Memo

To: Docket EPA-HQ-OAR-2022-0829

From: Joseph McDonald, U.S. EPA-OTAQ-ASD-LDVSEC

CC: Michael Olechiw, Director, U.S. EPA-OTAQ-ASD-LDVSEC

Date: January 23, 2024

Re: Automotive Life Cycle Assessment Literature Review and Meta-Analysis

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The U.S. Environmental Protection Agency (EPA) commissioned a comprehensive literature review and meta-analysis of recently published (primarily 2019-2023 publication dates) automotive life cycle assessments (LCA) focusing on attributional LCA of battery electric vehicles (BEV) and competing technologies that included internal combustion engine vehicles (ICEV) as well as other electrified vehicles such as hybrid electric vehicles (HEV), plug-in hybrid electric vehicles (PHEV), and fuel cell electric vehicles (FCEV). The literature review and meta-analysis were conducted under a contract to EPA by Eastern Research Group, Inc. (ERG), EPA Contract Number 68HE0C18C0001, Work Assignment 5-25. ERG's final report entitled "Automotive Life Cycle Assessment Literature Review" is attached to this memo.

In summary, the ERG report:

- Summarizes the findings of recent (2019-2023) peer reviewed automotive LCAs.
- Outlines the potential life cycle emissions impacts of vehicle electrification from cradle-to-grave that are relevant for EPA vehicle emissions regulations.
- Provides a review of electric-vehicle-specific LCA methods and best practices.
- Notes key knowledge gaps in contemporary automotive life cycle inventory (LCI) and LCA data.

The ERG report identified 10,000 potentially relevant LCA studies. Of these studies, 91 were identified for detailed review, with 74 studies further identified as meeting acceptance criteria of peer review and compliance with relevant ISO LCA standards.

ERG further identified 31 studies as having sufficiently consistent assumptions and context, and sufficient level of detail to allow intra-study comparison.

A box and whisker diagram of the percentage difference in GWP relative to ICEV for each type of vehicle electrification in ERG's meta-analysis is shown in the figure below. The elements of the box and whisker diagram are drawn horizontally, from left to right, and include the following elements:

- First quartile (Q1 or 25th percentile) designated by the left side of each box and representing the median of the lower half of the dataset
- Third quartile (Q3 or 75th percentile) designated by the right side of each box and representing the median of the upper half of the dataset
- Median (Q2 or 50th percentile) designated by the vertical line within each box
- The whiskers to the left and right of the box which represent 1.5 times the interquartile range (IQR)

Any comparisons to ICEV within the plot that were more than 1.5 times the IQR were considered to be statistical outliers. The only outliers identified were within the FCEV comparisons to ICEV. One of the outliers is shown within the figure at 66.67% above ICEV and an additional outlier exists outside figure bounds at 192.8% above ICEV.

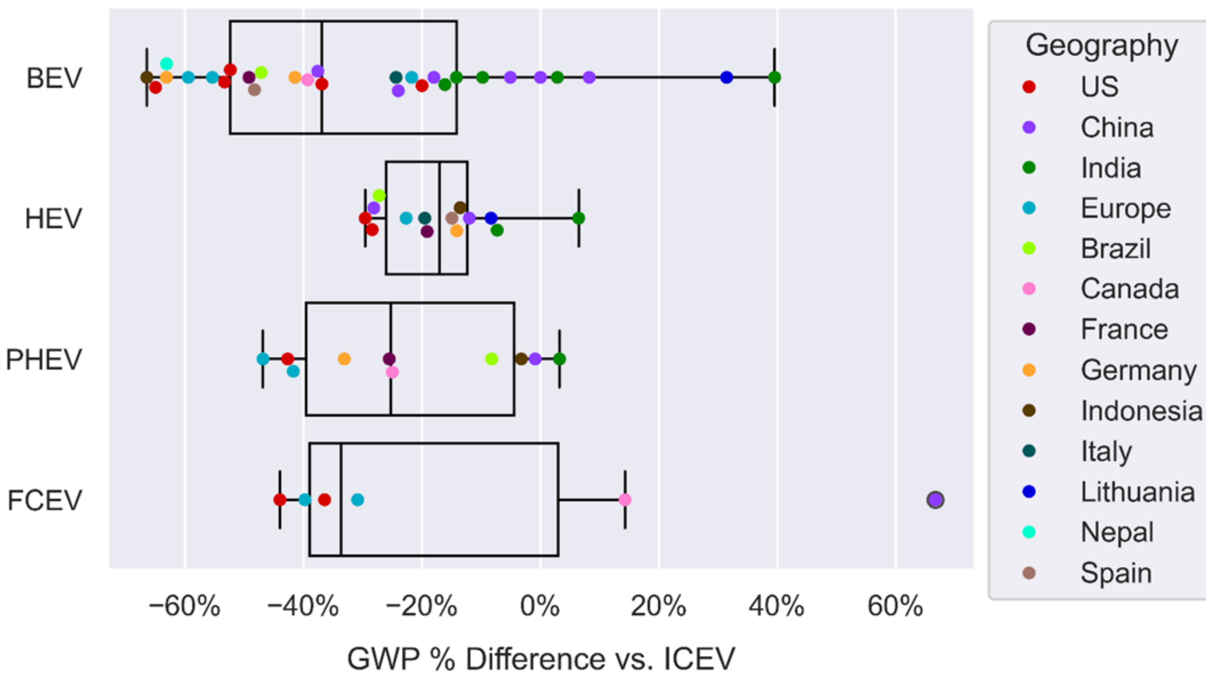

Figure 1: Distributions of intra-study percent differences in life cycle GWP results between EVs and ICEVs, colored by use phase geographic context.

The main contributors to GWP for all vehicle types were vehicle manufacturing (including resource extraction) and vehicle use phase. A total of 23 studies within the intra-study comparison found GWP impacts that were lower for BEVs relative to ICEVs, while 5 studies found that BEVs were higher than ICEVs. Those 5 studies represented a portion of the BEV use cases in India, China and Lithuania and employed electricity grid mixes predominantly reliant on coal and/or natural gas to generate power. Results for U.S.-based use cases all found BEVs to have a lower GWP relative to ICEV, with a minimum of 20 percent GWP reduction, a maximum of 65% GWP reduction, and a median of 37% GWP reduction for BEV impacts relative to ICEV.

Overall, ICEVs tended to have higher GWP results than BEVs, HEVs, and PHEVs, but were split evenly between higher and lower GWP when compared to FCEVs. Most studies found that BEVs had lower GWP values than ICEVs, HEVs, and FCEVs, and all studies evaluating both BEVs and PHEVs (five in total) found that BEVs had lower GWP values. Only 2 of the studies within the meta-analysis reported BEVs being outperformed by another type of electrified vehicle.

Automotive Life Cycle Assessment Literature Review

Prepared for:

U.S. Environmental Protection Agency
Office of Transportation and Air Quality
Office of Air and Radiation

Prepared by:

Eastern Research Group, Inc.
561 Virginia Rd.
Building 4, Suite 300
Concord MA, 01742

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LIST OF ABBREVIATIONS & ACRONYMS

ALCA	Attributional Life Cycle Assessment
BEV	Battery Electric Vehicle
BOM	Bill of Materials
CAP	Criteria Air Pollutants
CFF	Circular Footprint Formula
CFR	Code of Federal Regulations
CI	Carbon Intensity
CLCA	Consequential Life Cycle Assessment
CNG	Compressed Natural Gas
DRIA	Draft Regulatory Impact Analysis
eGRID	Emissions and Generation Resource Integrated Database
EGU	Electric Generating Unit
EoL	End of Life
EPA	U.S. Environmental Protection Agency
E-REV	Extended-Range Electric Vehicle
EV	Electric Vehicle
FCEV	Fuel Cell Electric Vehicle
GHG	Greenhouse Gas
GREET	Greenhouse gases, Regulated Emissions, and Energy use in Transportation
GVWR	Gross Vehicle Weight Rating
GWP	Global Warming Potential
HEV	Hybrid Electric Vehicle
HVO	Hydrotreated Vegetable Oils
IAM	Integrated Assessment Model
ICCT	International Council on Clean Transportation
ICEV	Internal Combustion Engine Vehicle
LCA	Life Cycle Assessment

LCI	Life Cycle Inventory
LCIA	Life Cycle Impact Assessment
LFP	Lithium Iron Phosphate
LMDV	Light- and Medium-Duty Vehicles
LMO	Lithium Manganese Oxide
LVW	Loaded Vehicle Weight
Mfct.	Manufacturing
MOVES	Motor Vehicle Emissions Simulator
NCA	Nickel Cobalt Aluminum
NCAP	New Car Assessment Program
NiMH	Nickel Metal Hydride
NMC	Nickel Manganese Cobalt
NPRM	Notice of Proposed Rulemaking
OMEGA	Optimization Model for Reducing Greenhouse Gases
PEM	Proton Exchange Membrane
PEMFC	Proton Exchange Membrane Fuel Cell
PHEV	Plug-In Hybrid Electric Vehicle
pLCI	Prospective Life Cycle Inventory
PM	Particulate Matter
RFS	Renewable Fuel Standard
RIN	Renewable Identification Number
SAE	Society of Automotive Engineers
SMR	Steam Methane Reforming
SSP	Shared Societal Pathway
T&D	Transmission And Distribution
TBW	Tire And Brake Wear
UF	Utilization Factor
WARM	Waste Reduction Model
WLTP	Worldwide Harmonized Light Vehicle Test Procedure
WTE	Waste-To-Energy
WTW	Well-To-Wheel

Executive Summary

The following report was compiled to support EPA's responses to stakeholder comments that cite or incorporate LCA on the proposed rule—Multi-Pollutant Emissions Standards for Model Years 2027 and Later Light-Duty and Medium-Duty Vehicles. By providing a summary review of recently published literature consisting of life cycle assessment (LCA) of battery electric vehicles (BEV) and key competing vehicle technologies for greenhouse gas (GHG) and criteria air pollutant (CAP) emissions reduction, this report:

- Summarizes the findings of recent (2019-2023) peer reviewed automotive LCAs.
- Outlines the potential life cycle emissions impacts of vehicle electrification from cradle-to-grave as relevant for the rulemaking process.
- Provides a review of electric vehicle-specific LCA methods and best practices.
- Notes key knowledge gaps in contemporary automotive life cycle inventory (LCI) and LCA data.

ES-1 Methodology

The review consists of peer reviewed, recently published (2019-2023, with certain exceptions), literature related to LCAs of BEVs and key competing vehicle technologies including hybrid electric vehicles (HEV), plug-in hybrid electric vehicles (PHEV), and fuel cell electric vehicles (FCEVs). The search for relevant literature focused particularly on studies that characterized the life cycle GHG and/or CAP emissions of these vehicles. An initial literature search and metadata collection, yielding 606 studies, was performed manually using combinations of keywords to form queries and search across major literature databases. Then, a programmatic search was performed via the SemanticScholar, CrossRef, and OpenAlex APIs to collect metadata for a broader set of 10,000 potentially relevant studies. This programmatic search yielded a small additional collection of relevant studies overlooked in the manual search, and helped to validate the completeness of the overall literature search. ERG ultimately reviewed 91 studies in full detail with 74 of those meeting acceptance criteria of peer review and ISO compliance.

ES-2 Life Cycle Stages Covered

LCAs were generally broken down into life cycle stages of resource extraction and refining, vehicle manufacturing and assembly, fuel production, use phase, and end-of-life. Distribution of the vehicle and maintenance are also often included in LCA studies but grouped into the other stages (e.g., maintenance happens within the use phase). This review summarizes key assumptions made by studies for each stage and also reviews LCA-supporting studies and models that were used in LCA model development. The common methodologies, findings, and main impact drivers identified in each life cycle stage are summarized:

- **Resource extraction and refining**
    - **Summary**: Resource requirements are usually based on vehicle weight or a bill of materials based on manufacturer data. Studies generally used background LCI databases such as ecoinvent. Several studies focused on developing LCIs for the extraction of key components such as lithium and graphite.
    - **Main Impact Drivers**: For electric vehicles (EV), battery materials including lithium and graphite require significant energy to refine.

- **Manufacturing and Assembly**
    - **Summary**: Manufacturing of EVs generally had higher impacts than internal combustion engine vehicles (ICEV) due to battery manufacturing. Most studies assumed manufacturing of glider kits were consistent across vehicle types and then used different inventories for each type of power train.
    - **Main Impact Drivers**: Electricity grid mix of manufacturing location.
    - **Data Gaps**: Newer assembly methods and part requirements, such as an increased number of semiconductors required for EVs, requires further LCI development.
- **Fuel Production**
    - **Summary**: Electricity grid mix is one of the main focal points of LCA studies on EVs. The generation mix for electricity for the use stage is one of the main drivers of impacts, particularly in areas with higher carbon intensity electricity (generated by natural gas or coal). Studies predict the future impact of EVs by assessing projected electricity grids. In the U.S., grid projections under the Inflation Reduction Act of 2022 show significant reductions in EV use phase emissions.
    - **Main Impact Drivers**: Impacts due to fuel production for EVs are directly related to the amount of coal and natural gas used to generate electricity. Liquid fuels are the main driver of impacts for ICEVs due to tailpipe emissions during the use stage.
    - **Data Gaps**: Electricity grid projections are constantly changing as national energy policy changes. While there are annual updates to U.S. grid mix projections, studies need to ensure they are using the most recent data. Hydrogen leakage is rarely considered by LCA studies but should be included.
- **Use Stage**
    - **Summary**: Fuel consumption for ICEVs and EVs (liquid fuel and electricity respectively) varies in the use stage depending on traffic, temperature, driver behavior, and other key factors. For PHEV's a utilization factor is used to determine how much of each driving mode (thermic vs. electric) is used. Studies generally use a base fuel consumption rate than modify it with factors specific to the use stage location. Maintenance and part replacement is usually included in the use stage.
    - **Main Impact Drivers**: If studies assume a short battery lifetime, then battery replacement during the use stage may be a main impact driver for the life cycle. Fuel consumption is directly related to the impacts seen in the fuel production stage. Non-exhaust emissions include particulate matter from tire and brake wear.
    - **Data Gaps**: Battery lifetime and the rate of battery degradation vary. Studies generally make simplifying assumptions about battery life, such as no replacements required or a constant performance over the vehicle life.
- **End-of-Life**
    - **Summary**: After the use stage the vehicle and its parts are either recycled, reused, or disposed of. Several LCI studies focused on battery recycling and reuse strategies to minimize life cycle impacts.
    - **Main Impact Drivers**: Recycling and reusing parts from older vehicles can reduce the amount of virgin material required from the resource extraction and refining stage. Electricity grid mix is identified as a key component of impacts related to the recycling process.

Our review highlights a number of key recommendations that should be addressed by automotive LCAs to ensure transparent, quality results. These best practice recommendations include following ISO 14040 and 14044 guidance for LCA studies and using EPA data quality for LCA guidelines (ISO 2006a; 2006b; A. Edelen and Ingwersen 2016). Studies should use recent data, usually less than three years old, to ensure LCI information is relevant. Studies should also publish LCI development methodology and data openly so that the results may be reproduced in other studies.

ES-3 Results and Discussion

Direct comparison between LCA studies can be difficult or even inappropriate depending on the scope, background data sources, or allocation methods used. To avoid making comparisons between studies that are not equivalent, intra-study comparisons were made where assumptions and context are consistent. From the 31 studies we identified as having sufficient details and criteria for intra-study comparison, Figure ES-1 ranks vehicle types against one another within studies and evaluates them on if global warming potential (GWP) impacts were higher or lower.

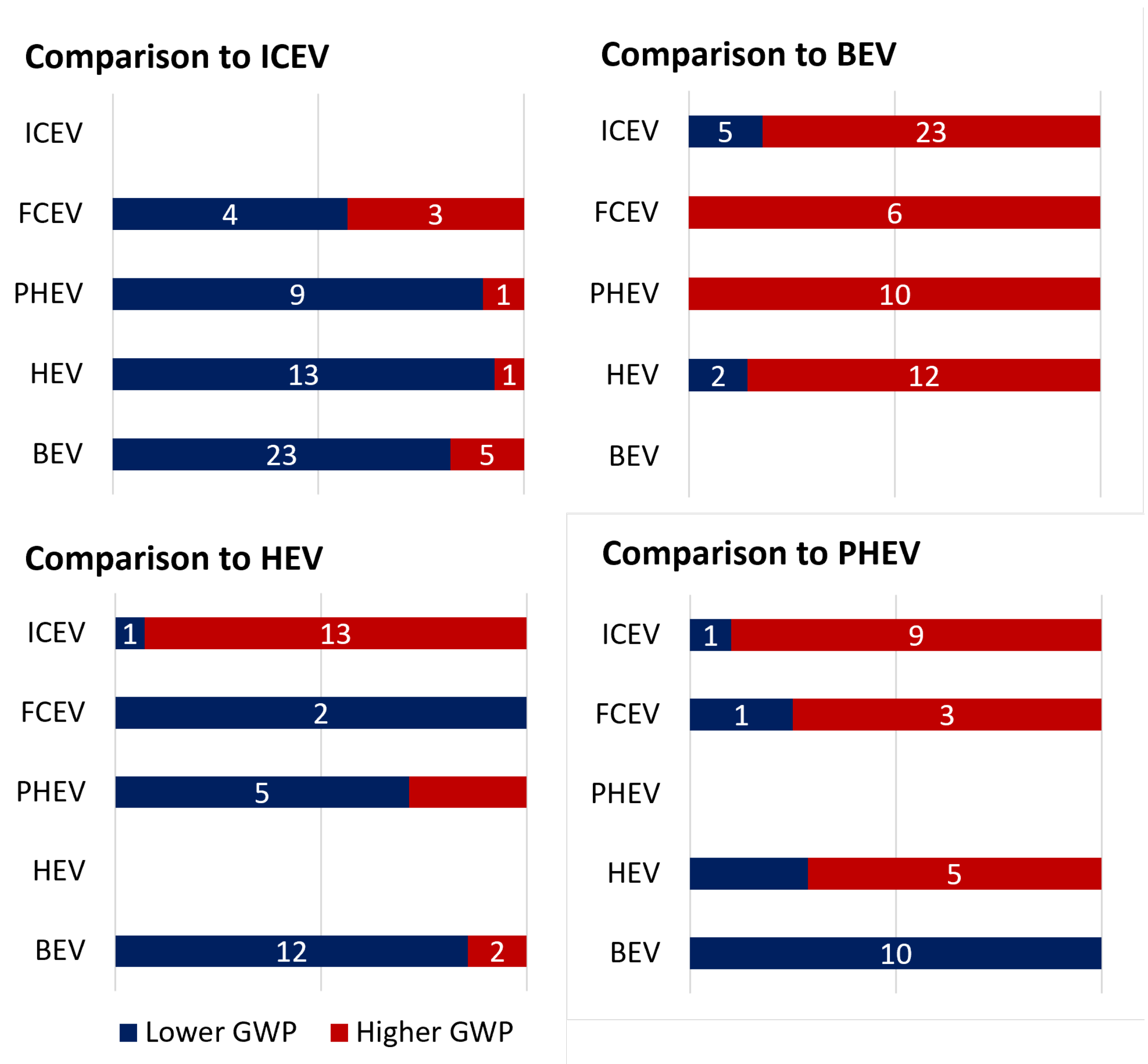

Figure ES-1. Counts of intra-study comparisons of life cycle GWP between vehicle types

Most studies found that ICEVs, HEVs, and FCEVs had higher GWP than BEVs, and all studies (five in total) found that PHEVs had higher GWP than BEVs. Only 2 of 30 studies reported BEVs being outperformed by another type of EV. The xEV vs. ICEV intra-study GWP comparisons from the upper left of Figure ES-1 are also visualized in Figure ES-2, except now as continuous numerical differences in place of categorical counts. The horizontal axis represents the difference in GWP values between each EV and ICEV GWP result, normalized to the ICEV result. Values below 0% have GWPs lower than ICEVs in the same studies, while values above 0% have higher impacts.

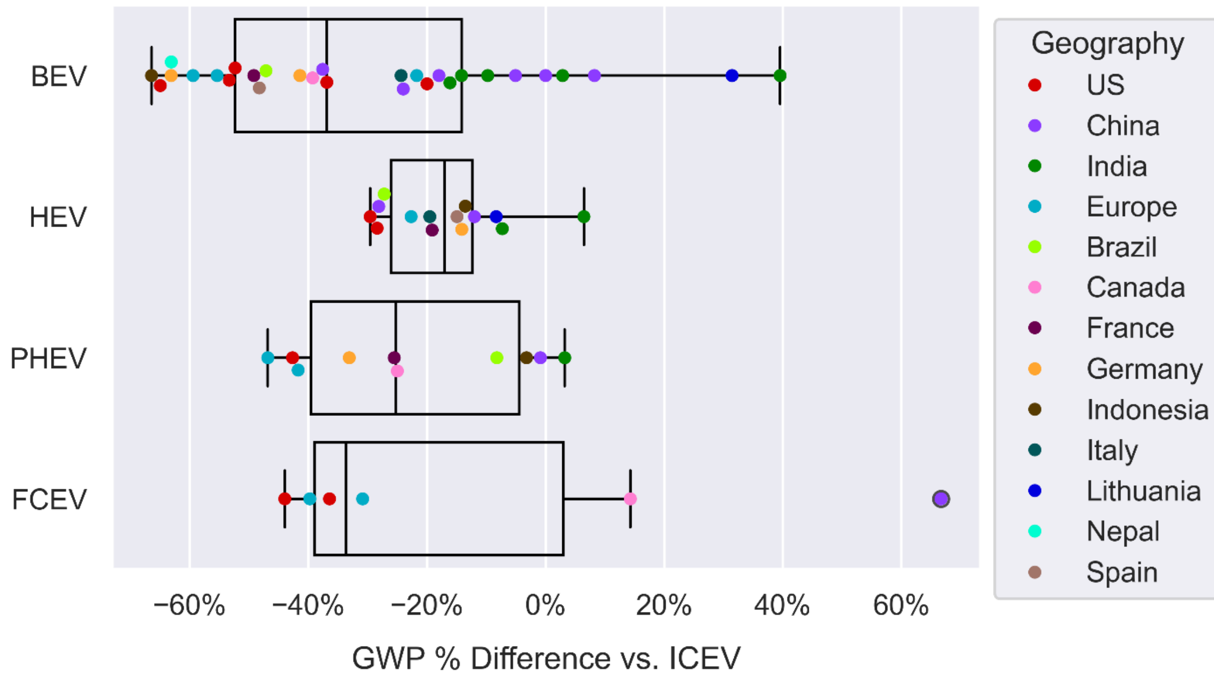

Figure ES-2. EV GWP, standardized to ICEV GWP

The main drivers of GWP for all vehicle types are car manufacturing (including resource extraction) and the use stage. The grid mixes used for both of these stages often had a significant influence on the vehicle's impact and study results, specifically for those studies where ICEVs outperformed EVs.

Additionally, of five identified ISO compliant, peer-reviewed studies that included particulate formation as an impact, all found that average EVs (BEVs, HEVs, and PHEVs) have higher particulate matter formation impacts than ICEVs. Criteria air pollutants were generally not included in impact assessments as independent categories. Rather GHG pollutants were assigned GWP factors and grouped into the GWP impact. Geospatial distribution is needed to determine if the difference between emitting CAPs during use (at the roadway in either urban or rural areas) or at the electricity generation location affects the impacts of ICEVs and EVs. This distinction is important for populations living near power plants, especially plants that have a high share of fossil fuel use.

Additional conclusions, limitations, and recommendations identified include the following:

- LCA literature broadly agrees that BEVs emit fewer GHGs than ICEVs over their respective life cycles in all but a select few geographic contexts. This aligns with EPA's draft Regulatory Impact Analysis (US EPA 2023b) despite its exclusion of upstream emissions from vehicle manufacture or emissions upstream of electric generating units and refineries.
- For CAPs, there is a geospatial distribution of impacts that should be considered in high-quality LCAs. However, regional-scale data is not widely available. Until data gaps are filled, LCAs should incorporate as granular geospatial data as is available.
- Openly publishing the LCI data on which a study relies is of singular importance to ensuring that LCA results are comparable across studies. This is of particular importance for government agencies to make data produced and/or used by the government more accountable. Provide at minimum full unit process data for the foreground processes and be explicit in the background data sources and associated LCI process names.

1 BACKGROUND

1.1 Notice of Proposed Rule and Study Objective

Life Cycle Assessment (LCA) is increasingly used as a decision-making tool for comprehensively estimating the environmental impacts of different product systems. During regulatory development of the new Multi-Pollutant Emissions Standards for Model Years 2027 and Later Light-Duty and Medium-Duty Vehicles, the U.S. Environmental Protection Agency (EPA) started to receive formal stakeholder comments that either cite or directly incorporate LCA (US EPA 2023b). The proposed emission standards for new light- and medium-duty vehicle (LMDV) applies to model years 2027 through 2032 and later as part of EPA's mission to protect public health and welfare and responds to the issuance of Presidential Executive Order 14037 "Strengthening American Leadership in Clean Cars and Trucks". The rule covers both greenhouse gas (GHG) emissions and criteria air pollutants (CAPs). Per Table 13-73 in Chapter 13 of the Draft Regulatory Impact Analysis of the proposed rule, it is anticipated that these new regulations will result in the electrification of approximately 67% of new light-duty vehicles sales by 2032 (US EPA 2023b). Thus, EPA has determined a critical need to review and assess automotive LCAs to better understand the potential life cycle GHG and CAP emissions impacts of vehicle electrification.

In support of this NPRM, EPA asked ERG to provide a summary review of recently published literature consisting of LCAs of battery electric vehicles (BEV) and key competing vehicle technologies for GHG and CAP emissions reduction, such has plugin hybrid electric vehicles (PHEV) and strong hybrid electric vehicles (HEV). This report summarizes the findings of this literature review. The main motivation for this report is to review and assess automotive LCAs to better understand the potential life cycle emissions impacts of vehicle electrification as relevant for the rulemaking process, and to provide a state-of-the-art review of electric vehicle (EV)-specific LCA methods, best practices, and key knowledge gaps.

