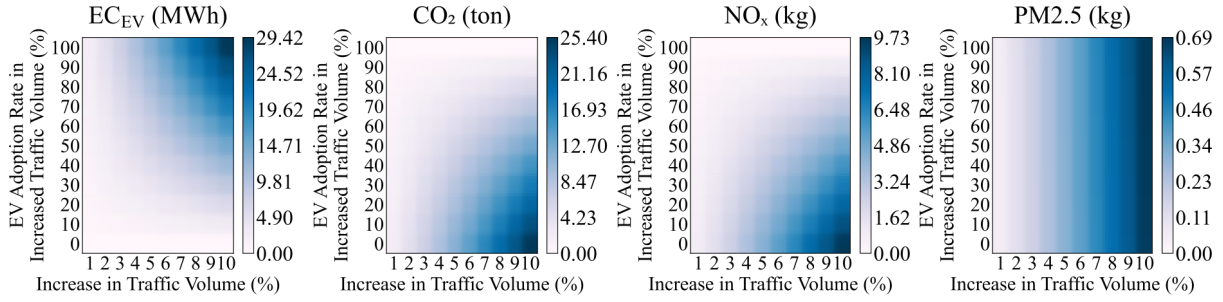


Figure 6. Predictive Analysis of Daily Grid Emissions Resulting from EV Charging in Atlanta, Los Angeles, New York, and Seattle Under the Mid-case Energy-sector Scenario. Daily CO_2, CH_4, and N_2O emissions generally decline between 2025 and 2030, despite the projected increase in EV electricity demand, reflecting reductions in grid emission intensity as renewable and low-carbon generation expands. New York exhibits the highest total grid emissions throughout the study period because of its comparatively high EV electricity demand, although all three pollutants decline substantially as the state transitions toward offshore wind, nuclear power, and other low-carbon energy sources. California shows temporary increases around 2026, followed by pronounced declines associated with the increasing contribution of solar and wind generation. Washington has the fastest reduction, with emissions approaching zero by 2030 because of its substantial hydropower capacity and declining reliance on fossil-fuel generation. Georgia shows lower total CO_2 and CH_4 emissions than New York and California because of its lower EV charging demand, but its emissions decline more gradually due to the continued contribution of natural gas and coal to electricity generation. The short-term increases observed around 2026 in several series indicate that growth in EV charging demand temporarily exceeds the reduction in grid emission rates before cleaner generation produces sustained emissions reductions.

