Does the metric matter? Climate change impacts of light-duty vehicle electrification in the US

Alexandre Milovanoff1,*, Heather L MacLean1, Amir F N Abdul-Manan2 and I Daniel Posen1

1 Department of Civil & Mineral Engineering, University of Toronto, Toronto, Canada
2 Strategic Transport Analysis Team, Transport Technologies R & D Division, Research & Development Center (R & DC), Saudi Aramco, Dhahran, Saudi Arabia

* Author to whom any correspondence should be addressed.
E-mail: alexandre.milovanoff@mail.utoronto.ca

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Abstract

Vehicle electrification is one of the most promising climate change mitigation strategies for light-duty vehicles (LDVs). But vehicle electrification shifts the greenhouse gas (GHG) emission profiles of conventional LDVs with emissions moving upstream from vehicle use to electricity generation and vehicle production. Electric vehicle (EV) deployment needs to be examined with life cycle assessment (LCA), both at vehicle and fleet levels. Climate change assessments of EVs are usually conducted using global warming potential (GWP), a normalized metric that aggregates GHG emissions. GWP suffers from some limitations as it ignores the emission timing over the product life cycle. In this study, we examine climate change impacts of four vehicle technologies (conventional, hybrid, plug-in hybrid, and battery electric vehicles) in the US at vehicle and fleet levels using four climate change metrics (GWP, dynamic global warming impact, radiative forcing impact, and global temperature change impact). One of our key findings is that while the choices of the metric, the analytical time period, and some other key parameters, such as methane leakage rate, may have substantial influences on the results, partial and full electrification remain effective solutions to reduce climate change impacts of the US LDVs. However, the transient effects that exist between GHG emissions, radiative forcing, and global temperature changes imply that climate change impact reductions of vehicle electrification take time to materialize and are overestimated with GWP. It is therefore critical to evaluate large-scale implications of climate change mitigation strategies with multiple metrics to fully capture and assess the expected benefits. We nonetheless found that GWP is a robust metric for climate change mitigation targets of vehicle electrification and remains a good choice for most analysis.

1. Introduction

Greenhouse gas (GHG) emissions from human activities, such as carbon dioxide (CO₂), methane (CH₄), and nitrous oxide (N₂O), are major contributors to global climate change (Forster et al 2021). In the US, fossil-fuel combustion from light-duty vehicles (LDV) accounted for 16% of national GHG emissions in 2020 (US Environmental Protection Agency 2022). To limit the global temperature increase to well below 2 °C, ideally to no more than 1.5 °C above pre-industrial levels by 2100, it is critical to mitigate GHG emissions from LDVs (Milovanoff et al 2020). Electrified vehicles (EVs), such as battery electric (BEVs) or hybrid electric (HEVs) vehicles, offer promising mitigation strategies for LDVs (International Energy Agency 2019). However, EVs that rely on electricity, like BEVs and plug-in hybrid electric vehicles (PHEVs), imply a shift in the GHG emission profiles of LDVs, with emissions moving upstream from vehicle use phase to electricity generation and vehicle production (Nordelof et al 2014). Furthermore, large-scale implications of EV deployment are
bound by the fleet turnover, as only a portion of the fleet is renewed annually (Milovanoff et al. 2020). Therefore, EVs need to be examined using life cycle assessment (LCA), a method that evaluates the environmental impacts of products across their life cycle stages (International Organization for Standardization 2006), both at vehicle and fleet levels.

When an EV is compared with a conventional vehicle at a vehicle-level with LCA, the key factors determining the climate change impacts of EVs are the sources of electricity to power the vehicle, and the size and type of the battery installed (Rosenfeld et al. 2019, Abdul-Manan 2015, Wu et al. 2019b, Mendoza Beltran et al. 2020). In the US, EVs tend to have lower life cycle GHG emissions over their lifetime compared to an average conventional vehicle (Wu et al. 2019a). When LCA is combined with models that simulate LDV fleet turnover to assess large-scale GHG emission implications of EVs within a city (Bohnes et al. 2017), region (Doluweera et al. 2020), or country (Milovanoff et al. 2020) over a period of time, GHG emission reductions are expected to take years to materialize. Importantly, climate change impacts of EVs are typically determined by aggregating the various GHGs emitted throughout the life cycle with characterization factors called global warming potentials (GWPs). However, there are known limitations associated with the use of GWPs in a time-resolved LCA model and, to date, there is little information on the climate change impacts of EVs at vehicle and fleet-levels using other climate change metrics.

Climate change from anthropogenic GHG emission follows a long and complex cause-effect chain. First, GHGs are emitted and accumulate in the atmosphere. Then, changes in GHG concentrations induce radiative forcing, a net change in the energy balance of the Earth system (Forster et al. 2021). Radiative forcing implies transient responses from the climate system that lead to changes in the global mean temperature. Ultimately, global mean temperature rises increase the likelihood of extreme and irreversible damages on ecosystems, communities, and the overall global economy (Stocker et al. 2013). Modelling the causal chain from GHG emissions to temperature changes and subsequently to socio-ecological impacts is complex and involves a high degree of uncertainty. To simplify the process of examining products and activities from a climate change perspective, GWPs have been widely used by the scientific community and date back to the First Assessment Report by the Intergovernmental Panel on Climate Change (IPCC) (Houghton et al. 1990).

GWPs are normalized metrics calculated by dividing the cumulative radiative forcing (CRF) of a GHG emission pulse over an analytical time period by that of a CO₂ emission pulse. GWPs are used to compare GHGs at one point in time after the emissions (e.g., 20 years or 100 years), however, this comes with several limitations. First, as a midpoint assessment technique, GWPs only consider the atmospheric concentration and radiative forcing components within the climate change cause-effect chain and therefore, they do not account for the climate sensitivity and the resulting socio-ecological damages (Shine et al. 2005, Sproul et al. 2019). Second, GWPs compare emission pulses over a fixed analytical time period and ignore the emissions timing over the product life cycle. Therefore, using GWPs implies that either all the GHGs are emitted at the same time (Peters et al. 2011b), or that the analytical time period is not fixed and moves along with the emissions. This is particularly limiting for systems with distinct temporal GHG emission profiles like a biofuel compared to a petroleum-based fuel (Levasseur et al. 2010). Given these limitations, several alternative climate change metrics have been proposed.