1.2 Life Cycle Assessment Overview

ISO standards 14040/44 defines LCA as the "compilation and evaluation of the inputs, outputs and the potential environmental impacts of a product system throughout its life cycle" (ISO 2006a). LCAs take a "cradle-to-grave" approach that can assist decision-makers in selecting the most environmentally preferable option while minimizing tradeoffs such as shifting impacts from one environmental medium to another or from one location to another. LCA is intended to evaluate the environmental impacts throughout a product's lifespan starting with raw material extraction and continuing through stages such as production, use, maintenance and the eventual end-of-life (EOL) management such as disposal, recycling or reuse of a product and its components. For an automotive LCA, these life cycle stages cover both vehicle parts and assembly as well as energy carrier supply chains. Energy carrier supply chains and location of emission impacts will differ based on whether the vehicle relies on electricity or liquid fuels.

ISO standards 14040/44 define four main phases of an LCA:

1. *Goal and Scope Definition* — this phase defines the purpose and scope of the project and intended audience.

2. *Life Cycle Inventory (LCI)* — this phase accounts for the actual environmental flows of a product system, which are the incoming and outgoing emissions, energy, materials, and waste for each unit process in the life cycle.
3. *Life Cycle Impact Assessment (LCIA)* — this phase characterizes the inventory results into the final results based on damages caused to make them meaningful to the audience (e.g., environmental impacts and human health risks).
4. *Interpretation* — this phase analyzes and draw conclusions from the results and uses tools such as contribution and sensitivity analyses to dig deeper into the findings.

LCA is an iterative process. Once one phase is completed, it may be necessary to refine a previous phase. While LCAs can cover a suite of different local, regional and global LCIA categories relevant to environmental flows to air, land and water, this literature review focused on LCIA categories relevant to the NPRM, including those resulting from air emissions of GHGs as well as CAPs. EPA has national air quality standards for six pollutants it categorizes as CAPs: nitrogen dioxide (NO_2), ozone (O_3), sulfur dioxide (SO_2), particulate matter (PM), carbon monoxide (CO), and lead (Pb) (US EPA 2014). In LCAs, GHGs are typically reported as global warming potential (GWP) using the unit of kilograms (kg) of carbon dioxide (CO_2) equivalents (eq.) across a time horizon such as 100 years (IPCC 2023). GWP represents the heat trapping capacity of GHGs. In addition to CO_2, other important GHGs include, but are not limited to, nitrous oxide (N_2O) and methane (CH_4). CAPs may result in a range of different impact categories that cause environmental and human health damages at the local and regional level such as photochemical smog formation, acidification, and respiratory effects (Bare 2011). While LCIA results comprehensively assess the tradeoffs across multiple impact categories, they do have limitations and embedded uncertainty. For example, most LCIA results will treat a single large, concentrated release with direct human exposure equivalently to the sum of multiple small releases occurring at different locations over a different period of time. LCAs can be used in combination with other tools such as fate and transport studies and health impact studies to better understand the possible environmental implications of the life cycle of different product systems at different temporal and geographic scales.

There are two types of LCAs: attributional and consequential. This report focuses on reviewing attributional LCAs, which are relevant to the scope of the current EPA rulemaking and assess the absolute LCA impact attributed to a product system, referred to by the UNEP-SETAC Global LCA Database Guidance Principles as “what portion of global burdens can be associated with a product (and its life cycle)” (UNEP-SETAC 2011). Alternatively, consequential LCAs seek to answer a different research question: how might a shift in the provision of goods or services alter emissions and impacts change given a new decision of some activity or production? Consequential LCAs attempt to model only the net consequences of a change (i.e., how might overall life cycle emissions change marginally under some model and set of assumptions about the future?).

As discussed throughout this report, there are existing publicly available or licensed LCI and LCA databases and tools. Use of different sources causes significant heterogeneity in the reviewed LCA literature transparency, methods, data quality, geographic coverage and temporal coverage. Throughout this report recommendations are highlighted for best practices when completing an automotive LCA.

1.2.1 Functional Units

Comparative LCAs can be compared on the basis of functional equivalence. The functional unit is the end product provided by the service being examined. The functional unit should be set in the goal and scope phase of the study. For example, reviewed automotive light-duty LCA studies typically use a functional unit of distance traveled by a vehicle across its lifetime. Per mass-distance units for hauling are often used in LCAs of medium duty vehicles.

Vehicle occupancy rate was rarely a considered factor in the studies reviewed. However, Bouter et al. set occupancy rates of 1.3 persons per passenger car and 17.4 persons per bus to better compare mobility options in France's urban transportation sector (2020). Their analysis found that bus occupancy rates impacted their competitiveness with BEVs and PHEVs when considering the transportation of one passenger for one kilometer. The goal and scope of the study will dictate whether occupancy rates should be considered to compare between transportation methods.

1.2.2 Scenario and Sensitivity Analyses

LCAs inherently involve making assumptions. To see the influence of the assumptions made in an LCI model, many reviewed studies conduct sensitivity analyses. To carry out such an analysis, the assumption of interest is changed and the entire LCA is recalculated. Amongst the literature reviewed, the most common scenario and sensitivity analyses modeled the following:

- Projected future grid mixes in a single location
- Current grid mixes in multiple locations
- Battery range and performance
- Driving behavior and vehicle lifetime miles
- End of life treatment method and allocation
- Component material types, weights, and carbon intensities
- Environmental temperature
- Component transportation distance
- Vehicle occupation rate

1.3 Literature Review Methodology

In order to aggregate best practices and provide a foundation for responses to LCA-related NPRM stakeholder comments, ERG conducted a review of recently published (2019-present), peer-reviewed literature related to LCAs of BEV and key competing vehicle technologies (e.g., PHEV and strong HEV), particularly those that characterized life cycle GHG and/or CAP emissions. ERG first manually searched and collected metadata for some 606 studies, then developed a Python script to programmatically search and collect metadata for a broader pool of 10,000 studies. Each batch of studies was initially screened for relevance using a combination of the ASReview tool (van de Schoot et al. 2021), tracing citations of and by other relevant studies, and manual review of study metadata and full contents. Across iterative rounds of discovery and relevance screening, ERG ultimately reviewed 91 studies in full detail, only 74 of which fully met the acceptance criteria established in the EPA project-level Quality Assurance Project Plan. To facilitate uniform study review and aid cross-study comparisons, ERG developed a review matrix template into which key study attributes were recorded for each paper. Upon populating the review matrix, ERG developed this report to summarize key scoping decisions, modeling practices, and findings of literature.

1.3.1 Keywords, Queries, and Searches

ERG assembled and categorized the keywords and phrases (collectively referred to as just "keywords" for brevity) listed in Table 1-1 in order to facilitate both the manual and programmatic construction of queries for search engines and APIs. Searching over the full set of keyword combinations was intended to help identify all relevant LCA and LCA-adjacent literature on electric vehicles and associated emissions of GHGs and CAPs.

Table 1-1. Query Keywords Grouped by Category

Category	Keywords	
Vehicle Technology	▪ battery ▪ battery-electric vehicle (BEV) ▪ brake ▪ electric vehicle (EV) ▪ extended range electric vehicle (EREV) ▪ fuel cell electric vehicle (FCEV) ▪ hybrid electric vehicle (HEV)	▪ hydrogen fuel cell ▪ {light-, medium-}duty ▪ passenger vehicle ▪ plug-in electric vehicle (PEV) ▪ plug-in hybrid electric vehicle (PHEV) ▪ tire ▪ zero-emission vehicle (ZEV)
LCA Element, Stage, or Scope	▪ cradle-to-grave ▪ extraction, mining, refining ▪ disposal, end-of-life ▪ distribution, transportation ▪ fuel {consumption, production} ▪ life cycle {assessment, analysis} (LCA) ▪ life cycle inventory (LCI) ▪ life cycle impact assessment (LCIA)	▪ manufacture ▪ maintenance, service ▪ operation, driving, on-road ▪ recycling, recycled material ▪ tank-to-wheel (TTW) ▪ well-to-tank (WTT) ▪ well-to-wheel (WTW) ▪ upstream, embodied
Emissions Type	▪ air {emission, pollutant, pollution} ▪ carbon dioxide (CO2) ▪ carbon dioxide equivalent (CO2e) ▪ {combustion, exhaust} ▪ criteria air {emission, pollutant, pollution} ▪ environment ▪ methane (CH4) ▪ global temperature potential (GTP)	▪ global warming potential (GWP) ▪ greenhouse gas (GHG) ▪ nitrogen dioxide (NO2) ▪ nitrogen oxides (NOx) ▪ nitrous oxide (N2O) ▪ {non-combustion, non-exhaust} ▪ ozone, ground-level (O3) ▪ particulate matter (PM) ▪ sulfur dioxide (SO2)

Keywords from Table 1-1 were first manually combined into queries and passed into search engines in order to identify relevant literature. Each query consisted of one or more example keywords from each of the above categories, plus logical operators that constrained how they were combined. Query syntax varied by search engine or literature database, but queries were first drafted and developed as pseudo-code. For example, a query searching for studies of on-road GHG emissions from PHEVs would be represented as follows: {"PHEV" AND ("tank-to-wheel" OR "driving" OR "operation" OR "on-road") AND ("GHG" OR "greenhouse gas" OR "LCA" OR "life cycle assessment" OR "life cycle analysis")}. Expansion and iteration on the sets of keywords and compiled query strings continued until the resulting literature included the most relevant sources. The final set of queries and search engines used to perform the literature search can be found as an appendix/supporting information to the summary report. Manual query construction and searches within science.gov, worldwidescience.org, Google Scholar, and Elicit collectively returned an initial set of 608 unique studies published in 2019 or later. The resulting study metadata included (at a minimum) digital object identifier (DOI), author(s), title, publication, year published, and abstract text. Where study metadata was incomplete, a combination of CrossRef (API accessed via the Python package *habanero*) and OpenALEX (Priem, Piwowar, and Orr 2022) metadata was used to fill gaps.

Following manual searches, a subsequent round of programmatic query construction and search was performed in Python. The Semantic Scholar Academic Graph (S2AG) RESTful API was queried for recently studies (2019-present) using every cross-category keyword combination (i.e., one keyword from each category) available in Table 1-1, and the top 25 results from each query were saved. The initial pool of roughly 26,000 studies was then filtered down to just 10,000 by removing duplicates and truncating a large portion of fully irrelevant entries. Semantic Scholar metadata contained many gaps, so DOIs were used to instead obtain metadata primarily from CrossRef (via *habanero*) and supplement with OpenALEX. A summary spreadsheet of initial search results was developed that includes the following fields: digital object identifier (DOI), author(s), title, publication, year published, and abstract text.

1.3.2 Relevance Screening

Following the rounds of literature searches and metadata curation, both titles and abstracts were reviewed for relevance. ERG reviewers used a combination of three techniques to identify relevant studies: (1) manual designation, (2) forward- and reverse-citation searches, and (3) the ASReview tool. The former two techniques are likely familiar to most readers who have previously read and/or written a literature review; the latter approach, however, constitutes a recent advancement in the field of literature review software. ASReview is a free, open-source machine learning tool introduced in a 2021 *Nature Machine Intelligence* paper that uses an "active learning" cycle in order to iteratively learn from users as they label each study (presented as title and abstract) as relevant or irrelevant to their review project (van de Schoot et al. 2021). ERG fed the curated sets of study metadata into ASReview v1.2.1 in order to produce approximate relevance rankings for the search results, then performed closer, manual reviews on studies in the highest ASReview-rank percentiles (ASReview LAB developers 2023). Additional sources of literature not returned by search engines, such as government agency reports, modeling documentation, and peer-reviewed NGO reports were collected and manually screened for relevance.

1.3.3 Acceptance Criteria & Full-text Screenings

The most relevant studies were prioritized for screening against the acceptance criteria laid out in the Quality Assurance Project Plan: peer-review (for all studies) and ISO compliance (for formal LCA studies only) (ISO 2006a; 2006b). Full-text reviews were then conducted on accepted studies; metadata for these studies can be found in Appendix B. Key study attributes were extracted and catalogued in a table of categorical, free-text, and numeric columns. Fields in this table were constructed to uniformly capture key scoping decisions, modeling practices, and study findings in order to facilitate cross-study comparisons. Geographic and temporal scopes of studies were also documented in order to contextualize and caveat findings from non-U.S. and/or older studies. Separately, reviews of manufacturer studies—which typically did not meet the acceptance criteria due to lacking transparent disclosure of LCI and LCA methods and data—were performed in Appendix C. Despite these shortcomings, these studies are often useful as sources of secondary data, given manufacturers' access to primary data on vehicles and supply chains. For this reason, we compile and review recent manufacturer LCA reports with the same critical lenses as those applied to accepted studies in Section 2.

2 LIFE CYCLE INVENTORY MODELING BY STAGE

Chapter 2 Overview:
The reviewed studies generally focused on the use and fuel production stages and on GWP impacts. However, reviewed LCI studies highlight the importance of the resource extraction and refining, manufacturing and assembly, and end-of-life stages in assessing the full life cycle impacts of vehicle use.

This section discusses each LCI stage and what effect the decisions about that stage have on the life cycle impacts. Life cycle emissions are generally not compared from study-to-study since this report does not intend to evaluate the comparative emissions between vehicle types. Rather, study scopes and methodologies are compared in order to identify best practices.

LCIs were generally broken down into life cycle stages of resource extraction and refining, vehicle manufacturing and assembly, distribution of vehicle, use phase, maintenance, and end-of-life. Some studies included the fuel cycle as well. Table 2-1 summarizes the numbers of studies that included each stage as well as the number of studies that include stage pairings. All combinations of part manufacturing, vehicle manufacturing, and on-road use were the most common. The EOL stage was the least commonly addressed but was still included in the majority of studies.

Table 2-1. Number of Reviewed Studies that Included each Life Cycle Stage

	Extraction & Refining	Part, Component, Module Mfct.	Vehicle Mfct.	On-road use	End-of-life
Extraction & Refining	56				
Part, Component, Module Mfct.	52	57			
Vehicle Mfct.	48	51	52		
On-road use	51	50	49	59	
End-of-life	43	46	44	45	47
Color Scale	Least Common				Most Common

Mfct.:Manufacturing

How to interpret Table 2
Table 2 shows the number of reviewed studies that included each life cycle stage in their LCI, with diagonal entries being the independent stages (i.e. just the End-of-Life) and non-diagonal entries being the inclusion of two stages (i.e. 46 studies included both Vehicle manufacturing and End-of-Life stages).

The vehicle maintenance and distribution stages had the least clear discussion in the reviewed literature. These were generally grouped into other phases for LCI and for discussion of life cycle impacts. Maintenance was generally included in either the use or manufacturing stage, while distribution was included in each stage that had movement of materials or products between different geospatial regions. This report does not include a detailed discussion or review of the distribution stage as a discrete LCI element. Vehicle maintenance is discussed in Section 2.4.5 as part of the use stage.

Table 2-2 shows the number of occurrences of each vehicle type as well as what other types it appeared with. BEVs were the most common and were usually compared to ICEVs. ICEVs were also used as a benchmark to compare HEV and PHEV to. FCEV were the least common vehicle examined and were most commonly compared with BEVs and ICEVs.

Table 2-2. Vehicle Comparisons in Reviewed Studies: Number of Studies that Included Each Vehicle Type

	BEV	HEV	PHEV	FCEV	ICEV
BEV	45				
HEV	20	24			
PHEV	15	16	16		
FCEV	7	5	5	8	
ICEV	37	22	14	8	41

Color Scale	Least Common	Most Common

How to interpret Table 3
Table 3 shows the number of reviewed studies that included different combinations of vehicle types in their LCI., Diagonal entries count the inclusion frequency of single vehicle types (i.e. whether or not BEV were included) and non-diagonal entries count the inclusion of a pair of vehicle types (i.e. 22 studies included both HEV and ICEV).

Most of the reviewed studies used some form of modeling software to assist in the preparation of their LCIs. One of the most common, the Greenhouse gases, Regulated Emissions, and Energy use in Transportation (GREET) model developed at Argonne National Lab, was used by 25 studies (Wang et al. 2022). GREET is commonly used in LCAs for all types of vehicles but has generally focused on light-duty vehicles. GREET has two main modules for vehicle LCAs: GREET 1 for well-to-wheel fuel-cycle LCAs and GREET 2 for the vehicle manufacturing cycle. The well-to-wheel fuel cycle in the GREET 1 model includes raw material extraction, transportation, refining, delivery, and vehicle fuel consumption. The vehicle cycle in the GREET 2 model includes raw material extraction, material processing, component manufacturing, vehicle assembly, and vehicle end-of-life. Many of the reviewed studies used one or both of the GREET modules. Unless explicitly stated otherwise, it is assumed that studies using GREET used its default parameterizations for all stages of the vehicle life cycle. GREET model results are limited to total energy consumption (non-renewable and renewable), CAPs, GHGs, and water consumption. OpenLCA, SimaPro, and GaBi are other common LCA software that are compatible with databases used to prepare LCIs and may quantify a larger suit of impact categories than the GREET model. It is not uncommon for studies to use a combination of programs and databases to make LCIs, particularly when the study is looking at multiple different vehicle types, fuel pathways, end-of-life scenarios, or impact categories.

2.1 Resource Extraction & Refining

Summary for Resource Extraction & Refining

Resource extraction and refining are significant contributors to EV life cycle emissions. These processes require regular re-evaluation as extraction technologies, resource types, and proven reserve locations change. This section specifically focuses on resource extraction and refining related to the vehicle. Section 2.3 discusses fuel production, which includes extraction and refining.

Impacts are shown to vary depending on where and how resources are being extracted and refined. LCI quantities also change as common LCI databases update with new information. Components related to battery production such as lithium and graphite are shown to have varying impacts based on database source.

Based on the reviewed literature, studies should consider the following recommendations:

- Use recent data (<3 years old) and verify that background LCIs have geospatial agreement.
- Studies that focus on resource extraction should report resource depletion impacts along with carbon intensity.

The reviewed studies generally took two approaches to LCI data for the resource extraction and refining stage: a bill of materials (BOM) or inventory detailing specific part/component inputs which were referenced from a database such as ecoinvent (Wernet et al. 2016) or GREET (Wang et al. 2022), or a generalized approach was used to estimate vehicle inventory based on curb weight. BOMs or LCIs were then used to determine the quantity and type of elementary flows required to be extracted and/or refined. In studies that used LCI data based on curb weight, the frame or glider was usually assumed to be shared between all examined vehicle types while the powertrain was modeled and inventoried separately. Section 2.2.1 and 2.2.2 details powertrain elements and glider kits respectively. Some studies generalized resource extraction and refining into the manufacturing stage. Oftentimes weight based relationships between the vehicles curb weight and the carbon intensity of production were used as a simplification to an LCI that used specific source locations for elemental flows (Andersson and Börjesson 2021).

The extraction and refining of materials for battery production is a major driver of impacts for EVs. Table 2-3 details reviewed studies that specifically examined resource and extraction of battery components. These studies generally seek to reconcile the various system boundaries, datasets, and any modeled parameters between databases. This background development is critical for accurate LCAs as extraction and refining methods evolve. Engels et al. examined graphite production in China and compared results to ecoinvent LCIs (2022). They found significantly higher graphite production intensities, 9.6 compared to the 2.1 tonnes CO_2eq/tonne graphite from ecoinvent v3.7.1. GREET 2022 has a similar, but still lower, value of 8.3 tonnes

CO_2eq/tonne graphite (Iyer and Kelly 2022). The higher GWP for graphite produced by Engels et al. would increase the life cycle GWP of GREET's 100-mile range BEV by about 250kg CO_2, and would have an even greater increase on studies that used ecoinvent values. It should be noted that nearly every study reviewed used graphite anodes.

Lithium production was also a major contributor to the impacts of manufacturing batteries in reviewed studies. Nearly every reviewed study used a lithium-ion battery. In the same manner as Engels et al., Schenker at al. examined lithium production from brine and reported a large gap in lithium carbonate production intensities (2022). Brine operations in Chile and Argentina had a range of 3.4 to 8 kgCO_2/kgLi_2CO_3, mostly driven by quicklime and other chemical use (Schenker, Oberschelp, and Pfister 2022). Meanwhile lithium production from brine from the Chaerhan salt lake in China had a GWP impact of 31.6 kgCO_2/kgLi_2CO_3 and a water scarcity footprint of 35.25 m^3/kgLi_2CO_3. The water scarcity footprint is over 7 times that of the Chilean operation and 20 times that of the Argentinian operations. These higher impacts are attributed by Schenker et al. to the Chaerhan process using more natural gas and coal power electricity (2022). Kelly et al. report similar brine processing impacts for lithium carbonate from Chile at 2.7-3.1 kg CO_2/kg Li_2CO_3 and also report a higher GWP impact for lithium carbonate produced from processed Australian spodumene ore at 20.4 kg CO_2/kg Li_2CO_3 (2021). These ranges of values highlight the need to examine background process suppliers in LCAs, as there can be a notable range of impacts based on where the process is located, and what method is being used for extraction/processing.

Recommendation
Lithium and graphite are examples of resources that have varying extraction and processing intensities depending on the age of the data and location of production. Use recent data (<3 years old) and verify that processes have geospatial agreement.

Table 2-3. GWP Impacts of Batteries and Battery Components

Reference	Product System	Product GWP Intensity	Background LCI Data	Notes
(Engels et al. 2022)	Graphite anode	9.6 tonne CO_2eq / tonne graphite	GaBi 10.0 SP40	Used primary production data from a graphite anode factory in China
Ecoinvent database v3.7.1	Graphite anode [graphite production, battery grade (CN)]	2.1 tonne CO_2eq / tonne graphite	Ecoinvent 3.7.1	
GREET 2022, (Iyer and Kelly 2022)	Synthetic graphite	8.3 tonne CO_2eq / tonne graphite	GREET	
(Schenker, Oberschelp, and Pfister 2022)	Lithium Carbonate (Li_2CO_3) from brines	3.4 (Chile) 7.4-8 (Argentina) 31.6 (China) kgCO_2eq / kg Li_2CO_3	Ecoinvent 3.8	GWP for Li_2CO_3 production in China is significantly higher due to the process used at Chaerhan salt lake.
(J. C. Kelly et al. 2021)	Lithium Carbonate (Li_2CO_3) from brines (Chile)	2.7-3.1 kg CO_2eq / kg Li_2CO_3	Primary brine facility data	GWP Range is due to different allocation methods
(J. C. Kelly et al. 2021)	Lithium Carbonate (Li_2CO_3) from ores (AU,CN)	20.4 kg CO_2eq / kg Li_2CO_3	Primary ore processing facility data	

2.2 Manufacturing & Assembly

Summary for Resource Manufacturing & Assembly

Manufacturing and assembly LCI and LCIA are primarily driven by vehicle weight and electricity grid mix, respectively. Battery chemistry and performance are a focal point of numerous LCI studies. While vehicle fluids and powertrain components are less varied than batteries, these items should not be overlooked in LCIs. There are data gaps in manufacturing and assembly LCIs related to newer assembly practices and semiconductor supply chains that should be considered in future studies.

Based on the reviewed literature, studies should observe the following recommendations:

- Consider how glider and drivetrain differences affect vehicle weight and the amount of resources required.
- Ensure the electricity consumed by manufacturing processes accurately reflects the grid mix at those process locations (i.e., this may differ other life cycle phases).
- LCI should include transportation of resources and components between manufacturing and assembly stages.

Once raw materials have been extracted and refined, the vehicle must be assembled. Generally, LCIs broke this down into four categories: the powertrain, the glider (chassis and body), batteries, and fluids. These are all discussed in greater detail in following subsections. Part, module, and final vehicle manufacturing and assembly typically do not occur at the same location, nor do raw material extraction and refining. Verifying that appropriate regions or specific locations are chosen for each step is important, not only to account for the varying utilities at each process location (discussed in more detail in Section 2.3.1.1), but also due to the transportation of items between locations. GREET, one of the most common modeling tools used by the reviewed studies, does consider this transportation by default in the vehicle life cycle (Wang et al. 2022). Studies that used GREET are assumed to have taken this transportation between the resource and extraction stage and the manufacturing and assembly stage into account, relying on default locations or customizing wherever appropriate.

Recommendation
LCIs should account for different process locations. Transport of resources and components between manufacturing and assembly stages produces emissions.

Many studies, including those using GREET assumptions, reported summary LCI information for vehicles based on the overall weight or by key subsystems. For example, Shafique et al. included detailed mass and energy inputs for an ICEV, EV, and PHEV divided into categories such as chassis, body, powertrain, battery, and fluids (2022). Others examined market data and averaged the sales information for vehicles to create an 'average' representative vehicle (Sun et al. 2021).The manufacturing stage was identified by most cradle-to-grave studies as a key source of life cycle differences among vehicle types, especially influenced by vehicle weight. Generally, vehicle gliders are assumed to be equal in weight amongst vehicle types. Weight differences between types occur due to the differing standard weights of powertrains between vehicle types.

Powertrain weights can be based on assumed weights for each vehicle type, like the assumed weights in GREET, included in Table 2-4. Total vehicle weight can have an impact on LCA results as higher weight vehicles require additional propulsion power to travel the same distance, at the same speed, as lighter weight vehicles. Vehicle weight and its impact on the use stage is discussed in 2.4.1. The following sections discuss powertrains and gliders in more detail by category of vehicle component.

2.2.1 Glider Components

A "glider kit" is simply a vehicle without an installed powertrain: studies such as Bieker's 2021 International Council on Clean Transportation (ICCT) paper use this term to refer to the collection of all non-powertrain vehicle components (frame, body, etc.) (Bieker 2021). A vehicle glider can be further divided into components including the body, exterior, and chassis. These items correspond to the chassis and body systems in GREET. Many LCAs comparing vehicle powertrain impacts either assumed identical glider kits or chose vehicles with similar sizes, shapes, weights, and performance to control for design or aesthetic differences impacting fuel economy or vehicle performance. The GREET model's standard passenger vehicle assumptions include equal vehicle body, exterior, interior, and chassis weight for all vehicle types (Wang et al. 2022).

