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Greenhouse gas emissions embodied in electric vehicle charging infrastructure: a method and case study of Georgia, US 2021–2050

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Abstract

Electric vehicle (EV) charging infrastructure buildout is a major greenhouse gas (GHG) mitigation strategy among governments and municipalities. In the United States, where petroleum-based transportation is the largest single source of GHG emissions, the Infrastructure Investment and Jobs Act of 2021 will support building a national network of 500 000 EV charging units. While the climate benefits of driving electric are well established, the potential embodied climate impacts of building out the charging infrastructure are relatively unexplored. Furthermore, 'charging infrastructure' tends to be conceptualized in terms of plugs and stations, leaving out the electrical and communications systems that will be required to support decarbonized and efficient charging. In this study, we present an EV charging system (EVCS) model that describes the material and operational components required for charging and forecasts the scale-up of these components based on EV market share scenarios out to 2050. We develop a methodology for measuring GHG emissions embodied in the buildout of EVCS and incurred during operation of the EVCS, including vehicle recharging, and we demonstrate this model using a case study of Georgia (USA). We find that cumulative GHG emissions from EVCS buildout and use are negligible, at less than 1% of cumulative emissions from personal light duty vehicle travel (including EV recharging and conventional combustion vehicle driving). If an accelerated EVCS buildout were to stimulate a faster transition of the vehicle fleet, the emissions reduction of electrification will far outweigh emissions embodied in EVCS components, even assuming relatively high carbon inputs prior to decarbonization.

Abbreviations and definitions

BEV	Battery electric vehicles. EVs that operate solely in full-electric mode.
DC plug	Direct current charging port. Fast charging rates range between 50 and 350 kW.
EV	Electric vehicle. Combination of BEVs and PHEVs.
GHG	Greenhouse gas
GWP	Global warming potential
ICEV	Internal combustion engine vehicle. Conventional vehicles that run primarily on combustion engines, including hybrid electric vehicles.
IPCC	Intergovernmental Panel on Climate Change
L1 plug	Level 1 EV charging plug. Charges at rates between 1 and 2 kW.
L2 plug	Level 2 EV charging plug. Charges at rates between 3 and 20 kW.
LDV	Light duty vehicle. Vehicles with gross vehicle weight <10 000 lbs, representing the full range of typical passenger vehicles including sedans, SUVs, and pickup trucks.

PHEV	Plug-in hybrid electric vehicle. An EV capable of operating in full-electric mode or on a combustion engine. The EV battery can be recharged via plug-in to an electric connection.
Plug	A single electrical connection for recharging one EV at a time.
Station	A single location where one or more vehicles may recharge.
VKT	Vehicle-kilometers traveled
VMT	Vehicle-miles traveled

1. Introduction

Electrification of the transportation sector is well underway in the United States (US) which, as of 2021, is the third largest market for EVs worldwide [1]. In 2015 there were an estimated 0.2 million fully electric vehicles (BEVs) and 0.2 million plug-in hybrids (PHEVs) on US roads; by 2020, this number had risen to 1.1 million and 0.6 million respectively [1]. The US EV market share has accelerated as well, from 2% of LDV sales in 2020 to 4% in 2021 and just over 6% in the first half of 2022.

Electrification is attractive for several reasons. The US transportation sector is almost entirely dependent on a single energy resource—petroleum—for fuel, and electrification enables transportation to be powered by low-carbon energy sources such as solar and wind, opening a path to zero tailpipe emissions and far lower life-cycle GHG emissions [2, 3]. Further, EVs come with both public and private performance benefits, including reduced on-road emissions of pollutants harmful to health and decreased vehicle operating and maintenance costs, helping to offset the higher average purchase price [4–7].

EVs are now a key pillar of national and global-scale action on climate change. At the 2021 Conference of the Parties to the UN Framework Convention on Climate Change (COP26), 39 countries and 12 automotive manufacturers signed on to a declaration calling for 'all sales of new cars and vans being zero emission globally by 2040' [8]. Ministers of Climate, Energy and the Environment from the G7 Countries (Canada, France, Germany, Italy, Japan, United Kingdom, and United States) acknowledged the need for 'a massive uptake of electrification technology' in the transportation sector [9]. The Infrastructure Investment and Jobs Act, passed by the US Congress in November of 2021, will support projects aimed at building a national network of 500 000 EV charging units [10]. In August 2022, Congress also passed the Inflation Reduction Act which included an extension of the Alternative Fuel Vehicle Refueling Property Credit, aimed at incentivizing homeowners and businesses to install charging equipment [11].

In scaling up electrification, there has been concern about shifting impacts from the vehicle use phase to the production phase, given the different range of materials and processes required to manufacture an EV versus a conventional combustion vehicle (ICEV) [12, 13]. On a vehicle basis, this issue has been widely investigated and reported [14–16]. Argonne National Laboratory regularly updates its measurement and forecasting of GHG emissions (GHGs) for different vehicle types and life cycle stages. It has shown, for example, that embodied GHGs for BEV manufacture and end-of-life management are almost twice those of a gasoline ICEV, with the majority of GHGs coming from battery production and disposal [15]. Of these, the majority are associated with fossil-derived energy inputs that are expected to eventually transition but will likely dominate during early build-out of infrastructure to enable decarbonization, emphasizing the point that vehicle electrification relies on decarbonization of both electricity and broader energy sectors to maximize effectiveness as a climate strategy. Once production/disposal emissions are rolled up with use-phase, the emissions intensity of EVs (gCO_2-equivalent per mile) is much lower than ICEVs [17].

EV charging infrastructure—the equipment and facilities that deliver electricity to vehicles and coordinate charging activities—must expand to meet increasing EV use, but its configuration and character could take many forms. This expansion suggests a potential concern about embodied emissions in EV charging infrastructure mirroring the burden shifting concern about the EVs themselves, but this issue is not widely explored. Embodied emissions of renewable energy infrastructure has received substantial attention as part of the overall effort to direct the scale and speed of energy system decarbonization [18, 19], and embodied emissions of digital infrastructure have come under similar scrutiny [20–22]. In particular, this issue arises because zero-carbon infrastructure will be built with carbon-based inputs until the zero-carbon system is large enough to sustain demand. Thus, it is likely that these concerns will arise for EV infrastructure, especially given its accelerated expansion, set to take place under US government funding programs.

Existing work on the design and expansion of charging infrastructure focuses on optimization of charging locations to meet travel demands [23, 24] and to mitigate effects on the electric grid [25, 26]. Levinson and West [27] argue that convenient charging infrastructure will not simply mimic the gas station model to which conventional car drivers are accustomed, and White *et al* [28] emphasize that increasing the quantity or density of available charging points is not enough to prompt fuel switching. They show that factors such as social norms and visibility of charging locations also play key roles. As such, the form and potential embodied emissions profile of EV charging infrastructure is subject to substantial uncertainty.

While charging infrastructure design and expansion are receiving increased attention, the environmental impact of infrastructure buildout and operation is relatively unaddressed. Just as EVs have embodied impacts, so will their supporting infrastructure. From a GHG perspective, the electric grid must decarbonize to support low-GHG driving, but the large-scale benefits of decarbonization will not be felt until EV use has expanded. Since expansion of EV use is predicated on charging infrastructure availability, the infrastructure is likely to be installed under a more carbon-intensive energy and industrial system than the one that EVs will be using after decarbonization. Research has yet to explore the scale and implications of this chicken-and-egg problem that EVs face. Our research is motivated to address this gap in the literature. We contribute a significant step in better tracking these impacts by (A) describing the material components of the EV charging system (EVCS), (B) operationalizing a model for estimating GHGs incurred during buildout and use of the EVCS, (C) providing a tool for conducting multi-scale forecasts of EVCS buildout and use, allowing a high level of customization in technological and demand scenarios, and (D) demonstrating the use of that tool with a case study of the US state of Georgia that contextualizes embodied EVCS emissions within a forecast of the state's entire LDV system from 2021 to 2050. Georgia is a useful case study for evaluating the potential relative environmental impacts of EVCS buildout for several reasons, including the dominance of a single utility in the state (Georgia Power); the relatively large population (∼10.7 million people) distributed across a range of densities from very rural to very urban; and the combination of essentially no explicit decarbonization policy with increasing investments in electric vehicle infrastructure and manufacturing [29–31]. Further, high quality state population data and the authors' access to local practitioners allowed for validation of the forecasts. The tool that accompanies this work can be reconfigured for other geographies, with guidance notes in the model file.