The goal of a climate change metric is to compare climate change impacts of different GHG emission profiles. The metrics can be absolute or normalized (Peters et al. 2011b). In a normalized metric, which is more commonly used in the literature, the equivalent climate change impact of a particular GHG is determined relative to a reference GHG (typically CO₂), or relative to the GHGs emitted from a reference technology. In contrast, absolute metrics represent the impacts of GHG emissions on some physical attributes as a function of time. GWP is the most common normalized metric and ends midway through the climate change causal chain, at the radiative forcing stage. The global temperature change potential (GTP), also a normalized climate change impact metric, was proposed by Shine et al. (2005) to account for the potential changes to the global temperature (at a given point in time) due to GHG emissions relative to that of CO₂. Peters et al. (2011a) built upon the GTP metric and suggested the integrated GTP (iGTP) metric. iGTP integrates the potential temperature changes due to GHG emissions over an analytical time period. The GTP and iGTP metrics are similar to the GWP metric but are a step further along the cause-effect chain as they include a climate response function. These metrics only compare GHG emission pulses and are, therefore, less appropriate for examining systems with different temporal GHG emission profiles. Several researchers developed different methodological approaches to enable the treatment of time in normalized climate change metrics. For example, O’Hare et al. (2009) proposed the fuel warming potential metric to assess CO₂ emissions of biofuels and petroleum-based fuels by dividing the CRF of biofuels over an analytical period by that of a reference fuel. Kendall et al. (2009), (2012a), (2012b) suggested time correction factors to differentiate present and future emissions. Alvarez et al. (2012) introduced the technology warming potential metric to assess pulse or sustained emissions of different technologies by comparing their CRFs with that of a reference technology. Finally, Sproul et al. (2019) went further along the climate change causal chain by developing the dynamic global warming impact (DGWI).
metric to estimate the social costs of future GHG emissions relative to the cost of emitting CO₂ today. The metric monetizes the potential social costs of emitting GHGs at particular point in time up to the year 2300 and discounts them to a present-day value.

A key limitation of a normalized metric is the aggregation of GHG emissions to a particular point in time, therefore losing the time-resolved physical impacts of the GHGs emitted over time. Hence, absolute metrics have emerged as a means to represent the impacts of GHGs on some physical quantities as a function of time. For example, Edwards and Trancik (2014) and Levasseur et al (2010) directly calculated radiative forcing of GHG emission profiles to compare alternative products or technologies. Peters et al (2011b) calculated radiative forcing and global temperature changes of GHG emissions from different conventional transport modes (e.g., car, bus, train, aircraft) over time. They argue that directly calculating physical impacts of GHG emissions as a function of time, such as global temperature changes, can inform different types of damages. For example, the level of temperature change is a relevant metric for examining heat waves or other potential weather events, while the rate of warming helps inform the impacts of GHGs on the ability of species to adapt/migrate, and finally the cumulative temperature change is linked to long-term sea-level rise (Peters et al 2011b). It is therefore essential to explicitly calculate climate change perturbations to better assess and inform the different aspects and impacts of climate changes.

LCAs applying alternative climate change metrics have typically focused on biofuels (Kendall et al 2009, O’Hare et al 2009, Levasseur et al 2010, Edwards and Trancik 2014), conventional transport technologies (Peters et al 2011b, Alvarez et al 2012, Edwards and Trancik 2014), natural gas vehicles (Edwards and Trancik 2014, Alvarez et al 2012), natural gas power plants (Alvarez et al 2012, Farquharson et al 2017, Lan and Yao 2022), renewable energy sources (Sproul et al 2019, Ravikumar et al 2014), and buildings (Kendall 2012). These studies indicate that early-life GHG emissions from capital investments or land use changes create larger climate change impacts than later emissions when radiative forcing and global temperature change are considered over a fixed time period. Conversely, when social damages are considered over long periods of time, later emissions have potentially higher associated damages than early-life GHG emissions (Sproul et al 2019).

Importantly, the studies also suggest that GWP tends to underestimate the climate change impacts of CH₄ (Edwards and Trancik 2014) and that CH₄ leakage rate from the natural gas supply chain could have significant influences on the climate change impact of natural gas vehicles and power plants (Alvarez et al 2012). There is however a lack of information on the climate change impacts of vehicle electrification beyond the use of traditional GWP. As EVs have different emissions timing than conventional vehicles (i.e., larger capital emissions than conventional vehicles, followed by lower operational emissions (Milovanoff et al 2020)) and rely on electricity that is currently heavily based on natural gas, especially in the US (US Energy Information Administration 2021), it is critical to ensure that they are properly evaluated using multiple climate change metrics as a means to inform robust decision making. It is important to note that GWP is currently the preferred metric for vehicle regulations globally (Kendall and Price 2012), but there is little information thus far on the robustness of this metric for evaluating vehicle electrification. In this study, we assess the climate change impacts of vehicle electrification in the US at vehicle and fleet levels as a function of time. Our key objectives are to analyze: (1) whether the choice of climate change metric affects the analysis of climate change impacts associated with vehicle electrification; (2) whether GWP is a robust metric to evaluate climate change impacts of vehicle electrification; and finally (3) whether LDV electrification is beneficial from a climate change standpoint regardless of the climate change metric.

2. Methods

In the following sections, we first present the steps to obtain temporally resolved GHG emission inventories at vehicle and fleet levels. Then, we assess the GHG emission inventories with four climate change metrics.

2.1. Temporally resolved life cycle inventories

We create temporally resolved life cycle inventories of GHG emissions at both vehicle and fleet levels for the US LDV fleet. We focus on three GHGs: CO₂, CH₄, N₂O.