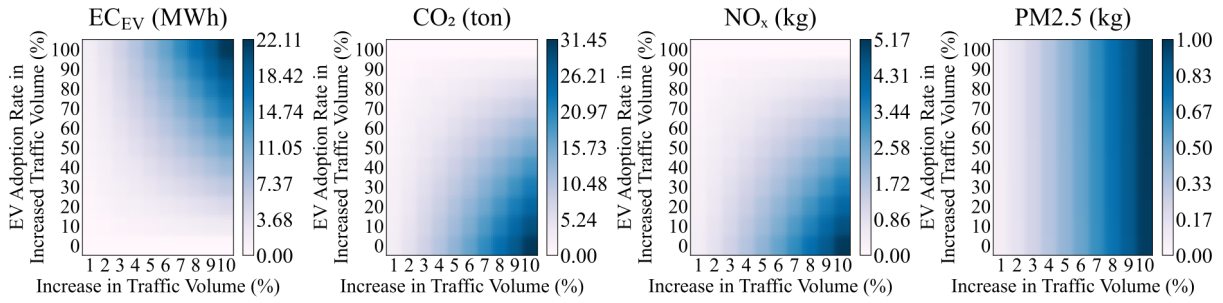
Discussion

Predictive energy and emissions analyses presented in the **Results** section directly depend on projections of increases in traffic volumes and changes in traffic composition, particularly the rising penetration rate of EVs. Nevertheless, projections of traffic volumes and composition, as well as the EV penetration rate in mixed traffic, depend on a broad variety of exogenous socioeconomic and geopolitical factors that are subject to substantial unpredictability. Therefore, projection uncertainty is inevitable. To address the associated uncertainties, in this section, we present the results of a comprehensive energy and emissions analysis for a broad range of increases in traffic volumes and EV penetration rates in mixed traffic. **Figure 7a** plots the estimated increases in daily vehicle emissions of CO_2, NO_x, and PM2.5, as well as EV electricity demand for battery charging, for traffic-volume increases ranging from 0% to 10% relative to 2024 with the EV penetration rate in the additional traffic varying from 0% to 100% at each traffic-volume level in Atlanta, Los Angeles, New York, and Seattle. The impact of increased traffic on emissions and EV electricity consumption is adverse because traffic speeds decline as congestion increases. However, increasing the EV penetration rate in the additional traffic mitigates vehicle emissions, while the resulting increase in EV electricity consumption for battery charging also increases emissions from the power grid. **Figure 7b** presents the corresponding daily increases in CO_2, N_2O, and CH_4 emissions from the power grid resulting from increased EV electricity demand for battery charging under rising traffic volumes and EV penetration rates in the additional traffic under the mid-case energy-sector scenario in Atlanta, Los Angeles, New York,

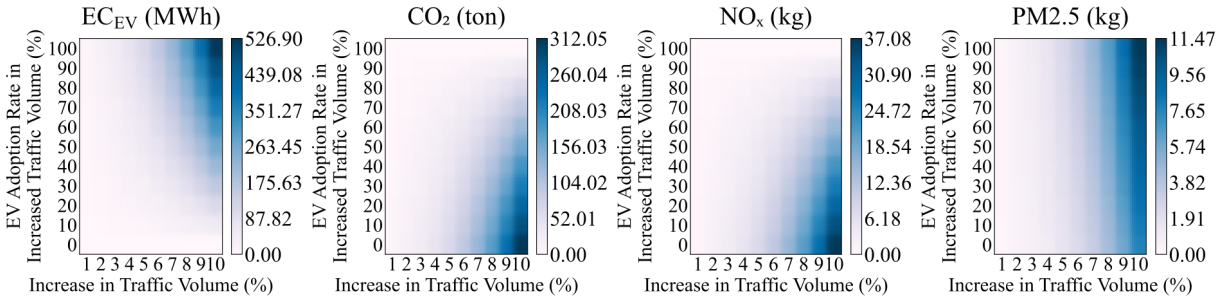
and Seattle. Although the opposing impacts of increasing traffic and rising EV penetration rates in mixed traffic on CO_2 and NO_x emissions are not unexpected, these results demonstrate how much the EV penetration rate must increase to entirely prevent or partially mitigate increases in CO_2 and NO_x emissions associated with rising traffic over time in these cities. However, increases in traffic and EV penetration rates have a negative synergistic impact on total PM2.5 emissions from tires and brakes due to the relatively greater weight of electric vehicles, even though regenerative braking systems reduce PM2.5 emissions from brakes. In addition to regenerative braking, conventional brake pads still engage in EVs when necessary, meaning that brake-related PM2.5 emissions from EVs are not entirely zero. Although the negative impact of increasing EV penetration rates on PM2.5 emissions may be marginal compared with the impact of increasing traffic volumes, it can become more significant under frequent stop-and-go patterns in dense and congested road networks, as observed in New York. As EV electricity demand increases with traffic and EV penetration rates in mixed traffic, the resulting CO_2, N_2O, and CH_4 emissions from the power grid also increase substantially under the mid-case energy-sector scenario, which assumes no fundamental changes in energy-sector policies compared with 2024 [35]. These results indicate the importance of clean energy generation for the effectiveness of transportation electrification in reducing air pollution.