Through this study, we aim to clarify the relative climate impact of EVCS buildout under various technological and socioeconomic pathways, and to establish methods for measuring and tracking the EVCS as it continues to expand.

2. Methods

2.1. EVCS GHG measurement framework

We measure embodied GHG emissions using a life cycle analysis framework (figure 1). The *Production* phase constitutes the buildout of the physical infrastructure required for supporting EV fleet scale-up. We focus on three major components of this infrastructure: plugs, charging stations, and electric grid upgrades. Emissions during this phase are *embodied*, i.e. resulting from the production of materials contained in the various components as well as operation of construction and installation equipment. EVCS *Use* phase emissions arise from the electricity required to manage charging transactions. We model these impacts by estimating the transfer and storage of data that occurs between charging plugs, drivers, and station operators, and for demand-response aspects of grid improvement. We model *Maintenance* and *End-of-Life* phase impacts by modeling equipment replacement over time, based on variable equipment lifespans; noting that information on EV charging infrastructure maintenance and disposal are scarce. Although we develop a maintenance phase option for the EVCS model, there is potentially a problem with including EVCS maintenance as an *additional* impact of scaling up charging infrastructure, since the counterfactual—hydrocarbon fueling infrastructure maintenance—could theoretically be offset as EV use replaces ICEV use. In our discussion, we explore the relative impact of including a maintenance phase within the EVCS system boundary.

EVCS components are aligned with life cycle stages in figure 1. Production phase emissions are referred to as *EVCS Buildout* emissions, and Use phase emissions as *EVCS Use* emissions. We also estimate *LDV Use* emissions, i.e. the sum of GHG emissions from electricity required for EV driving and combustion of fuels for ICEV driving. This allows for a comparison between total EVCS emissions and LDV emissions across scenarios.

Components of the EVCS, forecasting method, model assumptions, and emissions calculation procedures are described in the following sections.

2.2. Components of the EVCS

2.2.1. Buildout components

We developed a list of material components of the EVCS by considering what aspects of the system represent *additional* components, i.e. those that do not already exist and *must* be built in order to manage and supply the electricity required of a growing EV fleet. Thus, the material embodied in those charging plugs and stations already built are not included. Nor do we include Level 1 (standard 120 V wall outlets) plug materials in residential or non-residential contexts, as these are a standard aspect of building infrastructure with or without EVs.

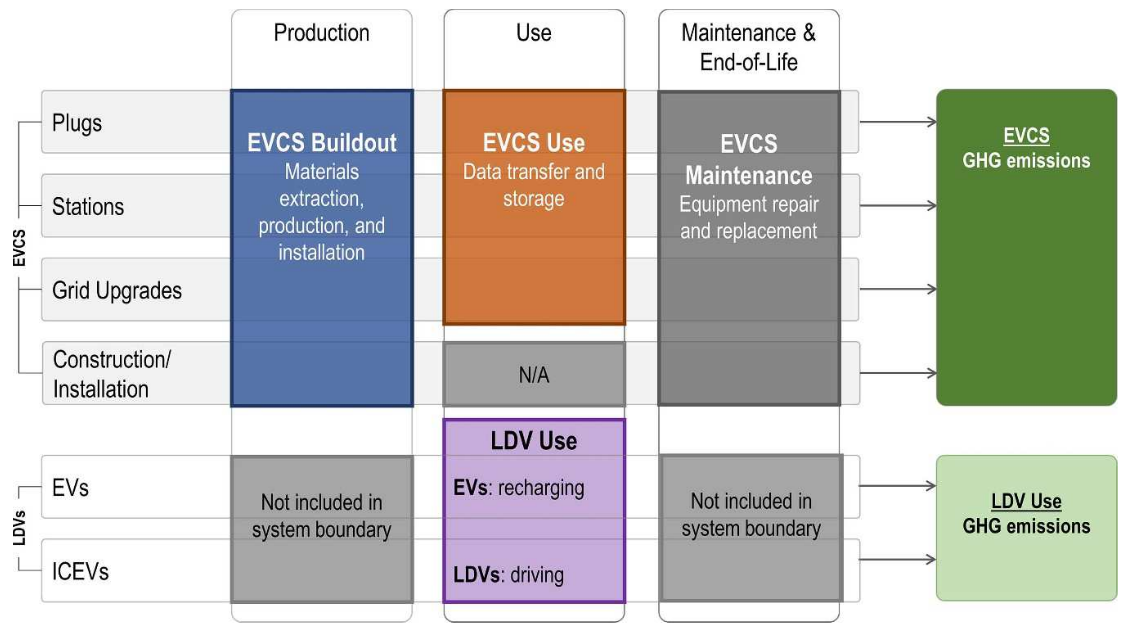

Figure 1. EVCS life-cycle GHG measurement framework.

2.2.2. Use components

The EVCS Use phase incurs impacts primarily to operate the digital infrastructure that supports charging, i.e. the charging station management system [32]. Inclusion of this digital layer in environmental assessment is important, especially as infrastructure systems become increasingly dependent on a dispersed network of data and communication facilities for their operation [21]. During use, the EVCS requires communication among chargers, station operators, and the grid for a variety of purposes including financial transactions, battery management, and charge management [33, 34]. Furthermore, the possibilities for EV-related communications are expanding, with the prospect of vehicle-to-grid and vehicle-to-everything technologies [35, 36]. In our model of the EVCS we track electricity required for data transfers and storage associated with non-residential plugs and with the *control* grid upgrade strategy, further described in section 2.3.4.

Figure 2 indicates whether EVCS components incur an embodied emissions (material) impact and/or an electricity use impact. The figure also includes modeled aspects of the EV system that influence the scale of the EVCS.

2.3. EVCS forecasting model

The EVCS forecasting model is published here as a Microsoft Excel-based tool, allowing users to customize a variety of material, socioeconomic, and technological assumptions. Supplementary material contains detailed information on assumptions, sources, and modeling equations. Here, we summarize the approach to forecasting key systems and subsystems of the EVCS.

2.3.1. Plug count

In order to estimate the quantity of charging equipment required to support a growing EV fleet, we rely on National Renewable Energy Laboratory (NREL)'s EV Infrastructure Projection (EVI-Pro) Lite tool, which is freely available online [37]. The tool allows users to estimate the quantity of charging facilities and additional electric load required to support a given number of EVs in a specific geographic area. It generates these estimates based on dynamics such as travel behavior, charging preferences, EV types, battery capacities, and spatial distribution of residential, workplace, and public facilities with potential to host charging sites.

The EVI-Pro Lite *Charging Needs* module outputs an estimated number of non-residential plugs of the following types: Workplace L2, Public L2, and Public DC. The distribution of plug counts varies based on the prevalence of PHEV versus BEV-type vehicles and the percentage of EV drivers with access to charging (of any level) at home. The module does not have a published algorithm for how plug counts are derived from fleet size, EV-type distribution, PHEV support level, and home-access user inputs. However, we were able to determine that the plug count-fleet size equation follows a roughly linear relationship, which differs based on input settings. We derived these linear equations for the Georgia case by running trials for home access settings of 50%, 75%, and 100% and at EV fleet sizes between 50 000 and 500 000 vehicles, and conducted follow-up testing to ensure our forecasted plug counts are within ±5% of EVI-Pro Lite outputs [38].