2.2.2 Powertrains

A powertrain includes the vehicle components that propel a vehicle and can be powered by a variety of fuel types and/or batteries. The powertrain is what primarily differentiates electric, hybrid, internal combustion, and fuel-cell vehicles from one another. The powertrain of ICEV, BEV, HEV, and PHEV generally consists of an engine unit, engine fuel storage system, powertrain thermal system, exhaust system, powertrain electrical system, emission control electronics, and the transmission system. Table 2-4 details the powertrain components for various vehicle types in Table 3.3 of the Car sheet in GREET 2022 (version "GREET 2022 rev1"). FCEV have a fuel cell stack along with a fuel storage system, but do not have an engine like an ICEV. FCEV specific components are discussed in greater detail in Section 2.2.5. Battery weights generally make up the largest proportion of powertrain weight for BEVs and PHEVs. Battery weight assumptions used in GREET can be found in
Table 2-5.

Table 2-4. Passenger Vehicle Component Weight Percentages (assumed) in GREET 2022 rev1, Car sheet, Table 3.3

		Percent of Total Vehicle Weight					
Component System	**Sub-components**	ICEV	HEV	PHEV30	EV100	EV300	FCEV
Powertrain System	Engine, fuel storage, powertrain thermal, exhaust, powertrain electrical, emission control electronics, fasteners	15.3	22.5	23.8	4.8	4.5	8.3
Transmission System		6.3	5.0	4.8	5.7	5.6	2.8
Chassis (w/o battery)	Cradle, driveshaft, differential, suspension, braking system, wheels/tires, steering system, chassis electrical	25.4	21.6	20.6	24.8	24.2	23.5
Traction Motor		-	2.1	3.0	7.2	9.3	4.2
Generator		-	2.1	3.0	-	-	-
Electronic Controller		-	1.8	1.8	5.9	5.9	3.7
Onboard H2 Storage		-	-	-	-	-	8.7
Body		52.9	44.9	43.0	51.6	50.4	48.9

Table 2-5. Battery Weights (Assumed) by Passenger Vehicle and Battery Type in GREET 2022 rev1, Car sheet, Table 2.1

	Vehicle Battery Weight (lb)				
Battery Type	ICEV	HEV	PHEV	BEV	FCEV
Pb-Ac	36	22	22	22	22
Ni-MH	-	89	635	2,853	94
Li-ion	-	43	342	1,174	49

2.2.3 Batteries

Summary for Batteries

EV batteries make up a significant portion of the vehicle's weight and are a significant driver of manufacturing phase impacts. Most studies examined lithium-ion batteries with varying cathode chemistries. Nickel-Manganese-Cobalt and Lithium-Iron-Phosphate batteries were the most commonly examined, but there are numerous different battery chemistries and types. Similar to other life cycle stages the use of low carbon intensity electricity is highlighted as a key component of lowering GWP impacts of EV batteries.

Based on the reviewed literature, studies should consider the following recommendations:
- Explicitly detail battery chemistry, type, and LCI.
- NMC111 batteries are not used in the U.S. and studies should avoid including in U.S. studies.
- Use recent battery data (<3 years old); battery performance and compositions are constantly being developed.

Battery lifetime, replacement schedule, and charge loss over time are all discussed in Section 2.4.5.

Recommendation
Battery size and content vary with battery chemistry and type. Studies should explicitly detail battery components in the LCI. NMC111 batteries are not used in the U.S. and studies should avoid including in U.S. studies.

While almost all studies assumed lithium-ion batteries with graphite anodes, there was some variety in the exact cathode used. Table 2-6 shows the types of batteries specified in the reviewed studies. NMC111 and LFP batteries were the most common and GREET uses the NMC111 battery as a default option for some EV profiles (Wang et al. 2022). However, NMC111 batteries have never been used in BEVs or PHEVs in the U.S., and newer LCAs typically avoid modeling their use within modern EVs. Several studies specifically focused on assessing multiple battery types, including less examined ones. Zhang et al. assessed alternative anodes for NMC batteries (silicon nanotubes and nanowire) as well as an iron-sulfur-lithium battery that had an iron sulfide cathode, lithium anode, and lithium sulfide electrolyte (Hongliang Zhang et al. 2023). Kannangara et al. considered in their LCA the standard NMC and LFP batteries as well as a nickel-cobalt-aluminum (NCA) battery (Kannangara, Bensebaa, and Vasudev 2021). A European Commission report examined a variety of battery chemistries, including various NMC batteries, LFP, LMO, Na-ion, solid-state, and NCA, and projected the market average technology mix of these battery types and battery performance to 2050 (Hill et al. 2020). After accounting for studies that did not have batteries within their boundaries, such as LCI supporting studies, six studies did not specify the type of battery examined and an additional three did not detail the type of NMC.

Table 2-6. Battery Types Specified in Reviewed Studies

Type of Battery	NMC*,ǂ				LFP*	LMO*	ZEBRA	NiMH	NCA
	111	811	622	Unspecified					
Number of Studies	15	7	5	3	12	3	2	3	3

Initialisms and names include NMC: Nickel Manganese Cobalt oxides, NiMH: Nickel Metal Hydride, LMO: Lithium Manganese Oxide, ZEBRA: Sodium-Nickel-Chloride, LFP: Lithium iron phosphate, NCA: Nickel cobalt aluminum
*NMC, LFP, and LMO all refer to cathodes used in lithium-ion batteries with a graphite anode.
ǂ NMC cathode compositions are labeled as molar ratios of Nickel:Manganese:Cobalt

Battery weight and specific energy (unit of energy per unit of mass) vary depending on the chemistry and construction of the battery. Popien et al. examined 10 different modern and emerging EV battery types (varying both chemistry and construction, but with a constant capacity of 80 kWh) and found that LFP batteries were the heaviest, having a mass of 542 kg (2023). NMC batteries were lighter at 442 and 418 kg for NMC622 and NMC811 respectively. All solid-state batteries (ASSB) were found to be about 25-40% lighter than batteries with liquid electrolyte. Impacts such as metal resource depletion and human toxicity had a greater range of values than GWP. In an LCI methodology study, Crenna et al. found that using older LCI data could result in battery impact estimates varying by nearly an order of magnitude (2021). LCIA and impact categories are discussed in more detail in Section 0.

Recommendation
The use of recent battery inventory data is critical to ensuring LCA results are accurate. Studies should use recent (<3 years old) battery data if possible.

In the reviewed studies, battery production is identified as a significant contributor to the life cycle emissions of EVs. The GWP impacts associated with battery production (including extraction of raw materials) usually result in EV manufacturing and assembly GWP to be higher than that of ICEV. Chordia et al. examined the impacts of battery production with ecoinvent between versions 2.2 and 3.7.1 with process adjustments to cobalt and copper supply chains, finding that the newer data set resulted in battery production GWP impacts were about 30% higher than previously reported at 185 kg CO_2eq/kWh (2021). Chordia et al. note that production intensity can be reduced through more efficient factory design that upscales production and increases material and energy efficiency (lowered from 188 to 109 CO_2eq/kWh for production with primary metals) and through less carbon intensive electricity (which results in a further reduction from 109 to 50 kg CO_2eq/kWh) (2021). The GWP impact of lower carbon intensity electricity is discussed in more detail in Section 2.3.1.1.

Battery technology affects all parts of the EV life cycle. As batteries develop there are constant efforts to make lighter, more efficient batteries that use less scarce resources. These developments can be difficult to capture in LCAs that require detailed LCI information that may not be available for emerging technologies. One method of forecasting future developments is using prospective LCIs, which use more complex modeling techniques to predict advancements in processes that affect the background LCI. Prospective LCIs are discussed in greater detail in Section 2.3.1.2.

2.2.4 Fluids

The production of the various vehicle fluids consumed during the use stage were not a focus of the reviewed studies. Studies typically used fluids as provided from a background LCI database such as ecoinvent (Wernet et al. 2016) or GREET (Wang et al. 2022). For further discussion of vehicle fluids, replacement schedules, and standard quantities assumed in GREET models, see Table 2-14 and Section 2.4.5.2.

2.2.5 FCEV-specific Components and Parts

FCEV have some additional equipment requirements to store and use hydrogen as an energy carrier. Rather than a combustion engine, a fuel cell, storage tank, and battery system are needed. While the battery is not the main source of power for transportation as in a BEV, an FCEV can still benefit from regenerative braking to reduce hydrogen consumption. These additional items result in a higher curb weight. Kannangara et al. used manufacturer specifications in their LCA and used an FCEV curb weight that was about 40% higher than ICEVs (1,863 kg vs. 1,301 kg) (2021).

All reviewed studies examined FCEVs that used a proton exchange membrane (PEM) fuel cell. A PEM fuel cell (PEMFC) uses a catalyst to turn hydrogen and oxygen into water and electricity, with the membrane allowing the transfer of protons while the anode/cathode and circuit allow the transfer of electrons (US EPA 2023a). Most catalysts in PEMFCs are platinum-based, though there is extensive ongoing research into alternative metals and non-metals that could lower PEMFC costs (L. Fan, Tu, and Chan 2021).

Hydrogen storage tanks on vehicles were generally made from carbon fiber and epoxy, though specific details were often limited to only the capacity of the tanks. Most studies assumed the use of compressed gaseous hydrogen, though Liu et al. examined liquid hydrogen (X. Liu et al. 2020). How hydrogen is stored, kept cool, or transported and distributed all affect the emissions intensity of the fuel cycle for FCEV. The hydrogen fuel cycle for FCEVs is discussed in Section 2.3.3.

2.2.6 Gaps in Manufacturing and Assembly LCI Data

Of the reviewed studies, several LCI-supporting studies examined battery manufacturing since it has been highlighted as a key driver of EV life cycle impacts. Chordia et al. examined how battery manufacturing can be made more efficient through optimized factories (2021). Similar studies are needed to assess the impacts of vehicle assembly in newer factories, particularly for those that use more robotic or automated assembly methods (Kituara and Yoshida 2021). Semiconductors play an important role in all electronics and are a critical component of modern vehicles. Similar to batteries and vehicle assembly, new production methods for semiconductors requires new LCI studies. Mullen & Morris highlight this data gap in a 2021 perspective on new semiconductors production methods (Mullen and Morris 2021).

2.3 Fuel Production

2.3.1 Electricity

Summary for Electricity

Electricity grid mix has a significant effect on the life cycle impacts of EVs. Regional grid mixes are constantly changing, usually to less carbon intensive forms of power generation. Some electricity is lost due to inefficiencies in the distribution systems used to deliver power from its origin to its point of use. LCIs account for transmission and distribution losses by assuming some, usually flat, percent of electricity is lost.

Projections of future grid mixes is identified in literature as being a key tool to predict the future impacts of EVs as more renewable resources are used to generate electricity. Models such as NREL's Cambium and EPA's Integrated Planning Model are used to predict grids at common benchmark years like 2030 and 2050. Older studies should be examined with care since they will be using less recent grid mixes and older projections.

Based on the reviewed literature, studies should consider the following recommendations:

- LCAs should consider the geospatial distribution of background and foreground processes and assign an appropriate grid mix for each process.
- Current grid mixes should be considered with recent data (<3 years old).
- Future grid mix projections should be used to ensure LCAs provide insight into how life cycle impacts will change over time.
- Electricity grid mix should be resolved at the same temporal resolution as the rest of the LCA. (e.g. year length resolution should use yearly average grid mix and finer hour length resolution studies should use hourly average grid mixes).

This section discusses the assumptions between electricity production and use in EV charging (i.e., effect of time of day on charging, battery charging efficiency, and transmission loss rates) and production. How the reviewed studies considered electricity grid mix is discussed in Section 2.3.1.1 and fuel consumption rate is discussed in Section 2.4.1. Electricity is both used to power foreground and background processes and is also used to fuel EVs. Most studies did not make a distinction between the electricity used, unless it was to specify the geospatial differences between processes (i.e., manufacturing occurs in China while use occurs elsewhere). The use of marginal versus average grid mix is discussed in Section 2.3.1.4.

2.3.1.1 Electricity Grid Mix

While not a specific stage in the LCA, assumptions about the electricity grid were a key part of the reviewed studies. Studies took a variety of different approaches to determining the electricity grid composition, but it was almost always the main driver of life cycle impacts for vehicles that were not using conventional fossil fuels. Grids were typically assumed to either be static (the composition did not change over time) or variable with time (forecast models were used to predict future grid compositions). For studies comparing different types of vehicles or use stage models, grid composition was generally assumed to be a static national or regional average. For the United States, Woody et al. and Burnham et al. examined the finest resolutions of electricity grid mix detail. Woody et al. performed a sensitivity analysis using electricity balancing area-level data combined with county level average temperatures and driving behaviors (city vs. highway) to compare the regional carbon-intensities of BEVs with HEVs and ICEVs (Woody 2022). Burnham et al used the National Renewable Energy Laboratory's Regional Energy Deployment System and Distributed Generation Market Demand Model to include current and forecasted state-level grids for the contiguous U.S. (Burnham et al. 2021). The results of the reviewed studies have to be examined in the context of the assumed electricity grids used. For example, Patella et al. presented a traffic simulation model for estimating emissions per km traveled in a city center by ICEVs, HEVs, and BEVs and assumed a static grid composition for Italy (2019). Patella et al.'s final conclusions are certainly affected by the mix of the electricity grid considered and examining a different grid would affect the final impacts.

Recommendation
Comparative LCAs should consider the different grid mixes assumed in both the manufacturing stage and the use stage of the life cycle. Use in different regions can result in different impacts.

Grid composition was often a focus in sensitivity scenarios by considering the average grid for multiple regions/nations or considering the future grid composition. 20 of the 62 reviewed formal LCA studies used electricity grid composition forecasts in sensitivity scenarios while six considered multiple regions/nations. The general expectation was that over time electricity grids would move to lower carbon intensity sources of electricity, and that this would lower the GWP impact of the examined vehicles.

Shafique and Lou estimated the GWP of the production, distribution, and use stages of BEV in 10 different countries with grid compositions for 2019, 2025, and 2030 (2022). In countries with low carbon intensity electricity, the use stage emissions (supplied by a grid mix of mostly renewables) were smaller than the manufacturing and assembly stage emissions (supplied by a grid mix of mostly fossil fuels). In these cases the grid mixes of the manufacturing nations (assumed to be the U.S., Germany, and China) accounted for >70% of the GWP impact in countries with a grid mix of mostly renewables (such as Sweden) (Shafique and Luo 2022). Joshi et al. examined ICEV, BEV, and FCEV with vehicle, battery, and hydrogen tank production in South Korea and vehicle use in Nepal (2022). Vehicle production for BEVs was found to be about 40% of total GWP using the present electricity grid mixes in South Korea and Nepal. These studies, which made valid assumptions for their respective cases, demonstrate that vehicle production location and the electricity mix of the use stage have significant effects on the life cycle impacts. These effects are not just limited to GWP either: Petrauskienė et al. reported that while BEV production caused about 35% of life cycle GWP, it was responsible for almost 80% of human carcinogenic toxicity (with production and use occurring in Lithuania) (2021). Bhosale and Mastud examined BEV production and use in India, finding that production and use of BEVs have equal effects on human carcinogenic toxicity (2023). Though these studies used very similar methods and approaches by following ISO 14040 and 14044 standards, assumptions in electric grid composition resulted in different findings.

Recommendation
Future grid mix projections should be used in sensitivity scenarios. These projections provide insight into how life cycle impacts will change over time.

Future grid mix projections are used in the reviewed studies to estimate how life cycle emissions may change over time. Table 2-7 details some target future grid mixes for various regions and countries. Many projections, including those in Table 2-7, consider different policy and market scenarios. For example the Cambium 2022 model forecasts that, based on market and regulatory data, by 2030 the U.S. average grid mix will have half the carbon intensity of the current mix (Gagnon, Cowiestoll, and Schwarz 2022). Projections like these are also rapidly updating as countries consider new measures to reduce the carbon intensity of electricity production. Other nations have pledged to reach net-zero emissions from electricity generation by certain dates, rather than detailing a specific grid mix target. More complex methods of forecasting for electricity grid mixes and background LCI improvements are discussed in Section 2.3.1.2.

Table 2-7. Example Possible Future Electricity Grid Mixes

	U.S. (2023)	**U.S. (2030)**	**U.S. (2030)**	**U.S. (2050)**	**Canada (2050)**	**Global Average (2027)**
	U.S. Current Grid	***NREL-Cambium Market Forecast (Mid-case)***	***EPA Integrated Planning Model Forecast***	***Predicted Market Forecast***	***Canada Energy Regulator Projection***	***Predicted Market Forecast***
Coal	20.1%	6%	7%	5%		29.7%
Oil	0.2%			0.1%	0.7%	1.5%
Gas	34.8%	20%	40%	19.2%	8.4%	21.3%
Nuclear	20.1%	16%	16%	12.9%	11.7%	9.4%
Hydro	5.7%	7%	7%	4.3%	54.5%	
Biomass	0.2%			0.1%	<1%	
Wind	10.7%	27%		20.4%	19.4%	
Solar	7.5%	24%		37.9%	4.3%	
Geo- thermal	0.2%			0.3%	<1%	
Non-specific Renewable	0.4%		28%	0.5%		38.1%
Carbon Intensity (gCO_2eq/ kWh)	(Not reported)	166	200	(Not reported)	8	(Not reported)
Reference	(EIA 2023a)	(Gagnon, Cowiestoll, and Schwarz 2022)	(US EPA 2023b)	(EIA 2023a)	(CER 2021)	(IEA 2023c)

Sums may not equal 100% due to rounding
EIA: Energy Information Administration
IEA: International Energy Agency
EPA: Environmental Protection Agency
CER: Canada Energy Regulator
NREL: National Renewable Energy Laboratory

2.3.1.2 Electricity Grid Projections with Integrated Assessment Models and Prospective Life Cycle Inventories

Summary on Prospective LCIs

Projections of future developments to foreground and background LCIs can be done with integrated assessment models in prospective LCIs (pLCI). These are more complicated than simply examining a future electricity grid mix and can be a useful tool for LCAs intending to inform policy decisions. The examined pLCI studies highlight that effect of improving the electricity grid mix used to make and power EVs. Battery improvements are also shown to be a key driver in reducing EV life cycle impacts.

Based on the reviewed literature, studies should consider the following recommendations:
- Studies should consider sensitivity scenarios of key processes that may be particularly sensitive to changes over time.
- Prospective LCIs are not appropriate for use in every LCA of EVs.

Many of the reviewed studies examined sensitivity scenarios where the electricity grid used was changed to a future projection; oftentimes one forecasted based on climate targets set by the EU or some other governing/regulatory body. While this is certainly beneficial for examining how the LCI and LCIA are affected, it does simplify a much more complex process. By assuming a static grid in either the base case or in the sensitivity case and then having assessed a car that will be used for years, the effect of the change in electricity grid mix over time is lost. Even if electricity grid mixes achieve 2030 or 2050 targets, the real carbon intensity and impacts of the life cycle of examined cars will be somewhere between the impacts under the current mix and the future mix. Prospective life cycle inventory databases, databases that project future inventories for background processes, are one option to resolving these differences between model assumptions and reality.

Steubing, Beltran, and Sacchi highlight in a commentary on the application of pLCIs that many LCAs focus on foreground technological development (such as new BEV developments) while ignoring background developments (such as less carbon intensive electricity grid mixes) which creates a 'temporal mismatch' (2023). In other words, the background developments most likely occur either first or concurrently to foreground improvements. Steubing et al. also outline ideal use cases, methods for the development, and potential pitfalls of pLCIs. Evaluating the effect of future grid mixes on impacts associated with EVs is one of the currently feasible uses of pLCIs. However just updating a single sector in the background database does not capture the impacts of adjacent, but still relevant, sector changes. For example, Sacchi et al. discuss how forecasted electricity production impacts with pLCIs are affected by road transport (to ship wind turbine and photovoltaic cells), and in turn biodiesel production, which has ecotoxicity impacts driven by pesticide use (2022). All of these sectors can see future reductions in impacts through development, which would influence the impacts associated with the foreground process being examined in the LCA. So while pLCIs can certainly give more insightful results on the change in EV impacts over time, both Sacchi and Steubing acknowledge that additional development of pLCI databases are needed and worthwhile (Steubing, Mendoza Beltran, and Sacchi 2023; R. Sacchi et al. 2022).

Integrated assessment models (IAM) use economic, technology, societal, and policy models to understand and predict how human society impacts the environment. O'Neil et al.'s shared societal pathways (SSP) outline possible future scenarios related to climate policy and society's responses to climate change to help construct future scenarios in IAMs. In the context of electric vehicles, several LCAs have utilized pLCIs generated by IAM using different SSPs as a framework for estimating both technological advancements as well as market penetration of emerging technologies. Essentially these studies use future projections to generate background processes used in LCIs, while attempting to avoid the problems outlined above (temporal mismatch of processes and insufficient sector forecasting). Table 2-8 shows the selected reviewed LCAs that used pLCIs. This is not a comprehensive list of EV LCAs that use pLCIs.

Table 2-8. Modeling Methods of LCAs using pLCIs

Reference	Years	SSP Scenario*	IAM	pLCI Database	Vehicles Examined
Romain Sacchi, Bauer, and Cox 2021	2020-2050	'Middle of the Road' (SSP2)	REMIND	ecoinvent 3.7	Medium and Large goods vehicles
Mendoza Beltran et al. 2020	2012-2040	'Green Road' (SSP1); 'Middle of the Road' (SSP2); Regional Rivalry (SSP3)	IMAGE	ecoinvent 3.3	ICEV, BEV
Cox et al. 2020	2017-2040	'Middle of the Road' (SSP2); 'Climate Policy'**	IMAGE	ecoinvent 3.4	ICEV, HEV, PHEV, BEV, FCEV
Xu et al. 2022	2020-2050	'Middle of the Road' (SSP2)	REMIND	ecoinvent 3.6	N/A (Lithium-ion battery cells only)

** SSPs are based on the scenarios originally described in (O'Neill et al. 2014), but some have been modified to fit more expansive scenarios by (Riahi et al. 2017) and (van Vuuren et al. 2017).*
***(Cox et al. 2020) examined a 'Climate Policy' SSP that was not originally defined in (Riahi et al. 2017).*

Sacchi, Bauer and Cox used the IAM REMIND along with ecoinvent to make pLCIs spanning 2020 to 2050 for medium and heavy-duty vehicles (2021). SSPs were used to forecast a future scenario were cumulative anthropogenic emissions reached 5,000 GT by 2100 (equivalent to a +4°C change over the 1990 baseline) (O'Neill et al. 2014). The resulting pLCIs captured changes not only in power generation, but also in material processing and vehicle manufacturing. The key LCA finding, aside from showcasing pLCIs generated with an IAM, was the estimated reduction in fuel cycle carbon intensity as well as reduction in direct emissions due to emerging technologies. Hauling intensities for 40-ton trucks dropped from about .15 Sacchi, Bauer and Cox used the IAM REMIND along with ecoinvent to make pLCIs spanning 2020 to 2050 for medium and heavy-duty vehicles (2021). SSPs were used to forecast a future scenario were cumulative anthropogenic emissions reached 5,000 GT by 2100 (equivalent to a +4°C change over the 1990 baseline) (O'Neill et al. 2014). The resulting pLCIs captured changes not only in power generation, but also in material processing and vehicle manufacturing. The key LCA

finding, aside from showcasing pLCIs generated with an IAM, was the estimated reduction in fuel cycle carbon intensity as well as reduction in direct emissions due to emerging technologies. Hauling intensities for 40-ton trucks dropped from about 0.15 to 0.06 kgCO_2eq/ton*km for diesel/petro ICEV from 2020 to 2050 with the greatest reduction occurring in the direct exhaust emissions. FCEV and BEV hauling intensities for 40-ton trucks dropped from about 0.3 and 0.12 to 0.08 and 0.05 kgCO_2eq/ton*km respectively. Sacchi et al. highlight that background forecasting allows for more insightful conclusions, particularly for determining the magnitude of impact of the foreground development relative to other changes in the LCA (2021).

Mendoza Beltran et al. completed a similar study on passenger vehicles with a pLCI generated out to 2050 assuming using different SSP scenarios that considered different levels of challenges to implementation of climate policy and adaptation to climate change impacts (Mendoza Beltran et al. 2020). However, this study only did a forecast of the fuel cycle using the IAM IMAGE, so results are slightly more limited in scope than if it had a full background LCI forecast. ICEV were projected to stay above 0.2 kg CO_2eq/vehicle*km in all scenarios, while EVs had a GWP impact of 0.05-0.2 kg CO_2eq/vehicle*km depending on the SSP. Greater reductions were realized in scenarios with a greater adoption of lower carbon intensity electricity production, rather than increased efficiency in existing higher carbon intensity electricity productions methods. A key difference between this study and Sacchi et al., aside from focusing on passenger vehicles instead of medium and heavy-duty trucks, is only forecasting for changes in electricity production. Cox et al. completed an LCA using pLCI generated from the same IMAGE IAM, forecasted out to 2040, but considered a more extensive amount of backgrounds changes (2020). BEV GWP was lowered from 0.2 to 0.08 kgCO_2eq/vehicle*km while FCEV GWP was lowered from 0.4 to 0.11. Notably, BEVs outperformed all other vehicle types when the electricity grid mix had a carbon intensity below 0.5 kgCO_2eq/kWh.

Prospective LCIs can also be used to focus on specific processes in the EV life cycle. Xu et al. examined lithium-ion battery cells using REMIND, ecoinvent 3.6, and the SSP2 'middle of the road' scenario (2022). In the base scenario using background inventory data for 2020, battery cell production accounts for about a third of the GWP impacts of LFP and various NCM battery cells, with the impact being mostly driven by the carbon intensity of electricity production. In the projected scenario, with an improved electricity grid mix that is less carbon intensive, in 2050 the cell production impact only accounts for as little as 10% of the GWP impact. These changes made component production the new largest driver of GWP. These findings show that after electricity grid mix improvements, efforts to improve battery cell component extraction and refining (specifically for cathode materials) would be needed to continue to reduce battery cell production intensity (Xu et al. 2022).

Prospective LCIs require serious consideration for the future scenario being projected and are more complicated than most of the sensitivity scenarios examined in this review. IAM's are certainly a powerful tool for generating LCIs that consider how foreground and background processes can change over time with different technological improvements but are most likely out of scope for the majority of studies. It is therefore doubtful that pLCIs become the standard for

> **Recommendation**
> Studies should consider sensitivity scenarios for processes identified in pLCIs as being particularly sensitive to changes over time (such as battery development or electricity grid mix).

sensitivity scenarios, but they do highlight the need to look beyond simple grid mix improvements.

