THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Batteries at Crossroads

Past, Present and Future Environmental Impacts of Lithium-ion Batteries

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Department of Technology Management and Economics

CHALMERS UNIVERSITY OF TECHNOLOGY

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The cover portrays the shadow of a growing battery stretching across the shimmering lithium ponds of South America's salars. This shadow becomes a metaphor for the environmental footprint of battery production and its far-reaching supply chains. Fragile and ancient, the salars are ecosystems now strained by the thirst for lithium. The image invites reflection on a central paradox of our time: in our pursuit of a low-carbon future, we risk wounding the very landscapes and lifelines that make such a future possible. The cover layout was conceived by the author and creatively brought into life by Aditi Patnaik (instagram: @aditipatnaik).

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Abstract

The global transition toward electric mobility is driving rapid growth in LIB production, with global capacity expected to more than triple between 2025 and 2030. This expansion raises critical questions about the environmental implications of large-scale manufacturing and the supply chains that sustain it. The central aim of this thesis is to apply life cycle assessment (LCA) to systematically evaluate these implications, with particular focus on production scale, the role of primary and recycled materials, and the influence of modeling choices on assessment outcomes.

The analysis begins by comparing LIB production across stages of technological maturity. Results show that scaling up can substantially reduce impacts per unit of capacity, largely through improved process efficiencies and economies of scale. These benefits, however, are accompanied by new burdens at the production site, including higher emissions, chemical use, and wastewater treatment requirements. When industrial-scale production is powered by low-carbon electricity, environmental hotspots shift upstream to raw material extraction and processing. An assessment of battery relevant raw materials reveals wide variability in environmental impacts, shaped by ore grade, extraction methods, and geographic supply configurations. This heterogeneity underscores the need for source-specific data in LCA studies, or, when unavailable, a broader spectrum of data to represent uncertainty. The thesis also investigates end-of-life strategies, with emphasis on hydrometallurgical recycling as a closed-loop pathway. Recycling can avoid up to 90% of the climate impacts associated with recyclable materials. Additional strategies – such as reducing scrap rates, increasing recovery of active materials, and optimizing chemical use – are shown to further enhance these benefits. Beyond the technological findings, the thesis highlights the methodological importance of modeling choices. Top-down approaches capture system-wide interactions, whereas bottom-up models offer process-level detail but may overlook broader dynamics. Likewise, differences between background databases, and their periodic updates, can alter results significantly, making reassessment essential.

Three lessons emerge: (i) production scale strongly influences environmental outcomes; (ii) raw material supply is heterogeneous and context-dependent; and (iii) modeling choices shape results. Viewed through the lens of past, present, and future, the thesis shows that past studies were constrained by unrepresentative data, present results reflect supply-chain and design variability, and future impacts may rise with reliance on low-grade ores. LIBs thus stand at a crossroads: indispensable for a low-carbon transition, yet demanding continuous reassessment of their environmental performance.

List of appended articles

1. Chordia, M., Nordelöf, A., & Ellingsen, L. A.-W. (2021). Environmental life cycle implications of upscaling lithium-ion battery production. The International Journal of Life Cycle Assessment, 26(10), 2024-2039. https://doi.org/10.1007/s11367-021-01976-0

2. Chordia, M., Wickerts, S., Nordelöf, A., & Arvidsson, R. (2022). Life cycle environmental impacts of current and future battery-grade lithium supply from brine and spodumene. Resources, Conservation and Recycling, 187, 106634. https://doi.org/https://doi.org/10.1016/j.resconrec.2022.106634

3. Kallitsis, E., Lindsay, J. J., Chordia, M., Wu, B., Offer, G. J., & Edge, J. S. (2024). Think global act local: The dependency of global lithium-ion battery emissions on production location and material sources. Journal of cleaner production, 449, 141725. https://doi.org/https://doi.org/10.1016/j.jclepro.2024.141725

4. Chordia, M., Wikner, E., Nordelöf A., Vaidya, K., & Arvidsson, R. (2025). Linking cell design and production energy demand to estimate environmental impacts of NMC lithium-ion batteries. (Manuscript under peer-review as of August 2025)

5. Chordia, M., Nordelöf A., Petranikova, M., & Arvidsson, R. (2025). Life cycle assessment of lithium-ion battery pack recycling for closed-loop recovery of transition metal hydroxides. (Manuscript under preparation as of August 2025).

for Maya,

May you find balance, virtue and truth in all your endeavors

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List of key abbreviations

BEV, Battery electric vehicle

CSI, Crustal scarcity indicator

EoL, End-of-life

ICEV, Internal combustion engine vehicle

LCA, Life cycle assessment

LFP, Lithium-iron-phosphate

LIB, Lithium-ion battery

NAM, Negative active material

NCA, Nickel-cobalt-aluminum

NE, Negative electrode

NMC, Nickel-manganese-cobalt

PAM, Positive active material

PE, Positive electrode

SOP, Surplus ore potential

1 Introduction

There are between 1.6 and 2 billion vehicles on the road worldwide (OICA, 2025). Among these, 40 million are battery electric vehicles (BEVs), which include both plug-in hybrids and full electric vehicles, thus representing between 2 and 3% of the total fleet (IEA, 2024). Most BEVs currently rely on lithium-ion battery (LIB) technology. There are several variants of LIBs for automotive applications such as, including LFP, NMC, and NCA.[1] Amongst these, NMC batteries are the most popular, accounting for over 65% of the market share in 2022, although LFP batteries are now beginning to compete with NMCs for market shares (IEA, 2023). The NMC chemistry is available in several variants defined according to the composition of its key constituents – nickel, manganese and cobalt. Within the NMC variants, high-nickel content formulations such as NMC622 and NMC811[2] dominate, comprising nearly 95% of NMC chemistries used in BEV applications (IEA, 2023). Their widespread adoption is driven by the advantages they offer in terms of energy density, driving range, and cost-effectiveness (Li et al., 2020). Accordingly, this thesis focusses on the NMC811 chemistry.

Even though BEVs still represent a small share of the global vehicle market, their share has increased rapidly since 2020, with one in every four vehicles sold in 2024/25 being a BEV (IEA, 2025b). In the recent past, governments world-wide have announced policy goals to electrify their transport sector (European Council, 2022; US 117th Congress, 2022). Several automotive companies have also declared their intention to divest from developing ICEVs and instead invest in BEVs (Ford, 2024; Volkswagen, 2025; Volvo Cars, 2024). This has led to a rapid expansion of battery production facilities and in particular LIB-based technology. To meet the growing demand for BEVs, large-scale LIB production facilities are being installed globally. Currently, an estimated 3 TWh of battery production capacity is already installed and operational worldwide, with expectations to reach up to 9 TWh by the end of this decade (IEA, 2025a). To support this production capacity expansion, existing mining and production operations need to expand, and new mining sites must be developed to keep up with demand for battery specific materials. BMI (2025) predicts that, by 2030, 293 new mines will be needed, including 52 for lithium, 45 for graphite, 28 for nickel, 26 for cobalt, and 61 for copper. Some of the demand for battery materials could also be met by recycling batteries at their end-of-life (EoL). Although, in contrast to production, global battery recycling facilities currently only have a capacity of about 300 GWh (i.e., a tenth of current production capacity), which is expected to reach approximately 1.5 TWh by 2030 if all the announced projects are developed as planned (IEA, 2024). Hence, it is more than likely that primary raw materials are going to meet a substantial demand for most battery raw materials for a foreseeable future (Ginster et al., 2024; Wesselkämper et al., 2024).

Anthropogenic activities have already driven the global surface temperatures over 1.1°C from pre-industrial levels (IPCC, 2023b). Projections indicate a high likelihood of temperatures

[1] LFP: Lithium-iron-phosphate; NMC: Nickel-manganese-cobalt; NCA: Nickel-cobalt-aluminum.
[2] 6-2-2 and 8-1-1 represent the relative share of nickel-manganese-cobalt in the cell chemistry, respectively.

reaching 1.5°C in the near term due to the cumulative CO_2 emissions already present in the atmosphere. Among the major contributors to GHG emissions, the transport sector alone accounts for nearly 15% of the total share of emissions. According to IPCC's sixth assessment report (AR6), using renewable energy-based electricity to power the BEVs offers the largest decarbonization potential in land-based transport on a life cycle basis. The AR6 further emphasizes that by diversification of the supply chain, efficiency improvements and a circular material flow, concerns regarding the environmental impacts of battery production and the raw material supply chain could be addressed. However, just switching to LIB-based BEVs from ICEVs is not sufficient to reduce the emissions from the transport sector. Often, there exists tradeoffs within the life cycle phases of LIBs that need to be deliberated upon. From this perspective, battery production has been identified as a highly energy demanding phase in the life cycle of BEVs (Bouter & Guichet, 2022; Nordelöf et al., 2014). Given the rapid expansion of LIB capacity achieved through large-scale production, assessing the environmental impacts throughout the life cycle is critical to understanding the implications of large-scale LIB production. This is the central theme of this thesis.

1.1 BEV vs ICEV

Operating a BEV is different from an internal combustion engine vehicle (ICEV). In the case of BEVs, the operational emissions depend on the composition of the electricity sources feeding the grid at the time of charging (Mehlig et al., 2022; Naumann et al., 2024). For fossil-fuel powered ICEVs, the operational emissions depend mainly on the engine thermal efficiency. Driving style, road and ambient conditions, as well as wear due to use influence the efficiency of both BEVs and ICEVs.

