When the Background Matters

Using Scenarios from Integrated Assessment Models in Prospective Life Cycle Assessment

Angelica Mendoza Beltran,[1] *Brian Cox*,[2] *Chris Mutel*,[2] *Detlef P. van Vuuren*,[3,4] *David Font Vivanco*,[5] *Sebastiaan Deetman*,[1] *Oreane Y. Edelenbosch*,[3,6] *Jeroen Guinée*,[1] *and Arnold Tukker*[1,7]

[1]*Institute of Environmental Sciences (CML), Department of Industrial Ecology, Leiden University, The Netherlands*
[2]*Paul Scherrer Institute (PSI), Aargau, Switzerland*
[3]*Netherlands Environmental Assessment Agency (PBL), Den Haag, The Netherlands*
[4]*Copernicus Institute of Sustainable Development, Utrecht University, Utrecht, The Netherlands*
[5]*UCL Institute for Sustainable Resources, The Bartlett School of Environment, Energy and Resources, University College London, London, UK*
[6]*Department of Management and Economics, Politecnico di Milan, Milan, Italy*
[7]*The Netherlands Organization for Applied Scientific Research TNO. Delft/Leiden, The Netherlands*

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Summary

Prospective life cycle assessment (LCA) needs to deal with the large epistemological uncertainty about the future to support more robust future environmental impact assessments of technologies. This study proposes a novel approach that systematically changes the background processes in a prospective LCA based on scenarios of an integrated assessment model (IAM), the IMAGE model. Consistent worldwide scenarios from IMAGE are evaluated in the life cycle inventory using ecoinvent v3.3. To test the approach, only the electricity sector was changed in a prospective LCA of an internal combustion engine vehicle (ICEV) and an electric vehicle (EV) using six baseline and mitigation climate scenarios until 2050. This case study shows that changes in the electricity background can be very important for the environmental impacts of EV. Also, the approach demonstrates that the relative environmental performance of EV and ICEV over time is more complex and multifaceted than previously assumed. Uncertainty due to future developments manifests in different impacts depending on the product (EV or ICEV), the impact category, and the scenario and year considered. More robust prospective LCAs can be achieved, particularly for emerging technologies, by expanding this approach to other economic sectors beyond electricity background changes and mobility applications as well as by including uncertainty and changes in foreground parameters. A more systematic and structured composition of future inventory databases driven by IAM scenarios helps to acknowledge epistemological uncertainty and to increase the temporal consistency of foreground and background systems in LCAs of emerging technologies.

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Address correspondence to: Angelica Mendoza Beltran, Institute of Environmental Sciences (CML), Department of Industrial Ecology, Leiden University. Einsteinweg 2, 2333 CC Leiden, The Netherlands. *Email*: mendoza@cml.leidenuniv.nl

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Introduction

A robust assessment of the environmental impacts of product systems is the basis for assertive policy, business, and consumer decision making (Hellweg and Canals 2014). Life cycle assessment (LCA) has developed into an environmental decision-support tool to assess product systems. Some LCAs, however, refer to product systems that either do not yet exist, that are not commercially available, or that refer to decisions about the future. These forward-looking applications of LCA, or so-called prospective LCA (in line with the definitions of Arvidsson and colleagues [2017] and Pesonen and colleagues [2000]), are thought to help in anticipating unintended consequences of future product systems and to support environmentally assertive product design (Miller and Keoleian 2015). Prospective LCA has proven to be valuable in a range of cases, from assessing future public policies (Dandres et al. 2014, 2012) and emerging technologies (Arvidsson et al. 2017; Frischknecht et al. 2009) to the analysis of future production and consumption systems (Van der Voet et al. 2018). Nonetheless, in addition to dealing with the uncertainty related to any complex system (ontic uncertainty), prospective LCAs suffer from a particular type of epistemological uncertainty, that is, uncertainty "that arises when future systems are modelled, because the future is inherently uncertain" (Björklund 2002, 65). Addressing epistemological uncertainty is therefore a crucial challenge in the development of prospective LCAs.

A common approach for dealing with epistemological uncertainty in prospective LCAs is to integrate future scenarios (Pesonen et al. 2000; Spielmann et al. 2005). In this study we use the following definition of scenario: "... a description of a possible future situation relevant for specific LCA applications, based on specific assumptions about the future, and (when relevant) also including the presentation of the development from the present to the future" (Pesonen et al. 2000, 21). Common approaches to integrating scenarios in prospective LCA draw from multiple databases exogenous to LCA to address future sociotechnical changes or so-called exogenous system changes (Miller and Keoleian 2015). For example, the New Energy Externalities Developments for Sustainability (NEEDS) project (NEEDS 2009) modeled the future supply of metals, nonmetallic minerals, electricity, and transport using different scenarios at various levels of optimism regarding technological improvements, cost reductions, and market growth rates. NEEDS and other external databases, such as the IEA (International Energy Agency 2010), were used in the Technology Hybridized Environmental-Economic Model with Integrated Scenarios (THEMIS) (Gibon et al. 2015) to integrate future changes in electricity production, industrial processes, and climate change mitigation policies into a hybrid input-output (IO) LCA model (Bergesen et al. 2014, 2016; Beucker et al. 2016; Hertwich et al. 2015). Another example is macro-LCA (Dandres et al. 2012), which combined LCA with future changes in economic structure and energy production based on computable general and partial equilibrium models, respectively. Finally, Van der Voet et al. (2018) identified important supply-related variables that are likely to change in the future of metal production (e.g., technologies' shares of production, resource grade, and efficiencies of technologies), and then adapted these using various assumptions and external data sources.

While the above examples are valuable for prospective LCA, they suffer from limitations. A first limitation is that the development of future scenarios is often inconsistent and lacks transparency. Scenario development involves two steps: scenario generation and scenario evaluation (Fukushima and Hirao 2002). Scenario generation refers to the formulation of assumptions about the future, while scenario evaluation refers to the assessment of such assumptions during the LCA phases, especially the life cycle inventory (LCI) phase and the life cycle impact assessment (LCIA) phase (Fukushima and Hirao 2002). Because scenario generation and scenario evaluation are often mixed, it is difficult to establish which inventory parameters have been changed and, most importantly, to discern whether future assumptions are coherent among technologies, economic sectors, and regions (consistent changes). Part of this issue arises from the use of different datasets as sources of scenario information, a procedure that increases inherent uncertainties (Gibon et al. 2015) and makes the process of scenario generation possibly unharmonized. Another limitation is that technology maturity (e.g., penetration and efficiency) is often not accounted for, thus misrepresenting future technology mixes (Dandres et al. 2012). Moreover, because technological development is intertwined with both economic development and predictions of product technology-supply mixes, such relationships should be appropriately reflected in a scenario covering all economic sectors worldwide. Finally, the reproducibility of some approaches can be hampered by the large amount of required data and the difficulty to trace the assumptions that were made during the scenario generation.

To overcome the above limitations for scenario development in prospective LCA, we first propose to explicitly differentiate between scenario generation and scenario evaluation. For scenario generation, we propose the use of system-wide integrated assessment models (IAMs) as a platform for calculations of consistent, worldwide scenarios covering all economic sectors. IAM scenarios are possible socioeconomic and technological pathways of future development (van Vuuren et al. 2014) that can help explore different futures in the context of fundamental future uncertainties (Riahi et al. 2017). Masanet and colleagues (2013), Plevin (2016), and Pauliuk and colleagues (2017) highlight the unrealized potential of IAM scenarios as consistent sources of information for prospective assessments.

For scenario evaluation, we introduce a novel approach that systematically integrates the scenario information of the technology-rich IAM Integrated Model to Assess the Global Environment (IMAGE) (Stehfest et al. 2014) with one of the most broadly used life cycle inventory databases in the LCA community, the ecoinvent database (Wernet et al. 2016). In contrast to the recent work of Arvesen et al. (2018) and Pehl et al. (2017), we concentrate on evaluating the usefulness of IAMs for prospective LCA rather than on informing the IAM with the prospective LCA results. Our approach can thus be

understood as an alternative opportunity to further reconcile the knowledge from the IAM and the LCA communities (Creutzig et al. 2012) that now hold different views on how to perform future environmental impact assessments.