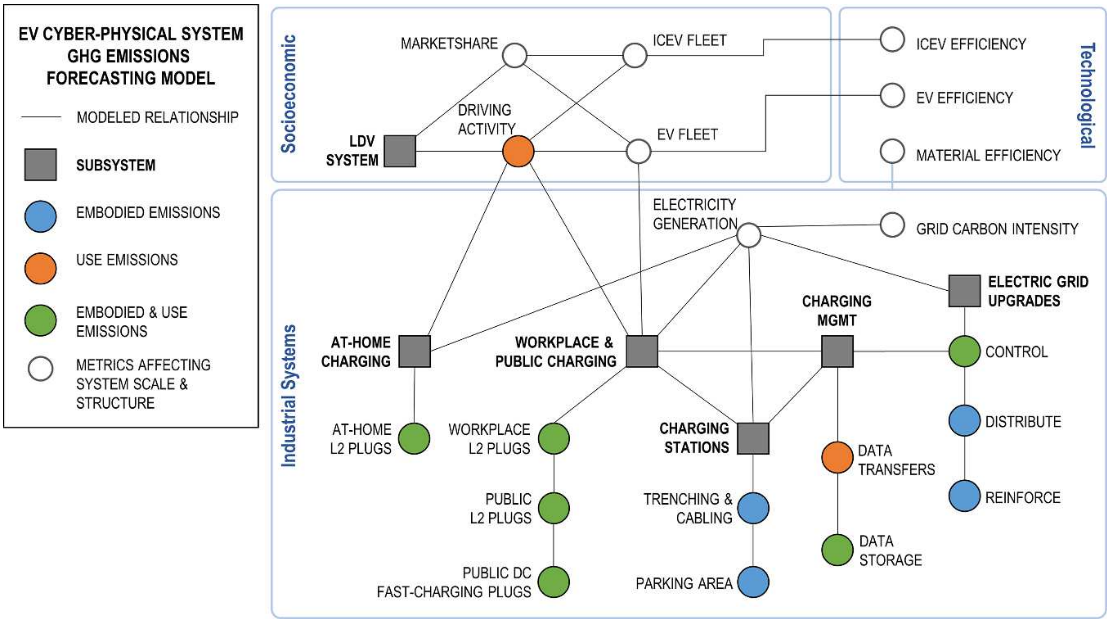

Figure 2. EVCS model; systems, settings, and impacts.

We assume PHEV drivers have access to enough charging capacity to enable full-electric driving 100% of the time, in order to yield a best-case scenario in which all EVs may operate solely on electricity. And we assume a the future EV fleet is composed largely of BEV-type vehicles rather than PHEV, based on the prevailing trend of increasing market share for BEVs [39]. Plug count equations are available in supplementary material.

The total number of plugs of type x (Workplace L2, Public L2, or Public DC) is calculated for each home-access level, based on county-level population projections. Here, we make the basic assumption that home access is more common as the urban classification becomes more rural, following the trend of more owner-occupied units in more rural counties (based on an analysis of Georgia county data) [40]; and we use discrete home access settings from EVI-Pro Lite, with home access set to 50%, 75%, and 100% for urban, suburban, and rural, respectively.

The equation and settings are as follows:

$$\mathrm{PlugCount}_x = \sum P(n\mathrm{EV})_{\text{urban class}} \tag{1}$$

where $P(n\mathrm{EV})$ is the derived plug count equation for plug type x and home-access setting corresponding to urban class. And:

$$x = \{\text{Workplace L2, Public L2, Public DC}\}$$

$$\text{urban class} = \{\text{HA50}\,(\text{urban}),\ \text{HA75}\,(\text{suburban}),\ \text{HA100}\,(\text{rural})\}.$$

In order to capture impacts from scaling up residential charging, we also estimate the number of L2 plugs installed in homes based on the number of EV drivers with home charging access and a general setting for whether residents prefer to install L2 chargers or operate on a standard L1 connection. We use a setting based on EVI-Pro Lite options. For the 'Most L1' setting, 80% of at-home chargers are L1 and 20% are L2. For the 'Most L2' setting, 20% are L2 and 80% are L1. The residential L2 equation is:

$$\mathrm{PlugCount}_{\text{residentialL2}} = (\%\mathrm{L2}) \sum (n\mathrm{EV} \cdot \%\mathrm{HomeAccess})_{\text{urban class}}. \tag{2}$$

Because the Plug Count equations differ by urban classification, the EVCS model requires a way to forecast the number of EVs in use in rural, suburban, and urban communities. This can be accomplished by using different population and vehicle ownership (LDV/p) forecasts for each urban class. For the Georgia case, we utilize official population forecasts at the county-level and vehicle ownership levels derived from Census data [40, 41].

2.3.2. EV fleet size

We base our projection of EV fleet size on *EV market share*, since market share is a commonly used metric in forecasts of EV growth in the US. Three market share scenarios—*Low, Mid*, and *High*—are compared in our analysis. The *Low* scenario comes from the baseline trajectory pulled from the NREL Automotive Deployment Options Projection Tool (ADOPT) [42]. In this trajectory, market share rises steadily to reach 69% of new LDV sales in the US in 2050. The *Mid* scenario is based on the rapid technology advancement scenario from NREL's *Electrification Futures Study* (EFS) [2]. In this scenario, market share rises rapidly from 2022 to 2030, then sees slower growth to 2050 reaching 75%. We developed a *High* scenario in order to explore an even stronger transition to EVs. This trajectory follows a logistic growth curve that fits the EFS trajectory in early years and reaches 90% market share by 2050. Since these trajectories are national-level, they are likely an overestimate when applied to state or regional cases outside of California, since California has such a large share of the total US EV fleet (42%) [43]. Therefore, some adjustment is required. In the case of Georgia, for example, each trajectory is shifted forward by four years to align with the state's 2019 EV market share of 1.2%.

The number of EVs sold for a given year (y) is the forecasted LDV sales in year y multiplied by the EV market share taken from the selected trajectory, or:

$$\mathrm{EVsales}_y = \mathrm{LDVsales}_y \cdot \mathrm{EVmarketshare}_y. \tag{3}$$

Whereas EV market share is an exogenous variable, total LDV sales is endogenous. We model LDV sales as a function of population, average vehicle ownership (LDV/p), and vehicle scrappage rates, i.e. the percentage of vehicles taken out of service or scrapped in a given year. Currently, this rate differs between EVs and ICEVs due to the lower average age of EVs on the road. In the future, it could differ depending on the long-term performance of EVs and changing consumer preferences/incentives. The derivation of LDV sales is thus based on different EV and ICEV scrappage rates:

$$\mathrm{LDVsales}_y = \left(n\mathrm{LDV}_y - n\mathrm{LDV}_{y-1}\right) + n\mathrm{EV}_{y-1} \cdot r\mathrm{EV}_{y-1} + n\mathrm{ICEV}_{y-1} \cdot r\mathrm{ICEV}_{y-1} \tag{4}$$

where:

nX_y = number of vehicles of type X (EV or ICEV) in use in year y

rX_y = % of vehicles of type X scrapped in year y.

