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RESEARCH ARTICLE

Comparing the climate and air pollution footprints of Lithium-ion BEVs and ICEs in the US incorporating systemic energy system responses

Pankaj Sadavarte¤*, **Drew Shindell**, **Daniel Loughlin**

Nicholas School of the Environment, Duke University, Durham, North Carolina, United States of America

¤ Current Address: School of Informatics, Computing and Cyber Systems, Northern Arizona University, Flagstaff, Arizona, United States of America
* pankaj.sadavarte@nau.edu

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Abstract

With rising travel demand and the need to tackle both the air quality and climate change challenges caused by fossil fuel vehicles, there is an urgent need to transition to cleaner and more sustainable fuels. While lithium-ion battery electric vehicles (BEVs) produce no emissions during operation, they increase electricity consumption, affecting emissions from that activity. Furthermore, there is an ongoing debate about the overall cleanliness of lithium-ion batteries when assessing emissions throughout their lifecycle compared to fossil fuels. To address these concerns, we use the Global Change Analysis Model (GCAM) integrated assessment model (IAM) to evaluate criteria air pollutants and carbon dioxide (CO_2) emissions across four scenarios of increasing BEV adoption in the United States (US). We include emissions from fuel and battery production, vehicle manufacturing, and operation for both BEV and fossil-based internal combustion engine (ICE) vehicles. Results indicate that each additional kWh of lithium-ion battery output leads to an average reduction of 220 kg of CO_2 in 2030 and 127 kg of CO_2 in 2050. There are also substantial decreases in CO emissions, although relatively small changes in SO_2 and NO_X. In a life cycle assessment, all else equal, the CO_2 emissions associated with BEVs are 30% higher than those of ICE vehicles during the first two years. However, after the second year, BEVs result in a reduction in cumulative CO_2 emissions. Accounting for the effects of both air pollution and climate change, the economic value of the damages attributable to ICEs over their lifetime is currently 2 to 3.5 times that of BEVs. This ratio increases over the coming decades as the emissions intensity of the electricity sector decreases.

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1. Introduction

The transportation sector accounts for 28% of greenhouse gas (GHG) emissions in the United States (US), of which light duty vehicles (LDVs), including cars, minivans, light trucks, and sports utility vehicles (SUVs), contribute about approximately 3/5ths [1]. Similarly, onroad traffic is one of the foremost sources of air pollutants such as CO and NOx, especially from fossil fuel based internal combustion engines (ICEs) [2–5]. To address air quality and climate challenges, the Intergovernmental Panel on Climate Change's (IPCC) latest Assessment Report (AR6) stresses the need for behavior-based management solutions combined with advanced powertrain technologies, such as electric vehicles, biofuels, and fuel-cells, to reduce energy demand and transport-related GHG emissions [6].

In recent years, there have been a growing consensus and substantial policy efforts to promote electric vehicles (EVs) to mitigate the GHG and air pollutant emissions from onroad vehicles [7–8]. Most BEVs utilize lithium-ion (Li-ion) batteries, and thus this technology is playing an important role in meeting environmental and climate goals [9–11]. Many studies have evaluated the impact of Li-ion BEVs on emissions, including assessing the direct benefits of eliminating tailpipe emissions, as well as the upstream emissions associated with activities such as material mining and processing and with battery and vehicle manufacturing [12–17]. A few studies have evaluated alternative assumptions about the technology mix within the electric power sector, including rapid decarbonization [18], but most have relied upon pre-defined electricity production profiles, often with fixed shares of generation capacity based on the current shares of each type [19–23].

We build upon the previous literature by evaluating the net emissions implications of BEVs through the year 2050, considering both onroad and upstream emissions, under alternative assumptions about BEV market share, and including a dynamic response of the electric sector profile to the BEV-related demand changes. This holistic, multi-sector, multi-pollutant analysis is performed using an integrated assessment model (IAM). We also bring a greater focus to the emissions contributions of the lithium-ion batteries used by the BEVs. The approach has similarities to the life cycle inventory (LCI) analysis of a life cycle assessment (LCA). Our life cycle-based perspective offers a comprehensive approach for evaluating the underlying emissions produced during and upstream of vehicle operation, covering various life cycle stages except for end-of-life (EoL). End-of-life emissions were excluded from this study given the uncertainty regarding the role of battery repurposing, reuse, and recycling, and a detailed approach required in accounting for battery use, reuse and recycle. Here, emission changes are estimated at different stages in the Li-ion supply chain, including (a) lithium extraction and processing, (b) lithium-ion battery production, (c) electric vehicle production, and (d) electric vehicle usage. These estimates are compared with analogous values for internal combustion engines (ICEs) and their fuels.

Section 2 describes model and methodology used in this study. Section 3 presents the results from the IAM describing the projections in transport and electricity demand, the national greenhouse gas emissions and trends after integrating the emissions from the fuel and vehicle production.

2. Methods

In this section, we describe the IAM used in the analysis, the scenarios used to examine the impacts of increasing BEV sales, and the source and application of life cycle emission factors. For fuel use and electricity, we rely on an integrated assessment model, while the emissions from production of vehicles, including batteries, are estimated from the relevant literature. Since the focus of the study is to understand the change in emissions from light duty passenger vehicles in the US per kWh of the lithium-ion battery added to the US fleet, our analysis revolves around the changes in the transport sector along with other linked sectors.

2.1 The Global Change Analysis Model (GCAM)

In this study, GCAM-USA v7.0 [24], is used to simulate the evolution of the US energy supply and demand for a range of BEV market share scenarios. GCAM is a human and earth system model that simulates the co-evolution of the energy, economic, agriculture, land, and water systems, simulating the market shares for various technologies and fuels while tracking the impacts on energy prices and the resulting GHG and air pollutant emissions. Within the energy system, GCAM includes representations of the electric, refining, industrial, residential, commercial, and transportation sectors of the economy. GCAM is a global model with 32-region coverage and a modeling time horizon that spans from 2015 to 2100 in 5-year increments.

GCAM operates by simulating more than a thousand global markets for goods and services, converging upon the prices at which supply equals demand in each. The model steps through time in typically 5-year increments, starting each new time period with the technological stock from the prior period. It then simulates retirement of that stock and demand for new stock, taking into account factors such as population growth and the endogenously determined prices of fuels and other resources. A logistic function is used to determine the mix of technologies that are purchased. This apportionment is typically driven by cost but can be influenced by policies such as pollutant taxes and caps, as well as market share constraints such as onroad vehicle electrification targets and renewable portfolio standards (RPSs) in the power sector.

In the context of a onroad BEV target, GCAM simulates which vehicle technologies are being displaced and the onroad impacts on fuel use and emissions. The model also captures many upstream impacts, simulating how the additional electricity demand would be generated, changes in refinery activity, and changes in oil and gas operations. Since GCAM endogenously calculates energy prices, prices for electricity would likely rise, accompanied by decreases in liquid fuel prices. These price changes, in turn, could impact technology and fuel choices across other sectors, such as industry, and residential and commercial buildings. Changes in the cost of onroad passenger travel could also impact overall travel demand, as well as how that demand is apportioned across passenger cars, motorcycles, buses, and other modes of transit. By taking this holistic view of the energy system, GCAM can simulate the impact of a policy or technology across all major economic sectors.

The emission projections produced by GCAM include GHGs such as CO2 and non-CO2 GHGs (e.g., CH4, N2O, halo- and fluro- carbon), as well as air pollutants including ozone precursors (NOx, CO, VOC) and aerosols (particulates, black carbon (BC), organic carbon (OC) and SO2). GCAM also produces land use and land use change (LULUC) outputs, including changes in land cover and the carbon emission associated with transitioning land from one use to another. Likewise, under water category, the model provides information on the supply and demand of water, including the competition for water resources across various economic sectors.

We use a variant of GCAM, GCAM-USA, version 7.0, that disaggregates the energy system to the state level for the US region [25]. GCAM-USAv7.0 is applied through GLIMPSE (GCAM Long-term Interactive Multi-Pollutant Scenario Evaluator), a decision support tool developed at the U.S. EPA to support long-term planning related to climate, the environment, and energy [26]. GLIMPSE v1.1 includes a reference case that is used as the basis for the scenarios constructed for this study.