Another aspect where BEVs and ICEVs differ is in the production phase and the sourcing of raw materials. ICEVs have been the primary mode for land-based transportation for over a century now, hence the industry is highly mature and the supply chains well established (Taub et al., 2007). Although innovations in the production methods and engine and powertrain technologies still occur, they are not as frequent judging by the frequency of patents filed related to ICEVs. Sinigaglia et al. (2022) even predict a saturation in patent applications for ICEVs by 2045. However, this is not the case for BEVs. The field of battery-powered transport is experiencing a large flux in aspects of battery technology, production technology, raw material supply chain, and recycling technologies, to name a few. This technological dynamism and variability in production and operational parameters complicates environmental assessments of BEVs.

Irrespective, to better understand the environmental impacts from the BEV life cycle, the family of environmental systems analysis (ESA) tools such as material flow accounting (MFA), environmental impact assessment (EIA), risk assessment (RA), and life cycle assessment (LCA) are employed. The choice of the ESA tool depends on the type of assessment needed, as each tool has its specific purpose and methodology for implementation (Finnveden & Moberg, 2005). Governments and organizations for several years now have recommended the use of LCA in environmental policy design due its core aspect of quantifying the inflows and outflows of materials and energy from a product system throughout its life cycle (Guinée et al., 2011). LCA is also the main methodology applied in this thesis.

Several LCAs comparing ICEVs and BEVs point to the electricity used for charging the batteries as a key factor for enabling BEVs to have lower GHG emissions than ICEVs over their respective life cycles (Muratori et al., 2021; Sacchi et al., 2022; Shafique & Luo, 2022). Further, within the BEV life cycle, it is the production of the batteries that has been pointed out as the hotspot in terms of energy demand in manufacturing (Jannesar Niri et al., 2024; Xia & Li, 2022). However, battery production at industrial-scale has been shown to improve the energy efficiency of the facility (Chordia et al., 2021; Knehr et al., 2024; Perez Clos et al., 2025), and thereby also reduce the environmental impacts linked to battery production per unit of output. Irrespective, challenges remain in LCAs of LIBs in terms of defining stable system boundaries, availability of representative data, cross-comparison of different production technologies, time periods and regional factors.

1.2 LIB production scale

Industrial-scale production of LIBs requires deliberation on cell design, materials and production processes (Kwade et al., 2018). This happens over a period of time and production scales – i.e., lab, pilot and industrial. To begin with, lab-scale facilities are set up to test whether theoretical concepts can be realized as practical and implementable solutions. This is characterized by a large number of design and material options, which need to be worked through and optimized. Further, lab-scale implementation also aids in developing a preliminary technical and economic evaluation of a process or a set of processes (Ram, 2016). Lab-scale production of cells is discontinuous and often relies on manual effort from the operator to keep the processes or production moving forward. This was highlighted by Erakca et al. (2021), who calculated the energy consumption of LIB cell production at lab-scale and reported a number of manual steps in between automated or machinery-run steps in cell production. Once a working prototype of a cell is ready and tested at lab-scale the next step is to understand the feasibility of production in a continuous and automated environment, simulating an industrial-scale production. For this, pilot- or small-scale facilities are set up that help optimize production processes, understand process interdependencies, mitigate risks, collect environmental and economic data, and ensure regulatory and quality compliance (Casey et al., 2019; Maranghi et al., 2020; Merrow, 2011; Sommer et al., 2024). This optimization is usually done in an iterative manner, involving multiple scale-up and refining steps to minimize the uncertainties at industrial-scale production and ensuring a successful process and plant design (Augustsson et al., 2017; Chaouki & Sotudeh-Gharebagh, 2021).

Industrial-scale operations are expected to manage trade-offs between throughput, quality, and costs (Keppeler et al., 2021). Also, as emphasized by Frith et al. (2023), successful industrial-scale technical capability should be in sync with the raw material supply chain and economic feasibility. Thus, industrial-scale operations are highly-automated (Keppeler et al., 2021), cost-optimal (Orangi et al., 2023) and also try to mitigate geopolitical aspects of raw material supply (Olivetti et al., 2017). Lastly, and importantly, industrial operations must also meet the environmental standards and regulatory criteria set by the respective local or regional authorities (Angel et al., 2007). For example, use of chemicals and disposal of wastewater is a significant challenge industries operating at large-scale must consider (Salomaa & Watkins, 2011). Hence, learnings from process scale-up aids in designing facilities to prepare for handling these environmental challenges (Kwade et al., 2018). These potential learnings from scaling up LIB production processes are discussed in this thesis.

1.3 Primary raw material supply

As mentioned earlier, industrial-scale operations require a continuous supply of raw materials to the facility to ensure efficient production (Olivetti et al., 2017). While some studies have assessed the current and future stocks of primary and secondary battery materials and the likelihood of them meeting the demand for BEVs (Maisel et al., 2023; Xu et al., 2020), others focus on the environmental, social, geopolitical, health and governance issues along the supply chain (Arvidsson et al., 2022; Jannesar Niri et al., 2024; Nsude et al., 2024). Several studies also point out the variation in the environmental impacts of batteries based on the supply chain of its key raw materials (Kallitsis et al., 2024; Peiseler et al., 2024). Variations in the environmental impacts along the supply chain usually relate to two aspects: (i) the source, including the ore grade at the mining and extraction site, and (ii) subsequent production, refining and upgrading processes used recover the metals from the ore up to the desired quality in the final product (Sengupta, 2021). It is often the case that post mining, the ore is transported to other facilities for processing, refining and upgrading, sometimes across national and continental boundaries. Thus, conducting supply chain specific environmental impact assessment of battery materials is critical to understanding the relevance of the source and the supply chain in the overall context of battery production (Istrate et al., 2024).

Specifically, at the mining and extraction site, the environmental impacts depend on a range of factors such as the grade, physical and chemical properties of the ore, depth of deposit, overburden, and the energy provision to the mine (Priester et al., 2019). Mines are often referred to by their ore grades, which could be used as proxy for the amount of valuable material in the deposit, the mining residue likely to be produced, water and energy inputs, and the chemical reagents needed for processing the ore (Priester et al., 2019). The mining residues consist of the overburden, including the barren rock, and the tailings produced as a result of milling (Sengupta, 2021). Handling the tailings is particularly challenging due to its chemical reactivity and toxicity of its constituents (da Silva-Rêgo et al., 2022; Lottermoser, 2007), which can lead to severe local environmental impacts such as soil contamination (Laker, 2023), water and air pollution (Laker, 2023; Zwissler et al., 2024), land degradation (Bakhtavar et al., 2006), ecosystem damage, and risks to human health (Ghebreigziabiher & Lohmeier, 2024). Some studies argue that ore grades are in decline or may decline over time (Calvo et al., 2016; Mudd, 2012; Northey et al., 2014). While mining operations over an extended period of time, despite producing from a lower-quality ore, could be interpreted as a sign of improvements in extraction and refining technologies to be more cost-effective (West, 2011), what is clear is that producing metal from lower-quality ore increases the energy expenditure, water and chemical requirements and the amount of mining waste generated in the form of tailings (Norgate et al., 2007; Priester et al., 2019). Thus, pointing to a likely increase in several environmental impacts from the supply chain in the future (Aramendia et al., 2023; Lagos et al., 2018). In the context of LIB production, this also points to a high variability in environmental impacts from the upstream supply chain of raw materials. How the source type, grade and the subsequent supply chain of raw materials influences the overall impacts from the LIB life cycle are further investigated in this thesis.

1.4 Secondary raw material supply and recycling

One way to reduce environmental impacts from the LIB life cycle, particularly from the energy-intensive raw material extraction and production phase, is to recover materials at the EoL of BEVs. Each unit of recovered material that replaces primary inputs lowers overall impacts (Wesselkämper et al., 2024). Policy directives such as the EU Battery Regulation further encourage recycling by imposing progressively stricter targets for recycled content in new batteries (EU, 2023). In response, recyclers are investing in secondary raw material supply chains to both comply with regulations and reduce burdens from primary extraction (Sommerville et al., 2021). Yet, most face logistical challenges due to heterogeneity in pack and cell design and the still-limited volumes of EoL batteries, which hinder economies of scale (Harper et al., 2019; Rehman et al., 2025).

The most common and commercially viable methods for recycling LIBs are pyrometallurgy and hydrometallurgy based (Chen et al., 2019). Pyrometallurgy involves high-temperature smelting to burn batteries and extract metal alloys, primarily recovering high-value metals like cobalt, nickel, and copper. This method has been effective due to the historically high cobalt content in portable batteries. However, as newer LIB chemistries – particularly for automotive applications – contain less cobalt, the economic viability of pyrometallurgy may decline (Chen et al., 2019). Moreover, emerging regulations now require recovery of even low-value materials to meet recycled content targets (Makuza et al., 2021). Hydrometallurgy, by contrast, uses aqueous leaching followed by purification techniques such as solvent extraction, ion exchange, precipitation, or electrolysis. It can recover a wider range of metals with high purity and lower energy use than pyrometallurgy per unit recovered material (Yao et al., 2018). However, the process requires prior mechanical pre-treatment, including crushing and sorting battery components, and can be costly due to the difficulty of separating chemically similar metals and the need for wastewater treatment (Chen et al., 2019). How can hydrometallurigcal recycling can alleviate the environmental impacts from the LIB lifecycle is assessed in this thesis.