Equation (4) requires LDV, EV, and ICEV fleet sizes to be known and which we derive in this section. The total number of LDVs on the road in year y is simply the product of the projected population and the projected vehicle ownership level (LDV/p) in year y:

$$n\mathrm{LDV}_y = \mathrm{population}_y \cdot (\mathrm{LDV/p})_y. \tag{5}$$

Based on the above equations, the model starts with known LDV and EV fleet sizes in year 2020 and generates sales and fleet projections for the period 2021–2050. The number of EVs and ICEVs in operation in year y is calculated as follows:

$$n\mathrm{EV}_y = \mathrm{EVsales}_y + n\mathrm{EV}_{y-1} \cdot \left(1 - r\mathrm{EV}_{y-1}\right) \tag{6}$$

$$n\mathrm{ICEV}_y = \left(\mathrm{LDVsales}_y - \mathrm{EVsales}_y\right) + n\mathrm{ICEV}_{y-1} \cdot \left(1 - r\mathrm{ICEV}_{y-1}\right). \tag{7}$$

2.3.3. Charging stations

To estimate the number of charging stations in operation, we take the total number of non-residential plugs divided by a *plugs per station* value. EVI-Pro provides this value at the state and metropolitan area level, based on data from the US Department of Energy (DOE) Alternative Fueling Station Locator [44].

From the number of charging stations, we forecast two material components of the EVCS:

2.3.3.1. Pavement

Parking area is modeled by applying a *new parking ratio,* defined as the percentage of charging stations requiring new parking. This percentage determines the number of charging stations added in year y, for which the install requires pavement material as an input. It is assumed that every plug at a charging station requires one parking space, and the amount of pavement required is derived from a standard parking space of 8 feet by 18 feet (13.4 m^2) and paving depth of 4 inches (0.1 m). Determining an appropriate value for this *new parking ratio* variable is difficult due to lack of existing research on how charging stations are likely to evolve spatially. We assume the new parking ratio scales with non-residential EV charging station installation costs, recorded in a study by the US Department of Energy [45]. This assumption is detailed in supplementary material.

2.3.3.2. Electrical install

The quantity of cabling and conduit required to connect all plugs to an electricity source is a function of the station's distance from that source, and the number of plugs. We model a variable, *trench-meters per station*, that provides a multiplier for estimating the total quantity of cable/conduit required for electrical install. According to the USDOE study of charging station costs, trenching is a main cost driver that factors into most projects [45]. Further assumptions are detailed in supplementary material.

2.3.4. Grid upgrades

We base our model of grid upgrades on the findings of Coignard *et al* at Lawrence Berkeley National Lab (LBNL [25]) in their study of electricity distribution impacts from widespread uptake of EVs. The study simulated EV charging loads at the level of distribution feeders (3–12 feeders per substation), in the San Francisco Bay Area. The main finding we take from the study is that 60% of feeders require capacity upgrades, once EV penetration reaches one EV per household. The study also suggests various approaches for addressing load growth at the level of distribution feeders, which we summarize into three grid upgrade approaches: (1) *Reinforcement:* add additional distribution lines at the feeder level, requiring additional transformers, (2) *Distributed energy resources:* add additional generating capacity at a smaller, distributed scale, along with requisite energy storage capacity, and (3) *Load control:* implement demand response strategies enabled by smart meter hardware and communications.

Using these parameters as guidance, we devised a model to calculate grid upgrades required, given the size of the EV fleet in a given year. First, we calculate the level of EV penetration at the household level:

$$\left(\frac{n\mathrm{EV}}{\mathrm{HH}}\right)_y = \frac{n\mathrm{EV}_y}{\mathrm{poulation}_y}\left(\frac{p}{\mathrm{HH}}\right)_y. \tag{8}$$

Next, we estimate the number of distribution feeders on the entire electrical grid, based on an average of 6000 households per feeder, from the LBNL study. The calculation is then:

$$\mathrm{FeederCount}_y = \frac{\mathrm{population}_y \cdot \left(\frac{p}{\mathrm{HH}}\right)^{-1}}{6000\,\frac{\mathrm{HH}}{\mathrm{feeder}}}. \tag{9}$$

Finally, the number of upgraded feeders required to accommodate EV penetration is:

$$\mathrm{UpgradedFeeders}_y = 0.6 \cdot \left(\frac{n\mathrm{EV}}{\mathrm{HH}}\right)_y \cdot \mathrm{FeederCount}_y. \tag{10}$$

Upgrade equipment installs in year y are calculated as the change in UpgradedFeeders from the previous year. Based on the chosen strategy, different material and energy use intensities are applied to the number of upgraded feeders in year y. Grid upgrade modeling and assumptions are further detailed in supplementary material.

2.3.5. Charging station management system

The charging station management system (charging management) supplies many essential functions of the EVCS, including energy delivery and load management, transaction handling, charge coordination at the charging station level, and communication between the EV driver and charge providers[46]. The EVCS model captures the charging management footprint related to two subsystems: (1) grid upgrades using the *control* approach, and (2) charging stations. Estimating the data and material parameters that constitute this system was especially difficult due to the scarcity of studies that ask and clarify such questions. Large over- and under-estimations of information and communication technology (ICT) systems are a common feature of impact studies and discussion in this sector [20, 47]. We aim at capturing a lower and upper-bound for the EVCS' digital layer by modeling two different sets of assumptions for charging management system components.

2.3.6. Lower bound assumptions

We assume that each charging plug requires hardware and data similar to that of a residential smart meter. Data transfer rates are taken from Passos *et al* who estimate that smart meters send approximately 14.4 kilobytes (kB) per day, or 5.26 MB/household/year [48]. Data storage requirements are from Luan *et al* who observed the accumulation of smart meter data in storage facilities, equivalent to 2.51 megabytes (MB) of data stored per meter per year [49]. For commercial entities to comply with internal revenue service (IRS) recordkeeping rules, this data would need to be stored for a minimum of three years, so the value is multiplied by three, giving 7.52 MB/household/year. To estimate the minimum hardware requirements for supporting these data functions, we use (a) the GE I-210 smart meter as the model on-site hardware (1.0 kg per unit [50]) and (b) a value of 2.5 kg data storage hardware per terabyte (TB) of data stored, estimated from cloud companies' published specifications [51].

2.4. Higher bound assumption

In this approach, every plug and home meter is modeled with characteristics of a personal mobile device. Data transfers and data storage are at the level of a typical wireless subscription: 30 GB of data traffic per month and 6.5 GB of data storage per year [52, 53]. And device material quantity is based on specifications for an Apple iPad 10.2 [52]. Charging management component specifications and data sources are further detailed in supplementary material.

2.5. GHG impact calculation

2.5.1. Materials

For equipment materials, we utilize GHG intensity factors from the US EPA Waste Reduction Model (WARM) [54], taking the sum of values for extraction, processing, and production stages of the life-cycle, published by WARM for specific materials. The amount of reclaimed/recycled material used as *input* can be modified in the EVCS model, which changes the GHG intensity based on WARM values for recycled-content production. WARM does not provide a GHG factor for hard plastic housing (used in charging plug hardware). For this, a Europe-based study of life cycle emissions for polycarbonate was used [55] and GWPs applied for CO_2, CH_4, and N_2O, yielding a CO_2-equivalent value aligned with the WARM intensity factor calculation method. The WARM-based and calculated polycarbonate GHG intensities all utilize GWPs from the IPCC Fourth Assessment Report [56]. These GWP values are somewhat outdated but we use them for consistency with WARM and EPA reporting.

2.5.2. Electricity generation emissions

The GHG intensity of electricity demand (for charging management system operation) is taken from a grid decarbonization modeling tool developed by Grubert [57]. The tool allows users to model future GHG intensities at the state and electric utility level based on varying assumptions about how generating capacity is added over time. For the Georgia case, we consider *upper-* and *lower-bound* cases. *Upper-bound* (natural gas): all new build power utilizes combined cycle natural gas technology; this scenario causes grid intensity to decrease at first, but rises again to 98% of current grid GHG intensity due to retirement of lower-carbon technologies such as nuclear and hydropower. *Lower-bound* (Zero carbon): all new build power is zero carbon, leading to a 2050 grid GHG intensity less than 1% of current. The EVCS tool also allows users to input a custom GHG intensity trajectory.