We perform vehicle-level LCAs of four vehicle technologies (ICEV-G = internal combustion engine vehicle using gasoline, HEV = hybrid electric vehicle using gasoline, PHEV = plug-in hybrid electric vehicle using electricity and gasoline, BEV = battery electric vehicle using electricity) and two vehicle size categories (car and light truck). The functional unit is one vehicle and the total travelled distance over the vehicle lifetime is 280 thousand kilometers (Davis and Boundy 2019). The life cycle stages include material production and manufacturing, battery production and assembly, vehicle manufacturing and assembly, fuel production and use and vehicle disposal. The GHG emission factors are taken from the GREET 2020 model (Wang et al 2020). We assume no battery replacement before the vehicle lifetime for BEVs and PHEVs (Baars et al 2021). The vehicle characteristics (e.g., fuel consumption, curb weight, electric battery capacity) are based on the 2020
sales-weighted average vehicle models by vehicle technology and size, as calculated in Milovanoff et al. (2020). Therefore, we do not compare vehicles of same size or same performances, but average vehicle technologies. The vehicles are assumed to be produced in 2020 and to be used from 2020 onward. Prospective annual average electricity mixes between 2020 and 2050 are used in this analysis and derive from the Annual Energy Outlook 2021 (US Energy Information Administration 2021). Another possible approach to estimate GHG emissions from electricity production exists by using marginal GHG emissions (Holland et al. 2022). This approach is however beyond the scope of our current study. In addition, we exogenously quantify emissions of methane leakage for natural gas-based electricity by considering three leakage rates: a lower bound at 0.9% based on Alvarez (2020), a default value at 2.3% based on Alvarez et al. (2018), and a higher bound at 4% based on estimates from Schwietzke et al. (2014). Emissions of methane leakage from coal-based electricity are also captured in our analysis using emission rates of the GREET 2020 model (Wang et al. 2020). Sections SI.1.1 and SI.1.2 (https://stacks.iop.org/ERIS/2/035007/mmedia) provide the full set of parameters and further details.

We perform fleet-level LCAs by running the FLAME (fleet LCA and material-flow estimation) model (Milovanoff et al. 2019) between 2020 and 2050. FLAME model estimates life cycle GHG emissions of the US LDVs as a function of time by simulating vehicle fleet turnover. It considers 2 size categories (car and light-truck) and 10 technology categories (e.g., internal combustion engine vehicles using gasoline or diesel, plug-in hybrid or battery EVs with short or long electric drive ranges). The life cycle stages are the same as in the vehicle-level LCA with the same GHG emission factors. Our analysis is technology-oriented and we develop four prospective scenarios of technology market shares for the analysis. Our baseline, called the constant scenario, assumes no changes to technology market share in new sales between 2021 and 2050. We develop a full electrification scenario that assumes all new vehicle sales are BEVs starting in 2035, based on recent commitments in California (Gavin Newsom Governor of California 2020), with market shares linearly interpolated between 2021 and 2035. Prior work (Milovanoff et al. 2020) showed that the choice of interpolation method (e.g., linear interpolation vs a Bass diffusion model) does not generally have a substantial impact on the results. Then we create the hybridization and the partial electrification scenarios that assume all new vehicle sales are HEV and PHEV, respectively, in 2035. The constant, hybridization, partial electrification, and full electrification scenarios represent fleet-level assessments of ICEV-G, HEV, PHEV and BEV deployment, respectively.

### 2.2. Climate change metrics

We convert the temporally resolved GHG emission inventories obtained at vehicle and fleet levels into climate change impacts using four metrics. First, we use the traditional normalized GWP metric. Then we use two absolute metrics (radiative forcing and global temperature changes) that solve the temporal inconsistency of the GWP metric and quantify absolute physical impacts. Finally, we use the normalized metric developed by Sproul et al. (2019), entitled DGWI, that aggregates GHG emissions based on their potential long-term social damages. These four metrics are selected to cover a wide range of components of the climate change cause-effect chain (from radiative forcing up to social damages).

### 2.3. Global warming potential

We aggregate GHG emission inventories using GWP (see equation (1)). GWP represents the ratio of the time-integrated radiative forcing due to a pulse emission of a GHG (also called absolute GWP) with the time-integrated radiative forcing due to a pulse emission of an equal mass of CO2 (see equation (2)). It is calculated over a fixed time-horizon (e.g., 20 or 100 years) starting at the pulse emission and aggregates the GHGs into a single unit (i.e., mass of CO2 equivalent). We choose to present the GWP results annually and cumulatively by aggregating GHG emissions with GWP.

\[
E_{eq}(y) = \sum_i GWP_i(H) * E_i(y)
\]

With \(E_{eq}(y)\) annual aggregated GHG emissions at year \(y\), \(GWP_i(H)\) the GWP due to a pulse emission of gas \(i\) over a time-horizon \(H\) [in kg CO2 eq./kg gas \(i\)] and \(E_i(y)\) the annual emissions of gas \(i\) [in kg gas \(i\)].

\[
GWP_i(H) = \frac{\int_0^H RF_i(t) dt}{\int_0^H RF_{CO2}(t) dt}
\]

With \(RF_i(t)\) the radiative forcing due to a pulse emission after \(t\) years [in W m\(^{-2}\) kg\(^{-1}\)]. Radiative forcing is the net change in the Earth system energy balance due to a set of perturbations (in this case, LDV emissions). It can be estimated with equation (3).

\[
RF_i(t) = A_i * R_i(t)
\]
With $A_i$ the radiative forcing per unit mass increase of gas $i$ in the atmosphere, also called radiative efficiency [in W m$^{-2}$ kg$^{-1}$], and $R_i(t)$ the fraction of gas $i$ remaining in the atm $t$ years after the pulse emission. In this study, we consider the radiative efficiencies of the 6th Assessment Report (AR6) of the IPCC (Forster et al. 2021): $A_{\text{CH}_4} = 2.01 \times 10^{-13}$ W m$^{-2}$ kg$^{-1}$, $A_{\text{N}_2\text{O}} = 3.59 \times 10^{-13}$ W m$^{-2}$ kg$^{-1}$, and $A_{\text{CO}_2} = 1.71 \times 10^{-15}$ W m$^{-2}$ kg$^{-1}$. Fraction of species as a function of time are assumed to be first-order decay equations for CH$_4$ and N$_2$O, and a sum of exponentials that considers carbon sink dynamics and are derived from the Bern carbon cycle-climate (Myhre et al. 2013) model for CO$_2$. See sections SI.1.6 and SI.1.7 for the explicit form of the equations and their coefficients.