1.5 LCA data

LCA studies are data intensive and require representative data to be able to model the product system. Data types used in LCA can be broadly categorized as foreground and background data (Zimmermann et al., 1996). The foreground data represents the data collected or generated by the LCA practitioner for the respective study, whereas the background data represents the pre-collected and sorted data available to the LCA practitioner in form of standard databases or other sources (Frischknecht et al., 2005). Collecting foreground data for inventory modeling in LCA is time consuming and arguably the hardest part of the LCA study. This is particularly the case when the system modeled represents upcoming technologies for which not a lot of data is accessible, and the industry is hesitant to share data due to proprietary information (Kuczenski et al., 2017). Often, such hurdles are overcome by using non-disclosure agreements (NDAs) between the project partners to make data accessible for LCA (Gortych, 2006; Witman & Johnson, 2008). This approach has been used to collect large-scale LIB production and recycling data from Northvolt AB[3], a battery manufacturer founded in Sweden in 2016.

Regardless of the data sources or collection methods, it is essential to consider what the data actually represents about the system being studied (Zargar et al., 2022). For example, in case of energy data in a factory or a machine, the energy consumption could be collected directly by the operator using a power meter or a similar monitoring system (Erakca et al., 2021). Another option could be to use the power rating of the machine and the time the machine operates (Degen et al., 2023; Knehr et al., 2024). Yet another way is to use technical permits which report the maximum permissible energy consumption of a machine or a factory, determined based on several aspects such as regulatory caps linked to emissions, energy modeling, economic factors, historical trends etc. (Article 1). This is not an exhaustive list, but each method of acquiring energy demand or other foreground data differs in terms of accuracy and scope. It is the responsibility of the LCA practitioner to assess the suitability of the data for the specific study (Edelen & Ingwersen, 2018; Pryshlakivsky & Searcy, 2021).

The combination of background data and software package used in LCA studies can also reflect different levels of accuracy and generate different results (Miranda Xicotencatl et al., 2023; Pauer et al., 2020). However, they are often not subject to much scrutiny in LCA studies as the focus of analysis is usually on the quality of the foreground data. Institutions providing and maintaining background databases often update their datasets when more accurate and representative information becomes available (Finnveden et al., 2009). Thus, it is up to an LCA practitioner to appraise their model in the context of the quality, transparency and reproducibility of the background data and its potential implications of study results (Guo et al., 2025). This aspect of how background databases could influence study results is investigated in this thesis.

[3] At the time of writing this thesis Northvolt is not in active operation.

2 Research aims and thesis structure

The previous chapter discussed several challenges related to the environmental assessment of LIB production. These challenes are broadly categorized into two types in this thesis. The first concerns the technological configuration and stage of development of LIB production systems – such as small-scale versus large-scale manufacturing and the use of primary versus secondary raw material supply chains. The second category relates to how these technologies are assessed using LCA models, particularly with regard to the modeling of foreground systems and the choice of background system databases. Against this backdrop, this thesis focuses on three key stages of LIB life cycle: raw material extraction and supply chains, large-scale LIB production, and EoL recycling. In this thesis recycling is treated as a means of supplying secondary raw materials back into the production cycle. Thus, the overarching aim of the thesis is,

"to assess environmental implications of large-scale LIB production."

This aim is addressed by means of the following research questions (RQs), which relate to the first category of challenges associated with environmental assessment of LIBs, as defined above.

RQ1: How does scale of production influence environmental impacts of LIBs?
RQ2: How does the origin and the supply chain of primary raw materials influence environmental impacts of LIBs?
RQ3: How does cell design influence environmental impacts of LIBs?
RQ4: How does recycling influence environmental impacts of LIBs?

Foreground system modeling choices and background system databases used to model LIB technology can influence the overall assessment. Thus, it is important to understand the implications of such choices when conducting LCAs. The following research questions pertain to the second category of challenges associated with environmental assessment of LIBs as defined above.

RQ5: How does the choice of foreground data modeling approaches influence environmental impacts of LIBs?
RQ6: How does the background system database influence environmental impacts of LIBs?

This thesis is structured into eight chapters. Chapter 1 provides a broader context to the field of research this thesis addresses, thus laying the foundation for the research questions presented in Chapter 2 (the current chapter). Chapter 3 offers an overview of the technical systems analyzed in the thesis. Chapter 4 outlines the application of the LCA methodology, while

Chapter 5 details the data sources, inventory modeling approaches employed. Chapter 6 presents the key findings of the thesis, including supplementary analyses conducted to support the research questions. Chapter 7 directly addresses the research questions, discusses the study's limitations, generalizes the results, and reflects on their relevance for various stakeholders in the LIB supply chain. Finally, Chapter 8 summarizes the main conclusions of the thesis.

This thesis comprises of five appended articles that together examine the environmental implications of large-scale LIB production, thus placing the LIB technology at a crossroads in the transition to low-carbon transport solutions for the society. Article 1 analyzes how the upscaling of LIB manufacturing influences environmental impacts, establishing the basis for large-scale LIB production assessments. Building on this, Articles 2 and 3 investigate the supply routes of lithium and other key battery materials, respectively, and highlight the uncertainties associated with assessing climate impacts along heterogeneous raw material supply chains. Article 4 advances the methodological framework for foreground system modeling in LCA by linking bottom-up and top-down modelling approaches and exemplifying it further with a case study on fourteen cells varying in format, internal design, NMC chemistry and optimization type to highlight how cell design shapes environmental outcomes. Finally, Article 5 evaluates the extent to which recycling can mitigate overall life cycle impacts, thereby connecting production and EoL phases. Collectively, these articles provide a comprehensive understanding of the past, present, and future drivers of environmental impacts from LIBs, highlighting the critical aspects that will shape their role in transition to low-carbon transport.

3 Technical systems

This chapter offers a concise overview of the technical systems examined in this thesis and the appended articles. It begins with the fundamental structure of a LIB cell and pack, followed by a summary of global lithium extraction and production methods. Subsequently, the key processes involved in LIB cell manufacturing and EoL recycling are described.

3.1 LIB cell and pack nomenclature

A LIB cell consists of both electrochemically active components and auxiliary elements essential for safety and functionality. The core electrochemical system includes a positive electrode (PE) and a negative electrode (NE), both immersed in an electrolyte. A separator is placed between these electrodes to reduce the distance between them, facilitating ion movement while maintaining electrical insulation to prevent short circuits. Each electrode comprises a porous layer deposited onto a thin metallic foil, which serves both as current collector and as mechanical support. This porous layer includes the active electrode material, a conductive additive to enhance electronic conductivity, and a polymeric binder to hold the structure intact. The performance of the electrode, particularly its capacity per surface area, is influenced by the type and amount of active material used and the thickness of this layer.

During battery discharge, the PE functions as the cathode and the NE as the anode; these roles reverse during charging (Newman & Thomas-Aleya, 2004). The terms PE and NE refer to the entire electrode assemblies, encompassing the active material, conductive agents, binder, and metal foil substrate (Renner, 2007). While the most common negative active material (NAM) is graphite, there is a larger variation in the positive active material (PAM) (Mekonnen et al., 2016). Some examples of PAMs used in LIBs are NMC, NCA, LCO and LFP. Within the NMC cell chemistry, there are several variants with varying shares of nickel, manganese, and cobalt. Some common variants are NMC111, NMC532, NMC622 and NMC811 (Noh et al., 2013). Increasing the nickel content and thereby lowering the manganese and cobalt share improves the energy density, power capability and lowers the cost of the LIB cells (Manthiram, 2017). In this thesis the focus is mainly on high-nickel content NMC cell chemistry (NMC811) due to its characteristics that favor automotive applications (Li et al., 2020). Structurally, a typical LIB cell resembles a layered "sandwich" of alternating electrodes and separators, which is rolled into a spiral – commonly known as a "jelly roll" – and encased within a housing filled with electrolyte.

A LIB pack consists of several components whose design and functionality depend on each other and influences the overall efficiency of the pack in the use phase. Some of the key components include the module, the electrical system, the thermal system, and the structural packaging (Kumar, 2024). The module consists of several key components such as the battery cells, which are the fundamental energy storage units, the electrical connects such as busbars and connectors, the mechanical housing for structural support and housing and a component of the battery management system (BMS) called the module logic board which is used for monitoring and controlling the voltage, current and temperature within the cells (Gregory, 2015). The cells can be cylindrical, prismatic or pouch type with each having its own unique characteristics. The modules are the building blocks of the battery pack and their configuration (in series or parallel) decides the overall voltage and capacity of the battery pack (Kumar et al., 2024). The electrical system comprises of the BMS, wiring, circuit breakers, sensors, and connectors. Mainly its the BMS that manages the overall performance of the pack. It does so by continually monitoring parameters such as voltage, current, temperature ensuring a safe, reliable and an efficient use of the entire pack system (Friel, 2014; Kumar et al., 2024). During charging and discharging cycles, the battery pack generates heat due to the electrochemical reactions. This heat needs to be dissipated effectively for safety and longevity of the cells. For this the thermal management system is designed using air or liquid cooling, and phase change materials (Bibin et al., 2020). The choice of thermal management system is usually driven by the cell and module design. Finally, the structural packaging is the physical enclosure housing the modules and the rest of the battery pack systems. Design of this is meant to provide the mechanical protection, and structural support for the thermal and electrical systems (Johnson, 2022).

3.2 Lithium extraction from brines and spodumene

Lithium is extracted globally from brine and spodumene ores. While facility-specific processes vary, both extraction routes can be generalized for LCA modeling. Brine-based operations typically yield lithium carbonate (Li_2CO_3), which may be further processed into lithium hydroxide monohydrate ($LiOH \cdot H_2O$). In contrast, spodumene-based facilities can tailor final steps to produce either compound.