2.5.3. Construction, installation, and maintenance emissions

Construction and installation impacts are allocated to each non-residential L2 plug, DC plug, and grid upgrade component added in a given year. We model emissions by estimating the type and quantity of fuel used by construction equipment and service vehicles required to install each type of component. For example, based on EV charger project descriptions, we assume 4 h of construction equipment operation (with fuel use rate averaged across several types of equipment such as trenching, paving, and hauling vehicles) and 4 h of service vehicle operation for travel and support (modeled as gasoline-powered pickup truck use). Equipment types, fuels, fuel use rates, and work hours related to each installation type are detailed in the supplementary material.

The overall GHG emissions value (G) for a given year y is then calculated as:

$$G_y = \left(\sum_{i=1}^{n} WF_i \cdot M_i\right)_y + \left(CF \cdot \sum_{j=i}^{n} E_j\right)_y + \left(\sum_{k=1}^{n} FF_k \cdot I_k\right)_y \quad (11)$$

where:

WF_i is the WARM GHG intensity factor for material type i
M_i is tonnage of material type i required for new construction/equipment installs in year y
CF is the carbon intensity factor for electricity generation in year y
E_j is the electricity use for demand purpose j in year y
FF_k is the fuel use emissions factor for constructing/installing EVCS component k in year y
I_k is the number of EVCS components of type k installed in year y.

Table 1. Baseline scenario attributes, Georgia EVCS forecast.

Attribute	Unit	2020 value
Household size, rural	pp/household	2.58
Household size, suburban	pp/household	2.65
Household size, urban	pp/household	2.72
LDV density, rural	LDV/person	0.823
LDV density, suburban	LDV/person	0.793
LDV density, urban	LDV/person	0.777
CV scrappage rate	% of CV fleet scrapped per year	5%
EV scrappage rate	% of EV fleet scrapped per year	1%
# of EVs, statewide	# EVs	31 032
Sedan-SUV split, rural	# Sedans/fleet	40%
Sedan-SUV split, suburban	# Sedans/fleet	50%
Sedan-SUV split, urban	# Sedans/fleet	60%
dVMT (daily veh-miles traveled), rural, GA	Veh-mi/LDV/day	53.4
dVMT (daily veh-miles traveled), suburban, GA	Veh-mi/LDV/day	45.4
dVMT (daily veh-miles traveled), urban, GA	Veh-mi/LDV/day	30.5
EV efficiency, Sedan	Wh/mile	361.0
EV efficiency, SUV	Wh/mile	500.0
CV efficiency, Sedan	mi/gal	25.3
CV efficiency, SUV	mi/gal	18.2
Plug materials [58]		
L2 plug material req, iron	kg per plug	24.50
L2 plug material req, aluminum	kg per plug	2.07
L2 plug material req, copper	kg per plug	2.49
L2 plug material req, rubber	kg per plug	1.45
L2 plug material req, plastic	kg per plug	1.00
DC plug material req, iron	kg per plug	193.79
DC plug material req, aluminum	kg per plug	11.20
DC plug material req, copper	kg per plug	12.13
DC plug material req, rubber	kg per plug	12.03
DC plug material req, plastic	kg per plug	1.00
Station materials		
Plugs per station	plugs/station	2.41
Percent of stations requiring new parking space	stations requiring new parking/new stations	35%
Pavement mass per parking space	kg/parking space	3100
Avg. electrical distance per station	trench-m per station	85.0
Cable material per trench distance, per plug, copper	kg/m/plug	0.50
Cable material per meter trench, per plug, rubber	kg/m/plug	0.48
Conduit material per meter trench, per plug, PVC	kg/m/plug	1.12

2.6. State of Georgia forecast, 2021–2050

2.6.1. EVCS baseline attributes

Table 1 consolidates baseline EVCS model inputs, for the Georgia case study, based on sources/methods described in the preceding sections. Sensitivity testing is carried out on a one-at-a-time basis for several key socioeconomic and technological variables, at $\pm 10\%$ levels.

2.6.2. Forecast starting conditions, 2020

In 2020, there were an estimated 31 000 EVs in Georgia, composed of approximately 19 600 BEVs and 11 400 PHEVs. The state population was 10.7 million, with an estimated 4 million households, putting the level of EV penetration statewide at 0.003 EVs per person and 0.008 EVs per household. EVs comprised just 0.4% of the total LDV fleet of approximately 8.5 million vehicles. The population of Georgia is mostly urbanized, with 57% of the population residing in urban counties, compared to 26% and 17% in suburban and rural counties, respectively. Using the assumptions detailed above, we assume approximately 20 400 EVs out of 31 000 with private access to charging at home and 4000 of those households have installed an L2 plug. According to the DOE's Alternative Fueling Station Locator, there are 1528 charging stations across the state, collectively hosting 3023 L2 plugs and 657 DC plugs [44]. While these plug quantities may meet the current demands of BEV drivers with ample access to home charging, they do not meet the level of EVCS deployment suggested by EVI-Pro Lite under full PHEV support and diversified home-access. In the baseline scenario we use 6500 L2 plugs and 2000 DC plugs across 3500 charging stations as the starting conditions of EVCS buildout.

Daily vehicle travel is estimated at 53 VMT (85 VKT) per LDV in rural counties, 45 VMT (72 VKT) per LDV in suburban counties, and 31 VMT (50 VKT) per LDV in urban counties. This results in an estimated 111 billion VMT (179 billion VKT) across the state in 2020.

3. Results

3.1. Georgia case study results

3.1.1. Fleet development

Under baseline assumptions, the LDV fleet in Georgia is expected to develop in correlation with population growth and urbanization. In 2050, there are an estimated 11 million LDVs on the road. Figure 3 depicts EV fleet development under the three market share scenarios, Low, Mid, and High. Under the High market share growth scenario, EVs comprise 63% of the total LDV fleet in 2050. Under the Mid and Low scenarios, EVs achieve 50% and 36% fleet share, respectively.

3.1.2. EVCS development

In order to accommodate fully electric driving under the High market share scenario, 1.8 million additional plugs are installed statewide over the period 2021–2050. Of these, 50% are residential L2 plugs, 45% are non-residential L2 plugs, and 5% are DC plugs. While the share of plug types is the same across scenarios, the total number of plugs varies, with Mid-range growth requiring 1.4 million plugs and Low growth requiring 1.0 million. Cumulative plug count trajectories are depicted in figure 4. The number of station installs and electric grid upgrades scale accordingly.

3.1.3. Embodied emissions

Figure 5 depicts embodied emissions of EVCS buildout under the High market share scenario. Cumulative embodied emissions in 2050 are 1.04 million mtCO_2e. Installation of electrical cables, wiring, and digital equipment at charging stations ('Station: electrical') represents 36% of these embodied emissions, largely a function of trenching distance and the GHG-intensive metallic components required. Construction represents the next largest share of emissions at 28%. L2 plugs represent 16% of cumulative emissions. While DC plugs are far more material intensive than L2 plugs, they represent only 6% of embodied emissions as there are far less of them installed over the forecast period. Pavement for parking spaces and trenching cover represents 9%, and grid upgrade equipment materials represent 6% of embodied emissions. Annual embodied emissions grow rapidly from 2025 to 2035 as EVs undergo high market share growth, peaking in year 2036 at 54 700 mtCO_2e.