For a given scenario, CO_2 emissions within GCAM-USAv7.0 are estimated using projected fuel use and the carbon content of various fuels. Similarly, the air pollutant emissions are estimated as the product of fuel use or service output and emission factors. For onroad vehicles, these emission factors are a function of technology, vintage, and vehicle age. This representation allows incorporation of technology- and vintage-specific emission control requirements, as well as deterioration of control effectiveness over time. In GCAM-USAv7.0, the air pollutant emission factors for transportation sector are derived from the Environmental Protection Agency's (EPA) MOVES 2014 model [27]. In this application, we use onroad factors derived from the more recently released MOVES 3.0 [28], which includes improvements such as updates to vehicle population, travel activity, and emission rates, as well as incorporation of impacts of the Heavy-Duty Greenhouse Gas Phase 2 rule and the Safer Affordable Fuel-Efficient (SAFE) Vehicles Rule [25].

In our analysis, we group the transport sector outputs from GCAM-USAv7.0 into the following categories: onroad light-duty passenger vehicles (LDV), onroad heavy-duty freight vehicles (HDV), buses, and domestic and international air, locomotive, and marine (ALM). GLIMPSE, which is built on GCAM-USA groups together categories such as ALM to keep on-road, (i.e., transport-LDV, and transport-HDV) and non-road separate. The LDV category is further disaggregated into the classes "Cars" and "Large Cars and Trucks", with the latter class including minivans, SUVs, and light pickup trucks. Within each class, the vehicles are further categorized based on fuel or technology, including battery electric vehicles (BEV), fuel cell electric vehicles (FCEV), hybrids, and conventional ICE vehicles. Note that GCAM-USAv7.0 does not differentiate among gasoline, diesel and biofuel at the pump, referring to the combination as refined liquids used in conventional ICE vehicles. Our study largely focuses on BEV in the LDV "Cars" and "Large Cars and Trucks" classes, as those classes together comprise 84% of annual onroad passenger travel, while the remaining 16% comes from public buses and 2-wheeled vehicles.

According to the new GHG standards set for light-duty vehicles, electrification of the two GCAM-USAv7.0 onroad LDV categories, "Cars" and "Large Cars and Trucks", is expected to reach 16% and 11%, respectively, where electrification includes both plugin hybrid and fully electric vehicles [29]. However, plugin hybrid vehicles are not separately categorized in the GCAM-USAv7.0. Instead, we assume these targets will be met by a combination of BEV and fuel-cell electric vehicles (FCEV). FCEVs are electric vehicles that employ a hydrogen fuel cell as an on-board power source [25]. We made an assumption of average battery size of FCEVs to be one-fourth of that of BEVs, similar to the relative size difference between BEVs and plugin hybrids (Table C in S1 Text) [30]

GCAM-USAv7.0 apportions share of sales within a market as a function of the relative costs of technologies, modified by a technology-specific parameter called a shareweight which is intended to represent consumer biases and other factors not explicitly included in GCAM. In addition, the logit parameter specifies how much differences in price matter. By convention, a shareweight value of 1.0 signifies that there is no bias for or against the technology, and that its share of new sales is determined solely on differences in price (assuming the shareweights of other technologies are also 1.0). Shareweights can be greater than 1.0, signifying a preference for the technology; below zero, indicating a bias against the technology such as range anxiety; or zero, indicating that there would be no sales share regardless of the cost [25]. The retirement of onroad vehicles is modeled using an s-curve which is parameterized by variables such as lifetime, half-life and slope.

Our scenarios, which are described in the next section, are derived from the GLIMPSEv1.1 reference scenario. The GLIMPSE reference scenario [26] builds upon the GCAM-USAv7.0 reference case in several ways, including the following: fixing a bug associated with stationary battery storage; incorporating a representation of the Regional Greenhouse Gas Initiative (RGGI), which caps electric sector emissions for 11 states; representing state-level Renewable Portfolio Standards (RPSs) that specify minimum renewable contributions to electricity production; including historical coal plant retirements through 2021; and updating emission factors and lifetime and retirement assumptions for onroad vehicles [31]. The GLIMPSEv1.1 reference scenario does not include representations of the Bipartisan Infrastructure Law of 2021 [32] and the Inflation Reduction Act of 2022 [33]. Note that the GLIMPSE reference case inherits most assumptions from the GCAM-USAv7.0 reference case, including that no new coal plants without carbon capture will be added to the power sector after 2015.

In addition to the combustion-based emissions from the transport sector, GCAM also includes emissions associated with extraction and refining of the fossil fuels and biofuels used in ICE vehicles (see section 2.3 for details). Since biofuels are considered to have lower life cycle emissions than fossil fuels, the use of blended fuel implicitly results in lower net CO_2 emissions than use of 100% gasoline [34–36].

2.2 BEV projection scenarios

Our study design takes the form of a parametric sensitivity analysis in which we scrutinize four scenarios of varying rates of BEV adoption in the US LDV market (Fig 1). Heavy-duty electric vehicles are also simulated, although GCAM-USA v7.0 is allowed to choose their market shares endogenously. These scenarios represent four increasingly optimistic views of plausible trajectories for BEV market share. The lowest trajectory is based on the GLIMPSE 1.1 reference scenario. This reference scenario (REF) estimates a BEV sales share of 14% in 2025, which rapidly reaches 32% in 2030, increases to a peak value of 34% in 2035, and then stabilizes to 31% in 2050. The other scenarios, given the names Optimistic (OPT), Progressive (PRG), and Ambitious (AMB), include higher BEV sales targets. These scenarios are implemented using lower-bound market share constraints that were constructed using GLIMPSE. In OPT, the BEV sales share is set to be approximately 50% higher than in the REF scenario, leading to a BEV sales share of 46% in 2050 (Fig 1).

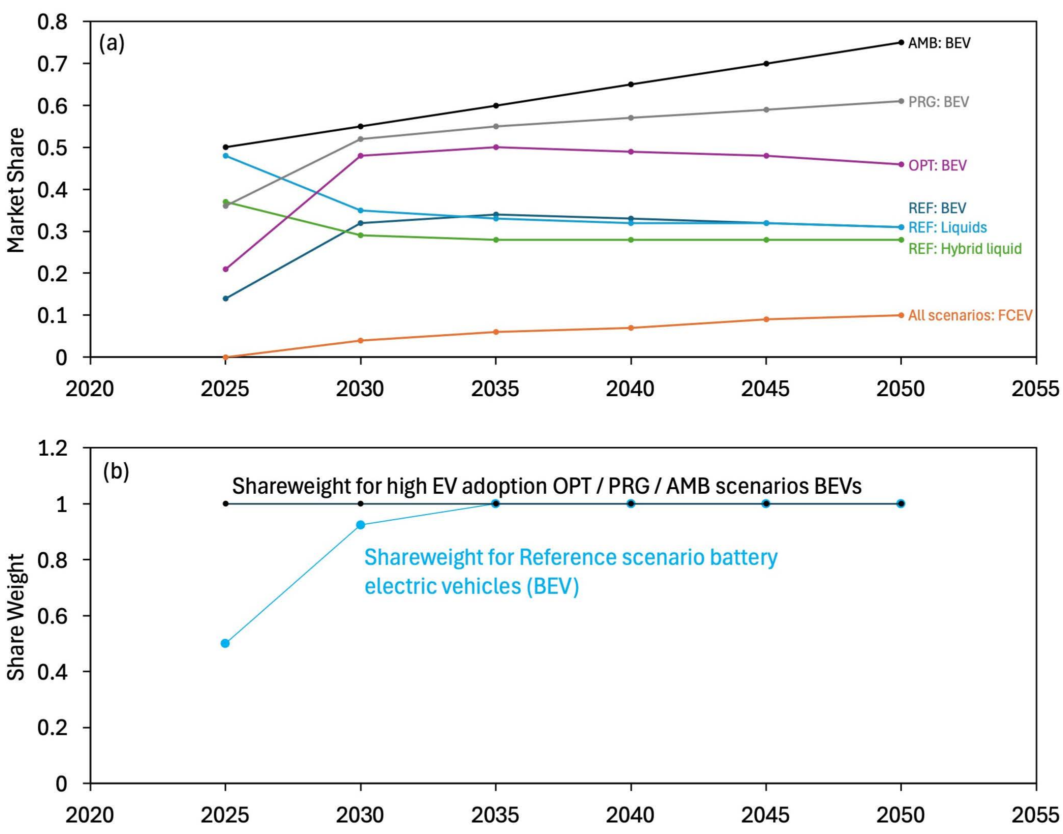

Fig 1. (a) Market share and (b) shareweight for reference and three defined high battery-based electric vehicle scenarios.