2.3.1.3 Losses Between Production and Battery

Electricity, once generated, must still be transmitted to the charger, then to the battery of the EV, and finally used. There are losses and inefficiencies with all of these steps. Common assumptions include 90%+ charger and battery efficiency and a small (<5%) transmission and distribution (T&D) loss. In calculating its upstream emission inventory, EPA's DRIA assumes a 2-8.5% T&D loss, increasing over time as power is supplied by more renewables that are further from high demand locations (US EPA 2023b). Sometimes these losses can be much higher and have a significant impact on the findings of the LCA. Joshi et al. examined BEV use in Nepal and considered a 15.27% T&D loss for Nepal and a 20-25% T&D loss for India (which provided about a third of Nepalese electricity in the study's 2020-2021 timeframe of analysis) (Joshi, Sharma, and Baral 2022). Studies such as Shafique et al. use ecoinvent to account for T&D losses, though the exact values are not reported (Shafique and Luo 2022). Gan et al. report a transmission only loss rate of 6.42% for China in 2017 and consider a battery charging efficiency, but do not report the latter (Gan et al. 2023).

> **Recommendation**
> Studies should explicitly report the assumptions about losses associated with T&D and battery charging. These can represent either significant or minor factors when considered the amount of electricity used for distance traveled. For the United States, see the EPA's eGRID technical guide, which estimated U.S. average gross grid loss at 4.5% for 2021 (USEPA 2023). EPA's Integrated Planning Model estimated a national average loss of 2% for the projected 2028 grid.

2.3.1.4 Time-of-Day Charging and Marginal Grid Mixes

In addition to losses throughout the electricity distribution chain, the time of day of EV charging also has an effect on impacts. Electricity grid mix varies throughout the day, particularly if there is insufficient capacity for the storage of intermittent renewable energy such as solar and wind generated electricity. Electricity usage is highest during the day when most people are awake. As a result, charging during peak hours can result in a higher GWP impact. Most studies did not consider how electricity grid mix or CI varies throughout the day, but rather used an average composition. This is a reasonable assumption for studies that have a 1-year temporal resolution. Some studies specifically focused on examining variations in these factors and used a much finer time resolution. Mierlo et al. examined two EV charging scenarios in Belgium, charging between 8:00 to 23:00 (peak hours) and between 0:00-8:00 (off-peak hours) (2023). Charging during peak hours resulted in an increase of 4 gCO_2eq/km, from 32 to 36, when comparing off-peak and peak hour charging respectively. The authors state that Belgium's electricity grid is such that nuclear power meets the base demand (the usage during off-peak hours) but more carbon intensive methods are used for electricity generation during peak hours (Mierlo, Messagie, and Rangaraju 2023). The variable generation needed to meet variable demand is called the marginal grid mix and is typically identified in studies as involving more carbon intensive methods than the base grid.

Baumann et al. completed a similar study examining how life cycle impacts can vary depending on when EV charging occurs (2019). Using 2014 German electricity production information, the

GWP of EV electricity consumption is found to vary between 0.264 to 1.034 $kgCO_2eq/kWh$, with higher values once again occurring during the day when people are active. Charging sessions were designed to represent different scenarios, and the general trend was that charging during off-peak hours has a lower GWP impact. The authors note that charging during peak-hours can still have low GWP if there is sufficient production of wind power (Baumann et al. 2019). The effect of changing electricity grid composition is explored in more detail in Section 2.3.1.1.

2.3.2 Liquid Fuels

Summary for Liquid Fuels

Liquid fuels are used in more than just ICEVs, and the type and intensity of production of liquid fuels have a significant effect on life cycle impacts of both ICEVs and EVs. U.S. EPA has specific programs for promoting lower carbon intensity fuels over time and these changes should be considered when comparing the future performance of EVs to ICEVs.

Based on the reviewed literature, studies should consider the following recommendations:

- Future forecasts of liquid fuel carbon intensity should accompany similar projections for changes in electricity grid mix.

Liquid fuels can be used to either generate electricity for EVs or combusted in ICEVs, depending on the fuel examined. Liquid fuels can be derived from either fossil fuels or renewable sources, but the general trend assumed in studies is that over time more renewable fuels are used. The reviewed LCA studies fell into one of three categories; those that used a carbon intensity of a liquid fuel that was calculated from another source, those that considered the well-to-wheel life cycle of the fuel in the LCA boundaries using database provided information (generally done with studies that used GREET) and studies that focused specifically on modeling the carbon intensities of liquid fuels (rather than using database provided carbon intensities/LCI data). For example, Andersson and Börjesson considered an ICEV, HEV, and PHEV that were powered by gasoline, E85 (fuel blend that is 85% ethanol) and hydrotreated vegetable oil (HVO) with carbon intensities of 90.2, 48.5, and 8.8 $gCO_2eq./MJ$ respectively. Carbon intensities were based on Swedish Energy Agency data for 2018. Other work, such as Kelly et al.'s report from the Argonne National Laboratory on fuel pathways, focused specifically on the carbon intensities of different liquid fuels (2022).

LCAs of renewable fuels are plentiful in part due to the Renewable Fuel Standard (RFS), which essentially regulates that an ever-increasing amount of blended and refined fuels need to be derived from renewable sources (U.S. 2010). The RFS also requires that the renewable fuels meet some threshold of GHG reduction compared to gasoline and diesel, with greater reductions leading to more valuable Renewable Identification Number (RIN) assignments. RINs are assigned to renewable fuels based on the pathway and amount of GHG reduction compared to the gasoline or diesel baseline, and they travel with the renewable fuel until it is blended with a fossil fuel or used. Parties that import or refine fuels must meet a certain obligation of RINs based on how much fuel they import or produce. RINs have monetary value and can be bought and sold, so they provide an economic incentive to invest in and produce renewable fuels. EPA has completed an impact analysis on the RFS and RINs, which includes a meta review and analysis of LCAs examining fuels covered by the RFS (US EPA 2022b). LCAs examining vehicles that use liquid fuels should consider this impact analysis and other works that forecast the carbon intensity of liquid fuels.

Under the RFS program, fuel pathways must meet a 20-60% GHG reduction compared to gasoline or diesel. 20% reduction qualifies for conventional biofuel RINs and 60% reduction qualifies for cellulosic biofuels (assuming all other requirements are met, not all feedstocks are eligible for every RIN category). RINs are nested such that they can be applied to less restrictive D-Codes. For example, D3 RINs can be used to fulfill obligations for D5 and D6 RINs, but D6 RINs cannot be used as a substitute for D3 RINs. The RFS fuel pathways comprise of a specific feedstock, process, and fuel type (product).
Approved pathways are outlined under 40 CFR part 80 subpart M (see § 80.1426) and are partially detailed in Table 2-9 below. Please note that pathways are limited to a specific feedstock, process, and fuel type, so the pathways detailed in Table 2-9 are not applicable for all feedstocks. New pathways are assessed for approval to receive RINs by petition under 40 CFR 80.1416. As of writing, there are 145 pathway assessments that have been approved each includes a life cycle analysis in the petition (US EPA 2023e).

Recommendation
Future forecasts of liquid fuel carbon intensity should accompany similar projections for changes in electricity grid mix. In the U.S., consult EPA's Renewable Fuel Standard program for future projections of liquid fuel compositions and carbon intensity (USEPA 2022a).

Table 2-9. RIN Requirements and Pathways

RIN D-Code (Type)	GHG Reduction Requirement	Feedstock Requirement**	Pathways
D6 (Renewable Fuel)	20%	Renewable biomass	A,B,C,D,E,O,R
D5 (Advanced Fuel)	50%	Renewable biomass	H,I,J,P,S,T
D4 (Biomass-based Diesel)	50%	Renewable biomass	F,G
D3 (Cellulosic Fuel)	60%	Cellulose, hemicellulose, or lignin*	K,M,N,Q
D7 (Cellulosic Diesel)	60%	Cellulose, hemicellulose, or lignin*	L

**corn starch is only eligible for D6 RINs*
***Some feedstock requirements are not absolute, for example pathway Q awards D3 RINs for biogas production at a wastewater treatment plant*

Table 2-10. Life Cycle CI from EPA Literature Review of Renewable Fuel Pathways (US EPA 2022b)

Pathway	LCA CI Range (g CO2eq / MJ)
Petroleum Gasoline	84 to 98
Petroleum Diesel	84 to 94
Corn Starch Ethanol	38 to 116
Soybean Oil Biodiesel	14 to 73
Soybean Oil Renewable Diesel	26 to 87
Used Cooking Oil Biodiesel	12 to 32

Pathway	LCA CI Range (g CO2eq / MJ)
Used Cooking Oil Renewable Diesel	12 to 37
Tallow Biodiesel	15 to 58
Tallow Renewable Diesel	14 to 81
Distillers Corn Oil Biodiesel	10 to 37
Distillers Corn Oil Renewable Diesel	12 to 46
Natural Gas CNG	72 to 81
Landfill Gas CNG	9 to 70
Manure Biogas CNG	-533 to 44

2.3.3 Hydrogen Production

Summary for Hydrogen Production

Hydrogen production can have a wide variety of impacts and intensities depending on the method of production and electricity grid mix. Steam methane reforming and electrolysis are the two most commonly examined methods with impacts being driven by the intensity of natural gas production and electricity grid mix respectively. Hydrogen leakage is identified as a missing component in LCIs for FCEVs. The GWP100 of hydrogen used for EPA reporting is 5.8 (Derwent et al. 2001) but recent literature suggests a higher value of 12.

Based on the reviewed literature, studies should consider the following recommendations:

- Studies should use recent (<3 years old), location-specific data for hydrogen production.
- Hydrogen has a 100-year GWP of 12, and should be considered in LCIAs that examine GWP.

The production of hydrogen is the main driver of FCEV life cycle emissions, in the same way that electricity production and liquid fuel combustion emissions are for BEVs and ICEVs, respectively. Hydrogen can be produced in a variety of ways, the most prevalent of which include steam-methane reforming (SMR), coal gasification, as a by-product of petroleum refining (IEA 2021). Additionally, the production of low- and zero-carbon hydrogen—via the electrolysis of water using electricity from renewables—is expected to expand significantly in the coming decades (Wappler et al. 2022). However, given that coal gasification facilities are primarily located in China and petroleum by-product hydrogen is typically consumed in other refining processes, the reviewed LCA studies often only considered SMR and/or electrolysis pathways.

The carbon intensity of hydrogen from electrolysis can vary drastically depending on the source of consumed electricity. Esposito et al. recently used EPA AVERT to model the marginal GHG emissions from new electrolyzer grid loads, with and without three key standards for clean hydrogen, finding that the absence of a renewable energy additionality standard could lead to the Inflation Reduction Act incentivizing hydrogen production with up to 5 times as many GHG emissions per kg as SMR (2023). Similarly, Ricks et al. also conclude that these three key standards—additionality, deliverability, and hourly matching—are needed to ensure that electrolyzer hydrogen consumes electricity with near-zero embodied emissions (2023). Where implemented, these standards provide certainty that an electrolyzer is consuming electricity from a particular source.

> **Recommendation**
> Given the variety in hydrogen production methods and intensities, studies should use recent (<3 years old), location-specific data for hydrogen production.

Electrolysis was also often used in sensitivity scenarios, wherein the grid mix was varied to reflect a future, less carbon intensive projection. Several studies assumed that either wind or hydro power was exclusively used for electrolysis, even if a different grid mix was used for the rest of the life cycle. The carbon intensity of hydrogen production varied across pathways, process efficiencies, and assumptions about upstream fuel cycle carbon intensity. Joshi et al. considered electrolysis powered by hydropower (exact carbon intensity of electrolysis not stated), while a mixture of Nepalese and Indian electricity grids were used for other portions of the life cycle (2022). Dulău examined multiple sources of hydrogen with carbon intensities of 0.3 to 19 $kgCO_2/kgH_2$ for electrolysis, 9 for SMR, and 19 for coal gasification (Dulău 2023). Yang et al. examined a copper chlorine cycle for thermochemically splitting water, but stated that if using nuclear power there are no GHG emissions associated with hydrogen production (2020).

> **Recommendation**
> Hydrogen has a GWP of about 12 and should be considered in LCIAs that examine GWP. Future studies should review recent literature on the impacts of hydrogen emissions. This is similar to how methane fugitive emissions are considered for natural gas processes.

A set of recent studies have estimated emitted hydrogen's GWP100 factor as ~12 due to its atmospheric reactions with other gases (Hauglustaine et al. 2022; Sand et al. 2023; Warwick et al. 2022). A recent analysis by Fan et al. estimated hydrogen leakage worldwide to be 2.7%, increasing in the future as hydrogen infrastructure expands (2022). While several studies acknowledge that hydrogen leakage occurs during its production and distribution, none of the reviewed studies considered the GWP of hydrogen in FCEV life cycles. Given this GWP risk, data and modeling assumptions on hydrogen leakage during production, distribution, and use should be explicitly provided in LCIs moving forward.

2.4 Use Stage

The 'Use Stage' is the focus of many of the reviewed studies and is typically the stage responsible for the most emissions. The use stage generally includes all on-road use and considers the fuel consumed, exhaust emissions, non-exhaust emissions such as tire and brake wear, auxiliary fuel consumption based on driving conditions, and maintenance/repair prior to the end-of-life stage. GREET and MOVES are common models used for the generating LCIs of the use stage. In addition to the typical use stage activities and emissions, these models also account for evaporative VOC emissions from refueling, vehicle fuel system permeation, and running losses. Numerous studies also complete actual experiments to determine fuel consumption or energy demand during the use stage. Some portions of the use stage such as part replacement and maintenance can be included in other stages like the manufacturing and assembly stage. Fuel production is typically not included in the use stage, and fuels' carbon intensity in the use stage are typically limited to tank-to-wheel or tailpipe emissions.

2.4.1 Fuel Consumption

Summary for Fuel Consumption

Vehicle fuel consumption and non-exhaust emission rates can be impacted by a variety of driver behaviors and conditions; vehicle weight also affects fuel consumption. Using fuel economy testing frameworks such as the EPA's 5-cycle test is one way to compare performance, however, it is important to note that real-world driving conditions might change these results. Traffic, travel distance, and weather are all identified as being key drivers of fuel consumption (and thus life cycle impacts).

Based on the reviewed literature, studies should consider the following recommendations:

- LCAs should account for these influencing factors to ensure comparisons between vehicles are accurate.
- FCEV studies should explicitly state assumptions about hydrogen production, distribution, storage, and consumption in the same way that non-fuel cell EVs should for electricity. Fugitive hydrogen emissions should be considered.
- Utilization factors used for PHEVs should correspond to the range of the vehicle. Increased all-electric-range increases the utilization factor.

Fuel consumption during the use stage is affected by more than just the technical specifics of the vehicle (such as engine size, vehicle weight, motor and battery efficiency, etc.). The rate of fuel consumption is also affected by the weather, traffic, vehicle acceleration rate, and driver aggression (M. Zhou, Jin, and Wang 2016). The total amount of fuel consumed can also be different depending on road structure; does the road system allow a short route to the desired destination or is a long route necessary due to poor road planning (Patella et al. 2019).

Figure 1 is from Zhou et al. and summarizes the main factors that influence the fuel consumption of a vehicle (2016). Zhou et al. identify in their review that aside from vehicle related factors, fuel use is affected most by traffic and driver aggression (up to 50% more fuel consumed in non-ideal conditions), and somewhat affected by roadway conditions/signaling (up to 20% more fuel consumed). Travel routing has a wider range of impacts on fuel use, from minimal to matching traffic impacts at up to 40% more fuel consumed (M. Zhou, Jin, and Wang 2016).

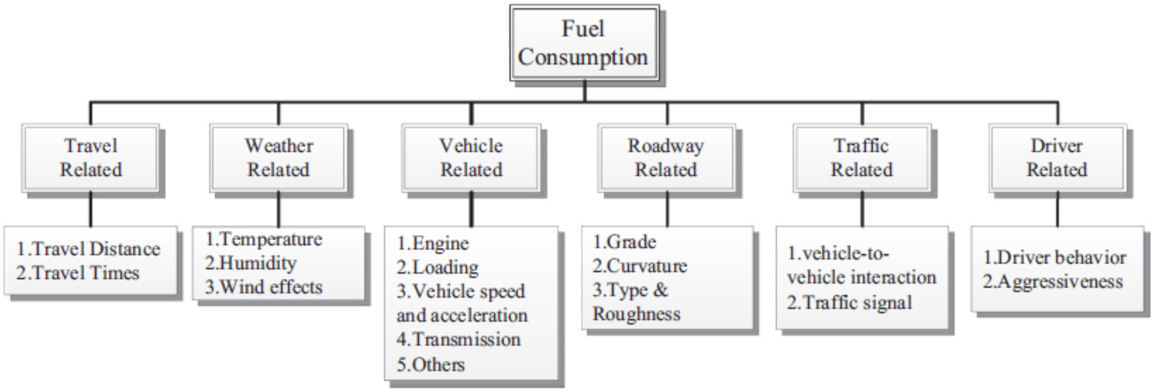

Figure 1. Factors affecting fuel consumption (M. Zhou, Jin, and Wang 2016)

Patella et al. found via traffic simulation that roadway and traffic conditions in Rome result in BEV having a quarter the use stage emissions intensity of ICEV in intra-urban areas (0.069 compared to 0.268 kg CO_2eq/km respectively) but are only 40% lower on Rome highways (0.092 compared to 0.159 kg CO_2eq/km respectively) (2019). Burnham et al. examined the effect of average temperature in different regions of the U.S. and found that BEV emissions intensity per distance can be up to 25% higher than baseline due to cold weather. ICEVs were less affected with the maximum adjustments for temperature being +7%. Even with this adjustment BEV still had lower cradle-to-grave emissions in every U.S. state (Burnham et al. 2021). Aljohani et al. completed a similar study to measure the impact of average regional temperature on vehicle emission intensity in Detroit and Los Angeles, finding that cold weather caused a 16 and 8% increase in fuel consumption respectively for EVs (2019). The European Commission's 2020 report conducted a sensitivity analysis that found a 43% increase in GHG emissions associated with ambient temperatures of 14°F (-10°C) when compared to the baseline of 68°F (20°C) in BEVs. However, those emissions in extreme temperatures were still less than baseline temperature emissions from ICEVs and HEVs (Hill et al. 2020).

Recommendation
LCAs should account for how fuel consumption can vary with driving conditions and vehicle weight. For BEVs, cold and hot conditions can increase fuel consumption, but can be mitigated by battery preconditioning. LCAs should state which, if any, preconditioning systems are used.

Other than motor/battery and engine performance, weather can also affect the use of auxiliary systems, which also impact fuel consumption. Auxiliary energy consumption is discussed in more detail in Section 2.4.2. Table 2-11 details the driving factor examined and its effect on fuel consumption in some of the reviewed studies. Please note that this is not a complete list.

Table 2-11. Fuel Consumption Factors and Effects Considered in Reviewed Studies

Reference	Study Type	Driving Factor Examined*	Effect Magnitude (% change in fuel consumption)
(M. Zhou, Jin, and Wang 2016)	Review	Travel	8.73–42.15
		Weather	1
		Roadway	3–20
		Traffic	22–50
		Driver	4.35–40
(Burnham et al. 2021)	Original Model	Weather	2–7 (ICEV) 3–25 (BEV)
(Patella et al. 2019)	Original Model	Travel	20 (BEV)
		Roadway	
		Traffic	
(Carlson, Wishart, and Stutenberg 2016)	Original Experiment	Weather	up to 7–18
(Bouter et al. 2020)	Original Model	Traffic	10–30
(Aljohani and Alzahrani 2019)	Original Model	Weather	8–16 (EV)
(Huang et al. 2019)	Original Model	Traffic	23–49 (HEV, ICEV)
(X. S. / X. L. / Z. Z. / F. M. / J. Yang 2020)	Original Model	Weather (Auxiliary power effects only)	10
		Travel	

**Based on (M. Zhou, Jin, and Wang 2016) classification*

For PHEVs and BEVs, which can have most or all miles traveled be electric powered, electricity consumption during the vehicle use stage is mostly impacted by the type and performance of the battery. Zhang et al. found that BEVs with 500-100km ranges, and usually heavier batteries, produced slightly more emissions in the use stage than shorter, 100-400km, range BEVs. Zhang et al. found a positive correlation between vehicle curb weight and power consumption for BEVs, PHEVs, and E-REVs, with electricity consumption increasing by 0.44, 1.1, and 1.5 kWh/100km, respectively, for every 100kg of curb weight (Zhang et al. 2023). As BEVs tend to weigh more than ICEVs or HEVs, this curb weight is an important component in BEV LCAs. Over time EV weight has been increasing, partially due increased ranges. From 2011 to 2019, the average purchased EV has increased by 800 lbs for BEVs and 200 lbs for PHEVs to 4,400 and 4,200 lbs respectively (David Gohlke and Yan Zhou 2020).

Following hydrogen production and distribution, assumptions about FCEV hydrogen consumption efficiency or rate were also main drivers for life cycle impacts. Dulău assumed a hydrogen fuel consumption rate of 7.6 and 8.4 g/km for the Toyota Mirai and Hyundai Nexo respectively (2023). Kannangara et al. examined a model FCEV representing the average of the 2020 Toyota Mirai and Honda Clarity; fuel consumption was modeled at 9.4g/km (Kannangara, Bensebaa, and Vasudev 2021). Joshi et al. assumed city and highway MPGe of 65 and 58 respectively for a Hyundai Nexo (also reported in the study as 1.95 and 1.74 miles/kWh) with a fuel cell efficiency of 50% (2022). Liu et al. used 5-cycle test data for the Toyota Mirai for fuel consumption rate, which was 1,937 Btu/mile (X. Liu et al. 2020).

Recommendation
FCEV studies should explicitly state assumptions about hydrogen production, distribution, storage, and consumption in the same way that non-fuel cell EVs should for electricity.

2.4.2 Auxiliary Energy Consumption

Auxiliary energy consumption includes powering car accessories such as the air conditioner, heater, steering pump, or lights. Adjustment factors for fuel consumption to account for auxiliary energy consumption range from negligible to significant. Burnham's adjustment factors for auxiliary energy consumption, which mostly account for weather related factors, are significantly higher than those reviewed by Zhou et al, who states that 'for a given vehicle model, certain factors, such as weather related factor[s], have a small effect and can be ignored'(Burnham et al. 2021; M. Zhou, Jin, and Wang 2016). Other research has found that, in addition to the weather effecting engine or motor/battery performance, those auxiliary loads can be responsible up to 18% of fuel consumption (Carlson, Wishart, and Stutenberg 2016). Weather related systems were found to have the highest impact of auxiliary systems.

2.4.3 PHEV Utilization Factor

LCAs examining PHEV need to not only consider the fuel cycles associated with the production of liquid fuels (usually gasoline) and electricity for battery powered driving, but also the ratio at which both occur. PHEV have a shorter electric range than BEV, but so long as the all-electric range (AER) of the PHEV is sufficient, the operation would be identical to a BEV. Plötz and Jöhrens found that PHEV AER of 60 km is sufficient to cover 75% of distances traveled by PHEV, in the remained liquid fuel must be used (2021). This ratio of electric to thermic (using fuel in a combustion engine) is called the utilization factor and is a key assumption in LCAs.

Utilization factor (UF) for PHEV can be determined by a standardized test such as the EU's WLTP (Worldwide harmonized Light vehicle Test Procedure) (UNECE 2014). In this test the vehicle is cycled through several test conditions that are representative of real driving data based on the vehicles power and weight. Eder et al. used the WLTP test method to determine UFs for PHEVs, specifically because PHEVs can operate in either a charge depleting mode (where electricity is the main source of power for the vehicle) or a charge sustaining mode (where electricity is only used from regenerated energy) (Eder et al. 2014). The methodology adopted used the same formula structure used by SAE J2841 for determining utilization factors for PHEV. Using the WLTP method, a PHEV would have to have a WLTP electric range of 20 km for a UF of 50%, and a range

Recommendation
Utilization factors used for PHEVs should correspond to the range of the vehicle. Increased all-electric-range increases the utilization factor.

of 80 km for a UF of 0.8 (Eder et al. 2014). Recently, a study funded by Germany's Federal Ministry found the UFs determined under WLTP were 'optimistic' and real UFs were significantly lower (Plötz and Jöhrens 2021).

In the reviewed studies UF assumptions varied, and sometimes multiple scenarios were evaluated. Table 2-12 details example utilization factors used in the reviewed studies. Please note that this is not an exhaustive list, but demonstrates the variety of assumptions used. Bouter et al. for example evaluated PHEV use in entirely thermic or electric modes as separate cases (2020). A Canadian case study by Kannangara et al. assumed PHEV had a UF of 60% (2021). This was derived from Tagliaferri et al. who themselves UFs ranging from 30% for HEV to 90% for extended range electric vehicles (E-REV) (2016). Shafique et al. assumed in a case study of PHEV in Hong Kong that distance traveled was evenly split between electricity powered and diesel/petro powered (2022). Kelly et al. used SAE guidelines for a PHEV with a 50 mile range, ending up with a UF of 70%, which is very close to the 60km 75% UF reported by Plötz and Jöhrens (Plötz and Jöhrens 2021; J. C. Kelly et al. 2022).

Table 2-12. Example Utilization Factors Used in Studies for EVs

Study	Single Utilization Factor or Multiple Scenarios?	Utilization Factor(s)
(Bouter et al. 2020)	Multiple: entirely thermic and entirely electric	0% and 100%
(Kannangara, Bensebaa, and Vasudev 2021)	Single Factor	60%
(Tagliaferri et al. 2016)	Multiple: different vehicle types (HEV, PHEV, EREV)	30%/60%/90%
(Shafique et al. 2022)	Single Factor	50%
(J. C. Kelly et al. 2022)	Single Factor	70%
(Plötz and Jöhrens 2021)	Single Factor	75%
(Hill et al. 2020)	Multiple: default, low variant, high variant	72%/45%/82%

2.4.4 Non-Exhaust Emissions

Summary for Non-Exhaust Emissions

Non-exhaust emissions for EVs are affected by weight and the amount of regenerative braking. Tire wear, brake dust, resuspended road dust, and evaporative emissions all contribute to non-exhaust emissions. These are normally particulate matter grouped in < 10 micrometer (µm) and <2.5 µm categories. The use of regenerative braking can lower particular matter while the increased weight of EVs increases tire wear. Models and experimental studies measure these wear rates for various vehicle weights and driving conditions.