3.1.4. Embodied vs. use emissions

Figure 6 depicts emissions from EV and ICEV use under each market share growth scenario. EV use phase emissions are significantly different under upper-bound (natural gas) and lower-bound (Zero carbon) GHG-intensity trajectories. Under a High market share growth and Zero carbon grid scenario, total use-phase emissions drop from 66 million mtCO2e in 2021 to 30 million mtCO2e in 2050. Under the natural gas scenario, the 2050 value is 48 million mtCO2e. This range narrows under the Mid and Low market share growth scenarios, due to ICEV vehicles maintaining a larger share of total transportation, unaffected by grid GHG intensity.

Overall, EVCS embodied emissions are a small fraction (<1%) of total LDV Use emissions under all scenarios. When the grid transitions to fully Zero carbon sources, total use phase emissions are lowered and embodied emissions' share rises slightly. However, embodied emissions are ultimately dwarfed by emissions from ICEV vehicles (still 37% of the LDV fleet, under the fastest growth scenario) that still occur in 2050.

3.1.5. Accelerated buildout comparison

Finally, we report on the relative impact of building out the EVCS ahead of EV fleet development and usage, by comparing LDV (EV + ICEV) Use emissions and EVCS buildout embodied emissions under combinations of Low, Mid, and High scenarios. In each combination, the difference in cumulative emissions, compared to the Low scenario, is reported in figure 7. The cumulative emissions pathway for each combination is depicted, with the 2050 value highlighted. High buildout has embodied emissions 122 000 mtCO2e higher than Low buildout, and Mid buildout is 63 000 mtCO2e higher. These values are orders of magnitude smaller than the emissions reduced if the EV fleet develops faster than the Low scenario. High fleet development yields LDV use emissions totaling 474 million mtCO2e below the Low scenario, and Mid fleet development use emissions are 204 million mtCO2e below. Given these results, even a slight uptick in EV development as a result of accelerated EVCS buildout would yield a positive 'return' on embodied emissions invested.

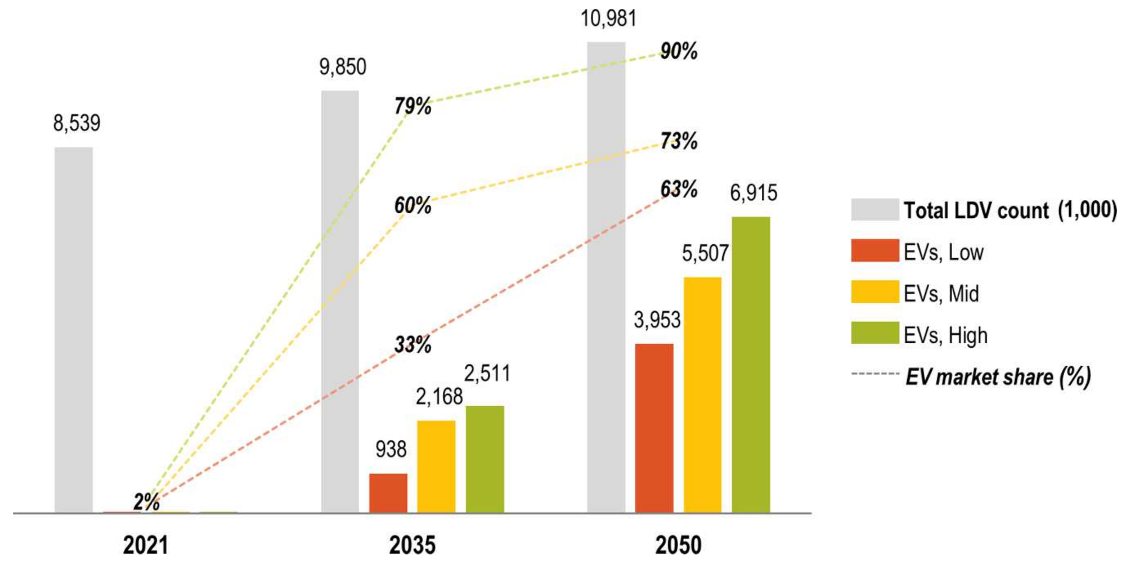

Figure 3. EV market share and LDV fleet development, 2021–2050.

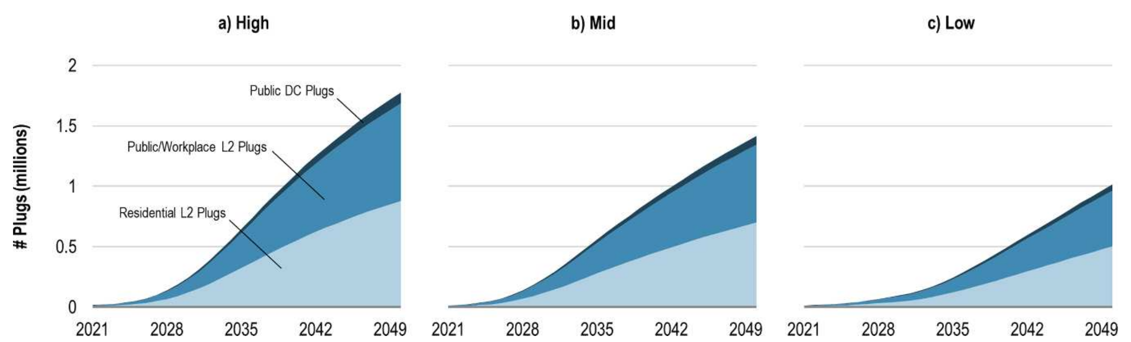

Figure 4. Cumulative plug counts, by type.

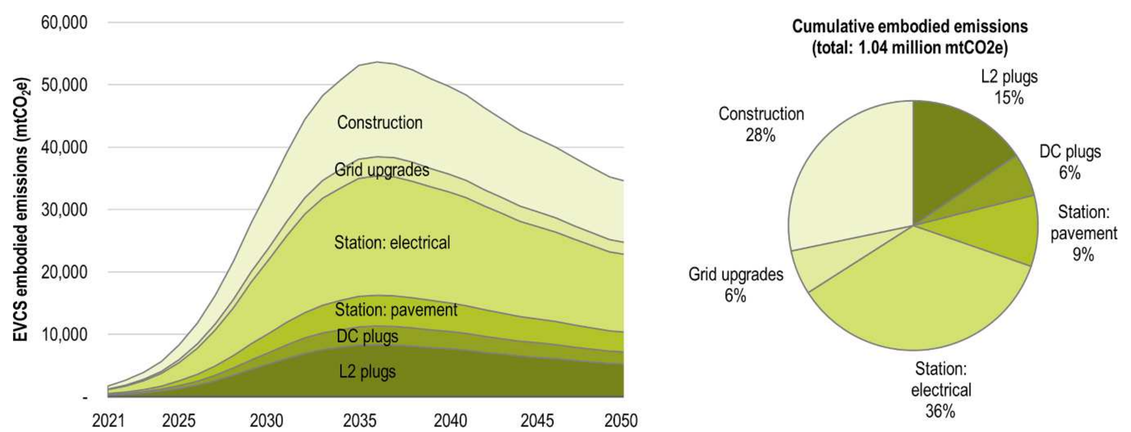

Figure 5. EVCS embodied GHG emissions development, (a) 2021–2050 (b) cumulative total, by subsystem.