As a result, GWP of CO$_2$ is 1 kg CO$_2$ eq./kg CO$_2$ regardless of the time-horizon, GWP of CH$_4$ are 82.5 and 29.8 kg CO$_2$ eq./kg CH$_4$ for 20 years and 100 years time-horizons, respectively, and GWP of N$_2$O are 273 kg CO$_2$ eq./kg N$_2$O for both 20 years and 100 years time-horizons.

### 2.4. Radiative forcing impact

The radiative forcing impact (RFI) metric represents the radiative forcing of the temporally resolved GHG emission inventories. It is calculated instantaneously and time-integrated over an analytical period. The instantaneous form (equation (4)) derives from Levasseur et al. (2010) and represents the instantaneous radiative forcing of all GHGs emitted and accumulated in the atmosphere at a given time. The time-integrated radiative forcing provides a more complete picture of the cumulative impacts of the GHG emissions on climate change as it is representative of the total energy added to the climate system by the temporally resolved GHG emission inventory (Forster et al. 2021).

$$\text{RFI}(y) = \sum_{i} \sum_{y_s < y} E_i(s) \ast \left( \int_{y-y_s-1}^{y-y_i} R_F(x) dx \right)$$  \hspace{1cm} (4)$$

With RFI($y$) the instantaneous radiative forcing at year $y$ due to the GHG emission inventories between years $y_s$ and $y$ [in W m$^{-2}$ year] and $E_i(s)$ the annual emission of gas $i$ at year $s$ (in kg). We consider the same equations and parameters as previously described for radiative forcing. From equation (4), we calculate a time-integrated radiative forcing impact (iRFI) by summing all instantaneous RFI up to a given point in time.

### 2.5. Global temperature change impact

The global temperature change impact (GTCI) metric represents the changes in global mean surface temperature at a given point in time due to the GHG emission inventories up to this point in time. It includes physical processes that are not included in the GWP and RFI calculations, such as the climate sensitivity and the exchange of heat between the atmosphere and the ocean (Shine et al. 2005). It is based on the concept of absolute global temperature change potential (AGTP), developed by Shine et al. (2005), that evaluates the temperature change after a period of time of a 1 kg pulse emission (equation (5)). The instantaneous form of the GTCI is representative of temperature changes at a given year and inform on absolute temperature change levels and rates of changes. The cumulative form refers to the cumulative warming up to a given year, akin to heating degree days or cooling degree days from the building science literature (Li et al. 2020), and can be used to inform sea-level rise impacts.

$$\text{GTCI}(y) = \sum_{i} \sum_{y_s < y} E_i(s) \ast \text{AGTP}_i(y - s, y) = \sum_{i} \sum_{y_s < y} E_i(s) \ast \left( \int_{0}^{y-y_i} \text{RF}_i(s) \ast CR(y - s - x) dx \right)$$  \hspace{1cm} (5)$$

With GTCI($y$) the GTCI at year $y$ due to the GHG emission inventories between years $y_s$ and $y$ [in degrees Kelvin (K)]; AGTP$_i(t, y)$ the AGTP at year $y$ due to a pulse emission of gas $i$ at year $y - t$ [in K kg$^{-1}$]; and CR($t$) the climate response to a unit increase in radiative forcing after $t$ years [in K (W m$^{-2}$)$^{-1}$]. We use the climate response function based on the Hadley Centre Coupled Model Version 3 (HadCM3), as referred in the IPCC AR5 (Myhre et al. 2013). This function is a sum of exponentials that can be associated with the responses of the ocean mixed layer (first term) and of the deep ocean (higher order term) to a forcing (see SI.1.9 for the explicit form of the function and its parameters). We then calculate a time-integrated form of the GTCI by summing all year-on-year changes up to a given point in time. This time-integrated form refers to the integrated global temperature change potential (iGTP) metric developed by Peters et al. (2011a).

We validate the results of the fleet-level GTCI by running a simple carbon cycle-climate model, MAGICC6 (Meinshausen et al. 2011a). To run the validations, we add the temporally resolved GHG emission inventories of the FLAME model to baseline emission pathways for CO$_2$, CH$_4$ and N$_2$O. Then, we simulate the emission pathways with MAGICC6 and calculate the annual differences in global mean temperature changes between the baseline emission pathways and the emission pathways that contain emissions from FLAME. We run the validations for four baseline emission pathways based on the representative concentration pathways (RCP)
2.6. Dynamic global warming impact

Our last metric aggregates GHG emissions with characterization factors and is called the dynamic global warming impact metric (DGWI). This metric aims to account for the downstream damages of climate change on socio-economic systems. It was developed by Sproul et al (2019) and compares the monetized damages of a marginal emission of a GHG released at a point in time to the monetized damages of a marginal CO₂ emission released now. It is a ratio of social costs of GHGs and converts present and future GHG emissions into a present-day value CO₂ equivalent. The damages, accounted for in the social costs of GHGs, are discounted back to present-day value using economic discount rates. We consider a discount rate of 3%. Overall, the DGWI approach is similar to the GWP approach, as it aggregates GHG emissions and does not convert the emissions into absolute physical impacts, but is based on economic damages, not CRF, and differentiates emissions over time. Another key difference is that it intrinsically considers an analytical time period of centuries, as it is based on long-term social costs of GHGs, and cannot be used for shorter analytical time periods.

3. Results

In the following sections, we first show the results of vehicle-level LCA of vehicle electrification in the US with multiple climate change metrics and examine the contribution of the life cycle stages and contributions of the individual GHGs. We then assess the sensitivity of the results to electricity sources and methane leakage rates. Finally, we show the results at a fleet-level.

3.1. Vehicle-based LCA of vehicle electrification with alternative climate change metrics

Figure 1(a) presents the cumulative life cycle CO₂, CH₄, and N₂O emissions of 2020 US average conventional (ICEV-G), hybrid electric (HEV), long-range plug-in hybrid electric (PHEV40), and long-range battery electric (BEV300) cars over their vehicle lifetime. Similar results can be found for light-trucks in section SI.2.1. Higher electrification levels provide lower life cycle CO₂ and N₂O emissions, but not lower life cycle CH₄ emissions. Indeed, about 40% and 19% of the US electricity generation were derived from natural gas and coal, respectively, in 2020 (US Energy Information Administration 2021). Extracting, processing, distributing and converting these sources into electricity emit CH₄ (Alvarez et al 2018, Burnham et al 2012), about 1.71 g CH₄/kWh on average in the US (or 0.48 g CH₄/MJ) compared with 0.1 g CH₄/MJ to produce and burn gasoline. Consequently, the well-to-wheels (excluding vehicle manufacturing) CH₄ emissions are 0.16 g CH₄/km, 0.26 g CH₄/km, and 0.37 g CH₄/km for a HEV, an ICEV-G, and a BEV300, respectively.