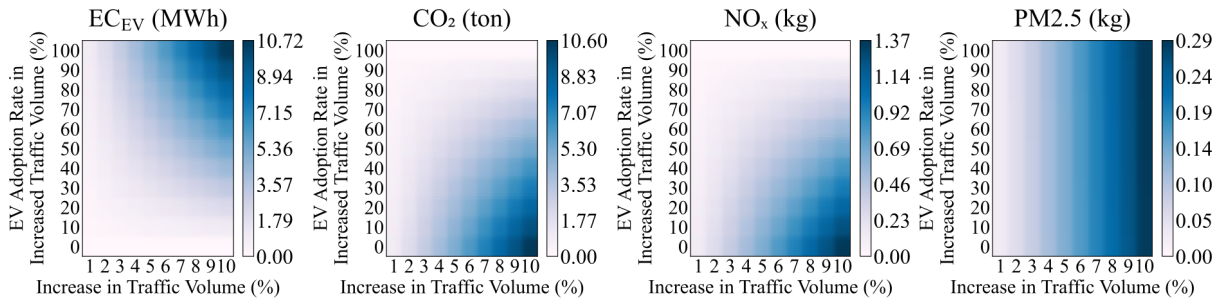
Atlanta



Los Angeles

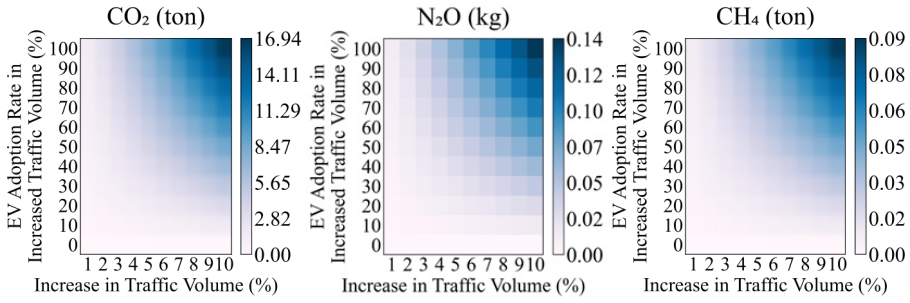


New York

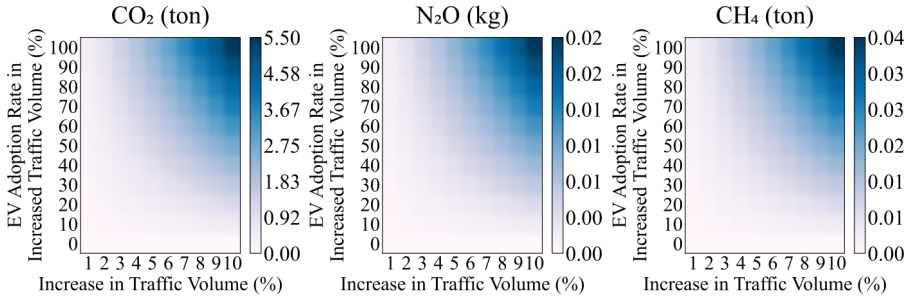


Seattle

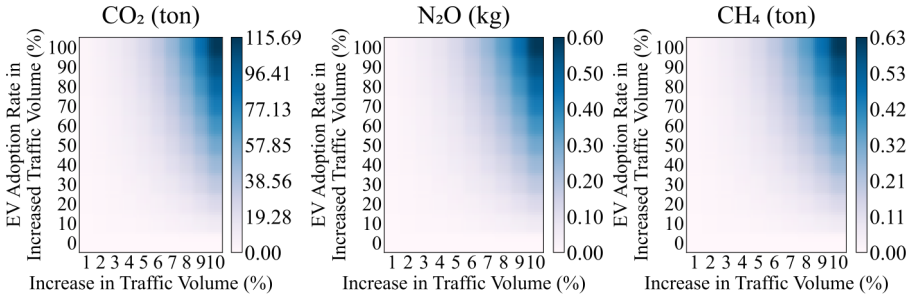
(a) Daily Increases in Vehicle Emissions Of CO_2, NO_x, And PM2.5 from Tires and Brakes, as Well as EV Electricity Demand for Battery Charging



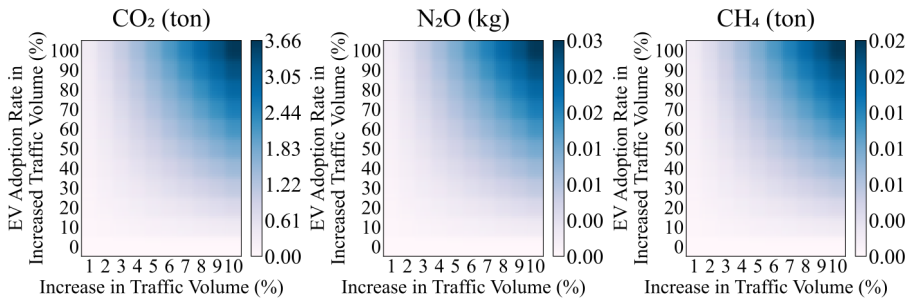
Atlanta



Los Angeles



New York



(B) Daily Increases in Grid Emissions of CO_2, N_2O, And CH_4 Resulting from Increased EV Electricity Demand for Battery Charging