3.2. Sensitivity testing

EVCS tool settings are high-level toggles that modify major factors in the development of the EV fleet, infrastructure, and impacts. Table 2 lists embodied and total emissions outcomes, as % difference from the baseline scenario, run with an upper-bound (*natural gas*) trajectory for the electric grid. We first test different settings, for five key toggles. Grid decarbonization does not affect embodied emissions in this model, since the carbon intensity of materials are modeled separately and assumed to rely on a mix of energy

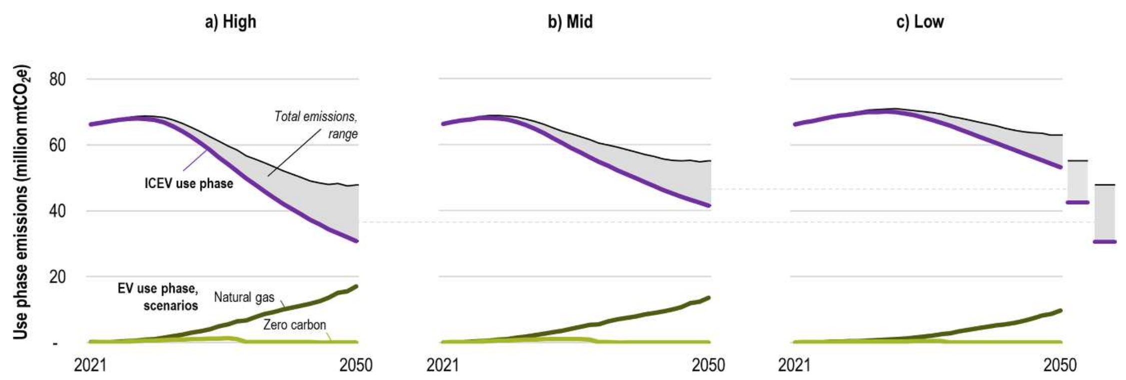

Figure 6. Vehicle use emissions and embodied emissions %, 2021–2050.

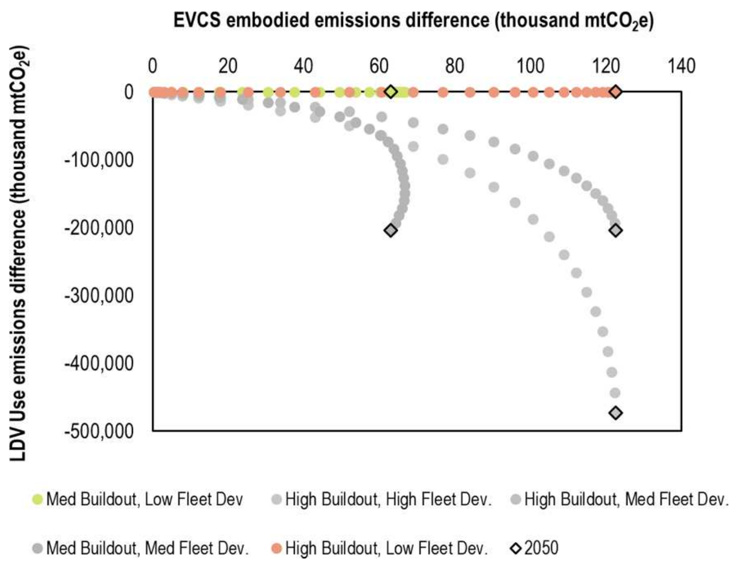

Figure 7. Accelerated buildout scenarios, showing cumulative trajectories.

sources, largely outside Georgia. Thus, modifying the carbon intensity of the grid only affects overall emissions, primarily from charging the EV fleet. A Zero-Carbon decarbonization pathway changes total emissions by −9.7% from the baseline. The EV market share pathways effect total emissions by a similar magnitude but in the opposite direction. As EV market share decreases, forecasted emissions rise, at +4.2% and +13.3% from the baseline, for the Mid and Low market share scenarios respectively.

The results also show that choosing *Control* or *Distribute* grid upgrade strategies, based on demand-responsive metering and distributed energy storage, can help offset increased EVCS embodied emissions, as they both decrease embodied emissions below the baseline. A *Reinforce* strategy increases embodied emissions due to the high material cost of replacing transformers at the distribution feeder level. A scenario where 80% of homes with EVs and private electricity access choose to install an L2 plug could increase the embodied emissions of the EVCS buildout, estimated at +39.9% from baseline. However, the resulting total emissions effect is again negligible, at less than +0.1%.

As EVCS expansion proceeds, it is expected that heavy-duty vehicles required for construction will also be electrified. While the embodied emissions forecast presented in results did not account for this potential decarbonization, we test an extreme decarbonization scenario here, in which construction vehicles and equipment are fully decarbonized by 2050. This scenario reduces cumulative embodied emissions, −14.3% from the baseline.

Next, we conduct sensitivity testing on a variety of model assumptions and input variables, tested on a one-at-a-time basis, from the Baseline scenario. Notably, all of the infrastructural factors have a negligible effect on total emissions. The *high-range* assumption for digital intensity, in which plug ICT hardware and data loads are equivalent to a mobile tablet device, do not significantly affect total emissions. Varying socioeconomic factors such as vehicle ownership and vehicle scrappage rates has the most impact on

Table 2. GHG impact sensitivity, select EVCS model settings & attributes.

Setting		Effect on EVCS embodied emissions	Effect on Total emissions
Model settings			
	GRID DECARBONIZATION		
	Zero carbon (ZC) pathway	None	−9.7%
	GRID UPGRADES		
	Control	−3.2%	<0.1%
	Distribute	−5.5%	<0.1%
	Reinforce	8.9%	<0.1%
	EV MARKET SHARE		
	Mid	−15.9%	4.2%
	Low	−38.1%	13.3%
	RESIDENTIAL L2 PLUGS		
	80% L2	39.9%	<0.1%
	CONSTRUCTION DECARB.		
	Full decarbonization	−14.3%	<0.1%
Attribute sensitivities			
Infrastructural	DIGITAL INTENSITY		
	Baseline × 2	0.1%	<0.1%
	High-range assumptions	0.3%	<0.1%
	EXCLUSIVE DC MULTIPLIER		
	+10%	2.3%	<0.1%
	PARKING EXPANSION		
	+10%	0.3%	<0.1%
	−10%	−0.3%	<0.1%
Socioeconomic	ICEV SCRAPPAGE		
	+10%	3.0%	−0.8%
	−10%	−3.2%	0.8%
	EV SCRAPPAGE		
	+10%	−0.1%	<0.1%
	−10%	0.1%	<0.1%
	LDV/PERSON		
	+10%	12.7%	3.7%
	−10%	−12.7%	−3.7%
	VMT/LDV		
	+10%	None	4.6%
	−10%	None	−4.6%
Technological	EV EFFICIENCY		
	+10%	None	−0.8%
	+20%	None	−1.6%
	ICEV EFFICIENCY		
	+10%	None	−3.6%
	+20%	None	−6.8%
	RECYCLING RATE		
	+10%	−1.5%	<0.1%
	−10%	1.5%	<0.1%

Dark green = greatest potential for GHG reduction from baseline
Dark red = greatest potential for GHG increase from baseline

embodied emissions. Increasing ICEV scrappage rates allows the EV fleet to grow faster and thus increases embodied emissions, however this increase is accompanied by an overall decrease in total emissions. Increasing vehicle ownership, on the other hand, has an emissions-increasing effect in both cases. Higher vehicle ownership increases the EV Fleet, requiring more infrastructure, but also increases overall travel activity driving up total emissions. The variable LDV/person is the only variable tested that has a greater than +1% effect on both embodied emissions and total emissions when tested at +10%, pointing to the significance of socioeconomic and structural factors in determining the environmental trajectory of EVCS. For example, one way that LDV/person could be reduced in the future is through investments in non-personal car transportation options and economic incentives for changing travel habits.

Among technological factors, only recycling rates (driven by advancement in recovery and recycling technologies for all required EVCS materials) affect embodied emissions. As expected, a higher recycling rate delivers lowered emissions, and vice-versa. Lastly, ICEV fuel efficiency increases show a potential for significant emissions reduction, due to the sheer scale of the ICEV fleet especially in early model years when decarbonization has not progressed.