When the temporally resolved GHG inventories are aggregated using normalized climate change metrics, such as 20 years GWP, 100 years GWP and DGWI (figure 1(b)), the BEV300 provides the lowest climate change impacts, followed by PHEV and HEV, with total reductions ranging between 35% and 52% compared to conventional ICEV-G. The largest reductions are obtained when BEV300 is compared against ICEV-G using the DGWI (52% reduction). Due to rising background GHG concentrations, the marginal impacts of additional GHG emissions are higher in the future than they are today, therefore, the DGWI characterization factors increase over time. Conversely, the climate change impact reductions of the BEV300 are lower when assessed using the 20 years GWP than using the 100 years GWP, at 46% and 50% respectively. This is because BEV300 has a higher life cycle CH₄ inventory compared to ICEV-G, given its reliance on natural gas-powered electricity, and that CH₄ has a more potent short-term GWP.

Transient effects exist between GHG emissions, radiative forcing, and GTCIs (figure 1(c)). Indeed, when each vehicle reaches its end-of-life, 14 years after the original production date or in 2034, the emissions stop and annual RFI peaks and starts to slowly decrease. Emitted GHGs remain in the atmosphere for decades (for CH₄) or centuries (for CO₂ and N₂O) after their emissions and continue to have radiative forcing. By 2100, or 66 years after the last emissions, the annual RFI of an ICEV-G is 46% lower than the maximum annual RFI in 2034. When climate responses of radiative forcing are added in the GTCI, additional transient effects are included. For example, the climate response function used in this study considers some transient responses induced by the kinetics of heat transfers from the atmosphere to the ocean mixed layer, to the deep ocean in response to increased radiative forcing. As a result, the annual GTCI of life cycle GHG emission inventories peaks in 2041 for BEV300 and 2045 for ICEV-G, or 7 and 11 years after the last emissions, respectively. By 2100, the annual GTCI of an ICEV-G is 22% lower than the peak annual GTCI in 2045. This illustrates the importance of achieving peak emissions as soon as realistically possible given that reductions in climate change impacts take time to materialize.
Figure 1. Vehicle-based life cycle (a) cumulative GHG emission inventories, (b) GHG emissions aggregated with normalized climate change metrics ($\text{GWP}(20) = 20$ years GWP, $\text{GWP}(100) = 100$ years GWP, $\text{DGWI} = \text{dynamic global warming impact}$), (c) absolute climate change metrics ($\text{RFI} = \text{RFI}$, $\text{GTCI} = \text{global temperature change impact}$) for an average internal combustion vehicle (ICEV-G), an average hybrid electric vehicle (HEV), an average long-range plug-in hybrid electric vehicle (PHEV40) and an average long-range battery electric vehicle (BEV300) of car size in the US.

Transient effects are not observable when GHG emissions are aggregated with normalized metrics and can be further explored with break-even times. It is common practice in the literature to calculate the break-even time of two vehicle technologies—how long do we need to use a vehicle before it has lower climate change impacts than a reference vehicle? When GHG emissions are aggregated with 100 years GWP, break-even times for a BEV300 relative to an ICEV-G is 1 year, whereas it is 10 years when a BEV300 is compared against a PHEV40. However, this definition of break-even time is not complete as it does not indicate when in the future the climate change impacts will be lower. When time-integrated GTCI ($i\text{GTCI}$) is considered, a BEV300 has lower impacts than an ICEV-G after 3 years and lower impacts than a PHEV40 after 43 years. It means that while a BEV300 needs to be used at least 10 years to have lower aggregated GHG emissions using 100 years GWP than PHEV40, the actual reductions in time-integrated global temperature changes occur after 43 years, or about 29 years after the vehicle end-of-life. This finding reveals that while GWP may be sufficient to determine the technology with the lowest climate change impacts, it is not sufficient to determine when the technology would lower the impacts and not appropriate to establish, for example, the risk of hitting climate tipping points.

Overall, electrifying a LDV in the US implies lower life cycle climate change impacts. In figure 1(c), ICEV-G have higher instantaneous and time-integrated RFI, have faster rate of warming, and higher instantaneous and time-integrated GTCI than HEV, PHEV40 and BEV300 by the end of the vehicle lifetime. But the choices of the analytical time period and of the metric influence the estimated benefits of electrification. Over short analytical time periods (i.e., 2020–2040 or 20 years for GWP), the most beneficial car technology from a climate change perspective is the PHEV40 with 43% and 41% reductions in $i\text{RFI}$ and $i\text{GTCI}$, respectively, compared with the ICEV-G. These reductions are slightly weaker than the 45% reductions in aggregated GHG emissions with 20 years GWP for PHEV40. Indeed, the RFI and GTCI metrics address the temporal inconsistency of the GWP aggregation. GHG emissions occurring earlier in the vehicle life cycle (e.g., production emissions) have larger cumulative impacts at a given time than later emissions. As a result, battery production emissions of EVs create a burden that takes time to offset. Over long analytical time periods (i.e., 2020–2100 or 100 years for GWP), BEV300 is the most beneficial technology from a climate change standpoint with reductions ranging from 50% to 48% relative to ICEV-G for GHG emissions aggregated with 100 years GWP and $i\text{GTCI}$, respectively. Table 1 presents a summary of vehicle-level assessment results for both car and light truck size categories. A graphical representation of the table is available in SI.2.5.