Figure 7. Daily Increases in Vehicle Emissions, EV Electricity Demand for Battery Charging, and Associated Grid Emissions Under Traffic-Volume Increases Ranging from 0% To 10% Relative to 2024, with EV Penetration in the Additional Traffic Varying from 0% to 100% in Atlanta, Los Angeles, New York, and Seattle. At a fixed EV penetration rate, increasing traffic raises vehicle emissions and EV electricity demand. At a fixed traffic-volume increase, a higher EV penetration rate increases electricity demand but mitigates vehicle CO_2 and NO_x emissions by replacing ICE vehicles in the additional traffic. In contrast, PM2.5 emissions are driven primarily by the increase in traffic and show substantially less sensitivity to the EV penetration rate, indicating that electrification provides limited reductions in non-exhaust emissions. New York has the largest absolute increases in EV electricity demand and vehicle emissions, consistent with its high traffic and congestion, while Seattle generally shows the smallest increases. The grid emissions shown in panel (b) increase with both traffic volume and EV penetration because both factors increase electricity demand for battery charging. New York has the highest absolute grid emissions because of its substantially greater charging demand, whereas Atlanta also exhibits relatively high grid emissions despite its lower electricity demand, reflecting the higher emission intensity of its fossil-fuel dependent electricity mix. Los Angeles and Seattle show comparatively lower grid emissions because of their cleaner regional energy mixes.

Method

Comprehensive energy and emissions analysis in urban road networks requires an integrated modeling approach that incorporates traffic dynamics and composition to dynamically estimate fuel consumption and emissions, as well as EV electricity demand for battery charging and the resulting emissions from the power grid. To address the need for an integrated modeling approach, we develop a modular framework of data-driven models in which the output of each model serves as the input to the next model in the integrated pipeline, as illustrated in **Figure 8**. In this modeling framework, traffic speed profiles are estimated from projected traffic volume profiles at the subregional level using a macroscopic traffic model trained on historical traffic data from the subregions (see **Note 1** in the **Supplementary Information** for details). Traffic composition, i.e., the percentage of each vehicle class by type, fuel, and age in mixed traffic, is also estimated from vehicle registration data, as explained in the **Results** section. Using the projected traffic volume profiles, the estimated corresponding traffic speed profiles, and the estimated composition of mixed traffic, the fuel consumption and resulting emissions of each vehicle class, as well as the electricity demand of EVs for battery charging, are estimated using a deep learning model trained on vehicle simulation results from EPA MOVES (see **Note 2** in the **Supplementary Information** for details). The resulting emissions from the electricity consumption of EVs for battery charging are also estimated using a machine learning model trained on energy-sector simulation results from NREL Cambium (see

Note 3 in the **Supplementary Information** for details). The estimated power-grid emissions from EV electricity consumption, together with the estimated emissions from vehicles, provide a comprehensive picture of road network emissions by accounting for the expected increase in travel demand and EV adoption, as well as changes in energy-sector policies and technologies over time. Details of each modeling module are provided in the **Supplementary Information**.