3.2.1 Li_2CO_3 production from brine

This process involves solar evaporation, chemical purification, and precipitation. Raw brine is extracted from underground aquifers and directed to solar ponds for progressive concentration and salt removal. Brine is pre-concentrated in lined ponds over several months, evaporating 80–90% of the water and sequentially precipitating salts such as halite, sylvinite, and carnallite. Environmental conditions (temperature, humidity, wind) influence evaporation and salt profiles. Lithium is enriched to ~4-6% in dedicated ponds, with secondary salts (e.g., potassium, sulfate, borates) also removed.

The concentrated brine then undergoes impurity removal: magnesium is precipitated with slaked lime (CaO), and sulfates with calcium chloride ($CaCl_2$). Solids like $Mg(OH)_2$ and gypsum are removed. Further purification includes crystallization and solvent extraction, particularly for boron, which is stripped using NaOH after acidification and extraction. Ion exchange may be used for residual ionic impurities.

The purified brine is then treated with CaO and soda ash (Na_2CO_3) at ~60°C to remove remaining calcium and magnesium. After filtration, Li_2CO_3 is precipitated by adding Na_2CO_3

at ~80°C. The slurry is filtered and washed to achieve high purity (~99.5%). The final Li_2CO_3 is dried and packaged, while residual solids are disposed. For a more detailed explanation, readers are directed to the supporting information document in Chordia, Wickerts, et al. (2022).

3.2.2 $LiOH \cdot H_2O$ production from spodumene

The production of $LiOH \cdot H_2O$ from spodumene involves ore concentration followed by chemical conversion through calcination, leaching, purification, and crystallization. Spodumene ore is mined via drilling and blasting, then crushed and screened through multiple stages. Optical sorting removes waste rock, and the ore is ground into a fine slurry using rod and ball mills. Magnetic separation eliminates iron, followed by de-sliming and froth flotation to remove mica and silicates. Spodumene is then floated using pH modifiers and collectors. The resulting concentrate (~2–2.5% Li as Li_2O) is dewatered and sent to the chemical plant.

Spodumene naturally occurs in a stable α-phase, which is calcined at ~1000°C to convert it to reactive β-phase. The β-spodumene is cooled, ground, and subjected to either acid or soda leaching. In acid-leaching, β-spodumene reacts with sulfuric acid to form lithium sulfate (Li_2SO_4), which is leached into solution and filtered. In the latter, β-spodumene is made to react with sodium carbonate (Na_2CO_3) under high pressure and temperature, producing Li_2CO_3, which is then converted to LiOH using calcium hydroxide. Solid residues (e.g., analcime, alumina sand) are filtered, while the lithium-rich solution proceeds to purification. Further, impurities in the solution are removed through staged neutralization with slaked lime, followed by pH adjustments and ion exchange to meet battery-grade standards. Ion exchange resins are regenerated with hydrochloric acid. The purified solution undergoes multi-step evaporation and crystallization. $LiOH \cdot H_2O$ is precipitated as the solution reaches supersaturation, and crystals are filtered, washed, and optionally recrystallized for higher purity. Final crystals are centrifuged, dried, and packaged. For a more detailed explanation, readers are directed to the supporting information document in Article 2.

3.3 Battery cell production

The production of NMC PAM begins with the preparation of nickel, manganese, and cobalt oxide and LiOH powders. The preparation of the NMC oxide powder can have different starting points depending on the type of raw materials procured – powder, crystalline metal sulphates or directly as metal hydroxide solutions. Depending on the starting point NMC oxide is synthesized by precipitating metal sulphate solutions with NH_3 and NaOH, followed by filtration, drying, and oxidation. LiOH is heat-treated, sieved, and purified and then calcined along with NMC oxide to form $LiNiMnCoO_2$. The resulting powder is ground, purified, and mixed with solvent and binder to create a slurry for PE.

The PE is produced by coating both sides of an aluminum foil with a slurry composed of $LiNiMnCoO_2$ powder, N-Methyl-2-Pyrrolidone (NMP) as solvent, polyvinylidene fluoride (PVDF) as binder, and conductive carbon black to enhance electron transport. The slurry is prepared in a high-shear mixer to ensure homogeneity of the mixture. The coating is typically applied using a slot-die to achieve uniform thickness. The coated foil is dried in a convection oven to evaporate NMP, which is recovered via condensation systems. The dried electrode is then calendared using precision rollers to compress the coating, reducing porosity, and improving particle contact. The PE is then slit to the required width and optionally tab-welded using ultrasonic or laser welding techniques.

The NE is manufactured by coating a copper foil with a slurry of mixed natural and synthetic graphite, carboxymethyl cellulose (CMC) as a thickener, and styrene-butadiene rubber (SBR) as a binder, dispersed in deionized water. The slurry is mixed under vacuum to prevent air entrapment and ensure uniform dispersion. Coating is performed similarly to the PE, with thicknesses typically ranging ~80–120 µm per side. The coated foil is dried in a controlled oven to remove water, which is condensed and reused. The dried NE is calendared to achieve the desired electrode density and surface smoothness. After calendaring, the electrode is slit, and the tab is optionally welded. Throughout both electrode production processes, particle size distribution, coating uniformity, and porosity are tightly monitored to ensure electrochemical performance and mechanical integrity.

The electrolyte is a critical component for lithium-ion transport within the cell and is formulated by dissolving lithium hexafluorophosphate ($LiPF_6$) salt in a mixture of organic carbonate solvents – typically ethylene carbonate (EC), ethyl methyl carbonate (EMC), and dimethyl carbonate (DMC) – in precise ratios to balance ionic conductivity, viscosity, and electrochemical stability. Additives such as vinylene carbonate (VC) and fluoroethylene carbonate (FEC) are introduced in small concentrations (typically <5%) to enhance solid electrolyte interphase (SEI) formation and improve cycle life, especially under high-voltage or low-temperature conditions. $LiPF_6$ is hygroscopic and thermally unstable in the presence of moisture, hence the entire process is carried out in a dry room with low relative humidity. Dry nitrogen gas is used to purge moisture from both the salt and the solvent mixture.

During cell assembly, the PE, NE, and separator are combined to form the electrochemical core. The electrodes are aligned with a microporous polyolefin separator typically made of polyethylene or polypropylene to prevent internal short circuits while allowing lithium-ion transport. The components are wound into a jelly roll. A polyimide adhesive tape is applied to secure the roll. The wound core is inserted into a cell container. The electrolyte is injected under vacuum to ensure complete wetting of the electrodes and separator. The electrolyte volume is carefully metered to avoid overfilling, which could lead to leakage or gas generation. An insulating ring is placed at the top to prevent electrical contact between the electrodes and the lid. The lid, which includes a safety vent and current interrupt device, is laser-welded or crimped to seal the cell hermetically. Any spilled electrolyte is removed through a washing step.

The final step is cell formation, which involves electrochemical activation of the cell. Cells are charged and discharged under controlled conditions in temperature-regulated chambers. This process forms the SEI on the anode surface, a critical layer that stabilizes the interface and prevents further electrolyte decomposition. Formation protocols vary but typically involve low current rates and multiple cycles. Voltage, current, temperature, and impedance are monitored to detect anomalies. Cells that fail to meet performance or safety criteria are classified as defective and handled as hazardous waste.

The cell production processes outlined earlier generate several streams of process water effluents. These streams are systematically collected and treated to remove contaminants, ensuring that discharged water complies with the environmental limits specified in the facility's permit. For a more detailed explanation, readers are directed to the supporting information document in Article 1.

3.4 Battery pack recycling

The recycling of LIB packs comprises a series of steps aimed at recovering critical and secondary raw materials. The process begins with collection, where spent LIB packs are retrieved from BEVs. The packs are then discharged (also called stabilization) to safely eliminate residual charge and reduce the risk of electrical or thermal incidents during further handling. This is usually achieved through brine or ohmic discharging processes (Harper et al., 2019). In the brine discharge process the pack is immersed in a brine solution which neturalizes the stored energy in the packs by acting as ionic medium that allows the current to flow between the electrodes gradually discharging the battery (Torabian et al., 2022). In the ohmic discharging process, the pack is discharged using an external load bearing circuit. Further, this electricity can be recovered and reutilized by either transferring to the grid or within the facility, thus offsetting some of the energy requirements (Harper et al., 2019). Following discharging, the packs are dismantled, during which components such as casings, wiring, and modules are separated. Modules are sent for crushing and sorting, where they are shredded and mechanically treated to produce sorted output fractions. These typically include plastics, ferrous and non-ferrous metals, and a fine powder known as black mass, which is rich in electrochemically active materials. Crushing is typically carried out in an inert atmosphere to prevent fires or risks of explosions. The final step involves hydrometallurgical treatment of the black mass. In this process, the material is leached using acid-based solutions, and metal ions are selectively precipitated. In the current configuration, the process is optimized to recover a NMC hydroxide precipitate, which contains the critical transition metals required for the production of new PAM materials. Additionally, LiOH and graphite are also recovered via precipitation.

4 Methods

4.1 LCA methodology

This thesis assesses the environmental implications of large-scale production of LIBs with high-nickel content NMC chemistry. LCA is employed as the core methodological framework, as it enables a comprehensive evaluation across multiple life cycle stages and environmental impact categories. In the context of LIBs, LCA facilitates comparative assessments to uncover environmental trade-offs among alternative options such as different raw material sources and supply chains, variations in cell design, and the use of primary versus secondary materials. Accordingly, LCA is applied throughout this thesis and is complemented, where appropriate, by additional analytical tools to support the assessment.