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The AMB scenario, which is the most ambitious scenario, assumes that BEVs reach a 75% sales share by 2050. This scenario is extrapolated from BNEF's projection of 60% sales share in 2040, similar to that found in Ou et al., [18]. To develop market shares over time for AMB, we work backwards, incrementing the target down by 5% every five years starting with 75% sales in 2050 and reaching a market share of 50% in 2025. Finally, in the PRG scenario, we assume a sales share that is an average of the OPT and AMB scenarios at each five-year interval, thus reaching 61% of sales by 2050. In implementing the high BEV scenarios, we found that the high sales shares were difficult to achieve under the shareweight assumptions in REF, which included some assumed bias against BEVs until 2035. Fig 1(b) shows the shareweights considered in our study. Under the REF, the default shareweight values are, for 2025: 0.5, 2030: 0.92, and 2035 onwards till 2050: 1.0. Under high BEV adoption rates, we have assumed shareweight value of 1.0 from 2025 through 2050, allowing the model to achieve the higher targets.

2.3 Emissions associated with additional factors

In life cycle analysis, vehicle-related emissions are typically represented using the following components: extraction and production of fuels (also referred as well-to-tank (WTT) emissions), vehicle manufacturing, and operation and maintenance, and combustion of fuel in ICE vehicles or energy associated with lithium-ion batteries in electric vehicles (also referred as TTW tank-to-wheel emissions). Because of the GCAM-USAv7.0 multi-sector coverage, it is used to characterize most WTT and TTW emissions for this study; however, vehicle and battery production are not represented in GCAM, so we rely on the literature to obtain emission factors for these activities.

For emissions associated with vehicle manufacturing, and operation and maintenance we refer to Hill et al., [37], Bieker [38], and Kelly et al., [39]. We follow the methodology from Bieker [38], where the vehicle weight-based emission factors (tonne CO_2 eq./tonne vehicle) compiled from passenger cars in European Union and United Kingdom by Hill et al., [37] are used to estimate emissions (Table A in S1 Text). Here CO_2 eq emissions are treated as CO_2 emissions, implicitly making the assumption that the impacts of non-CO_2 GHGs are negligible compared to CO_2 [39]. For the weight of the vehicle as per the fuel category in the US we refer to Kelly et al., [39] (Table A in S1 Text).

The GCAM model estimates the energy and emissions associated with 'fuel production', including extraction, processing, and refining of liquid and biofuels, as well as the production of hydrogen. This category forms the basis of our life cycle emissions for ICE vehicles. Changes in emissions associated with the transportation of fuels (e.g., via pipelines, rail, barges, and trucks) are not included in this study but are likely relatively small relative to changes in onroad, powerplant, and refinery emissions. Similarly, infrastructure-related activities such as construction of roads, refineries and oil rigs are beyond the scope of this study.

For life cycle GHG emissions from the extraction and processing of material used in lithium-ion batteries, we refer to Kelly et al., [40] and Bieker [38] studies. Li-ion batteries production involves steps including extraction of raw materials such as nickel, aluminum, and cobalt sulfate, as well as assembly of the battery cell, battery management system, and NMC111-graphite chemistry for the cathode. NMC111 indicates a cathode with equal molar ratios of Nickel, Manganese, and Cobalt (Ni:Mn:Co). Kelly et al., [40] used Argonne National Laboratory's Greenhouse gases, Regulated Emissions, and Energy use in Transportation (GREET® - Version 2020) model to examine Li-ion production including the associated supply chain and electricity mix in the US and other regions globally. By default, the GREET model contains material and production supply chain for NMC111, that dominates the global automotive markets [41]. Results from Kelly et al., [40] indicate that GHG emissions from NMC111 Li-ion battery produced in the US would generate 75 kg CO_2 eq/kWh emissions, which has been used in this study. This value was found to be within the range of values found in the literature [10,42]. Here CO_2 eq emissions are treated as CO_2 emissions.

2.4 Social cost of atmospheric release (SCAR)

We use the Social Cost of Atmospheric Release (SCAR), a multi-pollutant economic framework valuing both climate- and air quality-related impacts [43], to evaluate the societal impact of the emissions caused by increases in the share of lithium-ion electric vehicles in the US transport sector. US-specific values from the literature [43] were calculated with a declining discount rate over time. The 2007 per-tonne values are inflated to 2023 assuming an average inflation rate of ~2.6% (Table 1) to estimate the total SCAR. We have limited the estimation of damage cost to CO_2, CO, SOx, and NO_X pollutants only.

3. Results

In this section we present the results of the four scenarios described in Section 2.2. As our scenarios focus on increasing sales shares for LDV BEVs, we expect the greatest responses to be on energy use and emissions in the transport sector. However, we also quantify changes in energy and emissions from electricity generation, industry, commercial and residential sector as they respond to transport sector policy. Finally, when estimating the change in CO_2 emissions and other air quality pollutants per GWh lithium battery added, we only consider the analyses of the sales of new vehicles rather than the combination of new and existing passenger vehicles. This approach allows us to isolate the impact of the newly introduced Li-ion battery electric vehicles in the market.

3.1. Projection in travel demand and electricity production

Under REF, GCAM projects an increase in travel demand in all passenger vehicles except buses from 2020 to 2050. Table 2 shows the percent change in passenger-km travelled from 2020 to 2050 in four scenarios.

Although there is an increase in the LDV travel demand under all scenarios (Table B in S1 Text), we observe a small decrease in passenger-km across the high BEV defined scenarios, OPT – PRG – AMB relative to REF (Table 2). Demand response and mode shifting are expected as our scenarios push BEV adoption beyond the equilibrium levels simulated in REF. For example, increase in allocation of ridership to motorcycles (e.g., "2-Wheeler & 3-Wheeler") is indicative of GCAM simulating the dynamics of vehicle choice. In this instance, forcing BEV sales share beyond their equilibrium levels results in a higher cost of onroad travel in the "Cars" and "Large Cars and Trucks" categories. The model simulates that this would increase motorcycle ridership in response. Note that while the percent changes in motorcycle demand are large compared to many other categories, these percent changes occur within a relatively small category.

Using an average battery size per vehicle (Table C in S1 Text) and number of BEV vehicles in each scenario (see Text A in S1 Text, Table D in S1 Text), we estimate the total gigawatt-hours (GWh) of batteries required in the new passenger cars and trucks in each modeled year from 2020 to 2050 (Table 3). Our calculation of total GWh battery output includes an

Table 1. SCAR per-tonne damages used for economic evaluation (2023 $US).

Species	CO_2	SO_2	CO	NO_X
SCAR metric (damage in $USD per tonne of emissions)	170	75000	1100	130000

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Table 2. Percent change in passenger-km travelled from 2020 to 2050 in four scenarios.

Vehicle categories	Reference	Optimistic	Progressive	Ambitious
Cars, large cars and trucks	23	23	21	19
2-Wheeler & 3-Wheeler	126	141	152	160
Bus	-7	-5	-4	-1
Domestic Aviation	98	86	87	88
High Speed Rail (HSR)	1330	1300	1310	1310
International Aviation	69	68	68	68
Passenger Rail	28	29	30	31

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Table 3. Estimated quantity of batteries, in gigawatt-hour (GWh), added from sales of new light-duty vehicles (LDV) in the "Cars" and "Large Cars and Trucks" categories.