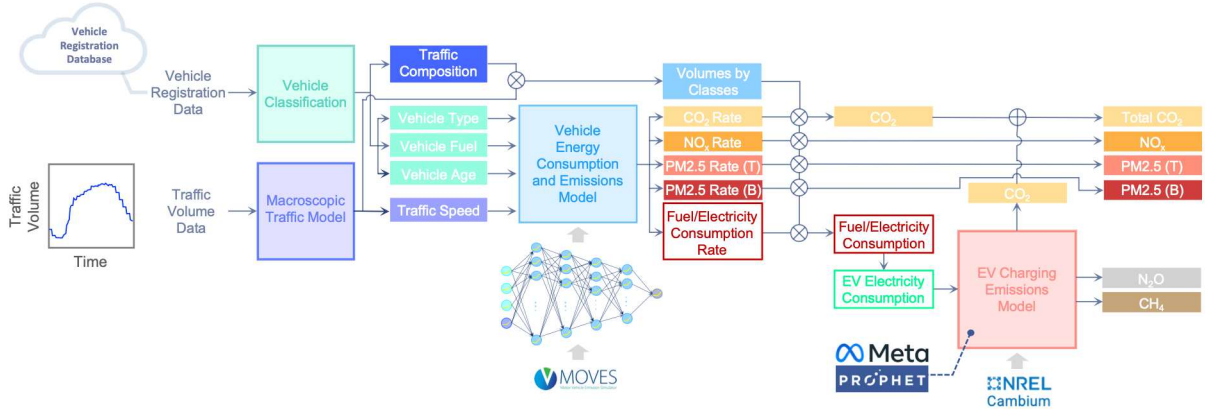


Figure 8. Modular Framework of the Integrated Modeling Approach for Predictive Analysis of Energy Consumption and Emissions in Urban Road Networks. Projected traffic-volume profiles are used to estimate traffic-speed profiles at the subregional level using a macroscopic traffic model, while vehicle registration data are used to estimate traffic composition by vehicle type, fuel, and age. These inputs are then imported into a deep learning model trained on EPA MOVES simulation data to estimate vehicle fuel and electricity consumption, CO_2 and NO_x emissions, and PM2.5 emissions from tires and brakes. EV electricity consumption is subsequently fed into a machine learning model trained on NREL Cambium simulation data to estimate CO_2, N_2O, and CH_4 emissions resulting from EV charging from the power grid.

Funding Declaration

The authors received no funding for this research.

References

1. Barth, M., An, F., Younglove, T., Scora, G., Levine, C., Ross, M. & Wenzel, T., 2000. The development of a comprehensive modal emissions model. National Center for Vehicle Emissions Control and Safety.
2. Scora, G. & Barth, M., 2006. Comprehensive Modal Emission Model (CMEM), version 3.01. User's Guide.
3. Ahmed, O., Ramadan, I. and Shawky, M., 2022. Modelling vehicle emissions and fuel consumption based on instantaneous speed and acceleration levels. Engineering Research Journal (Shoubra), 51(4), pp.106-116.
4. Panis, L.I., Broekx, S. and Liu, R., 2006. Modelling instantaneous traffic emission and the influence of traffic speed limits. *Science of the total environment*, *371*(1-3), pp.270-285.
5. Park, J., Seo, J. and Park, S., 2023. Development of vehicle emission rates based on vehicle-specific power and velocity. Science of The Total Environment, 857, p.159622.
6. Pathak, S.K., Sood, V., Singh, Y. and Channiwala, S.A., 2016. Real world vehicle emissions: Their correlation with driving parameters. Transportation Research Part D: Transport and Environment, 44, pp.157-176.
7. Rakha, H., Ahn, K. and Trani, A., 2004. Development of VT-Micro model for estimating hot stabilized light duty vehicle and truck emissions. *Transportation Research Part D: Transport and Environment*, *9*(1), pp.49-74.
8. Noland, R.B. and Quddus, M.A., 2006. Flow improvements and vehicle emissions: effects of trip generation and emission control technology. *Transportation Research Part D: Transport and Environment*, *11*(1), pp.1-14.
9. Abou-Senna, H., Radwan, E., Westerlund, K. and Cooper, C.D., 2013. Using a traffic simulation model (VISSIM) with an emissions model (MOVES) to predict emissions from vehicles on a limited-access highway. *Journal of the Air & Waste Management Association*, *63*(7), pp.819-831.
10. Dib, A., Balac, M. and Sciarretta, A., 2025. Deep learning approach to predict microscopic pollutant emissions from mesoscopic traffic simulations. *Transportation Research Part D: Transport and Environment*, *146*, p.104791.
11. Agarwal, A.K. and Mustafi, N.N., 2021. Real-world automotive emissions: Monitoring methodologies, and control measures. Renewable and Sustainable Energy Reviews, 137, p.110624.
12. Chen, X., Jiang, L., Xia, Y., Wang, L., Ye, J., Hou, T., Zhang, Y., Li, M., Li, Z., Song, Z. and Li, J., 2022. Quantifying on-road vehicle emissions during traffic congestion using updated emission factors of light-duty gasoline vehicles and real-world traffic monitoring big data. *Science of The Total Environment*, *847*, p.157581.
13. Tsanakas, N., Ekström, J. and Olstam, J., 2022. Generating virtual vehicle trajectories for the estimation of emissions and fuel consumption. *Transportation Research Part C: Emerging Technologies*, *138*, p.103615.
14. Smit, R., Brown, A.L. and Chan, Y.C., 2008. Do air pollution emissions and fuel consumption models for roadways include the effects of congestion in the roadway traffic flow?. *Environmental Modelling & Software*, *23*(10-11), pp.1262-1270.
15. Franco, V., Kousoulidou, M., Muntean, M., Ntziachristos, L., Hausberger, S. and Dilara, P., 2013. Road vehicle emission factors development: A review. Atmospheric Environment, 70, pp.84-97.
16. California Air Resources Board (CARB), 2021. Emission Factors Model (EMFAC) User's Guide. https://ww2.arb.ca.gov/msei-modeling-tools.