Based on the reviewed literature, studies should consider the following recommendations:

- Studies examining particulate matter formation or human health impacts should pay especially close attention to non-exhaust emissions.
- LCI database maintainers and LCIA method authors should also begin to incorporate these elementary flows and update endpoint methods.

In additional to fuel emissions (exhaust emissions), the use stage has operational emissions related to brake, tire, and road wear that release small particulate matter. Brakes release small particles as they slow the vehicle, and these emissions can vary with brake type, car speed, and weight. EPA measured PM from braking for non-asbestos organic and low-metallic brakes and found that PM10 (particulate matter 10 µm or less) varied between 2 and 30 mg/mile but was generally lower on lighter vehicles. Increasing the cargo in vehicles to two-thirds the difference between curb weight and gross weight increased PM10 emissions by up to 50%. EPA measured an average of 0.71 g/hr of PM2.5 during braking, compared to the default their own MOVES2014 average model value of 0.558 g/hr (US EPA 2022a). Table 2-13 includes some values for non-exhaust emissions found in both the reviewed studies and some common models. Please note that this is not a complete list.

Bondorf et al. completed a similar study on particle emissions during braking of BEVs (2023). Three driving cycles were used, WLTC Class 3b, WLTC Bake Part 10, and a real driving cycle on the roads of Stuttgart, Germany with a BMWi3. Regenerative braking and the use of a metal coating (with regenerative braking) on the brakes were found to reduce the number of particles sized 3-4 µm by 90% and an additional 79% respectively for the real driving cycle.

Recommendation
Non-exhaust emissions contribute to particulate matter formation. LCIA that include particulate matter or human health impacts should evaluate if non-exhaust emissions need to be included in the LCI.

Tire wear also releases small particles and causes road wear as well during the use stage. Park et al. found in laboratory simulations of road conditions that most (by count, not mass) tire wear particles made from traveling around 80km/hr are PM2.5 or smaller (2018). Woo et al. measured PM10 from road wear at 13.7 mg/km and tire wear at 10.1 mg/km for EVs while PM2.5 were measured at 2.1 and 1.6 for road wear and tire wear respectively (Woo et al. 2022). The rate of tire wear and associated PM emissions are affected by tire speed, load, slip speed, and harsh braking. As a result, tire wear can be a significant contributor to PM emissions in urban areas (Kim and Lee 2018).

Table 2-13. Examples of Non-Exhaust Emissions Assumptions in Models and References

Model/Reference	Vehicle Type	Emission Type	Emission Source	Value	Units
US EPA 2022a	Average of all vehicles	PM2.5	Brake Wear	0.71	g/hr
Bondorf et al. 2023	BEV	PM3-4	Brake Wear	(1.63-5.11) e+08	particles/hr
MOVES3 (Burnham 2021)	ICEV	PM10	Tire + Brake Wear	31	mg/mile
GREET 2022 (Wang et al. 2022)	EV, default	PM2.5	Tire + Brake Wear	4.0515	mg/mile
GREET 2022 (Wang et al. 2022)	EV, default	PM10	Tire + Brake Wear	3.0701	mg/mile
(Frosina et al. 2018)	PHEV	Gasoline (VOC)	Evaporation from tank	0.6-1.5	g gasoline/hr
MOVES4 (US EPA 2023c)	PHEV, ICEV (MY 2004-2010)	Gasoline (VOC)	Evaporation from tank	0-2*	g gasoline/hr
(Woo et al. 2022)	EV	PM10	Road Wear	13.7	mg/km

*MOVES4 uses a model that considers various vehicle characteristics to find evaporative emissions. The extract rate will vary depending on those characteristics (US EPA 2023c).

Timmers and Achten compared PM2.5 emissions during the use stage between EVs and ICEVs. PM2.5 emissions between EVs and ICEVs were found to be similar (within 3%) even with the use regenerative braking, mostly due to the increased weight of EVs (2016). Though regenerative braking may reduce particulate emissions from braking, the increased weight of EVs still causes higher road and tire wear. Their recommendation of reducing vehicle weight to limit non-exhaust emissions agrees with the previously discussed EPA experiments that found brake wear and weight were directly related. Beddows and Harrison completed a similar analysis and found total PM2.5 and PM10 emissions from BEVs were 10-15% higher with no regenerative braking, but almost 25% lower with 90% or 100% regenerative braking (2021). These non-exhaust emissions included brake, tire, and road wear as well as resuspension of road dusts. Lopez et al. also measured actual non-exhaust emissions in California and found that silicon from road dust and iron from brake pads made up almost half of the metal content of PM2.5 and PM10 emissions along highways I-5 and I-70 (2023). Particles mass distributions were found to peak around 7 μm, while particle number distributions peaks at 2.1 and 6.5 μm. Zinc was used as a marker for tier wear, but only accounted for 1-2% of the metal mass of PM2.5 and PM10 measured (Lopez et al. 2023). Imperial College London has published a brief on tire wear specifically, highlighting the potential health impacts of these non-exhaust emissions (Tan et al. 2023).

MOVES, EPA's Motor Vehicle Emissions Simulator, includes non-exhaust emissions during the use stage (US EPA 2022c). Burnham et al. used MOVES in their LCA, though the focus was on temperature and electrical grid mix differences between U.S. regions (Burnham et al. 2021).

MOVES4 includes evaporative emissions that occur during use, while parked, and while refueling, with rates varying by location (due to ambient temperature, air pressure, etc.) and car model year (US EPA 2023c). Frosina et al. examined evaporation of gasoline from a hybrid fuel tank using the Euro 6D emissions standards test and found losses between 0.6-1.5g gasoline/hour (Frosina et al. 2018). Ecoinvent also includes non-exhaust use stage emissions, and is commonly used in LCAs, though the user must make sure that they have selected the correct product system or processes to include these emissions (Wernet et al. 2016). Helmers et al. notes several potential inaccuracies in ecoinvent's non-exhaust emissions data and updates the data provided with more recent data from remote sensing studies. For particulate matter in diesel engines specifically, the adjusted value based on new research was "323 times higher than the original number [in ecoinvent 3], which considers particles from abrasion only" (Helmers, Dietz, and Weiss 2020). GREET, one of the more common models used for the use stage, includes non-exhaust emissions in the preset vehicles options as well (Wang et al. 2022). Other LCAs such as Kannangara et al. cite other non-model literature for wear rates for their LCI (2021).

2.4.5 Maintenance & Repair

Summary for Maintenance & Repair

Replacing an EV battery can greatly increase the impacts of the EV life cycle, but the number and frequency of replacements varies depending on vehicle and battery type. Other replaceable component impacts like those from tires and fluids can be assumed based on standard quantities and replacement schedules, such as those used in the GREET model. Often, the maintenance and repair phase is grouped into the use phase and/or is assumed to be negligible. Additional batteries used in a vehicle's lifetime may also be included in vehicle production phase. The recent EPA Model Year 2027 emissions standards and Euro 7 standards both assume that EV batteries will last for the vehicles entire lifetime.

Based on the reviewed literature, studies should consider the following recommendations:

- The functional life for vehicles should include battery replacement schedules if applicable.

Several vehicle components require maintenance and replacement throughout the lifetime of the vehicle. Components lose their efficacy or efficiency over time (batteries, engine oil, air filters, spark plugs, etc.), physically wear out (tires, brake pads, etc.), or deplete over time (windshield wiper fluid, fluids lost to leaks, etc.). The choice of whether to include multiple iterations of these components within the boundary of the LCA is an important consideration in the case of high-impact components.

2.4.5.1 Battery Replacement

Kawamoto et al. 2019 found that battery production emissions play a significant role in BEV total life cycle emissions so any replacement of the battery throughout the vehicle life cycle will influence a BEVs performance compared to other technologies. This study assumed CO_2 emissions for one lithium-ion battery of 6,337 kg vs 19.5 kg for a single Pb-Ac battery, meaning even a single Li-ion battery replacement could dramatically change the total life cycle emissions.

Generally, batteries are replaced when the battery reaches a degradation limit of 30% (F. Yang et al. 2018).

Li-ion battery degradation through use results in this need for battery replacement. This degradation occurs due to both cycling-capacity loss (dictated by the number of charging/discharging cycles) and calendar capacity loss (impacted by the state of charge, aging time, and ambient temperature) (F. Yang et al. 2018). Driving cycle and trip distance also contribute to the length of a battery's life. Liu et al 2020 found that driving and low speeds and low acceleration extends the battery lifespan whereas low and high temperature environments significantly reduce the battery lifespan. While most studies choose for batteries to maintain the same level of performance throughout the vehicle lifespan, in real world conditions, the batteries cycling capacity and calendar capacity are slowly degrading over time. That degradation decreases the vehicle's driving range and charging/discharging efficiency, leading to more frequent battery replacement needs. For vehicle operators maintain the same level of battery usage throughout the vehicle's lifetime, higher electricity use will be required for battery charging. Increased electricity usage simultaneously increases secondary emissions associated with vehicle operations (F. Yang et al. 2018). While most studies do not include degradation in their models, it is important to acknowledge the increased impact of all vehicles, and especially EVs and PHEVs, in the later stages of their life cycle. F. Yang et al. 2018 notes that due to differing operating conditions (distance traveled, ambient temperature, etc.) across the US, EV battery degradation and associated increased emissions vary, sometimes significantly, from state to state.

Battery lifetime assumptions varied in the reviewed studies. Lithium-ion (batteries used in BEV and most PHEV applications) and NiMH (batteries widely used in HEVs) battery lifespans are still uncertain during real-world use. Common battery capacity testing involves deep discharge and full recharge cycles whereas real world driving often involves much shallower discharge or incomplete recharge cycles. Manufacturer warranties for NiMH and lithium-ion batteries range from 100,000-150,000 miles, though these warranties are not always accurate indications of battery lifespan. Due to this uncertainty and based on sparse data and anecdotal information on battery lifespan, many studies, as well as the GREET model, assume no BEV battery replacement during the useable life of the vehicle. Table 2-14 includes a list of studies on BEVs that included maintenance in their scope and the number of battery replacements included in their analysis.

Recommendation

Replacing an EV battery can greatly increase the impacts of the EV life cycle, but the number and frequency of replacements varies depending on vehicle and battery type. The functional life for vehicles should include battery replacement schedules if applicable.

Table 2-14: BEV Battery Lifetimes and Replacement Schedules

Study	Battery Life	Vehicle Life	No. of Battery Replacements
(Kannangara, Bensebaa, and Vasudev 2021)	93,206 mi (150,000 km)	93,206 mi (150,000 km)	0
Bouter et al. 2020	120,000 mi	150,000 mi	1

Study	Battery Life	Vehicle Life	No. of Battery Replacements
Kawamoto et al. 2019	99,419 mi (160,000 km)	0 – 124,274 mi (200,000 km)	0-1
GREET 2	160,000 mi	160,000 mi	0
(Bieker 2021)	-	195,110 – 209,402 mi (314,000-337,000 km	0
EPA: Multi-Pollutant Emissions Standards for Model Years 2027 and Later Light-Duty and Medium-Duty Vehicles	-	150,000 mi	0
European Commission Euro 7 Standards	-	124,274 mi (200,000 km)	0

For Pb-Ac batteries, widely used in ICEVs as well as some HEVs and FCEVs, technology is more mature and therefore the battery lifespans are more certain. The GREET model assumes two Pb-Ac battery replacements during the 160,000 mi vehicle lifetime based on data collected by USCAR. Ni-MH and Li-Ion batteries are assumed not to be replaced during the vehicle lifetime. Most studies follow similar replacement schedules. There is potential for vehicle batteries to be reused in secondary applications after the vehicle's useable life. Battery reuse and recycling are discussed further in Section 2.5.

2.4.5.2 Non-Battery Replacements and Repair

Tires are also replaced during a vehicle's lifetime. Frequency of real-world replacement varies based on tire specifications and driving conditions. Rate of tire wear and associated PM emissions are impacted by tire speed, load, slip speed, and harsh braking. As a result, tire wear can be a significant contributor to PM emissions in urban areas (Kim and Lee 2018). Rate of tire wear in BEVs, PHEVs, and HEVs is also higher due to increased vehicle weight, torque capabilities, and power (Pitt et al. 2022; Y. Liu et al. 2022). The GREET model assumes tire replacement every 40,000 miles, or three replacements during a passenger vehicle lifetime. A 2021 review of vehicle tire LCAs found tire lifespans ranging from 50,000 km to 136,000 km (Dong et al. 2021). As vehicle lifespans varied from study to study, these tire lifespans might result in anywhere from no replacements to 4 or 5 replacements throughout the vehicles life.

The majority of studies did not provide detail on fluid replacement during vehicle maintenance other than stating the use of GREET. The GREET model, which was commonly used in studies, makes certain assumptions about fluid replacement frequency. Table 2-15 lists these assumptions, which are obtained from the GREET2 workbook (Wang et al. 2022).

Table 2-15. GREET Model Assumed Fluid Replacement Schedule

Fluid Type	Replacement Frequency	Vehicle Lifetime Fluid Weight Assumption (lbs)				
		ICEV	BEV	PHEV	HEV	FCEV
Engine Oil	4,000 miles	8.5	0.0	8.5	8.5	0.0
Windshield Wiper Fluid	8,000 miles	6.0	6.0	6.0	6.0	6.0

Fluid Type	Replacement Frequency	Vehicle Lifetime Fluid Weight Assumption (lbs)				
		ICEV	BEV	PHEV	HEV	FCEV
Power Steering Fluid	No replacement	0.0	0.0	0.0	0.0	0.0
Brake Fluid	40,000 miles	2.0	2.0	2.0	2.0	2.0
Powertrain Coolant	40,000 miles	23.0	15.8	23.0	23.0	15.8
Transmission Fluid	Once in vehicle lifetime	24.0	1.8	1.8	1.8	1.8

The GREET model also assumes two-thirds of each fluid, except for windshield wiper fluid, is combusted after being replaced, with the remainder being lost during maintenance. Windshield wiper fluid is lost to the atmosphere during use. Fluid-related impacts are generally negligible compared to other manufacturing and use-stage emissions.

Other replaceable components such as brake pads, filters, spark plugs and windshield wiper blades were generally not considered in the maintenance stage. The GREET model does not include emissions associated with the replacement of these components because of their small weight and because often the model has already aggregated these parts into larger components that are not replaced.

2.5 End-of-Life Processes

Summary for End-of-Life Processes

End-of-life processes are typically considered only in studies with cradle-to-grave boundaries. For EVs this means accounting for the various ways the vehicle components are reused, recycled, or otherwise disposed of. Battery recycling and reuse is highlighted as a key driver of minimizing end-of-life impacts. Battery recycling methodology, glider resource recovery, and incineration of plastics all affect life cycle impacts differently and should be carefully examined.

Based on the reviewed literature, studies should consider the following recommendations:

- End-of-life disposal methods should be consistent with the location of disposal, as landfilling and recycling practices vary.
- Reuse and recycling allocation methods should be follow ISO 14044 guidance (ISO 2006b).

At end of life, vehicle components can generally be either reused, recycled, incinerated, or landfilled. Pero et al. and Accardo et al. modeled EoL of vehicles based on ISO standard 22628:2002 “Road Vehicles Recyclability and Recoverability: Calculation Method” (ISO 2018), which divides the vehicle EoL stage into the following four sub-stages shown in Figure 2 (Pero, Delogu, and Pierini 2018; Accardo et al. 2023).

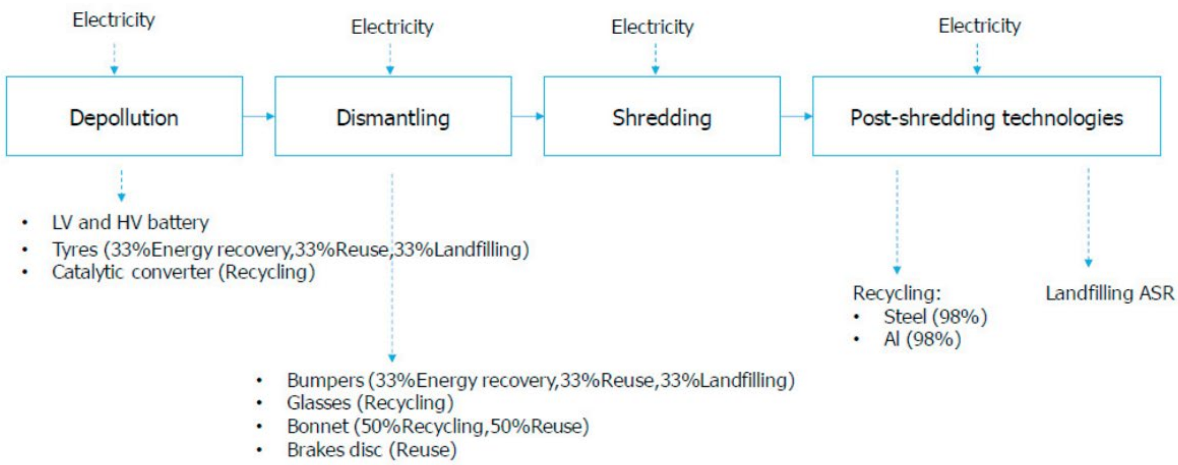

Figure 2. Allocation of components and materials to EoL processes (Pero, Delogu, and Pierini 2018)

In this case, modeling each of the four stages includes energy required for the processes, any credits associated with recycling material and/or energy, and releases to the environment due to landfilling or incineration. Depollution and dismantling both remove components for reuse and recycling. The shredding stage results in ferrous and non-ferrous metal fractions that can be recycled, and automotive shredding residue, which can be further processed to recover additional material or is landfilled. Accardo et al. assumed that the output of the shredding process consisted of 75.1% metal fractions and 24.9% automotive shredding residue (Accardo et al. 2023). Table 2-16 details the portion of the vehicle that is processed in each EoL stage, as reported by Accardo et al. (2023), based on ISO 22628 and European Commission Directive 2000/53 (ISO 2018; European Commission 2000).

Table 2-16. Contribution to Material Removal of each EoL Stage in Mass Percentage; Recreated from Accardo et al. 2023

EOL Stage	DIE-ICEV	CNG-ICEV	BEV
Depollution	1%	9%	17%
Dismantling	27%	24%	19%
Shredding	54%	51%	48%
Post-Shredding	18%	17%	16%

DIE-ICEV: Diesel oil internal combustion engine vehicle
CNG-ICEV- Compressed natural gas internal combustion engine vehicle

Evaluating the end-of-life process impact of a vehicle, especially for BEVs, is important because non-GWP impacts are more prevalent in end-of-life treatment (Pero, Delogu, and Pierini 2018). End-of-life processes in the reviewed LCAs were generally either part reuse (reduces the amount of parts needed to be produced) or part/vehicle recycling (reduces the amount of elemental flows in vehicle production). Battery recycling for BEVs and PHEVs was more completely detailed in several studies, partially due to the higher impacts associated with battery production. Studies that generalized vehicle production due to examining a single vehicle model, a glider kit with different power trains, or modeled LCI based on vehicle weight, generally used a weight-based recycling credit for end-of-life of the vehicle. Several studies used GREET2 for vehicle life cycle modeling, which includes recycling and disposal as part of the 'assembly, disposal and recycling' LCI/BOM generation for default pathways (Wang et al. 2022).

The main allocation method used to model credits associated with EoL treatment for vehicles is the avoided burden method for co-products and allocation that includes the closed loop recycling of materials to displace virgin materials in the production stage. In the avoided burden method, materials from one life cycle are removed from that life cycle and consumed again in another life cycle, such as through material recycling. Only virgin materials are considered during the production stage using this method, and the recycling rate of each material determines how much virgin input there will be for each material. Credits associated with reuse or recycling are credited during the EoL stage. This allocation method also includes credits associated with EoL energy capture from incineration or other waste treatment method. This allocation method is derived from the system expansion procedure described in ISO 14044 (ISO 2006b). The circular footprint formula (CFF) developed by the European Commission is a method that can be used to model multifunctionality in reuse and recycling scenarios. The equations used include a material, energy, and disposal formula and calculate which portion of credits should be allocated to the product being recycled vs. the product being created with the recycled materials. Accardo et al. compared these allocation methods and found that the net impact of the CFF method was 18-19% greater for ICEVs and 14% greater for BEVs than the avoided burden allocation method (2023). When comparing vehicle LCA studies, it is therefore essential that the allocation methods match to ensure reliable comparison. As many vehicle materials are recyclable, the avoided burden method is the recommended allocation method to capture any reduced impacts associated with that life cycle expansion.

2.5.1 Reuse

The simplest approach to end-of-life processing is to reuse parts directly into new or existing vehicles. Kannangara et al. assumed that on average 11.6% of the vehicle glider weight (excluding batteries and powertrain) can be reused as replacement parts (2021; Sawyer-Beaulieu 2009). Accardo et al. assumed the reuse rate for the entire vehicle was an average of 7.9% for diesel ICEVs and 3.6% for BEVs (2023). This reuse directly displaces the production of new parts.

EV batteries can be reused in second life applications such as stationary power storage, however considering these processes in EV LCAs creates some potential allocation issues. ISO 14044 highlights that recycling may need to allocate burdens to multiple inputs or processes (ISO 2006b). Koroma et al. resolved these issues by excluding second life reuse as stationary storage in the life cycle of the EV but returning the spent storage batteries to the EV life cycle for recycling, with all burdens of recycling being allocated to the EV (2022). The EV was credited for the avoided environmental burden of storage batteries, which lowered the life cycle impacts of EV use by approximately 2%. The exact magnitude of avoided burden from displaced

Recommendation
Studies should either exclude second life applications from EV life cycles, or take a similar approach to Koroma et al. (2022), and exclude the battery second life from the EV life cycle but return the battery for end-of-life processing (such as recycling or disposal) while crediting the EV for the avoided burden of storage battery production.

battery production may be difficult to quantify with existing data though. Iqbal et al. completed a review of EV battery reuse and found that battery lifetime in second life applications was both variable and difficult to predict without comprehensive tracking of the use during the first phase of battery life (2023). Reuse applications have their own environmental impacts, and in some cases the use of retired EV batteries to displace newly produced batteries does not result in net environmental benefit. Cui et al. estimated that second-life batteries are worth repurposing for energy storage if the part replacement rate is below 50% (2023).

2.5.2 Recycling

Kannangara et al. considered end-of-life recycling for vehicle gliders by shredding (2021). 88.4% of vehicle glider weight was processed in a shredding facility, with some losses (~19%) to landfill as shredding residue (Sawyer-Beaulieu 2009). Belboom et al. reported slightly higher recycling rates of 91.1% of vehicle's weight based on data from Belgian recycling facilities (2016). Accardo et al. assumed a smaller 79.8% recycling rate for diesel ICEVs and an 85.7% recycling rate for BEVs (2023). Studies that directly offset elemental flows in the LCI with recycled materials sometimes used recycling rates for each metal or material rather than weight based recoveries for the whole vehicle (Sun et al. 2021; Bouter et al. 2020).

The recycling of batteries for EVs uses a different process than the glider recycling by shredding and sorting. Lithium batteries can be recycled by pyrometallurgy, hydrometallurgy, or physical recycling. Pyrometallurgy involves incineration of most of the battery and recovery of nickel, cobalt, and manganese (Rajaeifar et al. 2021). Hydrometallurgy involves dismantling the battery and then leaching valuable materials into solution, with recovery rates typically in excess of 90% for all metals (Zhou et al. 2020). Physical recycling involves disassembly of the battery by shredding or crushing, and recovery of components without leaching or combustion (Zhou et al. 2020; Chen et al. 2022). Chen et al. investigated all of these common recycling routes for batteries and found that the physical recycling process had almost half the GWP impact as new battery production while hydrometallurgical recycling was 33% lower, and pyrometallurgical recycling was only 5% lower than new NMC811 battery production (2022). Sun et al. reported similar results for hydrometallurgical recycling, with a third of the GWP impact of production being offset (Sun et al. 2020).

2.5.3 Waste-to-energy

Aside from recycling material, energy can be recovered from waste material by combustion, commonly called waste-to-energy (WTE). Incineration of municipal solid waste has been a standard method of reducing the volume of wastes destined for landfills, however these facilities often create serious air quality and pollution concerns (C.S. Psomopoulos, A. Bourka, and N.J. Themelis 2009). WTE facilities account for about 1% of electricity generation in the U.S., and the amount of electricity produced (about 14 Terawatts annually) has been relatively constant from 2012-2022 (EIA 2023b). Incineration rates for landfilled waste varies worldwide (e.g. 90% in Taiwan and 13% in U.S.) and several studies have reported a lack of adequate pollution controls can lead to serious human health and environmental impacts (C.S. Psomopoulos, A. Bourka, and N.J. Themelis 2009; Kumar et al. 2023).

Recommendation
End-of-life disposal methods should be consistent with the location of disposal, as landfilling and recycling practices vary regionally.

Some studies explicitly detailed WTE for some end-of-life components. Sun et al. considered a life cycle of a passenger car in China where 20% of non-plastics and non-metals were incinerated (2021). Bellboom et al. examined three recycling pathways for electric vehicles and included waste valorization in a WTE facility for most fine post shredding material and plastics (2016). The total recoverable energy was 323 kWh and 1,400-1,850 MJ per electric vehicle. The energy created in WTE systems can also be credited to the total life cycle impact using the avoided burden allocation method.

Model resources also consider incineration emissions of common components like tires. The EPA's WAste Reduction Model (WARM) estimates net emissions of tire incineration to be 0.5 $MTCO_2eq$/Short Ton, while tire recycling offers a net emissions of -0.38 $MTCO_2eq$/Short Ton (negative due to the avoided virgin material for tire production) (US EPA 2020).