Scenarios	2020	2025	2030	2035	2040	2045	2050
Reference	8	152	454	586	740	761	770
Optimistic	8	205	692	886	1120	1150	1150
Progressive	8	370	780	986	1320	1450	1560
Ambitious	8	518	855	1080	1520	1730	1930

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assumption that specific energy capacity will increase from 40 kWh in 2020–150 kWh in 2050 (Table C in S1 Text). This calculation indicates that 770 GWh lithium batteries will be added from sales of new LDV in 2050 in the REF scenario, which is ~ 100 times higher compared to the 8 GWh total capacity in 2020. The increase in lithium battery demand for the other scenarios is roughly proportional to their higher BEV deployment targets, reaching 1150 GWh in OPT, 1560 GWh in PRG and 1930 GWh in the AMB scenario in 2050.

Compared REF, the high BEV scenarios further increase the need for electricity production. The 25.7 EJ of electricity produced in 2050 in the REF case increases to 27.9 EJ in the AMB scenario, which reflects an increase of 9% in the high BEV case (Fig 2). Fig 3 shows the electricity production by various fuel sources and the incremental difference relative to REF. In 2030, the electricity production in REF was dominated by gas (37%) and wind (17%), followed by nuclear (15%), coal (13%), solar (11%) and hydro (5%). By 2050, the mix of these sources transitioned to gas (44%), wind (22%), solar (17%) with small fractions from coal (6%), nuclear and hydro (4% each). Under the high BEV scenarios we observe an additional incremental shift to gas, solar, wind and nuclear - sources typically associated with lower emissions. This trend is driven both by the assumption in our scenarios that new conventional coal plants will not be built during the modeled time horizon and the inclusion of regional policies such as RGGI and state RPSs. The net impact of these factors is that the CO_2 and air pollutant intensity of electricity production declines over time.

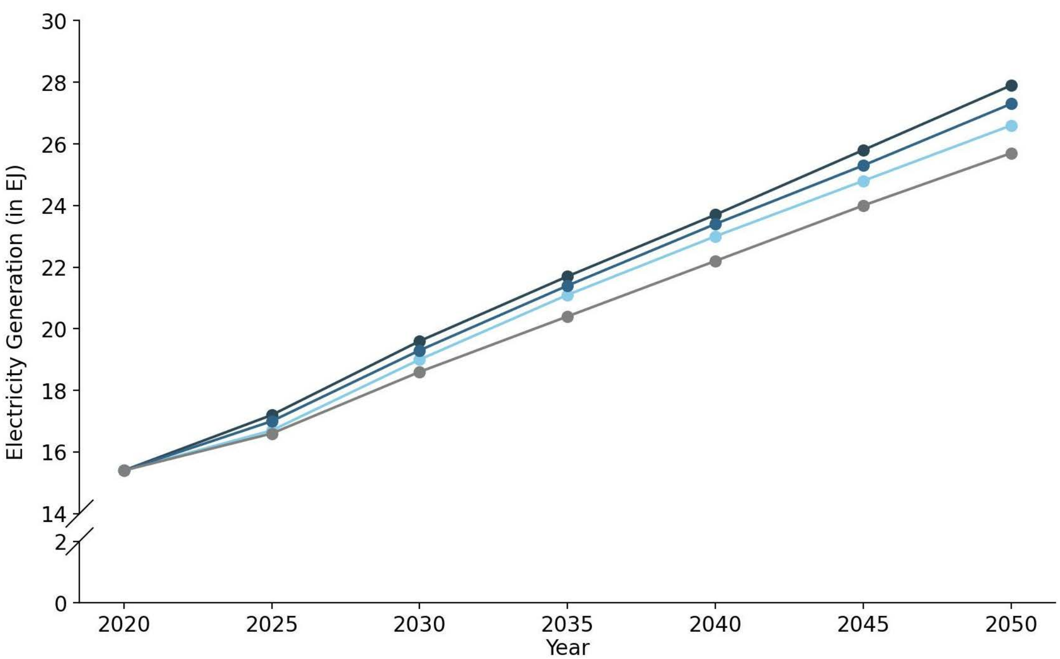

Fig 2. Total electricity produced (EJ) in each scenario.

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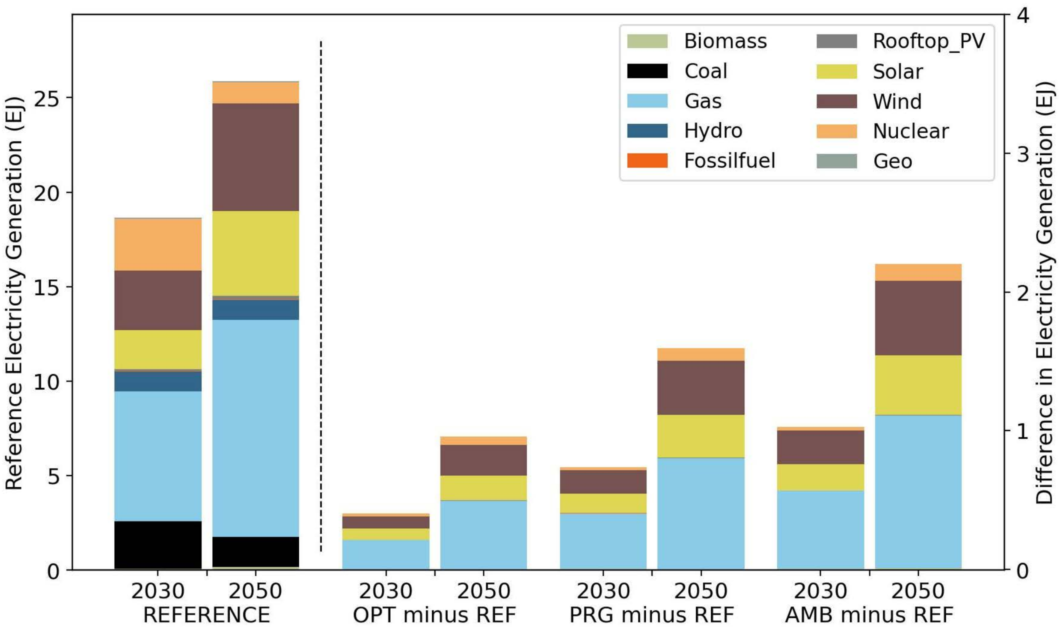

Fig 3. Electricity production (EJ) by different fuel mix in REF (left axis) and increase in electricity production in high BEV scenarios calculated as a difference with respect to REF (right axis).

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Over the period extending from 2020 to 2050, we also observe increasing demands for electricity across each economic sector (Table E in S1 Text, Fig 4), as well as shifts in the portions of consumed by each sector shifts. In 2030, residential and commercial buildings consume 35% and 33% each of generated electricity, followed by 24% industry, 6% transport-LDV, ~ 1.4% fuel production, and ~0.4% each for transport-ALM, and -HDV. In 2050, under the REF scenario the share consumed commercial by buildings drops to 27% and residential share drops to 33%, while shares to transport-ALM and -HDV increased to 2% each, and transport-LDV grow to 8%.

In Fig 4, we delve into the electricity demand trajectories for each scenario, exploring underlying sectoral changes. Under REF, overall electricity demand grew from 17.2 EJ in 2030 to 23.8 EJ in 2050, driven by increasing electricity demand from buildings (2.4 EJ), industry (1.9 EJ), and transport-LDV (1.1 EJ). For each of the high BEV scenarios, OPT, PRG, and AMB, electricity demand from transport-LDV increased substantially (in 2030, 1.4 EJ, 1.7 EJ, and 2.0 EJ, respectively; in 2050, 2.9 EJ, 3.6 EJ, and 4.2 EJ, respectively), driving the overall trend of increased growth. There were small decreases in electricity demand from other sectors, although these changes were small relative to the increases in LDV.