The main research question of this study was as follows: "How can IAM scenarios be systematically linked with LCI parameters to account for future changes in prospective LCAs?" To answer this question, we focused on a case study comparing the relative environmental impacts of two mobility alternatives in the future. Despite this focus, the utility of the proposed prospective LCA approach, for instance, for emerging technology LCA (ETLCA), is expected to be beyond the transportation sector. We believe that this wider, structural utility can be realized by linking all sectors available in IAM scenarios with LCI parameters. However, we did not choose such an ambitious scope because each sector has its own peculiarities and complexities, and we first needed a proof-of-concept for just one sector.

Electric vehicles (EVs) and internal combustion engine vehicles (ICEVs) are compared, given that future changes play a key role in the impacts of these two mobility alternatives. Drawing from previous research, we focused on changes in the electricity sector. Specifically, the relative carbon footprint of EVs is highly influenced by the electricity mix (Cox et al. 2018; Bauer et al. 2015), and extreme cases can lead to counterintuitive results; for instance, in Australia, the prevalence of coal power causes EV to underperform (Wolfram and Wiedmann 2017). Our approach can thus address a range of questions posed by different stakeholders, such as vehicle producers, who might be interested in the question, "What will be the environmental impacts of EVs in 2050 and what are their key drivers?"; and policy makers, who might be interested in the question, "Will a transition to EVs in the future bring environmental benefits?" Finally, we contribute to the integration of knowledge from the IAM and LCA communities, with the aim to increase the robustness of prospective LCA assessments, by linking macro scenarios into the micro- or product-level LCA (Guinée et al. 2011).

Methods

We first present an overview of the proposed approach. Next, we provide detailed insights into how scenarios are generated using IAMs and particularly IMAGE. Next, we present the Wurst software, which is the tool developed to adapt the LCI background data using the IMAGE scenarios as a source of information. Finally, we describe the case study and the scenarios used in the case study.

Approach Overview

This study presents a novel approach to introducing consistent and systematic future changes in a prospective LCA application to calculate more robust prospective results (see figure 1 for an overview). Such changes refer to the LCA background system, namely, those processes and emissions that are part of the supply chain of the studied product system, for example, the electricity mix used to charge and produce EV batteries. This means that indirect emissions are accounted for. In addition and in line with a full life cycle approach, direct emissions are accounted for but are left unchanged in the foreground system. In particular, despite the long-term focus of the study, no changes have been made to the processes, emissions, and parameters describing the product itself, for example, vehicle energy use, vehicle size, lifetime, driving patterns, and battery size. These parameters have been found to contribute to the variability of future EVs, but the largest contributor to variability is electricity used for charging (Cox et al. 2018). We keep the EV and ICEV foreground unchanged to focus on the background changes. Following Fukushima and Hirao (2002), we developed scenarios in two steps: (1) scenario generation and (2) scenario evaluation.

- Scenario generation: This step refers to the process of scenario formulation and calculation. The IAM model IMAGE (Stehfest et al. 2014) was selected as the modeling framework used to generate consistent scenarios. IMAGE was selected due to its wide coverage of world regions, technologies, and economic sectors as well as its range of scenarios that are key to addressing uncertainty. The following paragraphs provide descriptions of the IMAGE model, the type of scenarios developed by the model, and the specific scenarios used in the case study.
- Scenario evaluation: This step refers to the assessment of the scenarios in all the phases of LCA. Yet, in this study, particular attention is paid to the evaluation of scenarios in the life cycle inventory phase. We identified three steps needed to accomplish this: first, analyzing the background system to identify the inventory parameters (i.e., input and output flows as well as processes) that are affected by future changes; second, adapting these parameters using information from the IAM scenarios; third, using the adapted inventories to calculate the prospective LCA results of specific products.

Relevant inventory parameters were adapted using so-called cornerstone scenarios (Spielmann et al. 2005), as these scenarios refer to either unknown or new future situations for all parameters together. These scenarios have been chosen, as they better inform long-term and strategic decision making, which are fundamental characteristics of prospective LCA. The alternative is to use "what-if" scenarios, which test changes in specific parameters to compare well-known alternatives in a sensitivity fashion (Pesonen et al. 2000). However, we did not choose this option, as it is less structural than cornerstone scenarios because changes of only few parameters are captured. The approach of this study is distinct from other implementations of cornerstone scenarios (Spielmann et al. 2005) as we derived future changes of relevant parameters from the IAM-based scenarios instead of making separate assumptions for each parameter and then combining them. We developed and applied the Wurst model (v. 0.1) in this

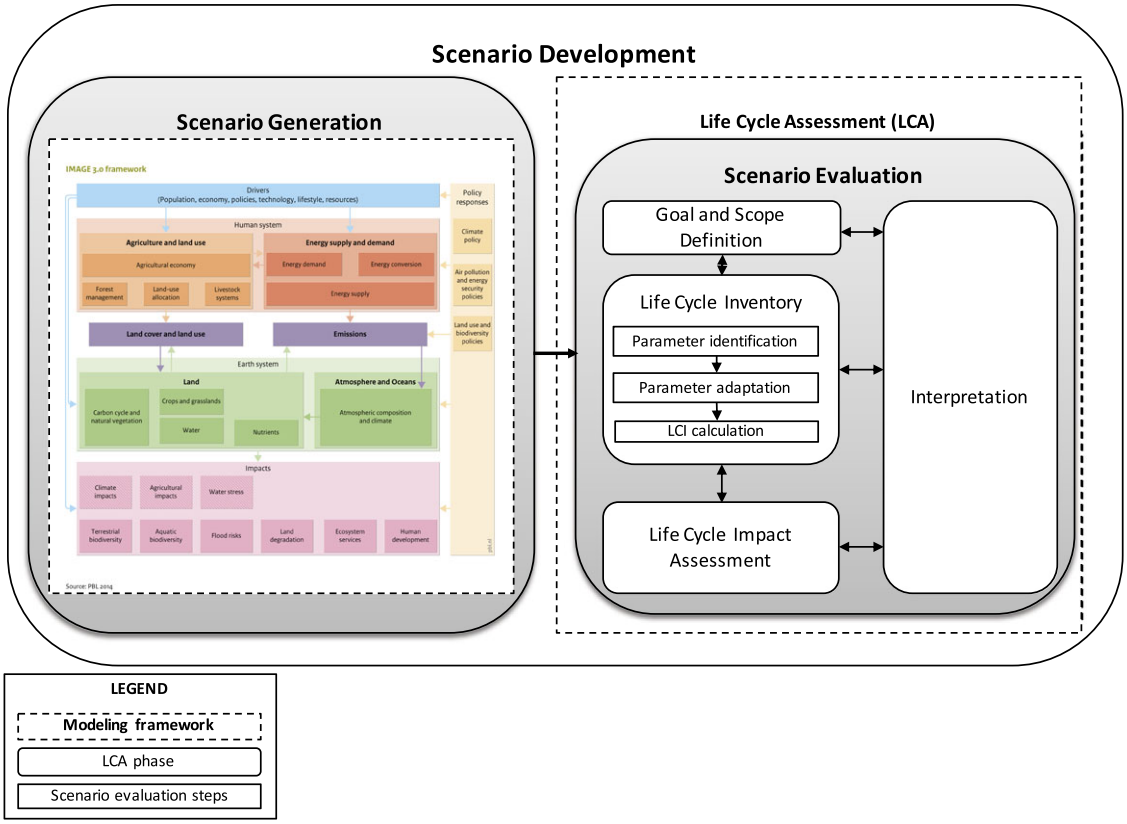


Figure 1 Overview of the proposed method for scenario development in prospective life cycle assessment (adapted from Fukushima and Hirao [2002]) using the IMAGE 3.0 framework (http://models.pbl.nl/image/index.php/Framework_overview) as an integrated assessment model (IAM).

study (https://wurst.readthedocs.io/index.html) for the parameter identification and adaption steps, as will be described in detail below. The LCA results of EVs and ICEVs were calculated with the Brightway2 (v. 2.1.1) software (Mutel 2017).

Scenario Generation: Using IMAGE to Develop Scenarios

We used the IAM IMAGE 3.0 to generate scenarios (for a detailed model description, see Stehfest et al. 2014). In general, IAMs have been developed to describe the relationships between humans (the human systems) and the natural environment (the Earth system) and the impacts of these relationships that lead to global environmental problems, such as climate change and land use change. IAMs build on functional relationships between activities such as the provision of food, water, and energy and their associated environmental impacts. The human system in IMAGE includes economic and physical models of the global agricultural and energy systems. The Earth system includes a relatively detailed description of the biophysical terrestrial, ocean, and atmosphere processes.