Finally, we tested the emissions effect of adding a *maintenance phase* estimation. Built on the construction/installation emissions module, this estimation assumed that charging plugs and grid upgrade components have an average lifetime of 15 years, causing maintenance impacts to start accumulating about halfway through the forecast period. At this replacement rate, cumulative EVCS emissions are increased by 17%, meaning the maintenance effect is non-negligible. However, we also note that EVCS maintenance impacts could be offset by a concomitant reduction in traditional gas station maintenance impacts, given a substantial shift from ICEV to EV use.

4. Discussion

4.1. EVCS model

Through this study, we defined the material and operational components of the EVCS and built a model for estimating GHG emissions incurred during buildout and use of the EVCS. The EVCS model comprises aspects of charging infrastructure that do not already exist and *must* be built in order to manage and supply the electricity required of a growing EV fleet. It also enables EV infrastructure forecasting by scaling components based on socioeconomic factors such as population growth, vehicle ownership, and driving habits. By rigorously defining EVCS system boundaries and relationships between socioeconomic and technological factors of the personal driving system, we have established a method upon which other EV infrastructure studies may be based. And because the model accounts for different driving and vehicle ownership characteristics of urban, suburban, and rural communities, such forecasts can be resolved at any level for which urban classification is defined.

As EV Infrastructure initiatives get underway at the state, federal, and global levels, the EVCS model provides a crucial tool for estimating the scale and material character of charging infrastructure, and the level of GHG emissions embodied therein. We anticipate that the model could also serve as a starting point for cost estimation, spatial planning, and regional environmental and social impact studies.

The model's fleet growth and plug count estimates are based on existing methodologies for a US context, but other aspects of the model are less well-established, presenting an opportunity for research and refinement. These include the charging station installation requirements. Will future stations rely primarily on existing parking spaces close to electrical connections, or will new pavement and electrical trenching add to the EVCS footprint? The charging management components of the EVCS are also roughly estimated in the model. Refining the subsystem components—including equipment required, average data transfers, and data storage loads—would require observation of EV charging transactions at driver, plug, and service provider levels, as well as a detailed investigation of network, data storage, and cybersecurity assets that are likely to support future optimized charging systems.

Technological change is another crucial aspect of model updating. As strategies for EV fleet growth and charging infrastructure scale-up evolve, so will the supporting technological configurations. This means that change in material intensities, material types, and energy/resource efficiencies needs to be modeled over the 30 year forecast period. One potentially influential example is the material profile of fast-charging facilities. It is possible that banks of extremely-fast chargers will require buffering capacity in the form of on-site batteries, which could greatly increase the material required per plug [59, 60]. While the EVCS modeling tool does provide the ability to modify the material profiles of EVCS components such as plugs, more material categories will be required to accommodate diverse technological scenarios.

The EVCS modeling tool is available in supplementary material as a Microsoft Excel format and loaded with mid-range assumptions used in the Georgia case study.

4.2. Georgia EVCS forecast to 2050

The main finding of the Georgia forecast case study is that the cumulative embodied emissions of EVCS buildout are less than 1% of the cumulative emissions of LDV driving out to 2050. Furthermore, the potential emissions reduction from increasing EV market share, yielding a greater share of total electrified miles driven, far outweighs the emissions cost of building out EV infrastructure. We thus conclude that policies and efforts aimed at accelerated EVCS buildout are warranted, in order to help stimulate the transition of the LDV fleet to electric.

We also found that overall LDV emissions are generally more sensitive to socioeconomic factors that affect fleet composition and miles-driven, compared with factors affecting EVCS buildout, such as parking space requirements, charging management system requirements, and material recycling rates. This indicates the importance of shifting travel modes and habits to decarbonize personal transportation, and reinforces the conclusion that EVCS buildout emissions can be a low priority concern. In light of these results, building out electrification infrastructure for other modes such as public transit and freight can be sped up and prioritized to maximize long-term emissions reductions. Finally, our forecast reveals that full electrification by 2050 will be difficult. Even the high market share scenario does not reach full LDV fleet electrification, which suggests that reaching the national net zero GHG goal will require additional policy or other structural changes.

4.3. Additional caveats

As part of methods development for this paper, the authors conducted an extensive review of peer-reviewed environmental assessments of digital technology [anonymous citation]. From this review, we summarized a set of equipment subsystems and socioeconomic dynamics that influence environmental outcomes. We were not able to incorporate all of these socioeconomic dynamics into our EVCS analysis, but we briefly address them here in order to highlight possible research directions.

4.4. Social and health effects

The EVCS model projects emissions using assumptions about EV fleet characteristics, LDV driving habits, and infrastructure buildout based on known differences by urban classification (urban, suburban, or rural). Future work could refine the model further to explore disparities in EV uptake and EVCS buildout at the community and/or socioeconomic level.

4.5. Costs

EVCS impacts and costs need to be communicated relative to relevant counterfactuals, including both a business-as-usual future and fully decarbonized futures that are less dependent on personal cars. Here, factors such as the lower maintenance requirements expected for EVs are an important factor that was not considered in our model. We also did not establish an ICEV refueling counterfactual, but this will be an important system to model as charging station providers gain market share and gas stations adjust pricing and potentially locational strategies accordingly.

4.6. Economic feedbacks

We have concluded that EVCS buildout can proceed ahead of schedule, a pathway that is likely to facilitate and perhaps accelerate decarbonization of personal travel. In making this conclusion, it must also be considered whether and where there are possible economic feedbacks—negative or positive—from such a buildout. If buildout is not strategic in terms of meeting and stimulating demand, then limited funds could be wasted. Subsidized buildout could also stimulate additional EV driving without simultaneously attracting ICEV drivers to switch, in which case the full potential emissions reductions will not be reached, at the cost of increased personal vehicle usage. Such economic feedbacks are an important part of future EV use, in the context of the larger transportation system.

4.7. Cybersecurity

As the transportation system becomes more reliant on ICT infrastructure, the importance of cybersecurity increases for both safety and privacy reasons. Moreover, electric grid configurations could feature EVs as an important resource for managing distributed energy resources, meaning communications between vehicle and grid will be a publicly shared security concern. Future research could explore the implications of cybersecurity for the embedded emissions footprint of the EVCS.

Finally, we believe this work represents an important early achievement in detailing the network of components that constitute the embodied materials and indirect energy use required to operate a greatly scaled-up EV system.

5. Conclusion

Vehicle electrification is a core strategy for eliminating fossil fuel use. Enabling such electrification requires not only vehicle deployment, but deployment of charging infrastructure for fueling. As decarbonization proceeds, strategic sequencing of interventions to minimize cumulative emissions becomes more relevant given that some infrastructure buildout might rely heavily on inputs that are currently GHG intensive, resulting in large embodied emissions, but are expected to rapidly decarbonize. Our detailed analysis of EV charging infrastructure systems, published here as a highly customizable Excel model, suggests that even under current emissions intensities, building out EV charging infrastructure has negligible impact relative to emissions associated with driving. As such, the GHG benefit of developing robust charging infrastructure to stimulate EV uptake is expected to far outweigh the GHG cost of accelerated charging infrastructure deployment.

In general, our model suggests that overall GHG emissions from charging infrastructure and driving light duty EVs are dominated by electricity used to charge vehicles, which means that overall emissions are sensitive not only to the dynamic GHG intensity of the grid, but also to sociotechnical factors like vehicle miles traveled per person and vehicles per person—far more than to factors like material choices, additional paved area to support charging, etc. Embodied GHG emissions for charging infrastructure are not sufficiently large to delay buildout of charging infrastructure, but attention to transportation service needs, access, and overall transportation system design remain critically important for facilitating an effective, just, and sustainable decarbonization transition.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary information files).

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