3.2. National CO_2 and air pollutant emissions and trends

In REF, from 2020 to 2050, the net CO_2 emissions decrease by 10%. This decrease is larger in the high BEV scenarios, where the net CO_2 emissions are reduced by 12% in OPT, 13% in PRG and 14% in AMB scenario (Table 4). In the case of CO, we observe a similar trend in emissions reduction from 2020 to 2050, as well as from REF to the high BEV scenarios. The CO emissions in REF decrease by 28% from 2020 to 2050 while these reductions are even higher in the high BEV scenarios (Table 4). However, we do not observe a similar trend in reductions for SO_2 emissions across the high BEV scenarios. The SO_2 emissions decrease by 9% from 2020 to 2050 in REF, with negligible change under the high BEV scenarios, unsurprisingly as there is no noticeable difference in coal-fired electricity generation (Fig 3). Across the high BEV scenarios, higher electric vehicle adoption results in clear but small reduction in NOx emissions (Table 4).

Emissions are further examined at the sectoral level to understand the changes driven by the high BEV scenarios. Fig 5 shows the sectoral CO_2 emissions from REF in 2030 and 2050 (left axis) and its difference with high BEV scenarios (right axis). Under REF, it is projected that, on average, electricity production in the US contributes 29% of CO_2, followed by 21% from industry, 13% transport-LDV, 11% transport-HDV, 9% transport-ALM, 10% buildings-residential and

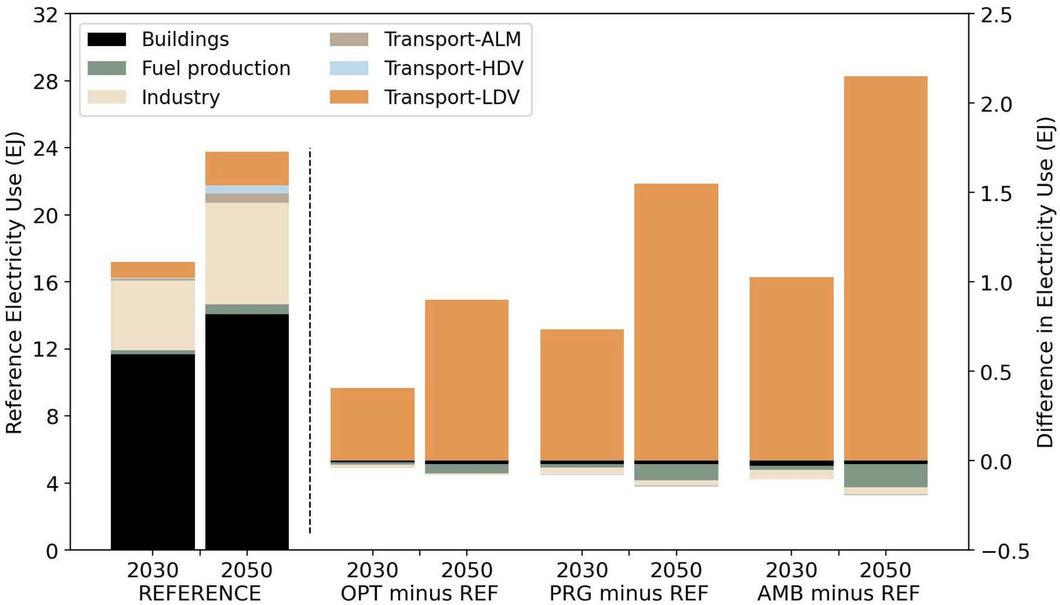

Fig 4. Electricity use (EJ) by different sectors in REF (left axis) and increase in electricity use in high BEV scenarios calculated as a difference with respect to REF (right axis). Buildings include both the residential and commercial sectors. Transportation is grouped into ALM – Air, locomotive, marine; HDV – heavy-duty vehicles; and LDV – light-duty vehicles.

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Table 4. Emissions for greenhouse gas and air quality pollutants from 2020 to 2050 across all scenarios (in Tg/yr).

	Scenarios	2020	2025	2030	2035	2040	2045	2050
CO_2	REF	4690	4640	4410	4290	4270	4230	4200
	OPT	4690	4620	4360	4230	4210	4150	4120
	PRG	4690	4590	4330	4190	4180	4110	4070
	AMB	4690	4560	4300	4170	4150	4070	4010
CO	REF	25.88	22.66	20.71	19.76	19.29	19.12	18.51
	OPT	25.88	22.48	20.24	18.92	18.18	17.85	17.29
	PRG	25.88	22.14	19.78	18.39	17.58	17.14	16.43
	AMB	25.88	21.81	19.37	17.90	17.02	16.46	15.62
SO_2	REF	1.83	1.85	1.73	1.70	1.72	1.71	1.66
	OPT	1.83	1.85	1.73	1.70	1.71	1.71	1.66
	PRG	1.83	1.85	1.73	1.70	1.72	1.71	1.65
	AMB	1.83	1.85	1.73	1.70	1.71	1.71	1.65
NO_x	REF	6.44	5.71	5.07	4.69	4.72	4.80	4.89
	OPT	6.44	5.70	5.07	4.68	4.71	4.79	4.87
	PRG	6.44	5.69	5.08	4.67	4.70	4.78	4.87
	AMB	6.44	5.70	5.08	4.68	4.70	4.78	4.85

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-commercial, and 7% fuel production (Fig 5). In the high BEV scenarios, we observe CO_2 reductions from transport-LDV (-54% in AMB 2050 compared to REF 2050) and fuel production (-19% in AMB 2050 compared to REF 2050), highlighting the increase in the market share of passenger BEVs and the decrease in the demand from the fossil fuel-based passenger vehicles. In contrast, CO_2 increases from electricity production (6% in AMB 2050 compared to REF 2050), a result of fulfilling the demand for additional electric charging in high BEV scenarios.

Fig 6a-c shows the sectoral change in CO, SO_2, and NO_x emissions. From Fig 6a-c, in REF, the industry sector accounts for ~40% of CO, SO_2, and NO_x. Apart from industry, for CO, the emissions are largely emitted from transport-LDV (37%). For SO_2, electricity production (32%) and industrial processes (19%) dominate, while for the largest emitters of NO_x are transport-HDV (22%) and transport-ALM (10%). A shift towards BEVs tends to demonstrate change in the most directly impacted sectors, including transport-LDV, electricity production, and fuel production. There are also relatively small changes in other sectors, including industry and transport-HDV.

The sectoral changes in CO in the high BEV scenarios are mainly governed by the level of BEV market share in the transport-LDV, where emissions are reduced as much as 50% in AMB. Increasing electricity production has a small impact on CO, leading to a 6% increase in AMB compared to REF in 2050. While CO emissions primarily originate from the incomplete combustion of fossil fuels in all sectors, light-duty vehicles are a major source. A minimal change in CO from the industry sector suggests no sudden shift in fuel technology (Fig 6a).

For SO_2 (Fig 6b), increasing the BEV sales share results in approximately a 54% reduction in emissions from transport-LDV and an 11% reduction from fuel production. However, industry, electricity production, and industrial processes are the major sources of SO_2, and from Fig 6b we see that SO_2 from industry tends to increase by 0.5% along, along with a very small increase from electricity production. The increase in the industrial sector is driven by cross-sector dynamics. The increased demand for electricity results in higher prices, and a small portion of electricity use in industry is replaced by other fuels, such as refined liquids, gas, and coal.