4.1.1 Goal and scope

An LCA study is defined by its *goal* and *scope*. While each appended article outlines specific goals within its defined scope, the overarching goal of this thesis integrates the individual goals of the appended articles. The goal of the LCA applied in this thesis is thus to *assess the impacts of production scale, primary and secondary material supply chains, and cell design across the life cycle of LIBs with NMC chemistry*. The intended audience includes actors, stakeholders, and decision-makers involved in various phases of the LIB life cycle. The aim is to inform them of potential environmental trade-offs within and between life cycle phases, in particular via RQ1 to RQ4, thereby supporting the development of NMC battery technologies. Additionally, the thesis engages with LCA practitioners on methodological aspects of data handling in LCA, particularly through RQ5 and RQ6.

The *scope* of the thesis is defined in alignment with the stated goal. As the focus is on assessing environmental implications of large-scale LIB production, the analysis centers on life cycle phases directly linked to production. For instance, production scale and cell design pertain to the production phase (factory gate to gate), primary material supply to the raw material extraction and processing phase (cradle to gate), and secondary material supply to the EoL phase (gate to grave). The use phase is excluded from the scope due to the emphasis on production-related aspects of LIBs. Arguably, material supply chain, production and recycling are aspects that the industry and policy actors have the most agency in and are also the life cycle phases most frequently addressed by the regulatory bodies, whereas the use phase is more application and consumer dependent. Although, the exclusion of the use phase does represent a limitation in the scope of this thesis, considering that cell design while part of the production phase, can influence performance during the use phase in BEV applications. Irrespective, furthering the knowledge on how cell design influences vehicle performance and how that affects the overall environmental impacts from BEVs remains an ambition to be investigated in future research.

The technical scope of the thesis covers the production of a LIB cell of NMC chemistry, including the primary and secondary supply chain of raw materials to the production facility. This technical scope is selected due to the high relevance of NMC LIBs in current automotive applications. Further, given the capacity expansion of LIBs already underway, the environmental impacts along the raw material supply chain become highly relevant to investigate. A summary of the technical system modeled and assessed in this chapter is presented in Chapter 3. Given the global nature of the LIB value chain, the geographical scope of the thesis is also global. As cell chemistries as well as production and recycling technologies are rapidly evolving, the temporal scope is set to around 2030. Nonetheless, insights related to life cycle trade-offs and LCA modeling likely remain relevant beyond this timeframe.

4.1.2 Functional unit

A final element in defining the scope of an LCA study is the selection of a *functional unit*. The functional unit of 1 kWh of theoretical cell storage capacity is selected to enable a consistent and comparable assessment of the environmental impacts associated with LIB production and end-of-life treatment. This unit reflects the core function delivered by the battery, i.e., energy storage, and is suitable given the study's focus on raw material extraction, cell production and recycling. These stages are directly influenced by the amount of capacity built into the cells, rather than how the stored energy is extracted in specific applications. Moreover, using a capacity-based functional unit allows for fair comparison across different chemistries, cell designs, or supply chain configurations, even when the LIBs vary in mass, or specific energy. This approach aligns with common industry practices and is also recommended in LCA of LIBs (Peters, 2023).

Following the goal and scope definition, the next phase in LCA is *inventory analysis*. This phase is informed by the goal and scope. As the study focuses on LIB production, data related to material supply, production, and recycling processes was collected from various sources. These are presented alongside research question-specific data and methods in following Section 4.2.

4.1.3 Impact indicators

Climate change and resource use impacts are most dominant in the discourse connected to the LIB supply chain. These impacts are also recommended for *impact assessment* at policy level for LCAs of LIBs (European Union, 2023). In this thesis, climate change impacts is assessed using IPCC 2021 characterization factors (IPCC, 2023a). The resource use impacts is assessed taking a long-term and near-term resource scarcity perspective. For the long term perspective, the crustal scarcity indicator (CSI) was used, which is based on the concentration of metals, minerals, ores and other materials in Earth's crust (Arvidsson et al., 2020). For the near-term, the surplus ore potential (SOP) method adopted in the ReCiPe impact assessment package (Huijbregts et al., 2016) is used. The SOP characterizes minerals based on the ore grades and commodity prices.

4.2 Research question specific methodology

LCA is the primary methodology applied for addressing the research questions. However, where necessary, LCA is supplemented with additional methods to support the assessment. These additional methods and the data used are discussed further in this chapter, specific to the research questions.

4.2.1 RQ1, scale of LIB production

The relationship between production scale and the associated environmental impacts of LIB production is examined through a three-step approach. The analysis for the first step is reported in Article 1 and those results are reproduced in Section 6.1. The subsequent analysis in steps two and three are carried out specifically for this thesis. In the first step, LCA is applied to compare the overall environmental impacts of LIB production across varying scales, enabling a system-level (i.e., cradle-to-gate) comparison of the influence of production capacities. The second step involved a process-level analysis, focusing on energy demand across all major cell production stages for facilities operating at different scales – laboratory, pilot, and giga-scale. This was intended to identify how specific production processes vary with scale and what can be learnt about a process or a system as whole before scaling it up. In the third step, a cross-comparison of multiple giga-scale facilities is performed to evaluate how differences in facility design, location, and system boundaries may influence energy consumption. The analyses in the second and third steps is based on a comparative evaluation of reported energy demand from both the peer-reviewed literature and industry sources.

For the first step, the aim is to understand how environmental impacts shift or vary depending on the scale of production. Here, LIB production at small- and large-scale (or giga-scale) is compared using the functional unit of 1 kWh theoretical cell storage capacity. The data used for giga-scale facility is compiled primarily from the environmental permit applications of a giga-scale battery cell manufacturing facility in Sweden (Northvolt, 2017a, 2017b, 2018, 2019, 2020). This data covers energy demand, cell materials, processing chemicals and other material inputs, emissions and wastes. Environmental permit applications generally represent the upper bound of permissible amounts in inflows and outflows from a factory, thus representing an upper-bound estimate in terms of assessed impacts. The small-scale facility (MWh/year) is modeled based on the production data reported in Ellingsen et al. (2014).

In the second step, the focus is on identifying scale-dependent differences in energy demand across cell production processes. For this, a review of the published literature is performed to compile data on energy consumption in LIB cell production facilities operating at various scales (lab, pilot and giga). The data for lab-scale production is based on Erakca et al. (2021), whereas the data for the pilot-scale facility is based on Thomitzek et al. (2019). The energy demand for giga-scale production is based on Article 4, which contains updated energy demand data from Article 1.

In the third step, the focus is only on the energy demand for giga-scale facilities. For this, energy demand data presented in Degen and Schütte (2022) and Knehr et al. (2024) is compared to the energy data in Article 4.

4.2.2 RQ2, primary raw material supply routes

To understand how the origin and supply chain of raw materials influence the environmental impacts of LIB production, another three-step approach is adopted. First, the cradle-to-gate impacts of LIB production are assessed in the context of different lithium supply routes using LCA. This analysis has previously been completed in Article 2 and is reproduced in Section 6.2. In the next step, other relevant battery cell materials and cell chemistries are analyzed. This is presented is Article 3 and reproduced Section 6.3. In the third step, literature published since the publication of Article 2 was reviewed to investigate additional brine-based lithium supply routes and their reported energy demand. Step three is thus additional work carried out in this thesis.

In the first step, two different starting points, each of brine and spodumene, are considered, representing varying ore quality. An LCA model is developed and the functional unit of 1 ton of battery grade $LiOH \cdot H_2O$ is used. This model is then coupled to a LIB cell production model (developed in Article 1) to understand how changes in the upstream lithium supply influence the impacts from the LIB life cycle. Data for this is based on feasibility studies and technical reports of a number of lithium mining and extraction companies. The full list of data sources is provided in Article 2.

In the second step, the analysis in Article 2 is expanded and different supply routes of other relevant battery materials such as nickel, cobalt, manganese and graphite are assessed in the context of LIB production. The full list of data sources for the supply routes assessed is presented in Article 3.

In the third step, lithium ore grades and the corresponding energy consumption associated with extraction and processing at the mine site are compiled. The aim here is to examine any possible relationship between brine grade and energy use at site.

4.2.3 RQ3, cell design

To understand how cell design influences the environmental impacts, multiple NMC cell types are compared. An LCA model is developed, and the functional unit of 1 kWh theoretical cell storage capacity is used. The cell composition related data was generated using the cell design and computation model (CCM).[4] Other flows, such as processing chemicals, emissions, wastes etc. are modeled using the environmental permit data from a battery manufacturer. This aspect

[4] Details about the CCM are provided in Section 5.1.2.

of how cell type influences the environmental impacts of production has been presented in Article 4.

4.2.4 RQ4, recycling

To understand how using secondary material can influence the environmental impacts from the LIB pack life cycle, recycling and material recovery is modeled along with LIB pack production. An LCA model is developed, and the functional unit of 1 kWh battery pack storage capacity is used. The battery pack sans the cells are modeled based on engineering judgment. The cells are modeled using the same principles as applied in Article 4, i.e., CCM and environmental permit data from battery manufacturer. Recycling and material recovery data modeled is acquired from environmental permit data as well. The aspect of how recycling and material recovery can influence the environmental impacts from the life cycle of a LIB pack is presented in Article 5.

4.2.5 RQ5, foreground system modeling

To examine different approaches to modeling the foreground system in LCAs of LIBs, the data handling procedures used in Article 1, Article 4 and Article 5 are revisited and explored in detail in Chapter 4. Further, alternate ways to model foreground system are discussed, including the pros and cons of these modeling approaches.