3.2. Contribution analysis of alternative climate change metrics

Fuel production (or electricity generation in the case of BEV and PHEV) and use are the most predominant phases of the life cycle climate change impacts of the assessed LDV technologies, regardless of the climate
Table 1. Climate change impact reductions of three vehicle technologies (HEV, PHEV, BEV) relative to conventional vehicles (ICEV-G) at a vehicle-level and of three alternative vehicle deployment scenarios (hybridization, partial electrification, full electrification) relative to no alternative vehicle deployment at a fleet-level in the US results are presented by climate change metric and time horizon. At a vehicle-level, short horizon represents 20 years GWP, 2040 for RFI and GTCl, and 2020 to 2040 for iRFI and iGTCl; at the fleet-level short horizon represents 2050 for RFI and GTCl, and from 2020 to 2050 for iRFI and iGTCl. Long horizon represents 100 years GWP 2100 for RFI and GTCl, from 2020 to 2100 for iRFI and iGTCl and 2300 for DGWI at both vehicle and fleet levels. Color code: green cells represent vehicle-level relative reductions and orange cells represent fleet-level reductions. Darker cells represent larger reductions. No technology or scenario included in this table has higher climate change impacts than ICEV-G/baseline.

| Climate change impact reductions relative to ICEV-G | Short horizon | Long horizon |
|----------------------------------------------------|---------------|--------------|
|                                                     | GWP RFI iRFI GTCl iGTCl | GWP RFI iRFI GTCl iGTCl DGWI |
| **Vehicle-level**                                  |                |              |
| Car                                                | 35% 35% 34% 35% 33% 35% 35% 34% 35% 34% 34% 35% | 45% 46% 43% 45% 41% 48% 49% 47% 49% 47% 48% 48% |
| HEV                                                | 46% 48% 40% 45% 37% 50% 53% 49% 52% 48% 52% 52% |              |
| BEV                                                | 35% 35% 34% 35% 34% 35% 35% 35% 35% 35% 35% 35% |              |
| PHEV                                               | 37% 38% 35% 37% 33% 40% 42% 39% 41% 39% 41% 41% |              |
| HEV                                                | 45% 41% 41% 45% 38% 50% 53% 49% 53% 48% 52% 52% |              |
| Light truck                                         |                |              |
| Fleet-level                                         |                |              |
| Hybridization                                       | 15% 18% 9% 12% 7% 15% 15% 14% 15% 13% 17% 17% |              |
| Partial electrification                             | 19% 22% 11% 17% 9% 21% 22% 18% 22% 18% 24% 24% |              |
| Full electrification                                | 23% 26% 13% 20% 10% 25% 27% 22% 26% 21% 28% 28% |              |

change metrics and analytical time periods. Figure 2 presents the normalized life cycle climate change impacts of four LDV technologies for three metrics and two analytical periods with life cycle phase contributions. Fuel use represents a large majority of the life cycle climate change impacts of ICEV-G and HEV while electricity production represents the majority for BEV300. When a short analytical period is considered (i.e., 2020–2040 or 20 years for GWP), the contribution of the vehicle production phase for BEV300 varies substantially across the climate change metrics. Indeed, for BEV300, vehicle production contributes 30% of the GHG emissions aggregated with 20 years GWP, 35% of the time-integrated RFI (iRFI), and 38% of the iGTCl. GHGs associated with vehicle production are assumed to be emitted at the starting year of the analytical time period and mostly remain in the atmosphere throughout the period, therefore creating larger cumulative climate change impacts at a given time than the electricity produced during the last year of the vehicle lifetime. As a result, BEV300 have larger life cycle iRFIs and iGTCls than PHEV40 over short analytical periods. This phenomenon is also true for long analytical time periods (i.e., 2020–2100) but with less influence (i.e., from 33% for vehicle production contribution with 100 years GWP to 34% with iGTCl) due to the decreasing fraction of species remaining in the atmosphere over time. These findings reveal how important decarbonizing each stage of the supply chain is to reduce long- and short-term climate change impacts.

For all technologies, CO2 emissions are the predominant sources of climate change impacts over the vehicle life cycles. Figure 2 dissociates the contributions of CO2 and CH4 & N2O by life cycle phase (n.b., CH4 and N2O are aggregated to simplify the reading of figure 2 but N2O has a very minor contribution, less than 1% of vehicle life cycle climate change impacts). CH4 emissions play a key role in the fuel production phase across the technologies. In addition, CH4 contributions to climate change impacts increase the further we go in the climate change cause-effect chain (i.e., from emissions to global temperature change) and when the analytical time period is reduced. For a BEV300, CH4 emissions contribute 9% of the life cycle GHG emissions aggregated with 100 years GWP, and 22% with 20 years GWP and 23% with iGTCl over a short analytical period. This is the consequence of a higher radiative efficiency and a shorter lifetime in the atmosphere for CH4 compared with CO2. Due to the substantial contribution of CH4 from electricity production in the BEV300 life cycle, it is therefore important to evaluate the influence of electricity sources and of methane leakage rates on the results.

3.3. Vehicle electrification and electricity sources

Climate change impacts of vehicle electrification strongly depend on the electricity sources. Figure 3 presents the normalized life cycle climate change impacts of an average PHEV40 and BEV300 of car size in the US for three metrics, two analytical time periods, and four prospective average electricity source mixes based on the national and regional average mixes. Results for light truck vehicle models are presented in SI.2.1 and have similar trends. The full set of projected electricity source mixes by electricity market region is presented in SI.2.1. The three regions selected here represent a high coal case (MISC = midcontinent independent system operator/central) with 53% of cumulative electricity generation from coal between 2020 and 2035, a high natural gas case (MISS = midcontinent independent system operator/south) with 78% of cumulative electricity
Figure 2. Normalized life cycle climate change impacts of car ICEV-G, HEV, PHEV40, BEV300 for three metrics (GWP = GHG emissions aggregated using GWP; iRFI = time-integrated RFI; iGTCI = time-integrated global temperature change impact) over two time periods (short period = 2020–2040 for iRFI and iGTCI or 20 years for GWP; long period = 2020–2100 for iRFI and iGTCI or 100 years for GWP) with contributions by life cycle phases and GHGs.