Because this study focuses on the electricity sector, we will briefly describe the energy model of IMAGE, "The Image Energy Regional Model" (TIMER) (de Vries et al. 2001; van Vuuren 2007). TIMER consists of a technical description of the physical flows of energy from primary resources through conversion processes, transport systems, and distribution networks to meeting specific demands for energy carriers or energy services. The model determines market shares for energy technologies based on the costs of competing technologies. It includes fossil fuels and renewable or alternative sources of energy to meet the demand, which depends on population size, efficiency developments, income levels, and assumptions on lifestyle. The model generates scenarios for future energy intensity and fuel costs, including competing nonfossil supply technologies. It models emission mitigation through the price signal of a carbon tax that induces additional investments in more efficient and nonfossil technologies, bioenergy, nuclear, and carbon capture and storage, thus changing market shares of different technologies. In this way, the TIMER model allows the generation of both baseline and mitigation energy scenarios as part of broader IMAGE scenarios, both of which are used to inform the background of the LCA in this study. (Details of the inputs and outputs of the model are provided at http://models.pbl.nl/image/index.php/Framework_overview).

Scenario Evaluation: The Wurst Software

IMAGE scenarios serve as a source of information to adapt the LCI background data (figure 1). Apart from being the most

comprehensive and widespread LCI database, the ecoinvent database also has the advantage of distinguishing between two types of processes: transformation activities and markets (consumption mixes) (Wernet et al. 2016). This is an important feature because it simplifies identifying and changing parameters in ecoinvent when using IMAGE scenarios. To systematically approach the identification and changing of parameters in ecoinvent, we developed Wurst, a Python-based software that enables the systematic import, filtering, and modification of LCI databases. The current version of Wurst (available for download at https://github.com/IndEcol/wurst) focuses on ecoinvent and includes IMAGE scenario data as well as other sources. Other LCI and scenario databases are to be incorporated in the future. For this study, a specific functionality of the software was developed to link data formats of ecoinvent version 3.3 and IMAGE. The corresponding functions for import, filtering, and modification of LCI databases are provided in the supporting information available on the Journal's website. For example, functions related to the regional match between databases in Wurst are used to generate ecoinvent LCI databases for different years into the future based on the IMAGE scenarios.

Data Import

We first imported ecoinvent and IMAGE scenarios data into Wurst, for which we wrote specific importing and cleaning functions. In particular, the "cutoff system model" of the ecoinvent database was imported (see Weidema and colleagues [2013] for details of this model). This means that monofunctional processes were adapted using the IMAGE scenario data to generate modified (future) monofunctional processes. After importing the data, we mapped the available technologies for both datasets (Appendix I in the Word file of the supporting information on the Web) as well as for all regions (Appendix II in the Word file of the supporting information on the Web). For the technology mapping, we assigned several related technologies in ecoinvent to an overarching IMAGE technology (Appendix I in the Word file of the supporting information on the Web) because ecoinvent provides more granular descriptions of technologies than IMAGE. Data for the overarching technologies in IMAGE are used to change the more detailed ecoinvent processes. Moreover, electricity generation technologies that will be relevant in the future according to the IMAGE scenarios but that are missing in ecoinvent were added to the latter to create an *extended ecoinvent*. These technologies are concentrated solar power (CSP) and carbon capture and storage (CCS), which we included using datasets from ecoinvent version 3.4 and from work by Volkart and colleagues (2013), respectively. For other technologies, such as natural gas combined heat and power generation with carbon capture and storage, which are missing in ecoinvent but less relevant in the future, we used proxy inventories from already existent technologies in ecoinvent (for all proxy technologies see Appendix I in the Word file of the supporting information on the Web). Technologies were left unchanged if they were related to other sectors, such as fossil-fuel and biofuel production, transport, and raw materials production. This choice is related to the focus of this study as a proof-of-concept as well as to the specific case study for which the electricity sector is most relevant, and it is not dictated by the IMAGE scenarios, which do include other sectors. In the discussion section, we elaborate on the possible implications of expanding the approach to other sectors, part of the IMAGE scenarios.

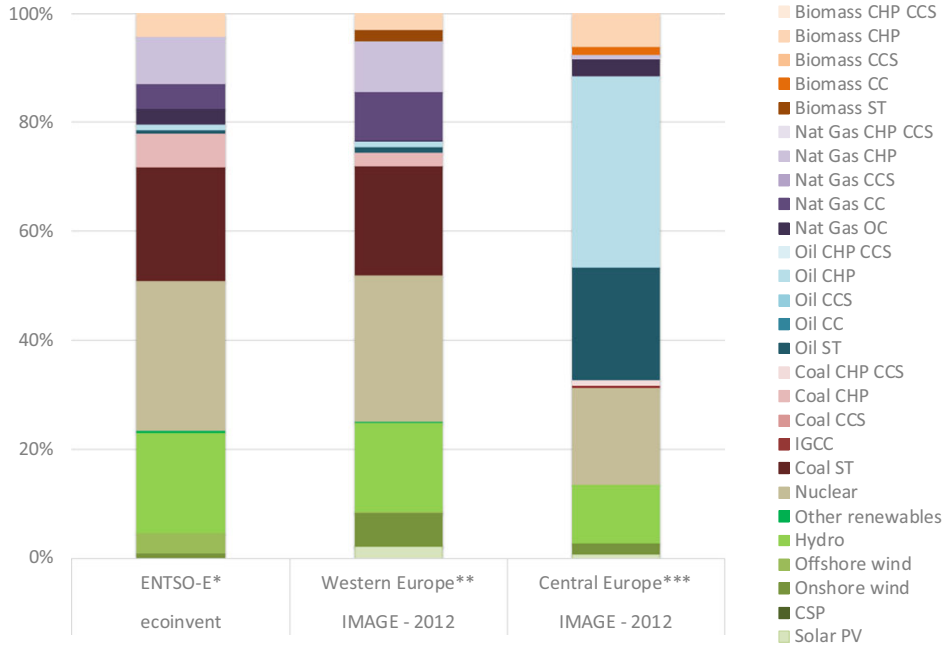
For the regional mapping, a one-to-one correspondence was assigned between IMAGE and ecoinvent regions where possible (Appendix II in the Word file of the supporting information on the Web). For regions in ecoinvent that involve more than one region from IMAGE, we used an average of IMAGE data. For smaller regions in ecoinvent, for instance, provinces in a country, we used the data of the larger region from IMAGE. An example of region and technology mapping is shown in figure 2, which illustrates that the electricity mix in ecoinvent has a closer match with that of IMAGE Western Europe, as electricity demand is dominated by Western European countries. In the interest of transparency, the complete region and technology mapping and the associated Python scripts are presented in Appendixes I and II in the Word file of the supporting information on the Web.

Parameter Identification (Data Filtering)

Parameters from ecoinvent that are to be modified were identified according to the process name and unit of the reference output flow. For instance, for electricity production technologies that use coal, the ecoinvent process names include the words *hard coal* or *lignite*, and the unit of the reference output-flow is kilowatt hours (kWh). For electricity markets, the same reference output-flow unit is used, but the names include "market for electricity, high/medium/low voltage." Such keys determine the processes that contain the parameters to be modified. These are technology-related parameters, that is, economic and environmental flows (input and outputs) such as greenhouse gas (GHG) emissions, for instance, carbon dioxide (CO_2) emissions to air, or market-related parameters, that is, electricity market mixes in ecoinvent, such as technology shares in high-voltage electricity markets. Because the changes to ecoinvent parameters depend on the region and the technology, the corresponding IMAGE parameters were filtered from the set of total IMAGE output variables using the following filtering criteria: the years, the sector (in this case, electricity production), the overarching technology (e.g., coal steam turbine), the regions, and the scenarios of interest. This procedure generates two subsets of data, one from ecoinvent and one from IMAGE, which are related to one another via the region and the technology, as was explained in the previous section.