2.6 Life Cycle Impact Assessment

Table 2-17 details the types and number of occurrences of various impact categories in the reviewed studies. In some cases, exact names were changed to match terms used in TRACI or ReCiPe (Bare 2011; Huijbregts et al. 2017). Global warming potential was by far the most common impact, with abiotic depletion, acidification, and different types of eutrophication potentials being the next most common. These are all "midpoint" indicator categories: sum totals of elementary flows scaled to the of emitting or consuming a single reference substance (e.g., translating all GHGs to CO_2-equivalent mass over a finite horizon). Less commonly evaluated were the "endpoint" categories, which relate to human health, ecosystem quality, and resource scarcity. Endpoint indicators rely on statistical modeling of pollutant fate and exposure to quantify damage to humans and ecosystems. Studies that examined multiple impacts typically reported that different vehicle types had impact trade-offs, where a decrease in GWP may also occur with an increase in ADP. Studies that have the requisite data should examine multiple impact categories to not miss these types of trade-offs.

Table 2-17. Impact Categories in Reviewed Studies

Impact Categories	Occurrences
GWP: Global Warming Potential	49
EQ: Ecosystem Quality	3
ETP: Ecotoxicity Potential	2
ETP-F: Ecotoxicity Potential, Freshwater Aquatic	9
ETP-M: Ecotoxicity Potential, Marine	8
ETP-T: Ecotoxicity Potential, Terrestrial	11
EP: Eutrophication Potential	6
EP-A: Eutrophication Potential, Aquatic	1
EP-F: Eutrophication Potential, Freshwater	7
EP-M: Eutrophication Potential, Marine	6
EP-T: Eutrophication Potential, Terrestrial	1
PMFP: Particulate Matter Formation Potential	11
FFP: Fossil Fuel Potential	13
HH: Human Health	3

HTP: Human Toxicity Potential	5
HTPc: Human Toxicity Potential, Cancerous	9
HTPnc: Human Toxicity Potential, Non-Cancerous	8
IRP: Ionizing Radiation	12
LOP: Land Use	11
SOP: Surplus Ore Potential	11
ODP: Ozone Depletion Potential	13
POFP: Photochemical Oxidant Formation Potential	13
ADP: Abiotic Depletion	4
TAP: Terrestrial Acidification Potential	15
WCP: Water Use	8

GHG emissions are aggregated into impact categories such as GWP, while CAP emissions can lead to various other impacts, such as acidification potential, photochemical oxidant formation, and human health (respiratory) effects. The counts of studies covering different CAPs, by vehicle type, are shown in Figure 3.

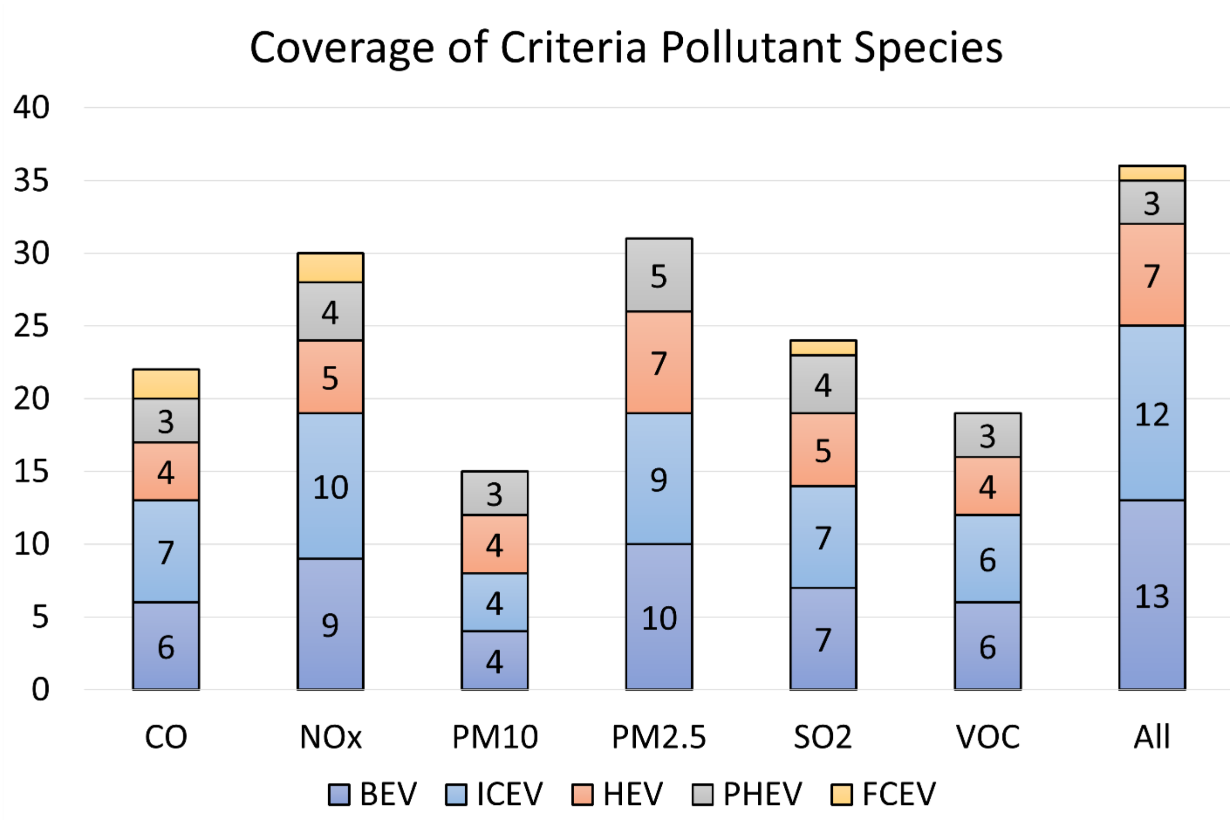

Figure 3. Counts of studies covering different CAPs by vehicle type

3 DISCUSSION

3.1 Intra-study GWP Comparisons by Vehicle Type

Direct comparison between LCA studies can be difficult or even inappropriate depending on the scope, background data sources, and allocation methods used. ISO 14040 and 14044 explicitly caution that comparisons between studies is only possible with studies that have equivalent context and assumptions (ISO 2006a; 2006b). To avoid making comparisons between studies that are not equivalent, we instead aggregate the findings of intra-study comparisons, which ensures consistent assumptions and contexts are inherent to each comparison. In total, 31 studies were identified as appearing ISO compliant, peer reviewed, and having sufficient detail for intra-study comparison (i.e. having LCIA results that include GWP for more than one vehicle type).

Reviews and LCI studies were not included in this set, but otherwise the studies covered in the intra-study comparisons were not filtered out by any specific scope or methodological elements (geography, background LCI database, publication year, etc.). Study results are summarized in Figure 4, where vehicle types are compared pairwise within studies and translated from numerical differences to simple classifications of higher or lower life cycle GWP impacts. The magnitudes of impacts are not averaged or otherwise summarized to avoid inappropriate comparisons. Only direct comparisons are made between vehicle types, which allows for inclusion of studies which do not include all vehicle types. Values used for these comparisons are detailed in Appendix A.

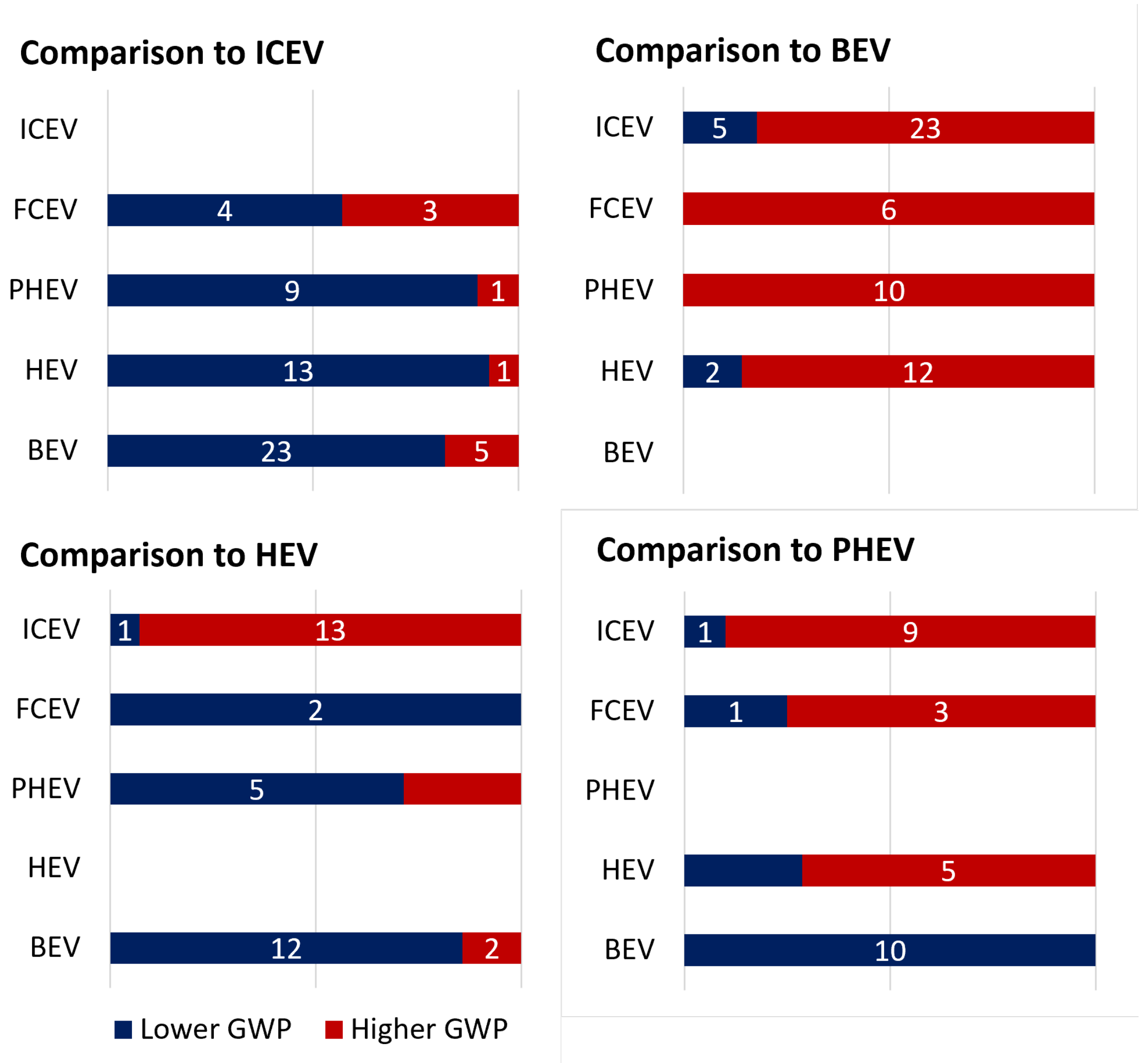

Figure 4. Counts of intra-study life cycle GWP comparisons between vehicle types

Figure 4 shows the direct comparisons of life cycle GWP impacts between pairs of vehicle types, based solely on whether a study found higher or lower impacts. For example, 23 studies found GWP impacts were lower for BEVs relative to ICEVs while 5 found that BEVs were higher than ICEVs. Overall, ICEVs tended to have higher GWP results than BEVs, HEVs, and PHEVs, but were split evenly between higher and lower GWP when compared to FCEVs. Most studies found that BEVs had lower GWP values than ICEVs, HEVs, and FCEVs, and all studies evaluating both BEVs and PHEVs (five in total) found that BEVs had lower GWP values. Only 2 of 30 studies reported BEVs being outperformed by another type of EV.

The main contributors to GWP for all vehicle types are car manufacturing (including resource extraction) and the use phase. The minority of studies that found ICEVs outperformed EVs employed electricity grid mixes reliant on coal or natural gas to generate power. Petrauskienė et al. and Das found BEVs had GWP impacts approximately 30-50% higher than ICEVs while Tang et al. and Yang et al. found <10% GWP difference between BEVs and ICEVs, with some examined alternative scenarios resulting in BEVs with lower GWP impacts than ICEVs (Petrauskienė et al. 2021; Das 2022; Tang, Xu, and Wang 2022; Z. Yang, Wang, and Jiao 2020). Das considered the 2017 grid mix for India (which used coal and natural gas for 80% of power generation) and found that ICEV GWP was 30-50% lower than EVs, mostly due to the high carbon intensity of the electricity grid (Das 2022). Petrauskienė et al. found BEV use in Lithuania had a higher GWP than ICEVs, with the difference being partly due to increased production impacts but mostly due to the domestic Lithuanian 2015 grid mix considered (2021).

However, the majority of reviewed studies found BEVs to outperform ICEVs, across most geographic contexts and including within the U.S. Tang et al. found that BEVs have GWP impacts between 45-110% of that of ICEVs in China, with the local grid mix being the main driver of differences between the vehicle types (2022). Yang et al. found similar results for China with battery production and electricity grid mixes driving BEV impacts (2020). These studies, when compared to the majority of studies that had BEVs outperforming ICEVs, show that lowering the GWP of BEVs (and EVs in general) requires improving the main drivers of emissions: electricity generation and vehicle manufacturing. Burnham et al. and Aljohani & Alzahrani both examine EV use in the U.S. and find that EVs have lower GWP than ICEVs even when considering the higher manufacturing emissions (Burnham et al. 2021; Aljohani and Alzahrani 2019). Burnham et al. also finds in a 2050 scenario (using projected fuel and electricity carbon intensities) that even with a nearly 30% reduction in fuel consumption for ICEVs, BEVs still have lower GWP in all U.S. states (2021). Kelly et al. comes to the same conclusion with current and future (2050 scenario) BEVs outperforming ICEVs in the U.S. even with future improvements to both fuel consumption and fuel pathways for ICEVs (2022). The county-level sensitivity analysis in Woody et al. found that BEVs in the U.S. outperform HEVs in 95-96% of counties and ICEVs in 98-99% of counties (Woody 2022).

Again, observing the aforementioned limitations on comparing results between LCA studies, Figure 5 provides insight into the distribution of intra-study quantitative differences among EV-ICEV GWP comparisons. The vertical axis represents the difference in GWP impact between each category of EV versus an ICEV, normalized to the ICEV impacts, all from the same study. Please note that only values in Appendix A were used; studies such as Tang et al. that have 10+ scenarios only have one entry representing the base scenario or baseline (Tang, Xu, and Wang 2022). Additionally, the 193% FCEV-ICEV comparison value from Joshi et al. is hidden to improve the readability of the figure. Values below 0% indicate that an EV had a lower GWP than an ICEV in the same study, while values above 0% have higher impacts. The median GWP from studies for EVs is lower than that of ICEVs, with most BEV, HEV, and PHEV values falling between 0% (no reduction to ICEV) to -50% (half the GWP of ICEV). FCEV values have a much wider range, partially due to both a lower sample size and variance in assumptions about hydrogen production (i.e., ranging from electrolysis powered by a normal grid mix to burden free hydrogen from renewable energy).

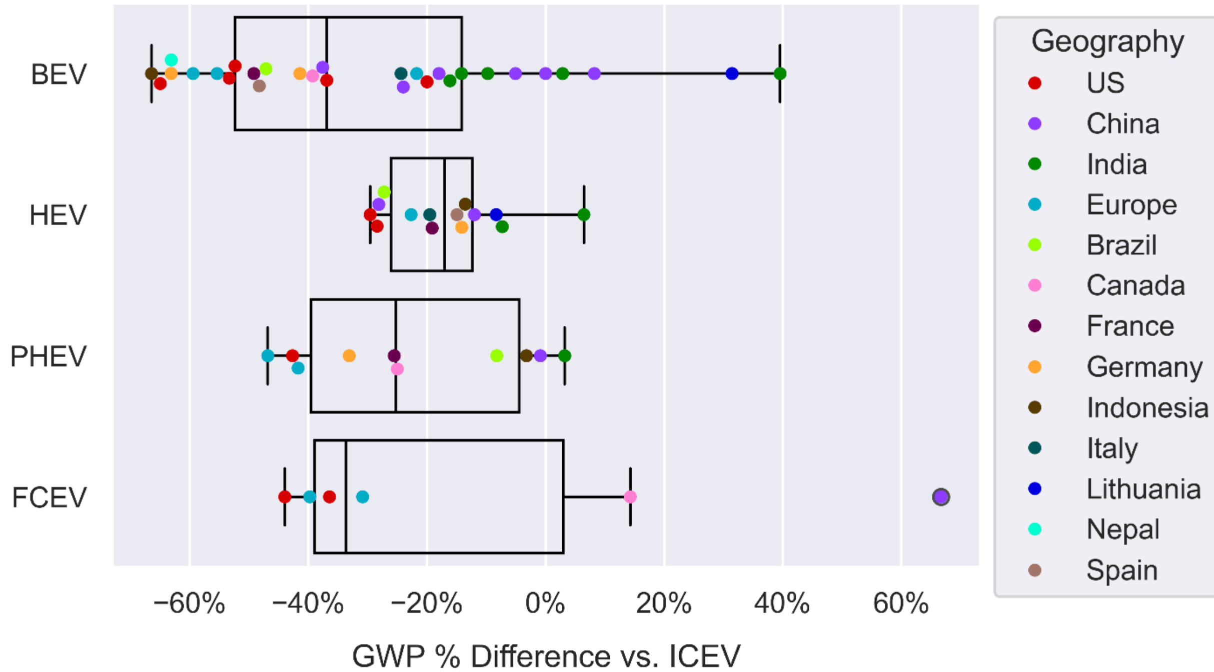

Figure 5. Distributions of intra-study percent differences in life cycle GWP results between EVs and ICEVs, colored by use phase geographic context

Most studies selected for intra-study comparisons did not analyze uncertainty when calculating the GWP impact; only 6 of 31 studies included some form of uncertainty analysis. Uncertainty in LCIA results are useful for determining the confidence level of any comparisons between vehicle types. For example in Gan et al.'s 2023 comparison of ICEVs, HEVs, and BEVs, the HEVs are reported to have the lowest GWP but shown to have error bars that overlap with the GWP of ICEVs (2023). The confidence of the comparisons are not reported in the study. Using Monte Carlo simulation, Kurada et al. found that while the EV average GWP impact is lower than that of ICEVs in China, the lower range of ICEV GWP includes some values below the range of EV GWP (in other words some simulations had ICEV outperform all EV simulations) (2022). Peshin et al. found that BEVs had lower lifetime GHG emissions than ICEVs in India, with uncertainty analysis showing there was a significant difference between the two vehicle types (2020). Future studies should consider uncertainty analysis, particularly analyses that examine the uncertainty associated with modeling the various key life cycle stages detailed in this review. Beginning to quantify the confidence of the conclusions found in LCIA results would be valuable to stakeholders making policy decisions.

3.2 Criteria Air Pollutant Impacts Comparisons between ICEVs and EVs

While nearly every reviewed study considered GWP in its LCIA, few specifically reported impacts for CAPs. Five studies that appeared ISO compliant and were peer reviewed included particulate formation as a midpoint impact. It is important to note that this is more expansive than the non-exhaust emissions discussed in Section 2.4.4, as it includes particulate matter formation from life cycle stages other than just the use phase. All five studies found that the average EVs (BEVs, HEVs, and PHEVs) have higher total particulate matter formation impacts than ICEVs, though the EV emissions are due to electricity generation (mostly from coal) and are not tailpipe emissions (Bhosale and Mastud 2023; Bouter et al. 2020; Burnham et al. 2021; Naranjo et al. 2021; Pipitone, Caltabellotta, and Occhipinti 2021). Burnham et al. found that in 15 U.S. states (i.e., 30%), 2020 passenger cars and trucks, as well as commercial trucks, have lower life cycle PM2.5 emissions as BEVs than as ICEVs, as presented in Section 3.2.2. and Figure 9 of their paper. Variance among states is primarily based on regional differences in grid mixes and other use stage factors. Critically, Burnham also found that 45 states (90%) had lower life cycle PM2.5 emissions in urban areas for MY 2020 BEVs than ICEVs, due to BEVs shifting emissions from tailpipes to EGU (2021).

Future LCA studies and LCI databases should aim to characterize the geospatial distribution of CAPs when comparing vehicle types and fuel pathways, to better capture the human health impacts of these shifts in technologies and emissions locations. As electricity and resource needs change to meet growing BEV demand, CAP emissions sources will be geospatially redistributed and thereby impact different populations at different rates. Regionalized impact assessment methods are needed to improve the accuracy of human health endpoint impact estimates. The geospatial distribution of impacts varies based on the specific impact category and the assumptions made and scenarios observed by the study (e.g. the grid makeup, driver behavior, etc.). Regionalized impacts can occur in every life cycle stage and depend on the geographical location of processes in that stage. For example, lithium mined in Chile will have location-specific impacts for some CAPs. The location of electricity generation can also influence the geospatial distribution of impacts. Depending on the distributions of population density and demographics in the region, endpoint impacts may also be different. Mejía-Duwan et al. found that California's Clean Vehicle Rebate Project (CVRP) would result in net primary PM2.5, NO_X, and SO_2 emissions reductions more often in the least disadvantaged communities in California as compared to disadvantaged communities, due in part to the disproportionate location of EGUs in these communities (2023). Without sufficiently detailed LCI metadata on emissions locations, as well as LCIA tools and methods that simplify and standardize geospatial workflows for LCA practitioners, questions of equity and environmental justice will likely remain inadequately addressed by future LCA studies.

Regional-scale data is not widely available in databases such as USLCI (National Renewable Energy Laboratory 2023). For TRACI in particular, a eutrophication method was recently released (Henderson et al. 2021), and smog formation potential is currently being developed. Sharma et al. provides a framework for a comprehensive assessment of spatial distributions (2023). This includes a complete value chain of the vehicle that includes cross-sectoral linkages (e.g. between transportation and power and industrial sectors) and market linkages (e.g. electricity trade and EV supply chain). It also should include an analysis of the atmospheric and socio-economic conditions that impact spatial distribution of pollutants (Sharma et al. 2023). While modeling the geospatial distribution of impacts may not be possible with current data, its equity implications highlight the need for increased efforts to model these changes.

3.3 Draft Regulatory Impact Analysis

In order to best estimate the impact of the proposed LMDV rule on GHG and CAP emissions, public health, and the economy, EPA prepared a Draft Regulatory Impact Analysis (DRIA) (US EPA 2023b). Specifically, the DRIA uses the OMEGA v2.1.0 model (US EPA 2023d) to estimate "emission inventories, fuel consumption, oil imports, vehicle miles traveled including effects associated with the rebound effect, and safety effects." OMEGA's emission inventories include estimates of both GHGs and CAPs emitted by on-road vehicles and electric generating units (EGU), and, for now, only CAPs emitted by petroleum refineries. It uses the EPA MOVES model to generate the vehicle emissions, EPA's Power Sector Modeling Platform v6.21 for EGU emissions, and additional air quality modeling (AQM) plus EIA AEO 2021 data for refinery emissions linked to gasoline and diesel fuel products.

Even without the GHG estimates from refinery activities, the DRIA results in tables 9-21 and 9-25 demonstrate that the proposed LMDV standards would enable a net GHG emissions reduction as new BEVs progressively replace ICEVs. However, various stakeholders have highlighted OMEGA's exclusion of upstream emissions associated with vehicle manufacture (e.g., GHGs emitted by energy commodities consumed during graphite production), as well as emissions upstream of EGUs and refineries (e.g., CH_4 emitted during fossil fuel extraction). Despite these exclusions, OMEGA's findings of BEVs providing a net GHG reduction when replacing ICEVs is uniformly supported and reinforced by the reviewed LCA literature that compares BEVs and ICEVs in the U.S. context, per the results discussed above in Section 3.1.

As best demonstrated in the U.S. context by both Burnham et al. and Kelly et al., the larger GHG burden of EV over ICEV manufacture—primarily due to battery manufacture—is eclipsed by the lower use phase GHG emissions of EVs (Burnham 2012; J. C. Kelly et al. 2022). These two studies constitute the newest, highest quality sources of comparative LCA modeling and results across vehicle types, given their adoption of the largest shares of the LCA modeling best practices (detailed below in Section 0) among all reviewed studies. These same factors also led the reviewed LCAs to agree that BEVs outperform HEVs and PHEVs in the U.S. context, as well as ICEVs, HEVs, and PHEVs in non-U.S. contexts where grid electricity is and/or will become sufficiently decarbonized. Additionally, the GHG intensity of battery manufacture is expected to continue improving and benefit from cleaner future grid electricity (Chordia, Nordelöf, and Ellingsen 2021; Xu et al. 2022).

With respect to CAP emissions, the DRIA results in tables 9-29, 9-33, 9-37 indicate that the proposed LMDV standards would provide a net reduction within each category of emissions. The reviewed LCA literature addressed CAP emissions far less frequently than GHGs, and only one recent study, Burnham et. al, characterized them within the U.S. context. Burnham et al. found that the total life cycle PM2.5 emissions of MY 2020 BEVs was higher in about 70% of U.S. states than those from MY 2020 ICEVs. Burnham also found that the urban emissions of PM2.5 was lower for MY 2020 BEVs in 90% of U.S. states, due to shifting emissions from tailpipes to EGUs. However, Burnham et al.'s findings were based on the grid projections from the 2020 version of NREL's Cambium tool, which was not yet informed by the passage of the IRA. Replicating Burnham's analysis with the updated grid projections would likely further reduce BEV life cycle CAP emissions and could lead to a closer alignment with the findings of the DRIA.

3.4 Key LCA Modeling Decisions

Table 3-1 and Table 3-2 detail the minimum recommendations and the best practices for completing LCA studies on EVs. These recommendations are drawn from examining common items in the reviewed literature that either varied greatly from study-to-study (such as LCI data availability) or were shown to be a common limitation (such as using quickly outdated electric grid mix data). LCA practitioners should first follow ISO guidelines for best practices, then consult these tables for ensuring their study is relevant and useful to the general, scientific, and LCA communities. In general, studies should attempt to follow all methodology best practices and all relevant life cycle stage recommendations. Best practices for data age are likely more stringent than most guidelines. This is due to how quickly electricity grid mixes are changing and how large of a driver grid mix is in EV LCAs and LCIAs for most impacts. LCAs should provide insight for decision making, which means the most recent electricity grid mix data is required. This recommended data age matches the EPA's highest data quality requirement for temporal correlation of life cycle inventory data (A. Edelen and Ingwersen 2016).