17. California Air Resources Board, 2026. *EMFAC2025 Technical Documentation*, Sacramento, CA: California Air Resources Board.
18. U.S. Environmental Protection Agency, 2023. Overview of EPA's MOtor Vehicle Emission Simulator (MOVES4), Report No. EPA-420-R-23-019.
19. U.S. Environmental Protection Agency, 2024. MOVES5 Technical Guidance: Using MOVES to Prepare Emission Inventories for State Implementation Plans and Transportation Conformity, Report No. EPA-420-B-24-043.
20. Faria, R., Marques, P., Moura, P., Freire, F., Delgado, J. and De Almeida, A.T., 2013. Impact of the electricity mix and use profile in the life-cycle assessment of electric vehicles. *Renewable and Sustainable Energy Reviews*, 24, pp.271-287.
21. Hawkins, T.R., Singh, B., Majeau-Bettez, G. and Strømman, A.H., 2013. Comparative environmental life cycle assessment of conventional and electric vehicles. *Journal of Industrial Ecology*, 17(1), pp.53-64.
22. Woo, J., Choi, H. and Ahn, J., 2017. Well-to-wheel analysis of greenhouse gas emissions for electric vehicles based on electricity generation mix: A global perspective. *Transportation Research Part D: Transport and Environment*, 51, pp.340-350.
23. Bastida-Molina, P., Hurtado-Pérez, E., Peñalvo-López, E. and Moros-Gómez, M.C., 2020. Assessing transport emissions reduction while increasing electric vehicles and renewable generation levels. *Transportation Research Part D: Transport and Environment*, 88, p.102560.
24. Holdway, A.R., Williams, A.R., Inderwildi, O.R. and King, D.A., 2010. Indirect emissions from electric vehicles: emissions from electricity generation. *Energy & Environmental Science*, 3(12), pp.1825-1832.
25. Hu, X., Zou, Y. and Yang, Y., 2016. Greener plug-in hybrid electric vehicles incorporating renewable energy and rapid system optimization. *Energy*, 111, pp.971-980.
26. Fernández, R.Á., 2018. A more realistic approach to electric vehicle contribution to greenhouse gas emissions in the city. *Journal of Cleaner Production*, 172, pp.949-959.
27. Jochem, P., Babrowski, S. and Fichtner, W., 2015. Assessing CO2 emissions of electric vehicles in Germany in 2030. *Transportation Research Part A: Policy and Practice*, 78, pp.68-83.
28. Rangaraju, S., De Vroey, L., Messagie, M., Mertens, J. and Van Mierlo, J., 2015. Impacts of electricity mix, charging profile, and driving behavior on the emissions performance of battery electric vehicles: A Belgian case study. *Applied Energy*, 148, pp.496-505.
29. Casals, L.C., Martinez-Laserna, E., García, B.A. and Nieto, N., 2016. Sustainability analysis of the electric vehicle use in Europe for CO2 emissions reduction. Journal of Cleaner Production, 127, pp.425-437.
30. Filote, C., Felseghi, R.A., Raboaca, M.S. and Aşchilean, I., 2020. Environmental impact assessment of green energy systems for power supply of electric vehicle charging station. *International Journal of Energy Research*, 44(13), pp.10471-10494.
31. Onn, C.C., Mohd, N.S., Yuen, C.W., Loo, S.C., Koting, S., Abd Rashid, A.F., Karim, M.R. and Yusoff, S., 2018. Greenhouse gas emissions associated with electric vehicle charging: The impact of electricity generation mix in a developing country. *Transportation Research Part D: Transport and Environment*, 64, pp.15-22.
32. U.S. Department of Energy, 2024. Alternative fuels data center. Energy Efficiency and Renewable Energy. https://afdc.energy.gov/data
33. National Association of City Transportation Officials (NACTO), 2024. Urban Street Design Guide. https://nacto.org/
34. U.S. Energy Information Administration, 2023. Annual Energy Outlook 2023 (AEO2023): Reference Case. Washington, DC: U.S. DOE. Available at: https://www.eia.gov/outlooks/aeo/.