Parameter Changes

Starting with the ecoinvent and IMAGE subsets, we modified the ecoinvent parameters according to a number of rules (figure 3). For GHG emissions available in both ecoinvent and IMAGE (i.e., methane, sulfur dioxide, carbon monoxide, nitrogen oxides, nitric oxide emissions to air), we used the emission factors from the IMAGE scenarios as technology parameters, replacing those of ecoinvent for the different



According to ISO 3166-1 2 letter country code:
*ENTSO-E countries are: AT, BE, CH, DE, FI, FR, GB, GR, IE, IS, IT, LU, LV, NL, NO, RS, SE, BA, BG, CZ, EE, HR, HU, LT, MK, PL, RO, SI, SK
**Western Europe countries are: AD, AT, BE, CH, DE, DK, ES, FI, FR, FO, GB, GI, GR, IE, IS, IT, LI, LU, MC, MT, NL, NO, PT, SE, SM, VA
***Central Europe countries are: AL, BA, BG, CS, CY, CZ, EE, HR, HU, LT, LV, MK, PL, RO, SI, SK

Figure 2 The 2012 electricity mix for Western and Central Europe regions in IMAGE and for the ecoinvent version 3.3 process Electricity, High-Voltage, Production Mix for the European Network of Transmission Systems Operators for Electricity (ENTSO-E). Technologies in ecoinvent are aggregated according to the map in Appendix I in the Word file of the supporting information on the Web and exclude the proxies for biomass steam turbine, oil combined cycle, and biomass combined cycle to show the original ecoinvent data without modifications.

technologies. Using the IMAGE emission factors ensures coherency between the data used to describe the present and the future emissions. Differences between the emission factors in IMAGE and ecoinvent may be due to the use of different data sources and different methods to derive them. Most IMAGE emission factors are derived from the Electronic Data Gathering, Analysis, and Retrieval system (EDGAR) database (http://edgar.jrc.ec.europa.eu/overview.php?v=431), with emissions and activity data per sector and country, while ecoinvent uses mostly bottom-up or parameterized data per technology; for example, the CO_2 emissions from burning coal in ecoinvent depend on the mass and carbon content of the coal burned in the process (Weidema et al. 2013). Emission factors in IMAGE were adapted by dividing them by the efficiency per technology in IMAGE because in IMAGE they are reported per MJ_{input} and not per $MJ_{electricity\text{-}output}$ as in ecoinvent. All other flows (economic and environmental), for example, emissions other than GHGs emitted to air, were scaled using future technology efficiencies of the IMAGE scenarios for year i and scenario j. The final amounts of these flows, in their original ecoinvent units, were multiplied by a scaling factor (SF) calculated as shown in equation (1).

$$SF_{i,j} = \frac{efficiency_{ecoinvent}}{efficiency_{IMAGE\ i,j}} \quad (1)$$

Further changes of market shares of electricity technologies are applied to high-voltage electricity markets in ecoinvent (Treyer and Bauer 2016). We replaced the shares of electricity-producing technologies defined in ecoinvent by the electricity mixes from the IMAGE scenarios. A different procedure was used for solar photovoltaics and small combined heat and power plants that supply electricity at the low- or medium-voltage level. We connected these technologies to the high-voltage level and assumed that all electricity generation is supplied at the high-voltage level. This procedure was chosen in favor of the systematic approach we propose, despite the error that this assumption might introduce, which we believe is small.[1] Moreover, as only electricity markets change, transmission grid markets and SF6 emissions generated during transmission were not adapted and were kept at the original ecoinvent levels. These market changes are expected to capture system changes that are not necessarily related to technology efficiencies.

In the supporting information on the Web (Excel files), we present per-year tables, generated in the modification functions provided in the supporting information on the Web, with the changes made to technology and market parameters for one of the scenarios used in this study. The final output consists of future ecoinvent databases that are year and scenario dependent.

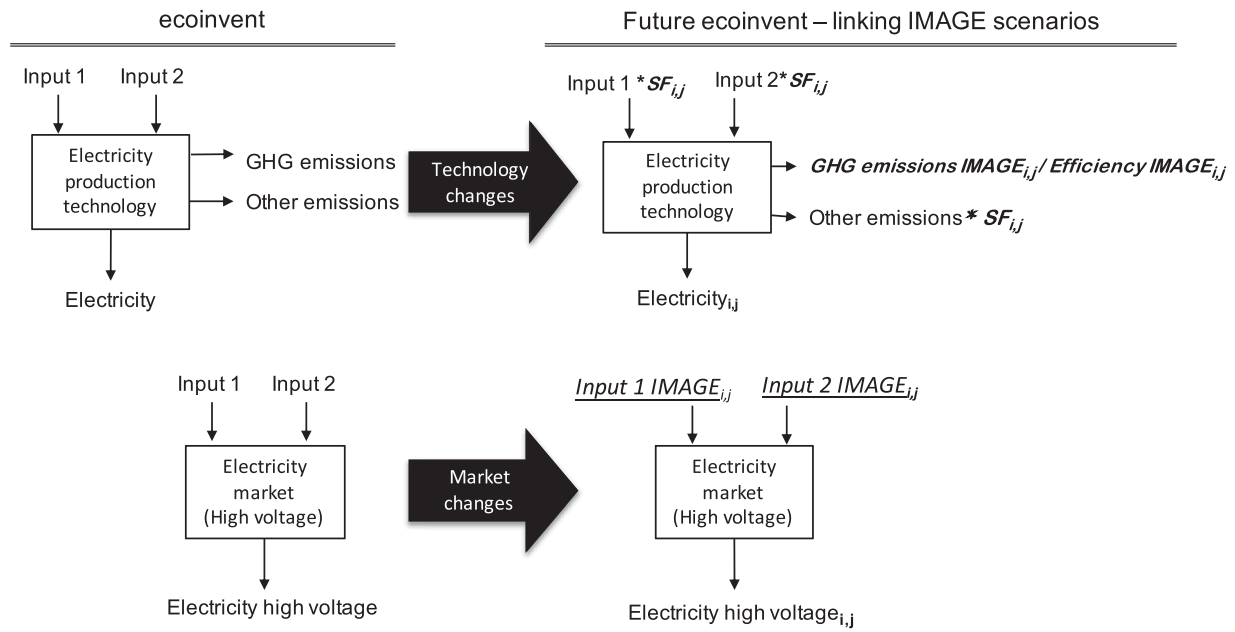


Figure 3 Schematic representation of technology and market parameters and their changes. Technology changes are presented in bold italics, and market changes are presented in underlined italics. Both are year dependent (i) and scenario dependent (j), as IMAGE data are year and scenario dependent. The scaling factor ($SF_{i,j}$) was calculated as shown in equation (1).

Life Cycle Inventory Calculation

The final step of the scenario evaluation involves the calculation of the LCI and characterized LCA results using the modeled future ecoinvent databases. Brightway2 (Mutel 2017) was used for this purpose. Brightway2 uses as input the future ecoinvent databases and calculates the inventory for the specified EV and ICEV (see case study section). The base year is 2012 because ecoinvent mostly represents the economy of this year. Selected future years are 2020, 2030, 2040, and 2050.

Case Study

For the case study, an EV was compared with its closest alternative, a small ICEV-EURO5 diesel vehicle. Both vehicles are assumed to be driven in Europe. For simplification purposes, the foreground description corresponds to processes as defined in ecoinvent, and they remain unchanged in the future (see Cox and colleagues [2018] for foreground changes). Such simplification is a modeling choice rather than an inherent limitation of the proposed approach. The EV is based on the unit process "transport, passenger car, electric" for the global average vehicle (Simons 2016), whereas the ICEV-EURO5 is based on the process "transport, passenger car, small size, diesel, EURO 5" (Del Duce et al. 2016). These processes include the assembly, operation, maintenance, and end of life of each vehicle. The functional unit is 1 kilometer driven by each vehicle, and so differences in use and further spending patterns are not considered (Font Vivanco et al. 2014, 2016). The effects of background changes on the LCIA results are studied separately for changes in technology and market parameters. The impact categories were chosen in line with those used in previous studies and relevant for the comparison (e.g., Bauer et al. 2015; Nordelöf et al. 2014). The impact categories are climate change, particulate matter (PM) formation, fossil cumulative energy demand, human toxicity, metal depletion, and photochemical oxidant formation. The characterization factors are defined according to the RECIPE 2008 (Goedkoop et al. 2013) hierarchist perspective at the midpoint level. For climate change, we use the global warming potentials (GWPs) of the Intergovernmental Panel on Climate Change Fifth Assessment Report (IPCC-AR5), with a time horizon of 100 years (IPCC 2013), considering biogenic carbon (for characterization factors, see Appendix III in the Word file of the supporting information on the Web).