Table 3-1. Life Cycle Assessment Methodology Recommendations

	Minimum Recommendation		Best Practices
LCI Information	LCI summary available	Process level LCI available Product system clearly defined	LCI files available (e.g., OpenLCA database or Excel workbook)
ISO Compliance	Functional unit defined; life cycle boundaries stated (ISO compliance not explicitly stated)		Full ISO 14040, 14044, 14067 Compliance
Data Source	Data <5 years old for foreground and background LCI.	Data <4 years old for foreground and background LCI.	Recent data (<3 years old) for foreground and background LCI.
Data Availability	Database version reported or primary data with collection methods reported		Database version reported or primary data with collection method reported Data openly available in SI of study
Data Quality	Cite all data sources		Cite all data sources Follow data quality guidance for life cycle inventory data (A. Edelen and Ingwersen 2016)
Sensitivity Scenarios	Sensitivity analysis of major drivers of life cycle impacts and uses range of values for timeframe of analysis		Sensitivity analysis of major drivers of life cycle impacts; uses range of values for timeframe of analysis and projected future values
Life Cycle Impact Assessment	Impact methods clearly stated	Most relevant impacts assessed, openly availably impact methods used and reported.	All relevant impacts assessed, openly availably impact methods used and reported Impact summary data available in SI
Background LCI	Geospatial consideration given to background LCI		Geospatial consideration given to background LCI Utilities of background LCI explicitly reported or cited

Table 3-2. Vehicle Life Cycle Stage Recommendations

	Minimum Recommendation		Best Practices
Resource Extraction and Refining	Major processes detailed (geospatial, process, uncertainty)		Major processes detailed (geospatial, process, uncertainty) Relevant resource depletion/scarcity impacts reported (i.e. water scarcity and abiotic depletion)
Manufacturing and Assembly	Transport of materials between stage locations considered utility and electricity grid mix of manufacturing location considered		Vehicle BOM or LCI reported and available in SI Transport of materials between stage locations considered Utility and electricity grid mix of manufacturing location considered
Fuel Production	Fuel Cycle data is <5 years old, data reported in methods	Fuel Cycle data is <4 years old, data reported in methods Fuel cycle properties (i.e. T&D losses, charging losses) reported	Fuel Cycle data is <3 years old, data reported in methods Fuel cycle properties (i.e. T&D losses, charging losses) reported Future projection(s) of fuel cycle data used in baseline and/or sensitivity scenario(s)
Use Stage	Fuel consumption reported	Fuel consumption reported, vehicle factors considered (i.e. vehicle weight and utilization factor)	Fuel consumption reported, vehicle factors(i.e. vehicle weight and utilization factor) and non-vehicle factors considered (i.e. weather and rural/urban road properties of use stage location)
End-of-Life	End-of-life methods used at disposal location considered		End-of-life methods used at disposal location considered ISO 14044 recommended allocation procedure (ISO 2006b)

Below is a list of common recommended factors/properties for LCAs on EVs. These are not complete and not always relevant based on study scope. It is ultimately up to the LCA practitioner to determine what factors and processes are important for their specific study.

Life Cycle Impact Assessment Methods: TRACI, ImpactWorld, ReCiPe. See the U.S. Federal LCA Commons for elementary flow databases that are compatible with these LCIA methods.

Resource Extraction and Refining (Major Processes for EVs): lithium, graphite, iron, steel, aluminum, plastics, carbon fiber, rubber, coal, oil, natural gas, copper.

Fuel Cycle Properties: overall carbon intensity, composition (electricity grid mix or liquid fuel blend), loss factors (transmission and distribution, charging losses, battery losses, venting flaring and fugitive emissions for gases).

Use Stage Vehicle Factors: Vehicle weight, battery properties (chemistry, charge density, efficiency), baseline fuel consumption, non-exhaust emissions, utilization factor. If the functional unit has a passenger element, then also consider average passengers.

Use Stage Non-Vehicle Factors: weather, road properties, driver behavior, travel properties (average trip distance and time), traffic. These are usually properties of the driver or of the use stage location.

Geospatial Factors: transportation methods and distances between processes/life cycle stages, utility emissions factors, electricity grid mix, disposal methods (recycling, landfilling), relative resource scarcity (such as water and mineral).

3.5 Data Openness

In addition to adopting the vehicle LCA best practices outlined above, openly publishing the foreground LCI data on which a study relies is of singular importance to ensuring that LCA results are both reproducible and comparable across studies. Omitting LCI data or masking it via aggregated system processes (instead of unit processes) hinders these goals, and makes studies difficult to validate and review alongside other more transparent works. Additionally, per ISO-14044 clause 4.2.3.6.2, any publicly released LCA study containing comparative results must meet a list of data quality requirements, including an assessment of reproducibility (ISO 2006b). This requirement compels study authors to explain whether the provided data and methodology details are sufficient for an independent LCA practitioner to reproduce the study results. Furthermore, an assessment of reproducibility should explicitly state if, where, and how omission or masking of confidential or proprietary data will limit the review and reproduction of results by an independent 3rd party.

In the context of passenger vehicles, foreground LCI data can be partially collected through tear-down studies. Such studies quantify the masses of different materials within each vehicle sub-system and component, ultimately producing a vehicle BOM. Still, a vehicle BOM only represents a subset of the full network of material flows between the unit processes within a vehicle product system. This network must be supplemented with additional energetic and material inputs required for component production and subsystem assembly steps. Such additional data may be provided through existing background LCI databases (e.g., industry averages), but . Most studies— about 60%—did make LCI data available through either supplemental material and/or detailed tables in the body of the paper. Of the studies reviewed that had LCI data, 35 provided complete LCI data of the foreground system, 3 stated data was available upon request, 5 provided partial LCI data, and 14 did not provide LCI data (though many did cite that data was taken from a LCI database such as ecoinvent).

Recommendation
Provide full unit process data for the foreground processes, a mapping of foreground to background processes, and citations for all background data sources. Clearly address data confidentiality, and avoid simply offering to provide data upon request. Document data quality through a defined schema, such as the LCI data quality guidance produced by EPA.

While the use of common models such as GREET and databases such as USLCI and ecoinvent help make studies more reproducible, studies typically augment data from these sources with current literature, primary data, and/or stakeholder-provided data (National Renewable Energy Laboratory 2023). Researchers should consistently cite the database, model, study, or other source from which they obtain LCI data, such that others can reproduce their findings and reuse said data for other works. Additionally, a mapping of how foreground and background unit processes connect within a product system should also be provided. Similarly, if customizing a model such as GREET, a full list of alterations from its default state—including cell addresses and values for each altered parameter—should be provided, as well as a specific version number (e.g., “GREET 2022 r1”). The same logic applies for other Excel models, as well as input and configuration files for IAMs like REMIND.

Along with the recommendation that studies use recent data, data quality assessment and reporting should follow the EPA's existing LCI quality guidance (A. Edelen and Ingwersen 2016). The following items should be reviewed and submitted with a study:

- Goal and scope definition
- Raw data (such as .zolca database file for openLCA)
- Unit process-resolved inventory
- Aggregated process inventory
- LCI results
- LCIA methods
- Dataset documentation (detail any database and/or background model modifications)
- Data quality indicators at the process and elementary flow level.

Studies are recommended to use the databases where available through the Federal LCA Commons and associated USLCI database, which should have metadata included for data quality assessment (Kahn, Antognoli, and Arbuckle 2022). This is an inter-agency initiative to provide public LCI background data for common processes such as commodity materials, fuels, electricity, transportation and waste management. Federal agencies provide their own repositories on the Federal LCA Commons and industry can also submit data through the USLCI. Efforts have been made to ensure Federal LCA Commons data can be interoperable through implementation of the Federal LCA Commons Elementary Flow List, a common nomenclature system to ensure LCI flows are properly captured in LCIA methods (A. N. Edelen et al. 2022). Agencies can submit data to the Federal LCA Commons through a collaboration server that tracks database changes in a transparent way over time and is compatible with the open-source openLCA software. Within this software, EPA's data quality guidelines can be applied, and this software allows for export in multiple standard LCA file formats useable by other common software products. USLCI hosts publicly available submission guidelines and other training material to support industry in publishing data by using a common framework. While the Federal LCA Commons may be expanded over time to support the growing need for LCAs, it does not currently represent a complete background LCI database and LCA studies practically will need to cite other established databases and peer-reviewed literature sources. When doing so, this report recommends including the full reference information and associated LCI process name.

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APPENDICES

Appendix A: Intra-study GWP Ranking

Study	GWP Impact ($kgCO_2/km$)					Comment
	ICEV	BEV	HEV	PHEV	FCEV	
(Aljohani and Alzahrani 2019)	0.343	0.216	-	-	-	Value calculated from lifetime emissions; only values for Detroit listed here
(Bhosale and Mastud 2023)	0.242	0.281	-	-	-	
(Bouter et al. 2020)	0.162	0.0823	0.131	0.121	0.162	French electricity grid values used for all vehicles; results from Table 6
(Burnham et al. 2021)	0.280	0.130	-	-	-	Values interpreted from Figure 3; units converted to km basis
(Das 2022)	0.269	0.375	-	-	-	Calculated via Figure 11 CO_2eq. values (using LFP BEV) and 160 Mm lifetime distance
(Gan et al. 2023)	0.295	0.280	0.212	-	-	BEV values for 300km range BEV using national average grid
(Joshi, Sharma, and Baral 2022)	0.507	0.187	-	-	1.484	
(J. C. / E. Kelly 2022)	0.237	0.113	0.167	0.136	0.133	BEV and FCEV are 300km range, all vehicles are sedans
(Kurada, Ali, and Gokulachandran 2022)	0.316	0.285	0.293	-	-	Values calculated based on lifetime emissions
(X. Liu et al. 2020)	0.227	-	-	-	0.144	FCEV values from SMR pathway
(Naranjo et al. 2021)	0.261	0.135	0.222	-	-	
(Patella et al. 2019)	0.382	0.289	0.307	-	-	Values calculated from Table 7 and Figure 3, assuming even split between rural and urban driving
(Peshin, Azevedo, and Sengupta 2020)	0.207	0.173	0.220	0.213	-	Values interpreted from Figure 3
(Petrauskienė et al. 2021)	0.160	0.210	0.147	-	-	Values interpreted from Figure 3
(Pipitone, Caltabellotta, and Occhipinti 2021)	0.187	0.110	0.161	-	-	
(Shafique et al. 2022)	0.280	0.213	0.246	-	-	Values originally reported relative to ICEV and are calculated from ICEV GWP
(Tang, Xu, and Wang 2022)	0.282	0.305	-	-	-	Values for vehicles used in Beijing
(Kannangara, Bensebaa, and Vasudev 2021)	0.280	0.170	-	0.210	0.320	Values are from the medium electricity CI scenario

Study	GWP Impact ($kgCO_2/km$)					Comment
	ICEV	BEV	HEV	PHEV	FCEV	
(Z. Yang, Wang, and Jiao 2020)	0.280	0.280	-	-	0.467	
(L. Yang et al. 2021)	0.228	0.187	-	0.226	-	
(Rashid and Pagone 2023)	-	-	0.208	0.176	-	

Appendix B: Reviewed, Accepted Literature Metadata

DOI	Year	Title	Authors	Study Type	Vehicle Types
10.3390/ app11031160	2021	Life Cycle Assessment of an NMC Battery for Application to Electric Light-Duty Commercial Vehicles and Comparison with a Sodium-Nickel-Chloride Battery	Accardo, Antonella; Dotelli, Giovanni; Musa, Marco Luigi; Spessa, Ezio	LCA, Formal	BEV, ICEV
10.3390/ app13031494	2023	End-of-Life Impact on the Cradle-to-Grave LCA of Light-Duty Commercial Vehicles in Europe	Accardo, Antonella; Dotelli, Giovanni; Miretti, Federico; Spessa, Ezio	LCA, Formal	BEV, ICEV
10.1109/ southeastcon42311. 2019.9020666	2019	Life Cycle Assessment to Study the Impact of the Regional Grid Mix and Temperature Differences on the GHG Emissions of Battery Electric and Conventional Vehicles	Aljohani, Tawfiq; Alzahrani, Ghurmallah	LCA, Formal	BEV, ICEV
10.1016/ j.apenergy. 2021.116621	2021	The greenhouse gas emissions of an electrified vehicle combined with renewable fuels: Life cycle assessment and policy implications	Andersson, Öivind; Börjesson, Pål	LCA, Formal; Fleet Modeling	BEV, HEV, PHEV
10.1016/ j.atmosenv. 2020.117886	2021	PM10 and PM2.5 emission factors for non-exhaust particles from road vehicles: Dependence upon vehicle mass and implications for battery electric vehicles	Beddows, David C.S.; Harrison, Roy M.	Non-LCA, LCI support	BEV, ICEV
10.5829/ ije.2023.36.05b.13	2023	Comparative Environmental Impact Assessment of Battery Electric Vehicles and Conventional Vehicles: A Case Study of India	Bhosale, A. P.; Mastud, S. A.	LCA, Formal	BEV, ICEV
10.1016/ j.matpr.2022.09.344	2023	Comparative environmental assessment of different battery technologies used for electric vehicles	Bhosale, Amrut P.; Bodke, Kaveri; Babhulkar, Anjali; Amale, Shivpriya; Mastud, Sachin A.; Chavan, Amol B.	LCA, Formal	BEV
https://theicct.org/ publication/a-global-comparison-of-the-life-cycle-greenhouse-gas-emissions-of-combustion-engine-and-electric-passenger-cars/	2021	A global comparison of the life-cycle greenhouse gas emissions of combustion engine and electric passenger cars	Bieker, Georg	LCA, Formal	ICEV, BEV, PHEV, HEV, FCEV
https://theicct.org/ publication/ghg-benefits-incentives-ev-mar22/	2022	More bang for the buck: A comparison of the life-cycle greenhouse gas emission benefits and incentives of plug-in hybrid and battery electric vehicles in Germany	Bieker, Georg; Moll, Cornelius; Link, Steffen; Plötz, Patrick; Mock, Peter	LCA, Formal	ICEV, BEV, PHEV

DOI	Year	Title	Authors	Study Type	Vehicle Types
10.1007/ s11367-020-01756-2	2020	Comparative environmental life cycle assessment of several powertrain types for cars and buses in France for two driving cycles: "worldwide harmonized light vehicle test procedure" cycle and urban cycle	Bouter, Anne; Hache, Emmanuel; Ternel, Cyprien; Beauchet, Sandra	LCA, Formal	BEV, HEV, ICEV, PHEV
10.1016/ j.jclepro.2020.120476	2020	Life cycle impact assessment of electric vehicle battery charging in European Union countries	Burchart-Korol, Dorota; Jursova, Simona; Folęga, Piotr; Pustejovska, Pavlina	LCA, Formal	BEV
10.3390/ atmos12111482	2021	Regional Emissions Analysis of Light-Duty Battery Electric Vehicles	Burnham, Andrew; Lu, Zifeng; Wang, Michael; Elgowainy, Amgad	LCA, Formal	BEV, ICEV
10.1016/ j.jclepro. 2022.133342	2022	Investigating carbon footprint and carbon reduction potential using a cradle-to-cradle LCA approach on lithium-ion batteries for electric vehicles in China	Chen, Quanwei; Lai, Xin; Gu, Huanghui; Tang, Xiaopeng; Gao, Furong; Han, Xuebing; Zheng, Yuejiu	LCA, Formal	BEV
https://greet.anl.gov/ publication-Li_ battery_update_2017	2017	Update of Life Cycle Analysis of Lithium-ion Batteries in the GREET® Model	Dai, Q.; Dunn, J.; Kelly, J. C.; Elgowainy, A.	LCI Modeling	#N/A
10.1007/ s10668-021-01990-0	2022	Comparative life cycle GHG emission analysis of conventional and electric vehicles in India	Das, Jani	LCA, Formal	BEV, ICEV
10.1016/ j.atmosenv. 2020.117612	2020	Pollutant emissions analysis of three plug-in hybrid electric vehicles using different modes of operation and driving conditions	Ehrenberger, S.I.; Konrad, M.; Philipps, F.	Non-LCA, LCI support	PHEV
10.1016/ j.jclepro. 2022.130474	2022	Life cycle assessment of natural graphite production for lithium-ion battery anodes based on industrial primary data	Engels, Philipp; Cerdas, Felipe; Dettmer, Tina; Frey, Christoph; Hentschel, Jan; Herrmann, Christoph; Mirfabrikikar, Tina; Schueler, Maximilian	LCA, Formal	BEV
10.3390/ su15032627	2023	Cradle-to-Grave Lifecycle Analysis of Greenhouse Gas Emissions of Light-Duty Passenger Vehicles in China: Towards a Carbon-Neutral Future	Gan, Yu; Lu, Zifeng; He, Xin; Wang, Michael; Amer, Amer Ahmad	LCA, Formal	BEV, HEV, ICEV
10.2478/ ata-2023-0003	2023	Life Cycle Assessment of a Hybrid Self-Power Diesel Engine	Hashemi, Fatemeh; Pourdarbani, Razieh; Ardabili, Sina; Hernandez-Hernandez, José Luis	LCA, Formal	HEV, ICEV
10.3390/ su12031241	2020	Sensitivity Analysis in the Life-Cycle Assessment of Electric vs. Combustion Engine Cars under Approximate Real-World Conditions	Helmers, Eckard; Dietz, Johannes; Weiss, Martin	LCA, Formal	BEV, ICEV
https://climate.ec.europa.eu/system/files/ 2020-09/2020_study_ main_report_en.pdf	2020	Determining the environmental impacts of conventional and alternatively fuelled vehicles through LCA	Hill, Nikolas; Amaral, Sofia; Morgan-Price, Samantha; Nokes, Tom; Bates, Judith; Helms, Hinrich; Fehrenbach, Horst; Biemann, Kirsten; Abdalla, Nabil; Jöhrens, Julius; Cotton, Eloise; German, Lizzie; Harris, Anisha; Ziem-Milojevic, Sabine; Haye, Sebastien; Sim, Chris; Bauen, Ausilio	LCA, Formal	ICEV, BEV, PHEV, HEV, FCEV

DOI	Year	Title	Authors	Study Type	Vehicle Types
10.1016/ j.scitotenv. 2018.12.349	2019	Fuel consumption and emissions performance under real driving: Comparison between hybrid and conventional vehicles	Huang, Yuhan; Surawski, Nic C.; Organ, Bruce; Zhou, John L.; Tang, Oscar H.H.; Chan, Edward F.C.	Non-LCA, LCI support	HEV, ICEV
10.3390/ su11092527	2019	Life Cycle Assessment of a Lithium Iron Phosphate (LFP) Electric Vehicle Battery in Second Life Application Scenarios	Ioakimidis, Christos; Murillo-Marrodán, Alberto; Bagheri, Ali; Thomas, Dimitrios; Genikomsakis, Konstantinos	LCA, Formal	BEV
10.1016/ j.jclepro. 2022.134407	2022	Comparative life cycle assessment of conventional combustion engine vehicle, battery electric vehicle and fuel cell electric vehicle in Nepal	Joshi, Ashim; Sharma, Raghav; Baral, Bivek	LCA, Formal	BEV, FCEV, ICEV
10.1016/ j.jclepro. 2021.128394	2021	An adaptable life cycle greenhouse gas emissions assessment framework for electric, hybrid, fuel cell and conventional vehicles: Effect of electricity mix, mileage, battery capacity and battery chemistry in the context of Canada	Kannangara, Miyuru; Bensebaa, Farid; Vasudev, Madhav	LCA, Formal	BEV, FCEV, HEV, ICEV, PHEV
10.3390/ su11092690	2019	Estimation of CO2 Emissions of Internal Combustion Engine Vehicle and Battery Electric Vehicle Using LCA	Kawamoto, Ryuji; Mochizuki, Hideo; Moriguchi, Yoshihisa; Nakano, Takahiro; Motohashi, Masayuki; Sakai, Yuji; Inaba, Atsushi	LCA, Formal	BEV, ICEV
10.2172/ 1875764	2022	Cradle-to-Grave Lifecycle Analysis of U.S. Light-Duty Vehicle-Fuel Pathways: A Greenhouse Gas Emissions and Economic Assessment of Current (2020) and Future (2030-2035) Technologies	Kelly, Jarod; Elgowainy, Amgad; Isaac, Raphael; Ward, Jacob; Islam, Ehsan; Rousseau, Aymeric; Sutherland, Ian; Wallington, Timothy; Alexander, Marcus; Muratori, Matteo; Franklin, Matthew; Adams, Jesse; Rustagi, Neha	LCA, Formal	BEV, FCEV, HEV, ICEV, PHEV
10.1021/ acs.est.3c01346	2023	Cradle-to-Gate and Use-Phase Carbon Footprint of a Commercial Plug-in Hybrid Electric Vehicle Lithium-Ion Battery	Kim, Hyung Chul; Lee, Sunghoon; Wallington, Timothy J.	LCA-Adjacent	PHEV
10.1016/ j.scitotenv. 2022.154859	2022	Life cycle assessment of battery electric vehicles: Implications of future electricity mix and different battery end-of-life management	Koroma, Michael Samsu; Costa, Daniele; Philippot, Maeva; Cardellini, Giuseppe; Hosen, Md Sazzad; Coosemans, Thierry; Messagie, Maarten	LCA, Formal	BEV
10.1007/ 978-981-19-3467-4_22	2022	A Comparative Life Cycle Assessment of an Electric, a Hybrid, and an Internal Combustion Engine Vehicle Using Monte Carlo Simulation	Kurada, Sricharan Dwijesh; Ali, Mirza Imtiaz; Gokulachandran, J.	LCA, Formal	EV, HEV, ICEV
10.1016/ j.est.2023.106635	2023	Life cycle assessment of a lithium-ion battery with a silicon anode for electric vehicles	Lavigne Philippot, Maeva; Costa, Daniele; Cardellini, Giuseppe; De Sutter, Lysander; Smekens, Jelle; Van Mierlo, Joeri; Messagie, Maarten	LCA, Formal	BEV
10.3390/ en12193612	2019	Research on Carbon Emissions of Electric Vehicles throughout the Life Cycle Assessment Taking into Vehicle Weight and Grid Mix Composition	Li, Yanmei; Ha, Ningning; Li, Tingting	LCA, Formal	BEV, ICEV

DOI	Year	Title	Authors	Study Type	Vehicle Types
10.1016/ j.envpol.2021.117320	2021	Real-world particle and NOx emissions from hybrid electric vehicles under cold weather conditions	Li, Chengguo; Swanson, Jacob; Pham, Liem; Hu, Shaohua; Hu, Shishan; Mikailian, Gary; Jung, Heejung S.	Non-LCA, LCI support	HEV
10.1016/ j.ijhydene.2019.10.192	2020	Comparison of well-to-wheels energy use and emissions of a hydrogen fuel cell electric vehicle relative to a conventional gasoline-powered internal combustion engine vehicle	Liu, Xinyu; Reddi, Krishna; Elgowainy, Amgad; Lohse-Busch, Henning; Wang, Michael; Rustagi, Neha	LCA, Formal	FCEV, ICEV
10.1111/ jiec.13415	2023	BEVSIM: Battery electric vehicle sustainability impact assessment model	Mehta, Rajesh; Golkaram, Milad; Vogels, Jack T. W. E.; Ligthart, Tom; Someren, Eugene; Ferjan, Spela; Lennartz, Jelmer	Non-LCA, LCI support	BEV, ICEV
https://theicct.org/ publication/ comparison-of-life-cycle-ghg-emissions-of-combustion-engines-and-electric-pv-brazil-oct23/	2023	COMPARISON OF THE LIFE-CYCLE GREENHOUSE GAS EMISSIONS OF COMBUSTION ENGINE AND ELECTRIC PASSENGER CARS IN BRAZIL	Mera, Zamir; Bieker, Georg	LCA, Formal	ICEV, BEV, HEV, PHEV, FCEV
https://theicct.org/ publication/comparison-life-cycle-ghg-emissions-combustion-engine-and-electric-pv-and-2w-indonesia-sept23/	2023	COMPARISON OF THE LIFE-CYCLE GREENHOUSE GAS EMISSIONS OF COMBUSTION ENGINE AND ELECTRIC PASSENGER CARS AND TWO-WHEELERS IN INDONESIA	Mera, Zamir; Bieker, Georg; Beatriz Rebouças, Ana; Cieplinski, André	LCA, Formal	ICEV, BEV, HEV, PHEV
https://group.mercedes-benz.com/ documents/sustainability/product/daimler-environmental-check-mb-eqs.pdf	2021	360° Environmental Check Mercedes-Benz EQS	Mercedes-Benz	LCA, Formal	BEV
10.1016/ j.enconman. 2021.114104	2021	Implication viability assessment of electric vehicles for different regions: An approach of life cycle assessment considering exergy analysis and battery degradation	Nimesh, Vikas; Kumari, Ranjana; Soni, Neelesh; Goswami, Arkopal K.; Mahendra Reddy, V.	LCA-Adjacent, Footprinting	BEV
10.1007/ s11367-014-0788-0	2014	Environmental impacts of hybrid, plug-in hybrid, and battery electric vehicles—what can we learn from life cycle assessment?	Nordelöf, Anders; Messagie, Maarten; Tillman, Anne-Marie; Söderman, Maria Ljunggren; Van Mierlo, Joeri	Review	BEV, HEV, ICEV
10.3390/ su11164328	2019	Traffic Simulation-Based Approach for A Cradle-to-Grave Greenhouse Gases Emission Model	Patella, Sergio Maria; Scrucca, Flavio; Asdrubali, Francesco; Carrese, Stefano	LCA, Formal	BEV, HEV, ICEV