35. Amirgholy, M., Chowdhoury, F.A., Wang, C. and Kanigiri, S.N., 2026. Predictive analysis of greenhouse gas emissions from electric vehicle charging in the United States. *Scientific Reports*, *16*(1), pp.12853-12853.
36. Daganzo, C.F., 2007. Urban gridlock: Macroscopic modeling and mitigation approaches. *Transportation Research Part B: Methodological,* 41(1), pp.49-62.
37. Geroliminis, N. and Daganzo, C.F., 2008. Existence of urban-scale macroscopic fundamental diagrams: Some experimental findings. *Transportation Research Part B: Methodological*, 42(9), pp.759-770.
38. Ampountolas, K. and Kouvelas, A., 2015, July. Real-time estimation of critical vehicle accumulation for maximum network throughput. In 2015 American Control Conference (ACC) (pp. 2057-2062). IEEE.
39. Knoop, V.L., Van Lint, H. and Hoogendoorn, S.P., 2015. Traffic dynamics: Its impact on the macroscopic fundamental diagram. *Physica A: Statistical Mechanics and its Applications*, 438, pp.236-250.
40. Amirgholy, M. and Gao, H.O., 2017. Modeling the dynamics of congestion in large urban networks using the macroscopic fundamental diagram: User equilibrium, system optimum, and pricing strategies. *Transportation Research Part B: Methodological,* 104, pp.215-237.
41. Saberi, M. and Mahmassani, H.S., 2013. Hysteresis and capacity drop phenomena in freeway networks: Empirical characterization and interpretation. *Transportation research record,* 2391(1), pp.44-55.
42. Ampountolas, K. and Kouvelas, A., 2015. Real-time estimation of critical values of the macroscopic fundamental diagram for maximum network throughput. In TRB 94th Annual Meeting Compendium of Papers (pp. 15-1779). *Transportation Research Board.*
43. Castrillon, F., & Laval, J., 2018. Impact of buses on the macroscopic fundamental diagram of homogeneous arterial corridors. Transportation Research Part B: Methodological, 6, pp. 286–301.
44. Ambühl, L., Loder, A., Menedez, M., & Axhausen, K. W., 2019. Understanding traffic capacity of urban networks. Scientific Reports, 9, 16283.
45. Mousavizadeh, O. and Keyvan-Ekbatani, M., 2024. On the important features for a well-shaped reduced network MFD estimation during network loading and recovery. *Transportation Research Part C: Emerging Technologies*, 161, p.104539.
46. 59. Ma, W., Huang, Y., Jin, X. and Zhong, R., 2024. Functional form selection and calibration of macroscopic fundamental diagrams. *Physica A: Statistical Mechanics and its Applications*, 640, p.129691
47. Jin, L., Xu, X., Sadabadi, K. F., Lazar, A., Don, D.P., Wang, Y., Needell, Z., Spurlock, C. A., Amirgholy, M., Asudegi, M. (2024). Macroscopic traffic modeling using probe vehicle data: a machine learning approach. Data Science for Transportation.
48. Ambühl, L., Loder, A., Bliemer, M.C., Menendez, M. and Axhausen, K.W., 2020. A functional form with a physical meaning for the macroscopic fundamental diagram. *Transportation Research Part B: Methodological,* 137, pp.119-132.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SupplementaryInformation.pdf