generation from natural gas between 2020 and 2035, and a high renewable case (NYUP = northeast power coordinating council/upstate New York) with 33% and 50% cumulative electricity generation from nuclear and renewable sources, respectively, between 2020 and 2035. Note that the projected electricity source mixes used in this study rely on the Annual Energy Outlook 2021 (US Energy Information Administration 2021) and only consider the current existing policies. If more ambitious policies regarding grid decarbonization are developed, such as reaching 100% clean electricity by 2035 (see a roadmap by Union of Concerned Scientists (2022)), vehicles relying on electricity will undoubtedly have lower climate change impacts than those reported in our study. However, such scenarios are beyond the scope of this analysis. When a BEV300 of car size is evaluated in the high coal case (MISC), its life cycle climate change impacts are higher than those of a PHEV40 and a HEV, regardless of the metric and analytical time period, but lower than those of an ICEV-G. This finding is consistent with the literature (Wu et al 2019a, Yuksel et al 2016), and highlights the climate change mitigation potentials of hybrid EVs in regions or countries that still heavily rely on coal-based electricity. The differences between the absolute climate change metrics (i.e., iRFI and iGTCI) and the GWP are, however, exacerbated the further along the climate change cause-effect chain. Compared to an ICEV-G, a BEV300 charged using the coal-heavy MISC mix has 27% lower aggregated GHG emissions when measured over the 20 years time horizon, but a 19% reduction in iGTCI. On the other hand, a BEV300 has lower life cycle climate change impacts than a PHEV40 and a HEV when the electricity derives from decarbonized sources like nuclear or renewables (NYUP), even when the impact is measured over a short analytical time period. In such a case, a BEV300 has the potential to reduce the aggregated life cycle GHG emissions by almost 75% using 100 years GWP, and by 64% when measured using the iGTCI metric.

Methane leakage rates have substantial influence on the life cycle climate change impacts of EVs especially when the electricity generation relies on natural gas. Figure 3 presents the sensitivity of the results to fugitive methane for the different electricity mixes, where the leakage rate varies between 0.9% based on the US EPA (2020) and 4.0% based on Schwietzke et al (2014). When focusing on short term impacts, a high natural gas electricity mix (MISS), combined with a 4.0% methane leakage rate, results in the highest climate change impact for a BEV300, even higher than a BEV300 powered by the coal-heavy MISC mix. Furthermore, a higher methane leakage rate has a disproportionate effect on iRFI and iGTCI compared to the traditional GWP method. For instance, a BEV300 charged with natural gas-heavy electricity (MISS) has similar impact to an HEV when evaluated with 100 years GWP but 10% higher impact when evaluated with iGTCI over a long period of time. This finding suggests that the climate change impacts of CH4 are potentially underestimated with a 100 years GWP, consistent with the findings by Farquharson et al (2017), Alvarez et al (2012) and Lan and Yao (2022). The underestimation derives from the high radiative efficiency and short lifetime of CH4. Although the analyses presented here show that the ICEV-G has the highest climate change impacts across the selected measurement metrics and assessment scenarios, we show that the methane leakage rate can affect the
climate change impact ranking of HEV, PHEV40 and BEV300. Therefore, it underscores the importance of accurately quantifying the methane leakage rate.

### 3.4. Fleet-based life cycle climate change impacts of vehicle electrification

When vehicle electrification is evaluated at a fleet-level, the large-scale reductions in climate change impacts take more time to materialize because of the fleet turnover. Figure 4 presents the life cycle climate change impacts of the US LDV fleet under three electrification pathways as a function of time relative to a constant, baseline pathway, with emissions inventoried up to 2050 and impacts analyzed up to 2100 (absolute values can be found in the SI, section SI.2.2). The estimated GTCI of the US LDV fleet are validated with the MAGICC6 model (see section SI.2.3). The time-integrated GTCIs (as presented in figure 4) of the full electrification scenario relative to those of the constant scenario have MNGE below 2.5% over the 2020–2100 period compared with results from MAGICC6, validating our method and procedure.

A key takeaway from figure 4 is that the fleet turnover limits the large-scale climate change impact reduction potential even under an aggressive electrification scenario over the 2020–2100 period. When cumulative life cycle GHG emissions are aggregated using 100 years GWP, 100% market share of BEV300 in new vehicle sales by 2035 (i.e., full electrification scenario) results in 25% reductions in cumulative emissions in 2050. This is half of the reduction in GWP achievable on an individual vehicle-level when a BEV300 is compared with...
with an ICEV-G for both car and light truck categories (see table 1). The reductions are lower when the GHG emissions are aggregated using 20 years GWP (23% reductions for full electrification scenario compared with constant scenario) due to the higher GWP of CH₄. The reductions are higher (28%) when the GHG emissions are aggregated using DGWI than 100 years GWP. Indeed, as the DGWI characterization factors increase over time, long-term GHG emission reductions have higher influence on aggregated present-day values. It is important to note, however, that the fleet-level analysis considers emissions up to 2050, whereas the end of life of a 2020 model year in the vehicle-level analysis is 2035. By 2050, DGWI characterization factors of GHGs have substantially increased compared to 2035 values (e.g., by 20% for CO₂. See table SI.8).

When absolute climate change impacts (i.e., RFI and GTCI) of large-scale vehicle electrification are examined, the transient effects of the climate system combined with the transient effects of the fleet turnover further limit and delay the reductions. A full electrification scenario only brings up to 10% reductions in IGTCI by 2050 and up to 20% by 2100 compared with a constant scenario (see table 1). This implies that large-scale vehicle electrification has climate change impact benefits for the US, but even with an aggressive electrification scenario (i.e., 100% EV sales by 2035), the temperature change potentials take time to materialize after the reductions in emissions. Therefore, it highlights the need to evaluate climate change mitigation strategies with multiple metrics to fully capture and assess the expected benefits.

This finding raises concerns regarding the use of GWP as an appropriate tool for climate change mitigation goals. Indeed, the near proportionality between cumulative GHG emissions and long-term global temperature change has been established in the literature (Matthews et al 2018). Many studies quantify national and sectoral climate change mitigation targets with GHG emission budgets (Robiou du Pont et al 2016, 2017, Milovanoff et al 2020, 2021). CO₂ emissions are often solely considered in the budgets (Matthews et al 2020), but other GHGs also play a critical role (MacDougall et al 2015). When multiple GHGs are included, they are usually aggregated using 100 years GWP (Robiou du Pont et al 2016, 2017, Milovanoff et al 2020, 2021). To examine the robustness of GWP as an appropriate metric for GHG emission budgets, we run a series of simulations with equivalent GHG emissions when aggregated using 100 years GWP but with different deployment pace and level of EVs. The simulations aim to assess how different GHG emission pathways with similar cumulative aggregated GHG emissions perform from absolute climate change perspectives. In other words, we investigated whether pace and depth of EV deployment could affect some climate change metrics more than others. More details about the simulations and associated figures are presented in SI.2.4. The results show that the absolute climate change metrics (i.e., RFI and GTCI) vary within 1% across the simulations. Thus, while the different climate metrics (and time horizons) may vary from one another regarding the relative climate impacts of different technologies, they are consistent in evaluating different EV deployment pathways as ‘equivalent’ to one another. This suggests that cumulative emissions aggregated with GWP provides a good proxy for assessing the climate change mitigation targets of vehicle electrification.