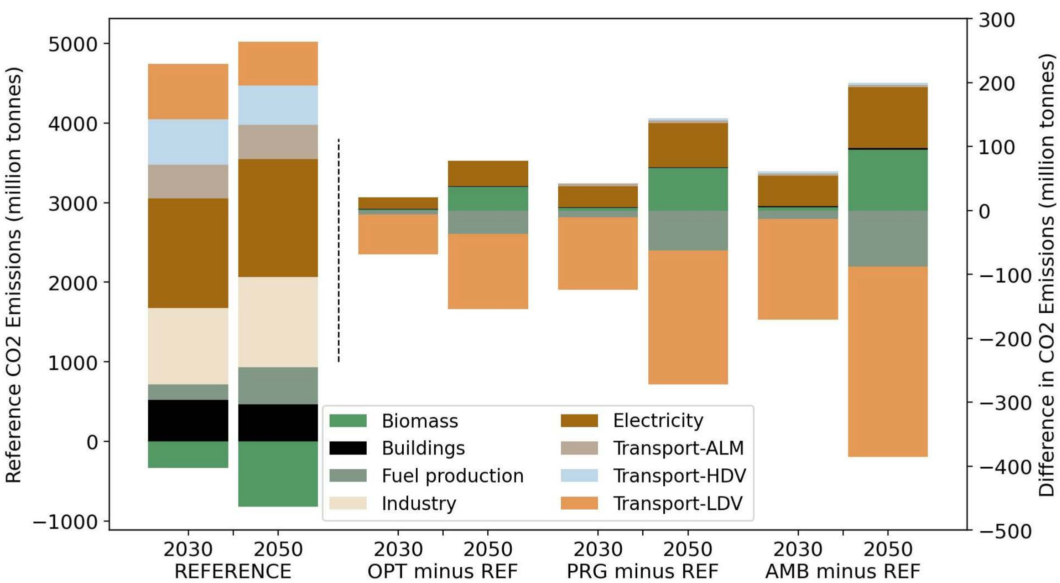

Fig 5. Sectoral CO_2 emissions (million Tonnes) in REF. The left-axis and right-axis shows the change observed in CO_2 emissions in high BEV scenario calculated as a difference with respect to REF. The negative CO_2 emissions from biomass in REF implies carbon dioxide drawn from the atmosphere. Buildings include both the residential and commercial sectors. Transportation is grouped into ALM – Air, locomotive, marine; HDV – heavy-duty vehicles; and LDV – light-duty vehicles.

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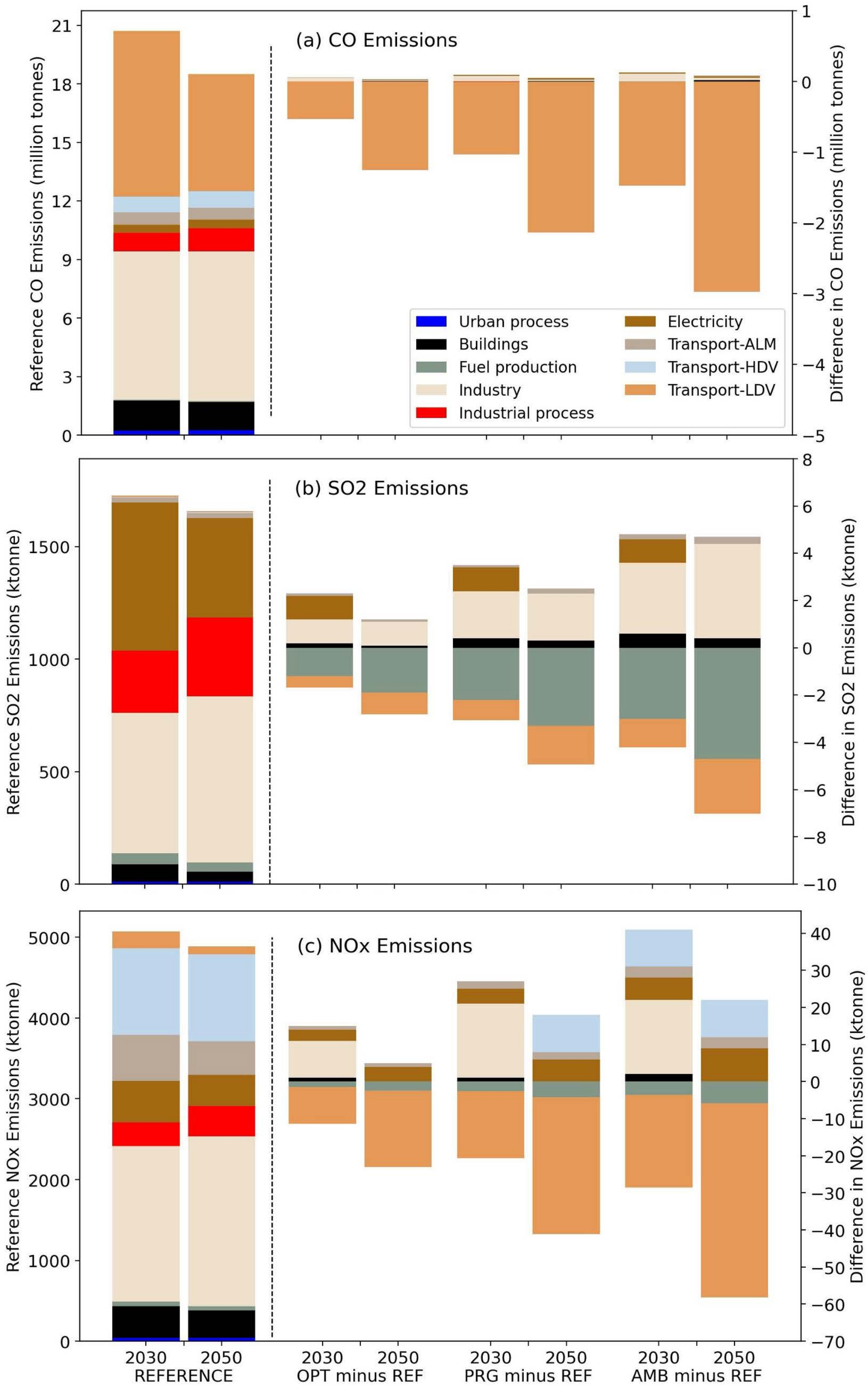

Fig 6. Sectoral. (a) CO (million Tonne), (b) SO_2 (ktonne), and (c) NO_x (ktonne) emissions in REF (left-axis) and change observed in emissions in high BEV scenario calculated as a difference with respect to REF (right-axis).

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This increase of SO_2 from electricity production appears 2030 but is no longer apparent 2050. This response reflects potentially important dynamics in the electric power sector. From 2020 to 2030 under REF, GCAM-USAv7.0 predicts that there will be some retirement of coal power plants. However, under the high BEV scenarios, there is increased demand for electricity, increasing electricity prices, and changing the economics of operating older, less efficient coal plants. In the model, the result is delayed retirement and an increase in coal plant emissions relative to REF. Though the differences in net SO_2 emissions relative to REF are very small, the SO_2 emissions under these scenarios represents both the offsetting effects along with the smaller change in magnitude relative to total emissions (Fig 6b).

Percentage-wise NO_x reductions from transport-LDV and fuel production are very similar to CO and SO_2, i.e., reductions of 53% and 12% for AMB in 2050 (Fig 6c). The increases in NO_x are mainly from electricity production (2%) and transport-HDV (0.9%), although these increases are minimal compared to their absolute contribution. High NO_x from industry in 2030 suggests greater use of coal that lower emitting sources by 2050.

Fig 7 shows the average emissions per kWh lithium-ion batteries added in 2030 and 2050. The numerator is estimated as the average difference in scenario-based total emissions with respect to the REF. Similarly, the denominator is calculated as the GWh batteries added in each scenario relative to the REF. Finally, we take the ratio of these to compute the change in total emissions per kWh battery added from the sales of new light-duty vehicles. We observe emissions benefits in the short-term (2030) where CO (-2732 g per kWh) and CO_2 (-223 kg per kWh) are reduced, while there is slight increase in SO_2 (1.8 g per kWh) and NO_x (21.9 g per kWh) from the shift towards BEVs. Although BEVs do not have direct emissions like ICE vehicles, the increment in SO_2 and NO_x can be attributed to increased use of coal-based thermal power. While GCAM-USA does not build new coal-fired powerplants, this response results from the decision of the model to delay the retirement of existing capacity, at least in some parts of the country. However, later in 2050, with a cleaner electricity generation sector projected to be in place, we find additional air quality benefits, i.e., reductions in SO_2 (-3.1 g per kWh) and NO_x (-36.1 g per kWh) along with CO (-2782 g per kWh) and CO_2 (-127 g per kWh). The incremental shift in air pollutant emissions can be attributed to the increasing demand for electricity across all the sectors, especially BEV based light-duty vehicles. The increased demand for electricity, combined with RGGI and state RPSs, results in power sector dynamics that serve to drive down the emissions intensity of electricity further. For example, within the Northeast, power sector CO2 emissions are capped by RGGI. Natural gas is a cost-effective component to the mix employed to meet the demand. However, to grow gas capacity while still meeting the RGGI CO2 cap, the model chooses to increase coal plant retirement. This dynamic has the co-benefit of reducing air pollutant emissions since coal plants generally have higher emissions of air pollutants than gas plants. In contrast, the shift in CO2 emissions is driven primarily by projected increases in biofuel usage in ICEs that lead to lower emissions in 2050 relative to 2030.