4.2.6 RQ6, background database

To understand how the choice of background databases can influence the results in LCA of LIB production a two-step approach is adopted. First, an LCA model representing small-scale production reported in Ellingsen et al. (2014) is replicated by remodeling the foreground system to ensure minimal deviation in LCA results using the same version of the background database as in the original study (Ecoinvent v2.2). In the next step, the same foreground system is remodeled using the latest available background database at the time (Ecoinvent v3.7.1). For this, LCA methodology is applied and the functional unit of 1 kWh of theoretical cell storage capacity is used. This work has previously been reported in Article 1 and reproduced in Section 6.1.

5 Data sources and foreground inventory modeling

The chapter presents an overview of the type of data sources, and foreground modeling approaches applied in this thesis, thus addressing RQ5. Additionally, other commonly used data sources and modeling approaches used in LCAs of LIBs are discussed with the aim of contrasting them with the approach taken in this thesis to understand their contexts and discuss the strengths and weaknesses of each of them. Although the type of data source and modeling method is not specific to LIBs, the focus in this chapter remains on the representation of LIB technology.

5.1 Data sources

LCA studies rely on data for modeling the product systems. Specifically for representing the life cycle of LIBs different approaches have been used to model the foreground system in various studies. These range from using process-simulations (Lappalainen et al., 2024; Rinne et al., 2021), machine power rating (Degen & Schütte, 2022), real time factory measurements (Erakca et al., 2021), physics-based models (Jinasena et al., 2021; Piccinno et al., 2016), machine learning based regression models (Sun et al., 2025), environmental permits or feasibility studies (Chordia et al., 2021; Chordia, Wickerts, et al., 2022) to name a few. In this thesis and the appended articles, the data sources are primarily environmental permit applications and feasibility reports. Specifically for Article 4, environmental permit data was coupled with a physics-based model which is described later in Section 5.2.6.

5.1.1 Environmental permits and feasibility reports

Environmental permits and feasibility studies present site-specific and factory-level data on material and energy flows, emissions, and waste generation. Specifically, environmental permits define thresholds for permissible emissions, waste, and material and energy inputs. In contrast, feasibility reports detail operational parameters for upcoming facilities, typically used to benchmark the economic viability of operating a facility. However, both sources generally provide precautionary estimates of material and energy use and waste generation, reflecting a compliance-oriented approach that prioritizes environmental protection and regulatory adherence.

Since these documents are not developed specifically for LCA studies, the data they contain must be carefully interpreted before being used in unit process datasets in LCA model. The most critical aspect is understanding the material and energy flows within the facility and correctly normalizing them to the unit process level. Operational parameters stated in such sources may differ from actual real-world performance, and the reported values may not reflect average operational conditions. Regardless, environmental permits and feasibility reports set a cap on energy, materials, wastes, emissions and cost with regards to the maximum allowable or planned operational performance of the facility under regulatory, technical, and economic constraints. To address the gap between real-world operations and the data in environmental;

permits and feasibility reports, it is essential to compare these sources to understand the margins and gain insights into process design.

5.1.2 Cell design and computation model

The CCM was originally presented in Chordia, Wikner, et al. (2022). The model was developed as part of an interdisciplinary effort combining LCA and battery design expertise. The CCM takes cell capacity as the starting point and calculates energy- and power-optimized versions of different cell types. The model provides two sets of data for each cell type: the first includes cell composition data, and the second comprises cell design data. Composition data includes the mass of each cell component in a fully assembled cell. Cell design data includes parameters such as electrode area and thickness, porosity, energy density, and related characteristics. This design data was used to link energy demand in cell production to specific cell design parameters, under the assumption that energy consumption in various cell production processes is associated with particular aspects of cell design. This modeling approach is explained in further detail later in Section 5.2.6.

5.1.3 Technical drawings or images

Drawings and images, when combined with technical literature, provide a valuable foundation for constructing a component-level inventory model. Engineering schematics, exploded-view diagrams, and manufacturing illustrations can offer detailed insights into the physical structure, materials, and configuration of a product or system. These visual resources help identify and quantify individual components along with their spatial relationships and assembly characteristics. When supplemented with information from technical manuals, datasheets, and peer-reviewed literature, these visuals can be translated into a comprehensive inventory list that specifies the mass, material composition, and function of each component. This approach is particularly useful when primary process data are unavailable, allowing for a bottom-up construction of inventories based on the physical design and engineering logic of the product.

5.2 Modeling approaches

There are different modeling approaches adopted in the LCA of LIBs. These approaches can be classified in several ways, one of which distinguishes between bottom-up and top-down methods. Bottom-up approaches to inventory modeling in LCA studies are typically process-specific and based on directly measured or calculated data. This method offers high granularity and precision in representing the flows to and from a process, making it particularly useful for capturing detailed environmental impacts at the unit process level. However, despite its strengths, the bottom-up approach may risk overlooking the broader context in which a specific process operates. It may fail to capture system-level interactions, feedback loops, or indirect effects that emerge when the process is integrated within a larger production system. Additionally, it may overlook statistically occurring process interruptions, operational variabilities, or anomalies that become evident only at higher scales or over longer time frames, thereby limiting its ability to represent real-world complexity. As a result, while bottom-up modeling can potentially provide deeper insights into individual processes, it may not fully reflect the environmental implications at the system or product level unless complemented by broader contextual data or modeling frameworks.

Physics-based modeling approaches represent a bottom-up modeling approach and use fundamental physical laws and equations to simulate and predict system behavior. These methods are prized for their theoretical rigor and transparency, offering a mechanistic understanding of processes by directly linking inputs such as force, energy, or mass to observable system parameters. This makes them valuable for detailed analysis, system optimization, and scale-up studies. Nevertheless, such models come with constraints. For example, their effective application often depends on access to precise system-specific data such as material properties, geometric details, and operational conditions which can be difficult to obtain or even proprietary. Moreover, real-world systems commonly exhibit non-ideal behavior, environmental variability, and equipment inefficiencies that are hard to fully capture through purely theoretical constructs. As a result, simplifying assumptions are often required, potentially limiting the accuracy, reliability, and broader applicability of the model results.

In contrast to bottom-up approaches to inventory modeling, top-down approaches are also used in LCA studies. These offer the advantage of capturing broader system-level interactions and often allow for easier data collection due to the availability of aggregated datasets. An example of a top-down approach is the use of environmental permit applications and feasibility reports, which typically provide facility-level data on material and energy inputs, emissions, and waste generation. Such data, while not process-specific, can be used to estimate average environmental performance across a facility or a site and serve as a basis for modeling when more detailed process-specific data are unavailable.

However, top-down approaches come with limitations as well. One of the primary challenges is the low resolution of data. Although low resolution of data does not automatically imply low precision, low resolution of the data can obscure the environmental performance of individual processes. Additionally, these approaches tend to rely on assumptions and generalizations about processes that may not reflect actual operational conditions. For example, as seen in the course of research carried out for this thesis, during LIB production facility-level energy use data for dry rooms may be distributed across multiple cell production processes, but without detailed sub-process data, it is difficult to allocate impacts precisely to positive and negative electrode or cell assembly. This can limit the usefulness of the results for process optimization.

When modeling specific unit processes, LCA practitioners often navigate across different levels of data granularity, i.e., highly process-specific to aggregated, and varying data quality to calculate relevant flows that provide insights into the environmental impacts LIBs. Bottom-up and top-down approaches can also be applied in combination to model a unit process, as demonstrated in several of the articles appended to this thesis, particularly in Article 4. To further elucidate these challenges of bottom-up and top-down approaches, the two are further discussed with examples below.

5.2.1 Bottom-up approach: Deriving a generic equation

This approach is based on modeling a "generic" unit process. In the context of an LCA, particularly during the cell design phase, data from several similar production processes can be used to develop a generic equation that links energy consumption in production to a specific cell design parameter. For example, the energy consumption in the coating step where active material slurry is applied to a metal foil can be approximated as a function of slurry viscosity. By collecting data from multiple cases where electricity consumption is recorded for different viscosity samples, a generic equation for energy consumption can be derived. This equation can then be used to estimate the energy demand for a cell design specification for which direct data is not available. Although the resulting equation will represent a generic coating process, it can still be suitable for use in LCA studies. A key limitation of this approach, however, is that deriving a robust generic equation requires a substantial number of data points, which are not readily available in open-source literature for LIBs.

5.2.2 Bottom-up approach: Parameter scaling

In this approach, an assumption is made that, within a certain limit, the calculated dependent variable varies linearly with the input variable. For example, the energy consumption (dependent variable) of a specific cell production process, such as coating, can be assumed to scale linearly with a cell design parameter like electrode area. Such assumptions are commonly applied in LCA studies, particularly in the modeling of background or foreground systems, where all inflows and outflows of a unit process are assumed to vary proportionally with the reference flow. The advantage of this method is that it does not require a large number of data points to derive a generic equation, which is often a cumbersome task during the inventory data collection and modeling phase of LCA. Although simplified, this approach can still be reasonably used to estimate energy consumption for given processes by extrapolating data from other similar production processes. An example equation is shown below:

$$E_2 = \frac{A_2}{A_1} \times E_1$$

Here, E_1 represents the energy consumption for coating an electrode with area A_1, and A_2 is the area of the electrode for which the energy consumption E_2 needs to be estimated. A similar approach to parameterized inventory modeling has previously been proposed by Mueller et al. (2004), where unit process flows are calculated by linking design parameters, such as torque to mass of the motor. This method enables the construction of generic models for estimating flows, allowing for approximate but quantitative LCA, which particularly useful in early design phases.