Scenarios Used in This Study

The IMAGE scenarios we used are the Shared Socioeconomic Pathways (SSPs) (O'Neill et al. 2014). This family of climate scenarios consists of a set of five storylines on possible human development trajectories and global environmental change in the twenty-first century (van Vuuren et al. 2017a). Of the five storylines (Riahi et al. 2017), we used three that cover different challenges for mitigation and adaptation to climate change as well as a broad range of primary energy supply technologies from different sources (e.g., coal, oil + gas, renewables, and nuclear) and different levels of final energy demand (Riahi et al. 2017; van Vuuren et al. 2017b). The storylines are SSP1, Taking the Green Road (GreenRoad); SSP2, Middle of the Road (MidRoad); and SSP3, Regional Rivalry (RegRivalry).

For each storyline, a baseline scenario was developed, assuming that such a pathway can unfold without specific additional policies and measures to limit climate change or to increase

the adaptation capacity (Riahi et al. 2017). Each SSP baseline has been used as a starting point for exploring climate policy scenarios. The climate targets explored correspond to the radiative forcing levels of the Representative Concentration Pathways (RCPs) (van Vuuren et al. 2011). The RCPs were used in the IPCC-AR5 as a set of scenarios exploring different long-term climate targets in 2100, that is, 2.6, 4.5, and 6.0 watts (W)/square meter (m^2). The SSPs explored these and an additional target of 3.4 W/m^2, which is more policy relevant (Riahi et al. 2017). In this study, we used the data for the scenarios reaching a 2.6 W/m^2 target, which is consistent with a two-degree target (UNFCCC 2010). Also, a 3.4 W/m^2 target is used for the SSP3.

The results for both types of vehicles were compared for the following scenarios (see table 1 for a summary): GreenRoad (SSP1), MidRoad (SSP2), RegRivalry (SSP3), GreenRoad-2.6 (SSP1-2.6), MidRoad-2.6 (SSP2-2.6) and RegRivalry-3.4 (SSP3-3.4). Also, we present a so-called 0-scenario, in which no background changes are assumed, that is, ecoinvent (original data) for 2012. For comparison, we also added the results for the 2012 IMAGE data, which are the same for all scenarios, as they correspond to historic data and not to forecast (scenario) data. The combination of the selected years, scenarios, and products yields a total of 52 inventories that were calculated. Finally, for reference, Appendix IV in the Word file of the supporting information on the Web shows the electricity mix for the IMAGE scenarios for Western and Central Europe regions.

Results

Here, we present the prospective LCA results for EVs and ICEVs and the disaggregated results according to market and technology changes.

Prospective Life Cycle Assessment Results for Electric Vehicles and Internal Combustion Engine Vehicles

Our results show that the uncertainty about future developments in the electricity sector is overall large but manifests differently according to the studied product (EV or ICEV), the impact category, and the scenario and year considered (figure 4). Regarding the product, uncertainty is larger for the EV, as is evident from the larger range of results, particularly in the long term (see purple lines versus orange lines in 2050, figure 4). As electricity production contributes more to the background impacts of the EV than to impacts of the ICEV, this result is expected. Also, because the foreground for both vehicles has not been changed, these results reflect only the changes and uncertainty related to the electricity sector and not to, for instance, future efficiency changes of EVs. For the impact categories, we observe that the selected IMAGE scenarios have a larger influence on the future impacts of the EV for climate change, PM formation, and fossil cumulative energy demand. These are impacts due to GHG emissions and use of fossil fuels. Thus, baseline scenarios that have a larger share of fossil-based technologies display a smaller reduction of these impacts than the original ecoinvent impacts for the EV. By contrast, ambitious mitigation scenarios that have larger shares of technologies emitting less GHG show large reductions of these impacts, particularly in the long term. For impacts such as metal depletion, almost no effect of the scenario is observed for the EV and the ICEV. This is mostly related to the fact that sectors that might contribute more to this impact, such as the raw materials production sector, were kept the same.

Considering the uncertainty about the future also makes it more complex to assess the relative environmental performance of EVs over time (Appendix V in the Word file of the supporting information on the Web). There are impact categories such as PM formation for which the results of the EV overlaps with those of the ICEV (see purple lines crossing orange lines, figure 4). To understand these results, it is important to compare the ICEV and EV results within the same scenario. For climate change, for instance, the impacts of both types of vehicles overlap in 2050 for EV-RegRivalry and ICEV-RegRivalry-3.4. However, this comparison is not fair, as effectively these scenarios represent different futures. For PM formation, on the other hand, EVs perform better than ICEVs in the MidRoad-2.6 and the GreenRoad-2.6 scenarios after 2040, while the opposite is true for other years and scenarios. Thus, for ambitious mitigation scenarios, EVs would lead to improvements in PM formation, while for nonambitious scenarios, such as the baseline scenario, the ICEV would be preferred regarding this impact category.

Finally, we observed striking differences in some cases between the original ecoinvent and the IMAGE-based adaptation of ecoinvent for 2012 (EV-ecoinvent and ICEV-ecoinvent, figure 4). Such differences comprise reductions of up to 16%, 15.5% and 13.8% of the EV impacts in the categories climate change, photochemical oxidant formation, and PM formation, respectively. For the ICEV, the differences are smaller, with reductions ranging between 0.1% and 4.6% for all impact categories. In the case of climate change and photochemical oxidant formation, the relative environmental impacts of both vehicles were reversed in the scenario results for 2012 compared to those of the original ecoinvent. To better understand these results, a breakdown in market and technology changes is necessary.

Prospective Life Cycle Assessment Results for Electric Vehicles and Internal Combustion Engine Vehicles by Market and Technology Changes

Of the technology and market changes considered for the electricity production technologies, the latter have the largest influence on the total change of impacts in general (see figure 5 for climate change impacts as an illustration for other impacts in Appendix VI of the Word file of the supporting information on the Web). Technology changes alone lead to the same impacts in both the baseline and the mitigation scenario, as technology efficiency is expected to improve in the future regardless of which electricity production technology has a larger penetration. Market changes are different for both scenarios given the higher penetration of technologies emitting less GHG in the ambitious mitigation scenarios. Together,

Table 1 Scenarios, years, and databases used for the prospective life cycle assessment of an ICEV and an EV

Vehicle	*Database used for background*	*IMAGE scenario (SSP)*[a]	*Year(s)*	*Label in this study*
ICEV/EV	ecoinvent	NA	2012	ICEV/EV-ecoinvent
ICEV/EV	ecoinvent adapted with IMAGE scenario	NA	2012	ICEV/EV-IMAGE-2012
ICEV/EV	ecoinvent adapted with IMAGE scenario	Green Road (SSP1: Low challenges to mitigation and adaptation. Global population peaks and declines in the twenty-first century. Total final energy demand in 2050 is around 500 EJ.)	2020, 2030, 2040, 2050	ICEV/EV-GreenRoad
ICEV/EV	ecoinvent adapted with IMAGE scenario	Green Road 2.6 (SSP1-2.6)	2020, 2030, 2040, 2050	ICEV/EV-GreenRoad-2.6
ICEV/EV	ecoinvent adapted with IMAGE scenario	Middle of the Road (SSP2: Medium challenges to mitigation and adaptation. Global population growth is moderate and levels off in the second half of the century. Total final energy demand in 2050 is around 600 exajoules (EJ).)	2020, 2030, 2040, 2050	ICEV/EV-MidRoad
ICEV/EV	ecoinvent adapted with IMAGE scenario	Middle of the Road 2.6 (SSP2-2.6)	2020, 2030, 2040, 2050	ICEV/EV-MidRoad-2.6
ICEV/EV	ecoinvent adapted with IMAGE scenario	Regional Rivalry (SSP3: High challenges to mitigation and adaptation. Population growth is low in industrialized and high in developing countries. Total final energy demand in 2050 is around 600 EJ.)	2020, 2030, 2040, 2050	ICEV/EV-RegRivalry
ICEV/EV	ecoinvent adapted with IMAGE scenario	Regional Rivalry 3.4 (SSP3-3.4)	2020, 2030, 2040, 2050	ICEV/EV-RegRivalry-3.4

[a]For detail narratives and parameters, see Riahi and colleagues (2017) and van Vuuren and colleagues (2017b).
EJ = exajoules; EV = electric vehicle; ICEV = internal combustion engine vehicle; NA = not applicable; SSP = shared socioeconomic pathway.

both changes account for technology improvements but also for market penetration of electricity technologies. The impacts calculated with both changes are in line with those of market changes alone, particularly for the mitigation scenario. For the baseline scenario, impacts are influenced by a combination of both technology and market changes (figure 5).