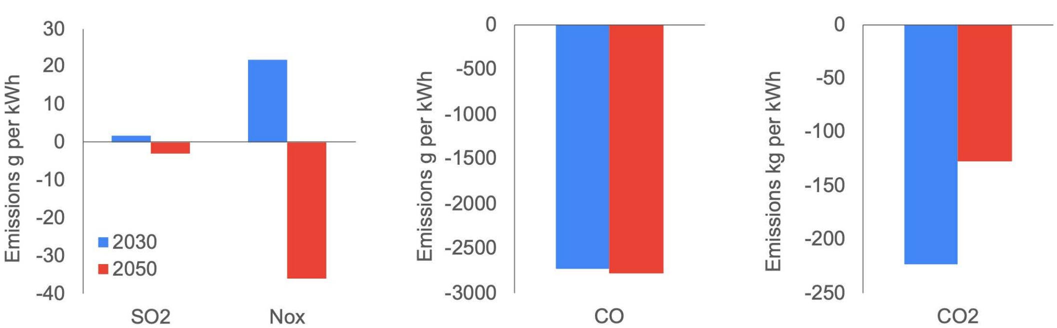

Fig 7. Average SO_2 (in g), NO_x (in g), CO (in g), and CO_2 (in kg) emissions per kWh of lithium battery from sales of new light-duty vehicles (cars, large cars, and trucks) calculated as a difference with respect to REF across all the three high BEV scenarios in 2030 and 2050.

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Finally, examining life cycle CO_2 emissions per vehicle by technologies shows that fossil-based ICEs (100-tonne CO_2 per vehicle) emit ~2 times the amount from BEVs (53-tonne CO_2 per vehicle), while hybrid vehicles (84-tonne CO_2 per vehicle) emit ~1.6 times the emissions of BEVs (Fig 8a). We assume an average life of 18 years for passenger cars in

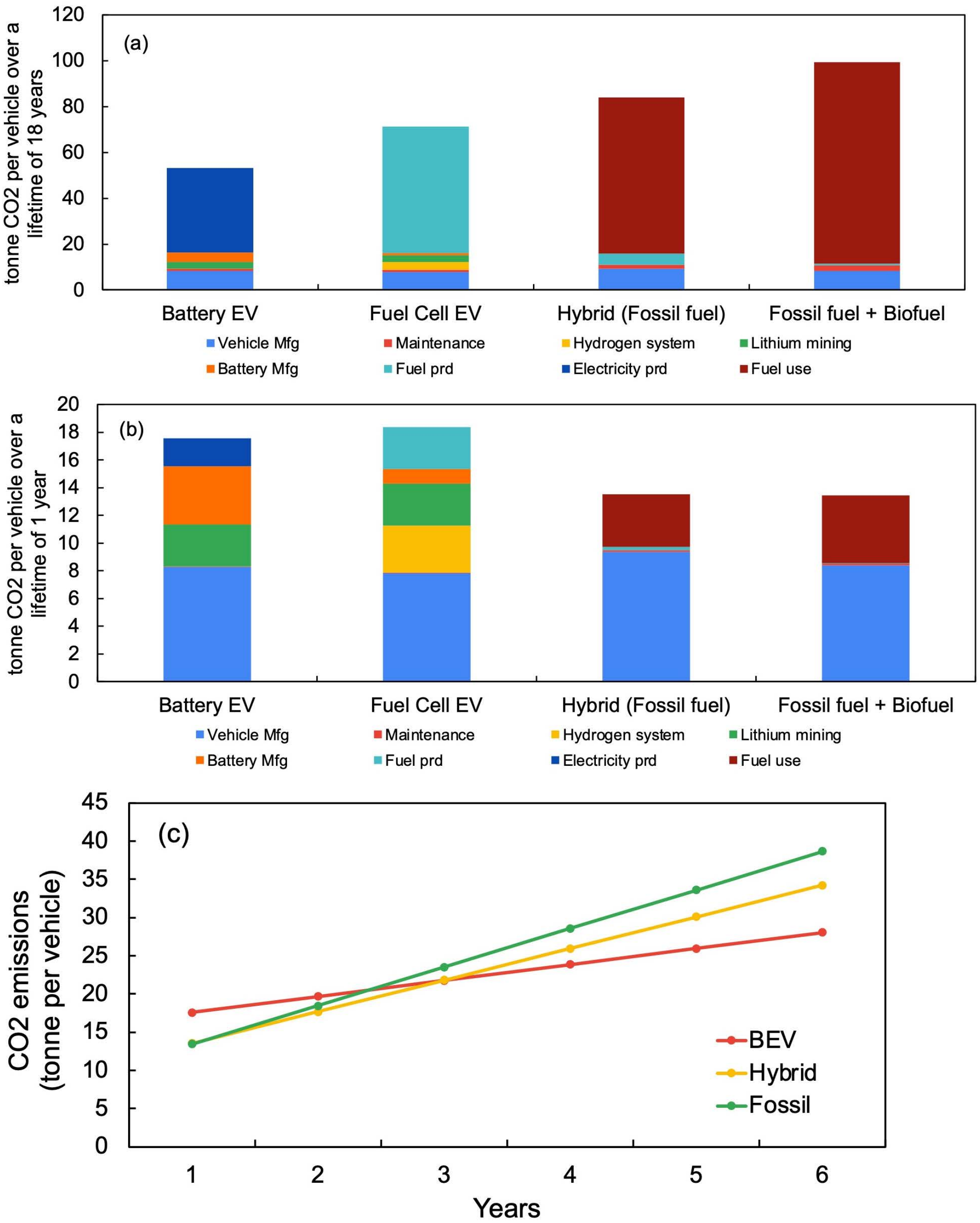

Fig 8. The life cycle-based CO_2 emissions from four technology-based categories of light-duty vehicles in GCAM/GLIMPSE from sales of new vehicles in 2030, (a) during lifetime, assumed to be 18 years (b) during first year (c) shows when the emissions from fossil fuel ICE surpasses BEV, plotted for first six years.

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the United States. Further, BEV and non-BEV vehicles are assumed to be driven similarly, including number of passengers per vehicle and distance driven per vehicle per year. Emission change for LDVs is calculated as weighted averages across the "Cars" and "Large Cars and Trucks" categories in GCAM-USA. Throughout the study we have not accounted for any methane leakage during the production of fossil fuel in case of ICEs or hydrogen fuel from natural gas in FCEVs. Categories within 'tank-to-wheel (TTW)', such as 'fuel use' in case of hybrid and fossil fuel vehicles, and within 'well-to-tank (WTT)', such as 'fuel production' and 'electricity production', contributes the majority of CO_2 throughout the lifetime. However, the CO_2 per vehicle for the first year demonstrates a different narrative where fossil-based vehicles emit less than BEVs (Fig 8b). In the initial first year, the BEVs emits 30% higher than the ICE vehicles. This difference can be explained due to the emission intensive lithium mining and battery manufacturing processes compared to fossil fuel production [39]. After the second year, we see the emissions from BEV and ICE vehicles are similar to one another. As the vehicle ages, the emissions from ICE vehicles increase, especially from fuel use (TTW), surpassing the BEVs before its second year on the road (Fig 8c).