DOI	Year	Title	Authors	Study Type	Vehicle Types
10.54097/ hset.v37i.6072	2023	Research on Carbon Emission of ICEV and BEV Based on Life Cycle Assessment	Peng, Chuanpu; Meng, Chenbo	LCA, Formal	BEV, ICEV
10.1109/ vppc49601.2020.9330819	2020	Life-cycle greenhouse gas emissions of alternative and conventional fuel vehicles in India	Peshin, Tapas; Azevedo, Ines M.L.; Sengupta, Shayak	LCA, Formal	BEV, ICEV, PHEV
10.1021/ acs.est.1c07718	2022	Should India Move toward Vehicle Electrification? Assessing Life-Cycle Greenhouse Gas and Criteria Air Pollutant Emissions of Alternative and Conventional Fuel Vehicles in India	Peshin, Tapas; Sengupta, Shayak; Azevedo, Inês M. L.	LCA, Formal	BEV, HEV, ICEV, PHEV
10.1016/ j.jclepro.2019.119042	2020	Comparative environmental life cycle assessment of electric and conventional vehicles in Lithuania	Petrauskienė, Kamilė; Skvarnavičiūtė, Monika; Dvarionienė, Jolanta	LCA, Formal	ICEV, BEV
10.3390/ su13020957	2021	Comparative Environmental Life Cycle and Cost Assessment of Electric, Hybrid, and Conventional Vehicles in Lithuania	Petrauskienė, Kamilė; Galinis, Arvydas; Kliaugaitė, Daina; Dvarionienė, Jolanta	LCA, Formal	HEV, ICEV
10.3390/ su131910992	2021	A Life Cycle Environmental Impact Comparison between Traditional, Hybrid, and Electric Vehicles in the European Context	Pipitone, Emiliano; Caltabellotta, Salvatore; Occhipinti, Leonardo	LCA, Formal	BEV, HEV, ICEV
10.1038/ s41598-017-16684-9	2017	CO2 Mitigation Potential of Plug-in Hybrid Electric Vehicles larger than expected	Plötz, P.; Funke, S. A.; Jochem, P.; Wietschel, M.	Review	BEV, PHEV
10.1007/ s11367-023-02134-4	2023	Comparative sustainability assessment of lithium-ion, lithium-sulfur, and all-solid-state traction batteries	Popien, Jan-Linus; Thies, Christian; Barke, Alexander; Spengler, Thomas S.	LCA, Formal	#N/A
10.1016/ j.jclepro.2021.125883	2021	Comparative life cycle assessment of conventional, electric and hybrid passenger vehicles in Spain	Puig-Samper Naranjo, Gonzalo; Bolonio, David; Ortega, Marcelo F.; García-Martínez, María-Jesús	LCA, Formal	BEV, HEV, ICEV
10.1016/ j.energy.2019.04.080	2019	Life cycle greenhouse gas emissions of Electric Vehicles in China: Combining the vehicle cycle and fuel cycle	Qiao, Qinyu; Zhao, Fuquan; Liu, Zongwei; He, Xin; Hao, Han	LCA, Formal	BEV, ICEV
10.3390/ su151411027	2023	Cradle-to-Grave Lifecycle Environmental Assessment of Hybrid Electric Vehicles	Rashid, Shafayat; Pagone, Emanuele	LCA, Formal	HEV, PHEV
10.3390/ en15197163	2022	Update on the Life-Cycle GHG Emissions of Passenger Vehicles: Literature Review and Harmonization	Raugei, Marco	Review	BEV, FCEV, ICEV, PHEV
10.1038/ s41467-023-38182-5	2023	Hidden delays of climate mitigation benefits in the race for electric vehicle deployment	Ren, Y.; Sun, X.; Wolfram, P.	LCA, Formal	BEV, ICEV
10.1016/ j.jfueco.2022.100083	2023	Environmental and energy impacts of battery electric and conventional vehicles: A study in Sweden under recycling scenarios	Safarian, Sahar	LCA, Formal	BEV, ICEV
10.3390/ en15072401	2022	On-Road and Laboratory Emissions from Three Gasoline Plug-In Hybrid Vehicles—Part 1: Regulated and Unregulated Gaseous Pollutants and Greenhouse Gases	Selleri, Tommaso; Melas, Anastasios D.; Franzetti, Jacopo; Ferrarese, Christian; Giechaskiel, Barouch; Suarez-Bertoa, Ricardo	Non-LCA, LCI support	PHEV

DOI	Year	Title	Authors	Study Type	Vehicle Types
10.1016/ j.jenvman.2021 .114050	2022	Environmental life cycle assessment of battery electric vehicles from the current and future energy mix perspective	Shafique, Muhammad; Luo, Xiaowei	LCA, Formal	BEV, ICEV, PHEV
10.1016/ j.retrec.2021.101112	2022	Life cycle assessment of electric vehicles and internal combustion engine vehicles: A case study of Hong Kong	Shafique, Muhammad; Azam, Anam; Rafiq, Muhammad; Luo, Xiaowei	LCA, Formal	BEV, ICEV, PHEV
10.3390/ su14063444	2022	Greenhouse Gas Emissions Performance of Electric and Fossil-Fueled Passenger Vehicles with Uncertainty Estimates Using a Probabilistic Life-Cycle Assessment	Smit, Robin; Kennedy, Daniel William	LCA-Adjacent, Statistical Modeling	BEV, ICEV
10.1007/ s43615-021-00012-5	2021	Criticality Assessment of the Life Cycle of Passenger Vehicles Produced in China	Sun, Xin; Bach, Vanessa; Finkbeiner, Matthias; Yang, Jianxin	LCA, Formal	BEV, ICEV
10.3390/ atmos13020252	2022	Life Cycle Assessment of Battery Electric and Internal Combustion Engine Vehicles Considering the Impact of Electricity Generation Mix: A Case Study in China	Tang, Bowen; Xu, Yi; Wang, Mingyang	LCA, Formal	BEV, ICEV
10.1016/ j.scitotenv.2021 .150407	2022	Real-world emissions and fuel consumption of gasoline and hybrid light duty vehicles under local and regulatory drive cycles	Tu, Ran; Xu, Junshi; Wang, An; Zhang, Mingqian; Zhai, Zhiqiang; Hatzopoulou, Marianne	Non-LCA, LCI support	HEV, ICEV
10.4271/ 2022-01-0749	2022	Life Cycle Assessment of Greenhouse Gas Emissions of Electric and Internal Combustion Engine Vehicles in India	Verma, Shrey; Dwivedi, Gaurav; Zare, Ali; Verma, Puneet	Review	BEV, ICEV
10.2139/ ssrn.3931673	2021	Real Driving Energy Consumption and CO2 Pollutant Emission Characteristics of a Parallel Plug-In Hybrid Electric Vehicle Under Different Propulsion Modes	Wang, Yachao; Ge, Yunshan; Yin, Hang	Non-LCA, LCI support	PHEV
10.3390/ su14063371	2022	A Review on Environmental Efficiency Evaluation of New Energy Vehicles Using Life Cycle Analysis	Wang, Nenming; Tang, Guwen	Review	BEV, EREV, FCEV, HEV, ICEV, PHEV
10.3390/ en15186853	2022	Life Cycle Assessment of Energy Consumption and CO2 Emission from HEV, PHEV and BEV for China in the Past, Present and Future	Wang, Renjie; Song, Yuanyuan; Xu, Honglei; Li, Yue; Liu, Jie	LCA, Formal	BEV, HEV, ICEV, PHEV

DOI	Year	Title	Authors	Study Type	Vehicle Types
https://greet.anl.gov/publication-greet-2022-summary	2022	Summary of Expansions and Updates in GREET® 2022	Wang, Michael; Elgowainy, Amgad; Lee, Uisung; Baek, Kwang Hoon; Bafana, Adarsh; Benavides, Pahola Thathiana; Burnham, Andrew; Cai, Hao; Cappello, Vincenzo; Chen, Peter; Gan, Yu; Gracida-Alvarez, Ulises R.; Hawkins, Troy R.; Iyer, Rakesh Krishnamoorthy; Kelly, Jarod; Kim, Taemin; Kumar, Shishir; Kwon, Hoyoung; Lee, Kyuha; Liu, Xinyu; Lu, Zifeng; Masum, Farhad H.; Ng, Clarence; Ou, Longwen; Reddi, Krishna; Siddique, Nazib; Sun, Pingping; Vyawahare, Pradeep; Xu, Hui; Zaimes, George G.	LCI Modeling	BEV, FCEV, HEV, ICEV, PHEV
10.1016/j.scitotenv.2022.156961	2022	Comparison of total PM emissions emitted from electric and internal combustion engine vehicles: An experimental analysis	Woo, Sang-Hee; Jang, Hyungjoon; Lee, Seung-Bok; Lee, Seokhwan	Non-LCA, LCI support	BEV, ICEV
10.1088/1748-9326/ac5142	2022	The role of pickup truck electrification in the decarbonization of light-duty vehicles	Woody, Maxwell; Vaishnav, Parth; Keoleian, Gregory A.; De Kleine, Robert; Kim, Hyung Chul; Anderson, James E.; Wallington, Timothy J.	LCA, Formal	ICEV, BEV, HEV
10.1016/j.seppur.2022.122063	2022	Life cycle carbon footprint of electric vehicles in different countries: A review	Xia, Xiaoning; Li, Pengwei; Xia, Zhenguo; Wu, Rui; Cheng, Yang	Review	BEV, ICEV, PHEV
10.1016/j.energy.2020.119314	2021	A hybrid life cycle assessment of the large-scale application of electric vehicles	Xiong, Siqin; Wang, Yunshi; Bai, Bo; Ma, Xiaoming	LCA, formal	BEV, ICEV, PHEV
10.1038/s41467-018-04826-0	2018	Predictive modeling of battery degradation and greenhouse gas emissions from U.S. state-level electric vehicle operation	Yang, Fan; Xie, Yuanyuan; Deng, Yelin; Yuan, Chris	LCA-Adjacent	BEV
10.1016/j.energy.2020.117365	2020	Life cycle assessment of fuel cell, electric and internal combustion engine vehicles under different fuel scenarios and driving mileages in China	Yang, Zijun; Wang, Bowen; Jiao, Kui	LCA, Formal	BEV, FCEV, ICEV
10.1016/j.jclepro.2020.124899	2021	Life cycle environmental assessment of electric and internal combustion engine vehicles in China	Yang, Lai; Yu, Biying; Yang, Bo; Chen, Hao; Malima, Gabriel; Wei, Yi-Ming	LCA, Formal	BEV, ICEV, PHEV
10.2139/ssrn.4102742	2022	Comparative Analysis of Life Cycle Greenhouse Gas Emission of Passenger Cars: A Case Study in China	Zhang, Haoyi; Zhao, Fuquan; Hao, Han; Liu, Zongwei	LCA-Adjacent	BEV, EREV, ICEV, PHEV

Appendix C: Manufacturer LCAs

C-1. Overview of LCAs from Manufacturer and other Organizations

The main body of this report examined peer-reviewed literature and highlighted studies that followed recommended best practices. A key component of both peer review and the recommended best practices is the transparent disclosure of LCI and LCA methods and data. Manufacturer-led studies do not typically meet these requirements since confidential data is not shared or disclosed, but these studies can still be useful and deserve a similar level of examination as the accepted studies in this report. In this appendix, recent manufacturer LCA reports are examined with a similar lens as that used in Section 2. LCA methodologies including how LCIs were constructed, how impacts were measured, and how the studies compare to the recommended best practices are discussed. Organizations such as Green NCAP also publish LCAs of vehicles (Green NCAP 2023b). Section C-7 outlines the methods and data used by Green NCAP with a limited comparison of results to the manufacturer LCAs.

Vehicle manufacturers have unique access to primary data such as vehicle material composition, logistics of their part supply chains, primary data from part suppliers' operations, and vehicle performance data. Much of this data is confidential or proprietary and is not disclosed in studies published by manufacturers, but third-party reviewers who have access to that data can still certify the results of the study. The methods used by studies vary in transparency, with methodology openness typically decreasing as the data used in the study includes more primary data. For example Volvo and Polestar use ecoinvent and Sphera databases for background LCI data, and include specific processes, flows, and process modifications in their report appendices (Evrard et al. 2021; Røyne and Berg 2023). Both of these studies highlight their ISO 14040/14044 compliance, though they do not claim to have a third-party validation/review of results. The LCA of the EQS by Mercedes-Benz does not include many methodological or LCI details, but does have a certificate from a third-party verifying that ISO standards were followed and that the methods and data were reasonable (Mercedes-Benz 2021). The LCA Nissan completed of their 2022 Fleet is also certified as following ISO standards, but minimal methodological details are included, and complete results are not provided in the report.

Table C-1 below details each manufacturer study examined in this section. These studies typically focus on a specific model, whereas most accepted reviewed literature examined average vehicle fleets or average representative types of vehicles. Some manufacturers have published multiple LCA reports since 2019, either on different models and/or annual updates to impacts associated with the same model(s), but given the methodological focus of this section, only the most recent reports are reviewed here (as they are assumed to reflect the latest sets of adopted methods and modeling). This is not an exhaustive review or list of all LCAs available from manufacturers or other organizations.

Table C-1. Manufacturer LCA Studies Reviewed

Manufacturer	Vehicle	Model Year	Reference
Mercedes-Benz	EQS	2021	(Mercedes-Benz 2021)
Nissan	2022 Fleet	2022	(Nissan Motor Corporation 2022)
Polestar	Polestar 4	2024/2025	(Røyne and Berg 2023)
Tesla	Model 3 / Model Y*	2022	(Tesla 2022)
Volvo	C40 Recharge	2020	(Evrard et al. 2021)

*Carbon Intensity is reported as an average of Model 3 and Model Y based on sales data

As discussed in Section 3.5, data openness and methodological transparency are inextricably linked to the analytic value of an LCA study, and are two key factors that facilitate or hinder inter-study comparisons of results. Manufacturer-reported LCA results that rely on opaque LCI data and methods naturally isolate themselves from comparison to other studies, and thereby limit usability for government agencies seeking to compare the environmental performance of passenger vehicles. Many manufacturers and organizations—including Argonne National Lab, Green NCAP, and the European Commission—are working to establish industry-standard LCA models through which many different manufacturers can compare the environmental performance of their vehicles (Wang et al. 2022; Green NCAP 2023b; Hill et al. 2020). These standard LCA models, where open-source, help establish methodological transparency and support reproducibility. However, all of these models require large quantities of data, which unless publicly released and curated (e.g., via the Federal LCA Commons and/or embedded within models such as GREET), will continue to hinder LCA reproducibility and comparability.

C-2. Mercedes-Benz EQS LCA

Mercedes-Benz's 2021 360° Environmental Check examines the life cycle of the EQS 450+ and is third-party validated (Mercedes-Benz 2021). The report comes with a validation statement by TÜV that the report is compliant with ISO guidelines, including 14040/14044 for LCA. TÜV also certified the Nissan LCA results. The validation statement includes details on how the review process was completed and what elements were excluded.

The study uses a mix of primary (part lists, internal documentation, the "MB database"), and secondary (IMDS, literature, Sphera) data to compile its LCI. Part lists and drawings were used to generate a BOM, with parts being assigned to various material categories to simplify the LCA. This is the same method used in other manufacturer studies, though unlike Polestar and Volvo, Mercedes-Benz does not detail the exact background LCI process or flows that were used for each material category. A combination of their own databases and Sphera database SP2021.2 were used for background LCI. At the time of the study, the EQS had not been produced yet, so estimates and modeled values of vehicle assembly intensity at a plant in Sindelfingen, Germany were used. The report includes the generalized BOM with material composition percents; other manufacturer studies reported GHG contribution of material categories. Reporting even the generalized BOM allows for the vehicle makeup to be used in other studies and aligns with the data openness recommendations discussed in Section 3.5.

The lifetime of the EQS is assumed to be 300,000 km, which is significantly longer than the 200,000 km lifetimes used by Volvo and Polestar, but still shorter than the 320,000 km (200,000 miles) used by Tesla (Tesla 2022; Evrard et al. 2021; Røyne and Berg 2023). Lifetime distance traveled significantly impacts the total emissions of vehicles examined, with BEVs' higher manufacturing emissions being compensated for by lower use stage emissions. The longer the lifetime, the better BEVs will perform compared to ICEVs (assuming constant performance and that electricity grid mix either stays the same or improves). Average EU electricity mix is assumed for the use stage, with a constant grid mix for the entire vehicle life. A sensitivity scenario is examined where renewable electricity is used both for battery cell production and vehicle charging. Energy consumption is based on WLTP data and is 15.6 to 19.8 kWh/100km.

The end-of-life assumes disposal in Europe where disposal follows ELV directive 2000/53/EC. This process includes the removal of replacement parts for material recycling prior to shredding. Vehicle fluids, battery, oil filter, tires, and catalytic converters are also removed prior to shredding (similar to studies that assumed global average disposal).

Mercedes-Benz used the CML 2001 impact method and included impact categories such as GWP, abiotic depletion potential, eutrophication potential, and criteria air pollutant emissions. Results for the EU average electricity case and for the sensitivity scenario that used renewable energy are shown, but these are not compared to an ICEV baseline. The EQS 450+ has a reported lifetime GWP of 39.7 tCO_2eq, lowered to 18.9 if using renewable energy.

C-3. Nissan 2022 Fleet LCA

Nissan has completed a fleet-wide LCA under their "Nissan Green Program" (NGP2022) (Nissan Motor Corporation 2022). They cite ISO compliance and certification by the Japan Environmental Management Association for Industry and third-party review by German company TÜV (the same company that has certified the ISO compliance of the Mercedes-Benz EQS LCA) (Mercedes-Benz 2021). There are minimal details on how the LCA was conducted and detailed results are not included. Results under their NGP2022 are shown as a comparison to the previous model year or to comparable vehicles in the same class. The functional unit—typically travel distance or vehicle lifetime—is not specified, which further hinders comparisons to other studies. Nissan's 2022 sustainability report shows the standard direct emissions from their facilities, but these are only a subset of the emissions included in a full vehicle LCA.

C-4. Polestar 4 LCA

The Polestar 4 LCA examines the carbon footprint of the Polestar 4 model years 2024 and 2025 for several configurations of the vehicle: single motor with standard range, single motor with long range, and dual motor with long range (Røyne and Berg 2023). Standard and long ranges are defined as battery capacities of 86 and 100 kWh respectively. The LCA uses similar methodology to Volvo's LCA of the C40 Recharge (Evrard et al. 2021). Polestar notes that the companies developed their methodologies closely together, though there are some differences. The LCA follows ISO 14040/14044 structure with a clear goal and scope definition. The study does not claim to be ISO compliant and does not include a claim of peer review. The functional unit is lifetime emissions for the Polestar 4 assuming a vehicle life of 200,000 km. Polestar used the "polluter pays" method for allocation, meaning that burdens for disposal are assigned to the process that generates the waste and the burdens of recycling are assigned to the process that uses the recycled content. No avoided material or energy credits are given for generating recyclable content (for both manufacturing and for vehicle end-of-life processes).

The study clearly outlines key assumptions and exclusions in the methodology section. A notable assumption includes using an average European grid mix for 2023-2038 based on IEA's STEPS energy projection that considered grid mix changes from current national climate targets and policy (IEA 2023b; 2023a). Most reviewed studies, and other manufacturer studies, assumed a static grid mix during the life of the vehicle. Prospective LCI studies focused specifically on using projected grid mixes and are discussed in Section 2.3.1.2.

Background LCI data is sourced from various cited sources (detailed in the appendix of the report) but mostly come from ecoinvent 3.9.1 and Sphera/GaBi. The vehicles are broken down in a BOM that assigns materials categories to parts; these aggregated material categories are then used in the LCA. This is the same method used in other literature and is done to make the total amount of data and modeling needed more manageable. Undefined vehicle mass is assumed to be polyamide. The battery is not detailed in the report, but Polestar states that the suppliers used for the battery cell modules completed a cradle-to-gate LCA of the cell modules and that these cells are not included in the material BoM.

The use stage is assumed to be in Europe or a global average from 2023-2038, where the vehicle is used for 200,000 km. Energy consumption is based on preliminary WLTP driving cycle data and is 14.7, 16.5, and 17.8 kWh/100km for the single motor, long range single motor, and long range dual motor variants respectively.

Vehicle end-of-life includes disassembly and shredding but does not include other processing steps like material separation and refining. The end-of-life processes considered are representative of global average practices, though the use stage is specifically limited to Europe. Disposal of materials, such as tires being landfilled or oil being incinerated, is included in the life cycle and attributed to the vehicle's emissions impact.

C-5. Tesla 2022 Impact Report

The Tesla 2022 Impact Report includes life cycle analysis and life cycle claims but does not include any detailed methodology (Tesla 2022). Unlike other manufacturer studies and reports, there are no claims of ISO compliance or ISO structure. There are minimal details about the background data used to generate the LCA results shown, but some foreground assumptions are detailed. Tesla uses an average vehicle that is a weighted average of the geographic distribution of their Model 3 and Model Y vehicles in the U.S., Europe, and China. Production emissions are an average of the production volume of each vehicle. The electricity grids examined in the use stage are not detailed other than being labeled for a specific region such as the U.S, New York, or Austria, and it is being assumed that the carbon intensity of the electricity does not change over the vehicle's lifetime. The report states that an average vehicle is used for 17 years or 200,000 miles (320,000 km) but does not specify if the LCA uses this value. A "premium ICEV" is stated to have a carbon intensity of 467 gCO_2eq/mile (comparable to much of the reviewed literature) with the weighted average of the Model 3 and Y having a carbon intensity of 134 gCO_2eq/mile. Tesla claims their BEVs have less life cycle emissions after 2 years of use. This would translate to approximately 19,000 km (11,750 miles) into the vehicle lifetime, far sooner than the breakeven point claimed in Volvo's manufacturer LCA with the lowest possible carbon intensity electricity for vehicle and battery manufacturing (breakeven at 49,000 km for wind power).

Tesla cites supplier LCAs in their results and states that LCAs have been provided by their upstream suppliers. However, this data is not given and no details of these LCAs are detailed (including how they were conducted, if the LCAs were peer reviewed, or if any results had been certified by a third-party).

C-6. Volvo C40 Recharge LCA

Volvo used LCA to examine the 2021 C40 Recharge compared to the 2020 XC40 ICEV and 2020 XC40 Recharge BEV (Evrard et al. 2021). The study uses similar methodologies to those discussed in Polestar's LCA, which are detailed in Section 0. The study directly follows ISO 14040/14044 in its formatting but does not include any details of peer review or certification by a third-party.

For LCI construction a BOM is used to sort all vehicle parts into different material categories. These categories are then used with ecoinvent 3.7.1 and GaBi LCA database. Each material category is provided by a unit process/system process from one of the databases, with exact process names and conditions detailed in the report's appendix. The C40 is produced in Ghent, Belgium with emissions calculated from primary data from 2020 and 2021. Production emissions are broken down by material category, with lithium-ion batteries accounting for 7 of the 26.4 tonnes of CO_2 that are caused by vehicle production (including materials production and refining). Similar to the Polestar LCA, details on battery LCI are not given. An LCA study from battery suppliers CATL and LG Chem is cited, but the study itself is not provided.

For the use stage it is assumed that the vehicle lifetime is 200,000 km and that the vehicle will use average EU28 electricity. Sensitivity scenarios are included with recharging powered by global average electricity, wind power, and different projected grid mixes based on IEA scenarios from 2017 (IEA 2017). Energy consumption is based on WLTP data and is 211 Wh/km for the C40 Recharge and 241 Wh/km for the XC40. These values are about 50% higher than the energy consumptions used in Polestar's analysis of their own Polestar 4 single motor standard range (Røyne and Berg 2023). At end-of-life the vehicle is disassembled with battery and other hazardous components removed. The vehicle is then shredded with no energy recovery. Burdens of recycling are not assigned to the vehicle and no credit for avoided material due to recycling are awarded. This method was meant to represent the global average disposal, rather than a specific EU policy like the EU directive 2000/53/EC that was used in the Mercedes EQS LCA.

Results are shown as life cycle emissions, with the XC40-ICEV having the highest at 59 tCO_2eq. The C40 Recharge has the lowest lifetime emissions at 42 tCO2eq. when charging with average EU electricity. The breakeven distance, when BEVs have lower emissions than ICEVs, varies depending on the type of electricity used. The lowest breakeven distance is 49,000 km (30,500 miles) when using wind power, 77,000 km (48,000 miles) when using EU average electricity, and 110,000 km (68,500 miles) for the global average. The study includes discussion of key limitations and assumptions and highlights many of the same points made in this review, such as the need to close data gaps in the production of electronic parts and the importance of projected electricity grid mixes.

C-7. Green NCAP LCA

In their 2023 update on European passenger vehicle GHG emissions, Green NCAP examines the GHG emissions of passenger vehicles (Green NCAP 2023b). The LCA methodology uses a generalized approach that is applied to all vehicle models examined. Production emissions are based on the Volkswagen 2021 Sustainability report and material category emissions for the

BOM are a combination of data from the company Joanneum Research, GEMIS, and ecoinvent 3.4. A generic BoM is used and scaled based on vehicle weight. A maximum vehicle lifetime of 16 years with a total distance of 240,000 km is assumed. For the use stage electricity grid mix is modeled for years 2022-2037 based on projections by Joanneum Research. Green NCAP states that the methodologies have been peer reviewed by the Paul Scherrer Institute (Green NCAP 2023b). Their report on data methodology was published alongside a web-based tool that compares lifetime emissions and emissions per distance traveled for different vehicles (Green NCAP 2023a).

Direct comparison of LCA results should only be done when the two studies have comparable scopes and methods. Nissan only reported LCA results as relative values to other models or vehicles, so it is not possible to do a direct comparison to Green NCAP's estimates (Nissan Motor Corporation 2022). Due to the lack of detail given by Telsa in their impact report, a direct comparison to Green NCAP's LCA results is not necessarily appropriate. However one element that stands out between the two estimates is the distance traveled in vehicle lifetime (240,000 km used by Green NCAP and 320,000 km used by Tesla) (Tesla 2022; Green NCAP 2023b). The Volvo LCA of the C40 Recharge has comparable methods and scope to those used in the Green NCAP LCA, with some slight differences such as recycling methods and electricity grid mix year data used. Green NCAP estimates the Volvo XC40-ICEV to have an average lifetime emissions of 61 tCO_2eq., which is comparable to Volvo's estimate of 59 (Evrard et al. 2021; Green NCAP 2023a). Green NCAP does not have LCA results for the C40 Recharge or for the other vehicles examined in the manufacturer LCAs.

C-8. <u>Appendix C References</u>

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