Furthermore, market changes appear to interact with technology changes when both are considered (figure 6). Impacts calculated with technology or market changes alone do not capture the joint effects of technology improvement and market penetration of different technologies. This becomes more evident in figure 6, where the changes in impacts for market and technology changes alone do not add up to the impacts calculated with both. To account for the actual individual contributions of each effect to the total impacts, one could use structural decomposition analysis (Hoekstra and Van Den Bergh 2002). However, this is beyond the scope of the present study.

Discussion

The aim of the present study was to demonstrate how IAM scenarios can be systematically linked with LCI parameters to account for future changes in prospective LCA. Integrating electricity scenarios from IMAGE with data from the ecoinvent database served to account for a limited yet relevant set of future background changes in the prospective LCAs of EVs and ICEVs. We showed that it is possible to use six IMAGE scenarios covering different socioeconomic pathways of development to calculate the impacts of two types of vehicles because the integration proposed in this study follows a systematic procedure. For prospective LCA, this is an important modeling effort that helps to understand the effects of background changes independent of the product evolution, which is represented in the foreground (Miller and Keoleian 2015). As the results showed, the limited set of background changes accounted for proved to

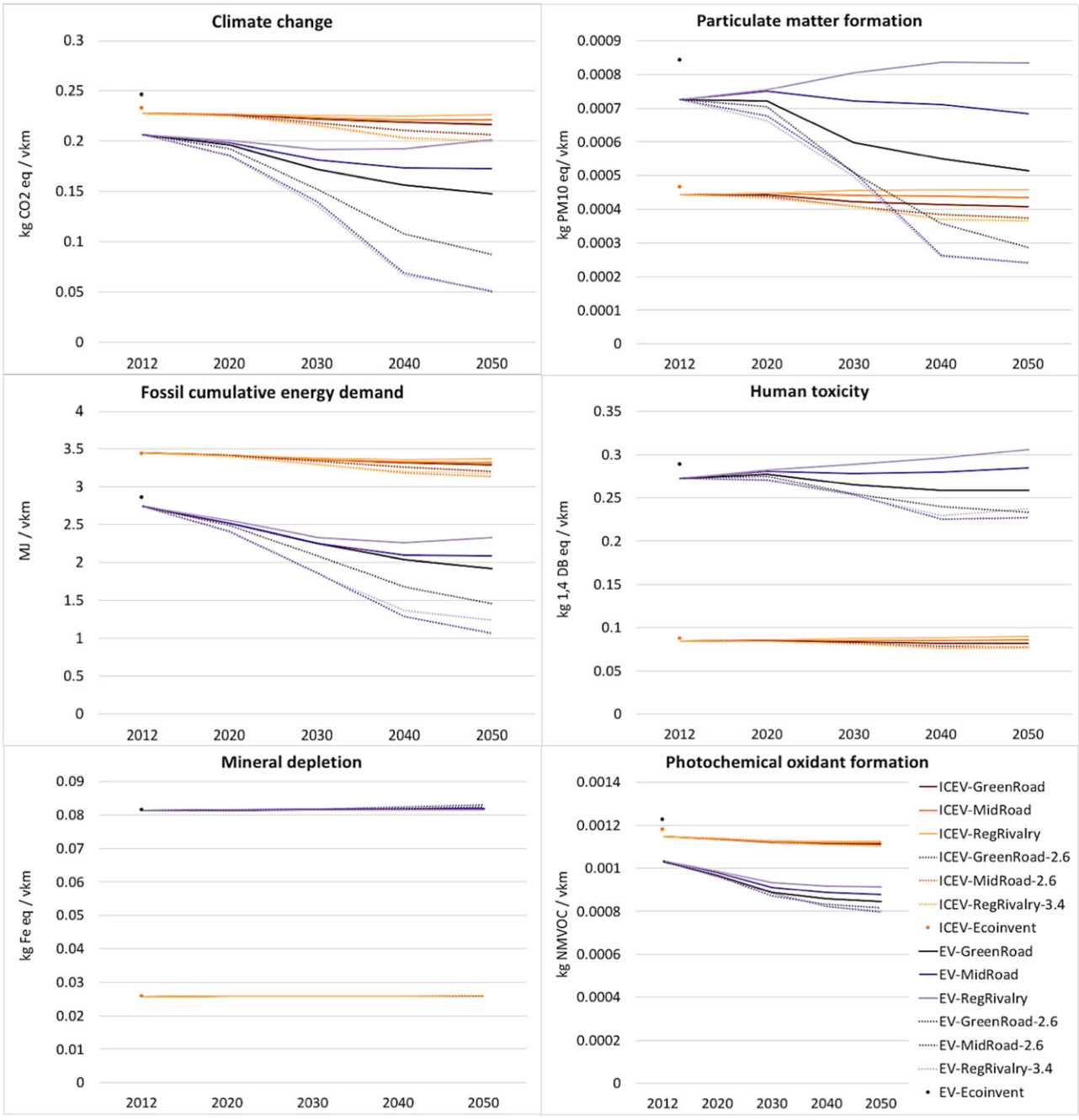


Figure 4 Prospective life cycle assessment results, for various impact categories and per vehicle-kilometer (vkm), of an EV and an ICEV, considering background changes based on six IMAGE scenarios. EV = electric vehicle; ICEV = internal combustion engine vehicle; vkm = vehicle-kilometer.

be important in the case of some key impacts for EVs and can influence the relative environmental performance differences between EVs and ICEVs. For uncertainty analysis, this is also an important effort, as epistemological uncertainty can be acknowledged by means of relevant and consistent scenarios representing possible futures, as was shown in the results. This type of uncertainty cannot be reduced given the fact that the nature of the system we studied is nonstationary, complex, and based on human behavior (Plevin 2016). However, this study showed that exploring future pathways and related impacts rather than predicting them can help to outline and better inform directions for action by acknowledging the presence of this type of uncertainty and by making the assumptions and constraints as transparent as possible.

In line with the literature, our results show that future developments in the electricity sector will critically affect whether and by how much EVs would outperform ICEVs for key impact categories such as climate change. Previous studies