4. Discussion

In this study, we perform life cycle climate change impact analyses of US LDV electrification at vehicle and fleet levels using four different metrics: GWP, RFI, GTCI, and DGWI. One of our key findings is that while the choice of the metric, the analytical time period and some other key modelling parameters (e.g., methane leakage rate) may influence the results, partial and full electrification remain effective solutions to reducing climate change impacts of the US LDVs. However, we also demonstrated that, even with aggressive electrification (i.e., 100% EV sales by 2035), the impacts on global temperature change are moderated by the delay in fleet turnover and the time lag associated with the overall climate responses.

The choice of the appropriate technology (e.g., hybrid, plug-in hybrid electric or battery electric) is highly dependent on the potential electricity sources that feed them. This finding is in line with the literature (Marmiroli et al 2018) and our analysis highlights an important parameter that is often neglected in the assessment of vehicle electrification: methane leakage rate of the natural gas supply chain. As the US derives 40% of its electricity from natural gas in 2020, and is expected to continue relying on this source in the coming decades (US Energy Information Administration 2021), fugitive methane emissions of the gas supply chain have large climate change impacts (Alvarez et al 2018). Estimates of methane leakage rates vary in the literature (from 0.9% based on the US EPA (2020) to 4% or higher (2014)) depending on the applied methods and considered facilities. This range creates large uncertainties in the life cycle climate change impacts of plug-in hybrid and battery electric vehicles, especially in regions heavily dependent on natural gas such as in the territory of US midcontinent independent system operator. For example, the life cycle GHG emissions aggregated using 20 years GWP of a battery electric car in the US midcontinent increase by +43% when methane leakage rates vary from 0.9% to 4%. It is therefore critical to decrease methane leakages by deploying emission detection systems and avoiding abnormal operating conditions (Alvarez et al 2018).
Another important parameter in assessing climate change impacts is the analytical time period. This parameter is often overlooked as the 100 years GWP is the most common climate change metric. Some studies (Pereira and Posen 2020, Burnham et al 2012) acknowledge the limitation of considering only one analytical time period and perform sensitivity analyses using 20 years GWP metrics. Ocko et al (2017) even propose to consistently report both analytical time periods to make explicit the potential trade-off between short-term and long-term climate effects. However, GWP metrics are inherently flawed when temporal considerations are added to the analysis, as GWP aims to compare GHGs without temporal resolutions. In our study, we use metrics with consistent analytical time periods, and we also show that the choice of the analytical time period can affect the outcome of the analysis. For example, we found that a plug-in hybrid electric car has smaller time-integrated radiative forcing and temperature change impacts than a battery electric car over a short analytical time period but larger impacts over a long analytical time period. The question of the appropriate time horizon for climate change impact assessment is, however, challenging as climate change is both slow rates of change enable more adjustment potentials for species and ecosystems while faster rates provide increases or stagnation. We need to find a trade-off between rapid and deep reduction strategies and considering both slow- and short-term analytical periods in the analysis may be a practical way to manage these trade-offs. In addition, analytical time periods are also important when the rate of warming is assessed. Slow rates of change enable more adjustment potentials for species and ecosystems while faster rates provide insufficient adjustment time (Kirschbaum 2014). Different climate change damages can result from different rates of changes and assessing potential temperature changes of energy systems as a function of time can help convert these changes into damages. We therefore echo Ocko et al (2017) that multiple analytical time periods should consistently be used to assess short- and long-term climate change effects of products and services.

Finally, four different climate change metrics are presented in this analysis, each with their own limitations, assumptions, and applications. GWP is easy to use, as only one value per GHG is needed, and does not require large datasets or a sophisticated model. But GWP is developed to compare GHGs and is not appropriate to compare emissions at different times. DGWI is also relatively easy to use and solves the lack of temporal considerations of GWP. However, it requires more input data as annual characterisation factors per GHG are needed and they only consider one long-term analytical period. This method is, therefore, only relevant for long-sighted analysis of potential climate change social damages. Absolute metrics such as RFI and GTCI are more complex to implement, each relying on many layers of functions and parameters, but provide quantitative evaluations of climate variables as a function of time. They can take two forms (instantaneous and time-integrated), each offering different insights. For example, sea-level rise is associated with both, the magnitude of the temperature changes (i.e., instantaneous GTCI) and the length of time over which oceans and glaciers are exposed to cumulative warming (i.e., time-integrated GTCI) (Kirschbaum 2014). Some other important tipping points in the climate system, such as artic sea-ice melting, can be linked to cumulative warming. It is, however, important to note that going further along the cause-effect chain of climate change increases the uncertainty of the calculations (Reisinger et al 2010).

Our analysis shows that large-scale electrification of vehicles offer climate change impact reductions compared to conventional internal combustion vehicles. However, the impacts reductions weaken further along the climate change causal chain: from 23% using GWP to 10% using iGTCI for a 20 years time horizon, or from 25% using GWP to 21% using iGTCI for a 100 years time horizon. Indeed, the timing of emissions matter: GHGs emitted earlier in the vehicle life cycle (e.g., vehicle and battery productions) create larger cumulative climate change impacts when evaluated with time-integrated RFI and GTCI than with GWP. We therefore recommend the use of multiple metrics to solve the lack of temporal considerations of GWP and to cover more components of the climate change cause-effect chain, particularly when contrasting between different alternative technologies. We nonetheless found that GWP is a robust metric for climate change mitigation targets of vehicle electrification and remains a good choice for most analysis.

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Data availability statement

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

ORCID iDs

Alexandre Milovanoff https://orcid.org/0000-0003-2778-4098
I Daniel Posen https://orcid.org/0000-0001-5093-140X

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