5.2.3 Bottom-up approach: Physics-based equations

A representative example of a physics-based bottom-up modeling approach is the estimation of energy demand for mixing as provided in Piccinno et al. (2016), which could be applied to model electrode slurry mixing in LIB production for example. This method uses fundamental physical equations to relate mechanical power input to parameters such as impeller speed, diameter, mixture density, and mixing time. While this approach is theoretically robust and allows for detailed energy modeling, it also presents significant practical challenges. Accurate values for key parameters – such as slurry viscosity, impeller geometry, and operational settings – are often proprietary or vary across production lines. Moreover, real-world conditions, including batch size, temperature, and equipment efficiency, introduce variability that is difficult to capture. These limitations necessitate assumptions and approximations, which can affect the reliability and generalizability of the modeled energy demand. An equation used by Piccinno et al. (2016) to calculate the energy consumption (E) in mixing/stirring is shown as an example.

$$E = \frac{N_P \times \rho_{mix} \times N^3 \times d^5 \times t}{\eta_{Stir}}$$

Here, N_P is the impeller-specific dimensionless power number, ρ_{mix} is the fluid density, N is the rotational speed, d is the impeller diameter, t is the mixing time, and η_{stir} is the stirring efficiency. Piccinno et al. (2016)'s approach allows for detailed modeling of energy use based on physical parameters. However, it also presents several challenges as it requires detailed knowledge of equipment specifications, fluid properties, and operational conditions. It can be noted that changes in design parameters like impeller diameter (d) significantly affect the results due to the fifth-power relationship, adding uncertainty to this approach.

5.2.4 Bottom-up approach: Visual and technical modeling

In this approach, detailed images supplemented with technical datasheets of a LIB pack is used to model the mass composition of the components. Note that this type of information does not assist in modeling the production related aspects and that needs to be added to the model. This approach was taken to model the LIB pack in Article 5. Shown in Figure 5-1 (left) is an exploded view of a LIB pack, highlighting some of its key components. The technical specifications of the battery pack obtained from an original company website and other websites such as Batterydesign.net are used to extract data about the pack and the cells. This information is used to recreate a battery pack inventory. Previously published LCA of a LIB pack (Ellingsen et al., 2022) was used for benchmarking a bare minimum list of components and where deemed necessary, inventory for some components not clearly presented in the images were used to incorporate into the LIB model in Article 5. A simplified version of the entire battery pack is shown in Figure 5-1 (right). Similarly, Figure 5-2 represents the exploded view of a module and on the right is the simplified representation for modeling in LCA.

Drawings and images, when combined with technical literature, provide a valuable foundation for constructing a component-level inventory model. Engineering schematics, exploded-view diagrams, and manufacturing illustrations can offer detailed insights into the physical structure, materials, and configuration of a product or system. These visual resources help identify and quantify individual components along with their spatial relationships and assembly characteristics. When supplemented with information from technical manuals, datasheets, and peer-reviewed literature, these visuals can be translated into a comprehensive inventory list that specifies the mass, material composition, and function of each component. This approach is particularly useful when primary process data are unavailable, allowing for a bottom-up construction of inventories based on the physical design and engineering logic of the product.

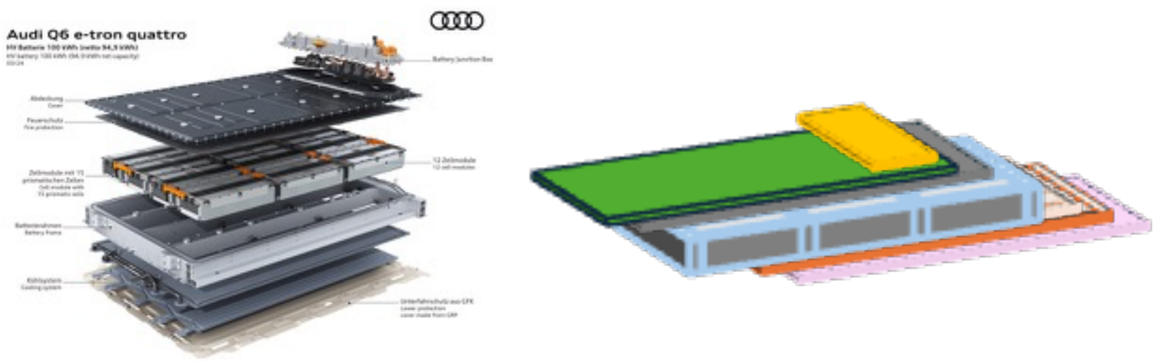

Figure 5-1: (Left) An exploded view of a LIB pack highlighting its relevant components (AUDI, 2025). (Right) A simplified representation of the LIB pack.

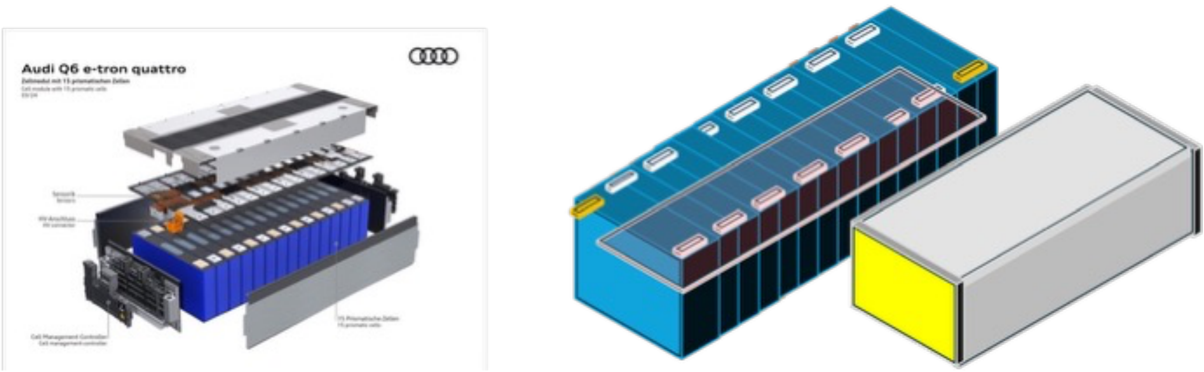

Figure 5-2: (Left) An exploded view of a LIB pack module highlighting its relevant components (AUDI, 2025). (Right) Simplified representation of the internal part of a module and the outer casing.

5.2.5 Top-down approach: Scaling factory level data to unit-process

Top-down modeling in LCA typically relies on aggregated data derived from environmental permits, feasibility studies, technical reports, and similar sources. In this thesis, such documents serve as key inputs for constructing the LCA model. These data sources generally provide facility-level information on material and energy inputs, as well as outputs in the form of products, emissions, and waste streams. To make this information compatible with unit process modeling in LCA, it must be scaled or normalized to the reference flow of the relevant process. The method of normalization depends on the goal of the study. If the objective is to evaluate environmental impacts at the facility level, the aggregated data can be directly normalized by the total facility throughput, assuming a single product type is manufactured. This effectively condenses the entire facility into a single representative unit process. While this approach enables rapid modeling, it limits insight into specific production stages. For instance, if a facility reports its total annual electricity consumption and the total storage capacity produced (e.g., in Wh per cell), the average energy demand per unit of storage capacity can be calculated by dividing the former by the latter. However, this method obscures process-level differences and operational inefficiencies, particularly when multiple cell types are produced at the same site. Alternatively, if the LCA seeks to assess environmental impacts at the level of individual processes, the facility-wide data must be disaggregated. This involves normalizing aggregated values by the reference flow of each specific unit process, using throughput data where available.

The assumption that a facility produces only a single cell type is an oversimplification that can obscure important differences in environmental impacts across cell types. More specifically, it limits understanding of how production processes vary depending on the design and performance characteristics of different cells. In attributional LCA, this challenge – commonly referred to as the problem of co-production – is addressed through allocation. This involves partitioning the total environmental burden among co-products based on predefined criteria such as mass, energy content, or economic value. The credibility of the resulting impact estimates depends heavily on the appropriateness and transparency of the chosen allocation method.

Additional challenges in top-down modeling include temporal variability, data confidentiality, and limited transparency in reporting. Despite these limitations, top-down normalization remains a practical approach when detailed bottom-up data are unavailable. Moreover, it can be effectively combined with bottom-up data to enhance the completeness and consistency of the overall LCA model, as demonstrated in Article 4 and further discussed in the following Section 5.2.6.

5.2.6 Combining bottom-up and top-down approach

One of the motivations for combining bottom-up and top-down approaches is to circumvent the challenges associated with co-production and the need for allocation. To enable this, a key simplification is made: the facility is assumed to produce a single cell type. As discussed in the previous section, this assumption limits the ability to differentiate between cell types and their associated environmental impacts. To address this limitation, cell-specific data are used to normalize factory-level inputs more accurately. An exampple of how bottom-up and top-down approaches can be integrated to construct unit process models is shown in Article 4. Application of this methology is used to address RQ5 and is dicussed in detail in Section 6.4.

6 Results

This chapter presents a summary of the main results of the thesis. Each sub-section specifies the research question being addressed and indicates the corresponding article from which the results are drawn. Where applicable, additional analyses conducted to complement the findings reported in the articles are also highlighted.

6.1 Article 1: Upscaling LIB production

The results presented in Article 1 address RQ1 and RQ6 of this thesis. The primary objective of the article is to investigate the environmental implications of upscaling LIB production. To achieve this, the environmental impacts of LIB production in a small-scale facility (MWh per year) are compared with those from a large-scale production facility (GWh per year). A secondary objective is to examine how changes in the background system database used in the LCA model influence the overall environmental impacts of a product system. For this purpose, the small-scale production facility is modeled using two versions of the Ecoinvent database (v2.2 and v3.7.1), and the differences in the results are analyzed to identify the causes of variation in impact assessment outcomes.