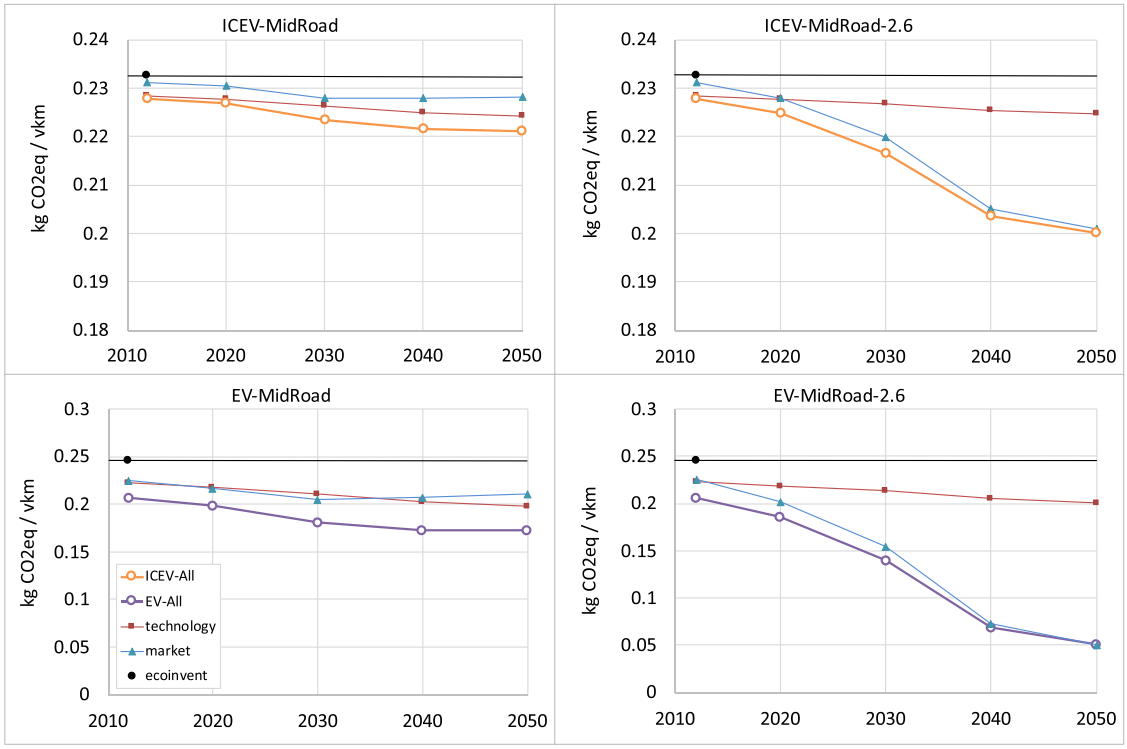


Figure 5 Prospective life cycle assessment results for climate change impacts and per vehicle-kilometer (vkm) of the EV and the ICEV. The results correspond to the MidRoad and MidRoad-2.6 scenarios including background adaptions of technology parameters only (red squares), market parameters only (blue triangles) and both changes (purple line for EV and orange line for ICEV, corresponding with the results shown in figure 4). Original ecoinvent background data are shown with a black dot and a constant black line in time. EV = electric vehicle; ICEV = internal combustion engine vehicle; vkm = vehicle-kilometer.

have, however, mostly focused on market changes related to increased diffusion of low-carbon power technologies. For example, Wolfram and Wiedmann (2017) estimated that the carbon footprint of EVs in Australia in a business-as-usual scenario for the diffusion of renewable energies would decrease about 50% from 2009 to 2050. This magnitude is within the range of our results for MidRoad scenarios (which would be conceptually equivalent) and for climate change, which describe a decrease due to market changes alone of 14% to 80% between 2012 and 2050. Similarly, Messagie (2017) described reductions of about 60% in the carbon footprint of EVs when replacing the average European Union electricity mix by that of countries where renewable and nuclear power prevail, such as Sweden or France. The contribution of our case study is therefore the consideration of technological changes in addition to market changes as well as the investigation of epistemological uncertainty by means of various future scenarios.

Some important limitations of our study need to be discussed. First, we do not consider dynamics in the use of fuel/electricity; that is, we did not calculate the impacts of the use phase using yearly updates of background systems, which could offer more refined comparisons between the studied car technologies. Concretely, such dynamics are expected to further favor the EV, as changes in the electricity sector have a bigger influence on this technology. Second, some future emissions for electricity technologies were adapted using best available data rather than using specific emission factors. Therefore, future emissions for these substances should be carefully assessed. For instance, in the case of PM emissions, changes were made according to future technology efficiency, as IMAGE does not explicitly model different sizes of PM emissions despite modeling black carbon emissions, which cover several PM sizes altogether. Hence, results for PM formation do not account for developments such as end-of-pipe solutions, which would be better captured in specific emission factors for PMs. In this sense, there is room for improvement of the present approach, and it would make sense to invest in finding more suitable proxies, other than technology efficiency, modeled within the IAM model to change the LCI parameters wherever possible.

Third, we focused on the electricity sector, leaving all other sectors unchanged. By doing so, we ignored other layers of complexity, realizing that additional changes are to be expected for other technologies in other sectors (e.g., the steel sector and fuel production sector in the case of vehicles) and that these would affect the life cycle impacts of ICEVs and EVs found in this study. For instance, if we had coupled changes in the background for the main industry sectors (e.g., the steel sector), fossil-fuel production, transport, and other sectors, such as the agricultural sector, this would have resulted in the possibility to evaluate the life cycle impacts of each product, accounting

	year	Background adaptation	Fossil Cumulative Energy Demand	Climate Change	Human Toxicity	Mineral Depletion	Particulate Matter Formation	Photochemical Oxidant Formation		Fossil Cumulative Energy Demand	Climate Change	Human Toxicity	Mineral Depletion	Particulate Matter Formation	Photochemical Oxidant Formation
ICEV-MidRoad	2012	technology	1,1%	1,8%	1,7%	0,1%	6,4%	2,9%	EV-MidRoad	7,1%	9,4%	3,0%	0,1%	19,5%	15,0%
	2012	market	-1,4%	0,6%	2,2%	0,1%	-1,2%	0,7%		-2,6%	8,4%	2,4%	0,1%	-3,7%	5,6%
	2012	All	-0,5%	2,1%	3,9%	0,1%	4,6%	2,6%		3,9%	16,0%	5,3%	0,2%	13,8%	15,5%
	2020	technology	1,4%	2,1%	2,0%	0,1%	7,5%	3,5%		9,0%	11,2%	3,5%	0,1%	22,8%	18,4%
	2020	market	-0,5%	1,0%	-0,2%	0,0%	-2,8%	1,3%		5,0%	12,0%	-0,9%	0,0%	-8,8%	9,5%
	2020	All	0,5%	2,4%	1,8%	0,0%	3,7%	3,5%		11,6%	19,4%	2,6%	0,1%	11,0%	20,1%
	2030	technology	1,8%	2,7%	2,6%	0,1%	8,9%	4,3%		12,2%	14,1%	4,5%	0,2%	27,4%	22,6%
	2030	market	0,6%	2,0%	-0,4%	-0,2%	-3,2%	1,7%		11,9%	16,5%	-1,4%	-0,3%	-11,1%	11,7%
	2030	All	2,0%	3,9%	2,3%	-0,1%	5,1%	4,6%		20,9%	26,2%	3,3%	-0,2%	14,4%	25,6%
	2040	technology	2,3%	3,3%	3,4%	0,1%	10,1%	4,7%		15,9%	17,7%	5,9%	0,2%	31,1%	24,5%
	2040	market	1,0%	2,0%	-1,7%	-0,3%	-4,6%	1,8%		13,5%	15,8%	-3,9%	-0,5%	-16,4%	11,6%
	2040	All	3,1%	4,8%	2,1%	-0,2%	5,6%	5,0%		26,4%	29,5%	2,8%	-0,4%	15,7%	27,6%
	2050	technology	2,6%	3,6%	3,8%	0,1%	10,7%	4,9%		17,5%	19,3%	6,5%	0,2%	33,0%	25,8%
	2050	market	1,0%	1,9%	-3,1%	-0,4%	-4,1%	1,9%		12,3%	14,4%	-6,4%	-0,6%	-14,5%	12,3%
	2050	All	3,3%	4,9%	1,3%	-0,3%	6,5%	5,2%		26,7%	29,6%	1,3%	-0,5%	18,7%	28,2%
ICEV-MidRoad-2.6	2012	technology	1,1%	1,8%	1,7%	0,1%	6,4%	2,9%	EV-MidRoad-2.6	7,1%	9,4%	3,0%	0,1%	19,5%	15,0%
	2012	market	-1,4%	0,6%	2,2%	0,1%	-1,2%	0,7%		-2,6%	8,4%	2,4%	0,1%	-3,7%	5,6%
	2012	All	-0,5%	2,1%	3,9%	0,1%	4,6%	2,6%		3,9%	16,0%	5,3%	0,2%	13,8%	15,5%
	2020	technology	1,3%	2,1%	2,0%	0,1%	7,4%	3,5%		8,8%	10,9%	3,4%	0,1%	22,5%	18,3%
	2020	market	0,1%	2,0%	2,0%	0,0%	0,6%	1,9%		9,9%	17,8%	3,1%	0,0%	3,2%	12,8%
	2020	All	1,0%	3,3%	3,7%	0,0%	6,2%	3,8%		15,5%	24,2%	5,9%	0,0%	19,7%	21,5%
	2030	technology	1,7%	2,5%	2,4%	0,1%	8,7%	4,3%		11,4%	13,3%	4,1%	0,1%	26,5%	22,5%
	2030	market	2,9%	5,5%	5,4%	-0,2%	6,7%	3,0%		28,6%	37,1%	9,5%	-0,4%	25,8%	19,6%
	2030	All	4,0%	6,9%	6,8%	-0,2%	11,8%	4,9%		34,8%	43,1%	11,8%	-0,4%	39,6%	27,6%
	2040	technology	2,2%	3,1%	3,1%	0,1%	10,6%	5,1%		14,8%	16,4%	5,3%	0,2%	32,4%	26,6%
	2040	market	6,4%	11,8%	11,7%	-0,7%	18,0%	5,1%		50,7%	70,1%	21,2%	-1,1%	65,7%	31,2%
	2040	All	7,2%	12,5%	12,4%	-0,6%	20,3%	6,0%		54,6%	71,9%	21,9%	-1,1%	68,7%	32,8%
	2050	technology	2,4%	3,4%	3,4%	0,1%	11,2%	5,3%		16,6%	18,3%	5,9%	0,2%	34,3%	28,0%
	2050	market	8,1%	13,6%	11,3%	-1,1%	19,1%	5,6%		61,1%	79,6%	20,7%	-1,9%	69,7%	34,0%
	2050	All	8,6%	13,9%	11,9%	-1,1%	21,1%	6,4%		62,7%	79,3%	21,3%	-1,9%	71,4%	35,0%