We have also compared GCAM results with the Energy Policy Simulator from Energy Innovation LLC (available at: https://energypolicy.solutions/simulator/us/en; accessed 9 Jan 2024) and found them strikingly different. The policy simulator shows that for a unit change in CO_2 from the transportation sector, the CO_2 from electricity generation decreases by one-third of a unit. Whereas, in GCAM for the same unit change in transportation, the CO_2 increases by one-third of a unit from the electricity generation sector. This is explained by the underpinning assumptions in the policy simulator where the share of renewables rises with increasing BEVs as their batteries are assumed to be able to charge when excess power is available on the grid and hence, they facilitate increased deployment of variable renewable electricity sources. This ultimately causes further reduction in the CO_2 emissions from electricity generation than those under the slower shift away from fossil-based power generation found in GCAM-USAv7.0. Using the electricity generation CO_2 results from GCAM, the tonnes of CO_2 emissions over the 18-year vehicle life cycle become negative (i.e., the electricity production bar in Fig 8 is the same magnitude but the opposite sign, more than offsetting other positive emissions). Hence the reduction in life cycle GHG emissions for BEVs relative to ICEs shown here based on GCAM results may be considered conservative.

3.3. Economic valuation

We evaluated the environmental damage per vehicle using the median value of the SCAR metrics in the broad categories of BEVs and ICEs for REF and AMB (e.g., representing reference and ambitious BEV sales shares). Our estimate of emissions leading to environmental damage costs around \$1605 per year for a 2020 fossil operated passenger car is similar to an earlier estimate of \$1700 per year from a typical midsize US gasoline powered vehicle [43]. Similarly, for battery powered electric vehicles, we estimate damages costing \$626 per vehicle for 2020. This is unsurprisingly lower than \$815 per year for a BEV where electricity is assumed to be generated exclusively from coal [43] and declines over time as the electricity sector becomes cleaner (lesser emissions) with values of ~\$450–650 per vehicle in 2025, depending upon the scenario. In comparison with results from the earlier paper a decade ago [43], values are fairly similar due to the offsetting impacts of including life cycle emissions here (versus operation-related emissions only in the 2015 study) combined with cleaner electricity and vehicles for current systems. The difference in value between BEVs and ICEs can be explained by the suite of pollutants (CO_2, SO_2, CO, NO_x) considered for calculating the damages, with the bulk of the difference coming from the relatively lower CO_2 emissions (~75% of the 2050 benefits, for example, with the remainder nearly all from NO_x and CO reductions).

Our calculation shows the environmental damage from an ICE passenger car is about 2–3 times higher than BEVs in both scenarios for the recent and time periods, 2020–2025 (Table 5). Under both scenarios, the damages from either type of vehicle decrease over time as cleaner sources of fuel are used for electricity generation and fossil powered ICE vehicles achieve tighter emissions standards. The decrease is larger for BEVs, however, so that the ratio of damages from

Table 5. Ratio of environmental damages per vehicle for ICEs/BEVs.

Scenarios	2020	2025	2030	2035	2040	2045	2050
Reference Scenario	2.0	1.9	2.0	2.1	2.2	2.3	2.6
Ambitious Scenario	2.0	2.9	2.8	2.7	2.8	3.0	3.4

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ICEs to BEVs becomes greater over time (Table 5). The growth in the ratio of damages from ICEs to BEVs is even larger in AMB than in REF, indicating that greater deployment of BEVs provides ‘positive feedback’ on the electricity grid leading to cleaner generation overall.

4. Discussion and conclusions

There are several studies that have examined the air pollutant emissions implications of vehicle electrification. Ou et al., [18] used GCAM-USA to conclude that air pollutant emission reductions were possible from onroad vehicle electrification, but that the magnitude of those reductions were impacted by assumptions about how the electric sector will transform into the future and by the potential for fuel switching in other sectors. We also find the potential for air pollutant benefits, but take a different approach based upon exploring the modeled responses to increasingly higher electrification targets. Unlike Ou et al., [18], we also use a much more recent version of the GCAM-USA model (7.0 vs. 5.4), incorporate emissions associated with battery production, take a more battery-centric approach, and translate emission changes into monetized benefit estimates.

Several studies have also incorporated life cycle-based emissions [18–23]. Many of them converge to conclude that Li-ion battery electric vehicles (BEV) have lower overall GHG emissions and cause lesser air pollution than fossil fuel internal combustion engine (ICE) vehicles, while a few disagree [21,44]. This disagreement may arise from differences in the system boundaries used for life cycle assessment (LCA) in these studies, variability in electricity grid mix, driving patterns, and different technology alternatives which result in varying outcomes depending on which life cycle stages are included, and consequently, lead to different conclusions when analyzed spatially. Usually, such studies either analyze the policy interventions in the transportation sector for a year, or if not, multiple years but with a pre-defined mix of fuel technology for electricity generation [18, 38]. Our study provides a unique perspective on how the variable adoption rates of BEVs would eventually affect the CO_2 emissions and criteria pollutants not only from the transportation sector but also dynamically considering the effects from the electricity generation sector as well without setting any targets for that sector’s fuel-mix (instead the model chooses fuels based on cost-optimization). Comparison of the relevant subset of these results with the existing studies shows that the emissions of vehicles with different powertrains lie in the range of values found in literature thereby indicating that the assumptions made in this study (Table G in S1 Text) are reasonable.

Our analyses show that considering the life cycle approach for BEVs and ICEs under higher BEV sales scenarios, emissions associated with BEV are higher than ICEs within the first two years of onroad usage, assuming both the categories of vehicles have travelled similar kilometers. Beyond two years, the emissions associated with BEVs are lower than those associated with the ICEs. The higher initial emissions in BEVs originate from mining of critical components and production of lithium-ion batteries. As fuel technology for electricity generation switches to more renewables, the emissions associated with BEVs are further decreased making the technology cleaner and more sustainable.

Considering the change in emissions per kWh of lithium-ion battery added to the market due to sales of BEVs, we observe reductions of criteria pollutants. We find that there is a reduction in emissions from onroad light duty vehicles (LDV) in REF. Higher rates of BEV adoption would accelerate the emission reduction and help achieve climate targets in future while also improving air quality. It is important to consider that many assumptions have been made to arrive at this conclusion, including those regarding the mileage of the passenger car, life of a vehicle, and average battery size of the passenger car in the US, to name a few. Moreover, we have not considered the associated emissions due to infrastructure required to meet the increasing demand for electric charging nor that for fossil fuel-based vehicles.

Economically speaking, the social costs associated with the emissions associated with vehicles show that the life cycle environmental damage due to BEVs is substantially lower than that caused by ICEs. These differences are dominated by the reduced damages associated with climate change attributable to CO_2 emissions. Recent epidemiological evidence (e.g., Burnett et al., [45]; Turner et al., [46]) suggests that air pollution is likely more damaging to human health than was known when the social costs of air pollution used here were evaluated [43], hence the differences between ICEs and BEVs may be roughly 40% greater in $ per vehicle than those reported here. Nonetheless, when accounting for resource extraction and processing over the whole life cycle, including vehicle manufacturing, and long-term operations, our results indicate that BEVs provide large benefits, with damages currently only about one-quarter to one-third those of ICEs accounting for both climate and air pollution. Those relative benefits are furthermore projected to increase over time as the US electricity grid becomes cleaner.

Note that this application does not explore several categories of emissions, including end of life emissions associated with the disposal or recycling of BEV or ICE components. We also have not considered emissions associated with infrastructure changes (e.g., emissions associated with building charging stations and manufacturing new electricity production technologies). We also focus primarily on damages associated with climate change and air pollution, where there may be other types of damages that are incurred. These limitations represent potential directions for expanding this work.

Supporting information

S1 Text.
(PDF)

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Author contributions

Conceptualization: Drew Shindell.

Data curation: Pankaj Sadavarte, Drew Shindell.

Formal analysis: Pankaj Sadavarte.

Funding acquisition: Drew Shindell.

Investigation: Pankaj Sadavarte.

Methodology: Pankaj Sadavarte, Daniel Loughlin.

Project administration: Drew Shindell.

Software: Pankaj Sadavarte.

Supervision: Drew Shindell.

Validation: Pankaj Sadavarte, Daniel Loughlin.

Visualization: Pankaj Sadavarte.

Writing – original draft: Pankaj Sadavarte.

Writing – review & editing: Drew Shindell, Daniel Loughlin.

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