Figure 6 Changes in the impacts per vehicle-kilometer (vkm) (as percentage change from the original ecoinvent) for the EV and the ICEV using the MidRoad and MidRoad-2.6 scenarios, considering background adaptions of technology parameters only ("technology" rows), market parameters only ("market" rows), and both changes simultaneously ("all" rows). Shades of red highlight an increase and shades of green highlight a decrease of impacts compared to ecoinvent and were applied to cover the range of outcomes for all impacts per scenario and type of vehicle. EV = electric vehicle; ICEV = internal combustion engine vehicle; vkm = vehicle-kilometer.

for a fully consistent macro-level scenario. We did not choose this full scope of all sectors yet, as the present study mainly aimed to prove the concept. However, we believe that the general principles of our method, especially the treatment of technological and market changes, can also be applied when addressing other sectors. The availability of datasets for these other sectors in the IMAGE scenarios suggests that including them is the logical next step toward a more structural construction of future LCI databases using IAM scenarios, which would be more meaningful for LCAs of emerging technologies. Therefore, we recommend the expansion of our approach to other sectors—for example, transport, agriculture, or bulk materials production—while keeping in mind that new challenges may arise. For instance, other sectors might not be as widely

covered geographically and technologically in the ecoinvent database and/or in the IMAGE scenarios. Also, because of the particularities of each sector, updating parameters will likely involve ad hoc solutions. For example, emission factors related to land use may be inconsistent between IMAGE and ecoinvent due to definitions of land use emissions accounting for different sources. Despite these challenges, expanding the scenarios to other background sectors will add robustness to prospective assessments and will demonstrate the wider utility of this approach for prospective LCA and ETLCA. Linked to the background of an LCA, IMAGE scenarios enable more robust comparison of the environmental impacts of alternatives, as their impacts may or not be driven by the same sectors on the background, which would in any case be adapted according to the consistent IMAGE scenarios. Finally, the richness of IAM scenarios may help to deal with changes beyond technology and market parameters as defined here. For instance, IMAGE scenarios might also be used to determine changes in characterization factors used in LCIA that depend on background concentrations and climate-induced efficiency changes of power plants or vehicle operation.

We still consider the results of this study to be representative for EVs because the largest contribution to the EV impacts is electricity production to recharge the battery (Cox et al. 2018). Also, the implemented technology and market changes in the electricity sector have roughly changed the individual performance of about 75% of all the ecoinvent processes and have reduced their overall impact by 10% using the MidRoad-2.6 scenario for 2040 (Cox et al. 2018). For ICEVs, there could be changes in the production of oil due to changes in the resource accessibility and possibly due to new extraction technologies. Hence, our results can be read as an exploration keeping the status quo for fossil-fuel production.

Finally, we relied on inventories of technologies that are yet to be deployed, in particular CCS and CSP. While these inventories are crucial for achieving ambitious climate targets, there still are large parameter uncertainties for these inventories. In addition, the robustness of prospective assessment would be increased by addressing parameter uncertainty not only in the background but also in the foreground, as this uncertainty is expected to be large in the case of emerging technologies. Cox and colleagues (2018) made an effort in this direction for the case of EVs and found that electricity production for battery charging is responsible for most of the variability, as was mentioned above.

Conclusions

The approach developed in this study is meant to create more consistency regarding the temporal scopes of foreground and background systems considered in ETLCAs by addressing epistemological uncertainty for background changes in prospective LCA. Whereas foreground systems are modeled according to some expected future state of an emerging technology, background systems are generally not modeled and simply adopted at the current (or even outdated) temporal state. Including temporal developments in the background system can contribute to improving the temporal consistency of modeling emerging technology systems. Also, this can increase the fairness of comparing emerging technologies to competing incumbent technology systems (also including future background systems), thus adding robustness to the assessments. Our work presented a first proof-of-concept for one sector, which can be further expanded to also cover other sectors in the near future.

We evaluated scenarios from an integrated assessment model, the IMAGE model, in the LCI phase of a prospective LCA using ecoinvent version 3.3 as a background dataset. Future changes include electricity production technologies and their developments in terms of efficiency and emission factors, as well as electricity market changes, which were more extensively studied in previous literature. Advantages of our approach include a systematic integration of data, based on consistent worldwide scenarios, with reproducible, transparent, and traceable assumptions and results. Also, the approach meets demands to link macro scenarios into the micro or product level of LCA to help increase the robustness of the assessments. Because of this study's focus on the background system, we assumed that the product did not change, that is, the foreground remained constant. It is to be expected, however, that some emerging technologies will evolve rapidly in time and might even further shape the background in the future. Thus, for prospective LCA, this method is a modeling effort helping to understand only exogenous background changes. For uncertainty analysis, this is an effort that acknowledges, rather than reduces, epistemological uncertainty via the use of a broad spectrum of socioeconomically driven scenarios, which leads to explorative instead of predictive results that can help outline and better inform directions for action in product design and policy making. Translating the findings of this type of prospective LCA to responses in design and policy making is a vital step needed to give further meaning to the outcomes beyond the explorative domain for ETLCA and is a topic for further research. Further research is also needed to capture additional uncertainties related to the choice of IAM and intrinsic uncertainties of IAM scenarios.

Our case study on the effects of future changes in the electricity sector on the prospective LCA of an EV and an ICEV shows that the new approach is both feasible and valuable. Background changes can be very important for future environmental impact assessment of EVs and ICEVs, and thus our results suggest that policy making and the vehicles' design can be crafted for these vehicles to have lower impacts in the future. Climate change impacts can be altered up to 80% by 2050 in an ambitious mitigation scenario compared to impacts calculated without accounting for background changes. The uncertainty about future developments in the electricity sector is overall large, but it manifests differently depending on the studied product (EV or ICEV), the impact category, and the scenario and year considered. Considering the uncertainty about the future also makes assessing the relative environmental performance of EVs over time more complex and nuanced. Depending on the scenario, year, and impact, EVs can perform better or worse than ICEVs. Electricity market changes have a larger influence

on the total impacts of both types of vehicles than changes in electricity technologies. For both types of vehicles, market changes can thus determine if the impacts are higher or lower than the impacts calculated with the original ecoinvent background. Interactions between market changes and technology changes are observed when both are considered.

It is still possible to find more suitable data within the IAM model to account for technology changes. Also, it is important to further improve the inventories for relevant future technologies in line with the scenarios, such as CCS and CSP, or to account for their parameter uncertainty. Moreover, for future assessments, the approach has yet to account for foreground parameter uncertainty, just as it should consider the cross-sectoral consistency of the IAM scenario. This would lead to a more systematic construction of future inventory databases using IAM scenarios for more robust prospective LCAs. The method may accommodate information flows from LCA to IAM, as such loops of information could help refine the data quality in both modeling frameworks and lead to even more robust assessments. Then, ETLCAs with a different technological profile could be calculated and technologies could be compared for their future impacts in a wider and more consistent context.

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Note

1. The error is introduced because of the additional losses when converting from high to medium to low voltage, which technically does not take place if technologies supply the grid already at the low-voltage level. Furthermore, imports and exports happen at the high-voltage level, so technically technologies supplying at the medium or low voltage would not be in the import export mix. This is important for some countries with high losses. For other countries the error introduced is smaller. Region-power losses between high and low voltage are in the order of 2.5% to 23% (Treyer and Bauer 2016).

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