The small-scale facility, originally reported in Ellingsen et al. (2014), is modeled using Ecoinvent v2.2. This study is selected as it presents a coherent and transparent inventory data. The data for the large-scale facility is collected from Northvolt AB and modeled using Ecoinvent v3.7.1. To isolate database effects, the small-scale facility is first replicated in v2.2 with less than 0.2% deviation in climate impacts, a minor discrepancy attributed to truncation errors. The same model is then updated to v3.7.1. The climate impacts of the small-scale facility increased by 30% compared model based on v2.2. These results are shown in Figure 6-1. The main driver for this increase is an update of the cobalt sulfate data although, other product materials, chemicals and energy input too result in a change in climate impacts calculated with the Ecoinvent v3.7.1

The cobalt sulfate production data used by Ellingsen et al. (2014) is based on inventory data published by Majeau-Bettez et al. (2011), who, in turn had modelled cobalt sulfate production by adjusting the inventories for primary cobalt metal in Ecoinvent v2.2 with stoichiometric calculations for the sulfate solution. Looking further back, the Ecoinvent v2.2 database relies on production routes aggregated according to their market share in 1994. In Article 1, the production of cobalt sulfate is modelled with new primary data from a refinery in Canada (Ausenco, 2020), with cobalt hydroxide as input. The cobalt hydroxide production data in Ecoinvent v3.7.1 represents an industry average covering 30% of the world production of refined cobalt in 2012 (CDI, 2016).

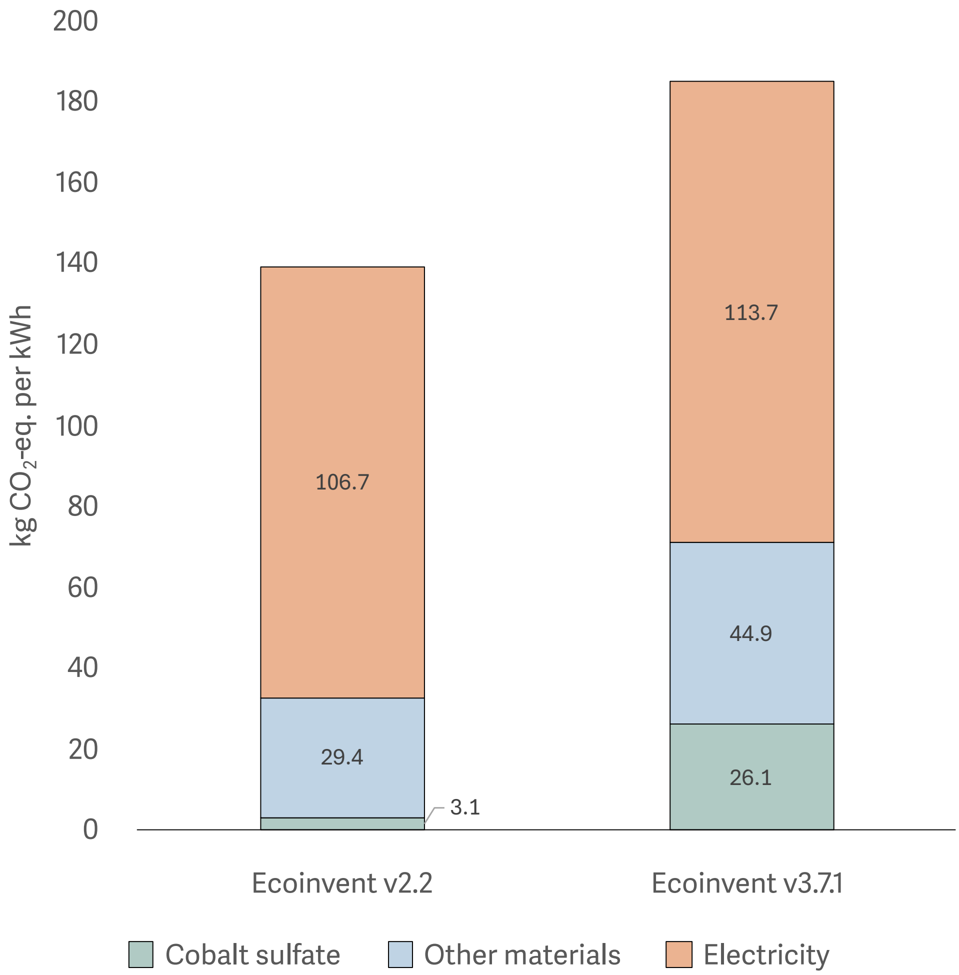

Figure 6-1: Climate impacts of small-scale LIB production modeled using different versions of the Ecoinvent database. The values are shown in the figure to exemplify the effect of updates in the background system database.

The climate impacts of small- and large-scale LIB production are compared in high-carbon and low-carbon energy scenarios. The high-carbon scenario is represented by the South Korean electricity mix, whereas the low-carbon scenario is represented by the Swedish electricity mix. When comparing the small-scale and large-scale LIB production facilities, modeled using Ecoinvent v3.7.1, the climate change impacts for large-scale production are nearly 40% lower under a high-carbon energy mix. When the large-scale model is coupled with a low-carbon energy mix, the climate impacts are reduced by nearly half compared to the high-carbon scenario. These results underscore the environmental advantages of scaling up LIB production. Large-scale facilities typically operate continuously with minimal interruptions, which enhances the efficient use of infrastructure and reduces material and energy losses associated with process machinery. Furthermore, sourcing electricity from low-carbon energy systems significantly amplifies the climate benefits of industrial scale production. These results are shown in Figure 6-2.

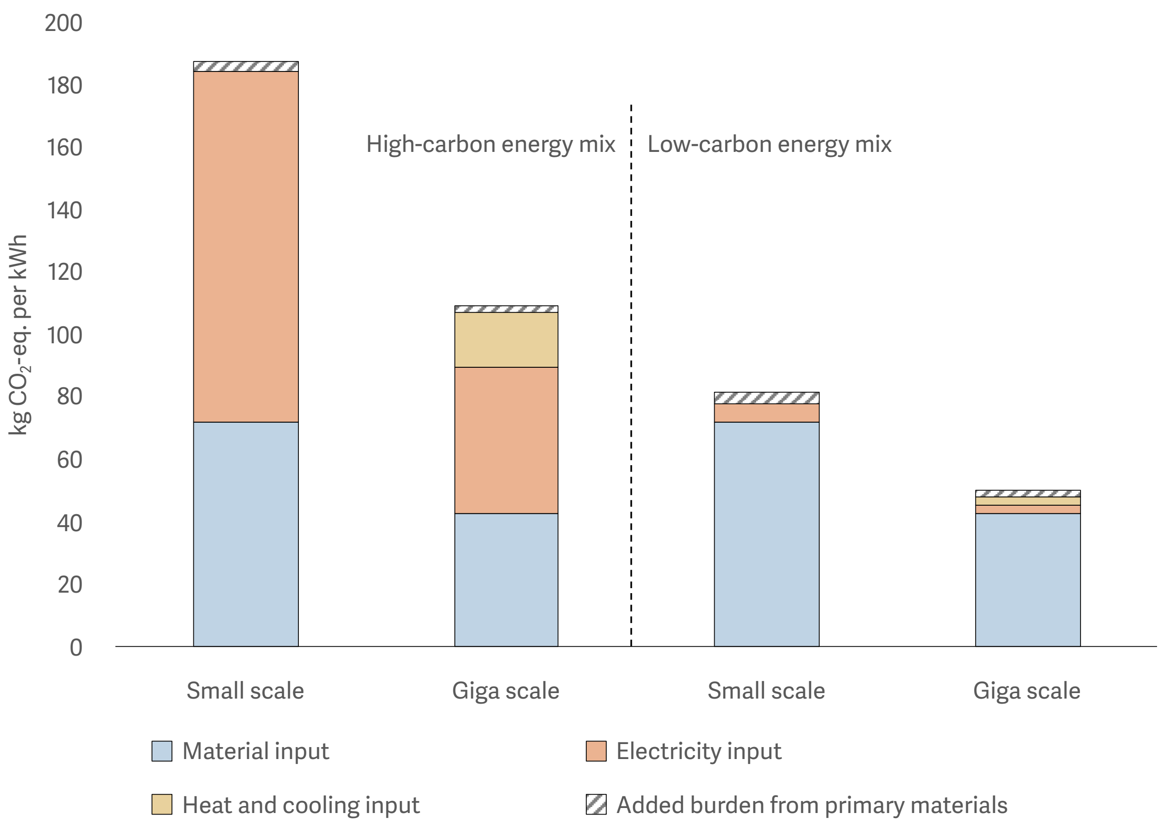

Figure 6-2: Climate impacts of large-scale LIB modeled using high-carbon and low-carbon intensity energy scenarios.

As production impacts from large-scale facilities decreased, the environmental burden increasingly shifted upstream to raw material extraction and processing. However, further analysis reveals that the data quality for several battery-relevant raw materials in the background system is inadequate. For example, the nickel and cobalt datasets relied on industry averages reported by the Nickel Institute and the Cobalt Development Institute. While average industry data are practical, offering a sector-wide representation of typical performance and supporting macro-level analyses, policy evaluations, and benchmarking studies, they also entail methodological limitations. Such averages enhance comparability across studies and ease data collection when site-specific or proprietary data are unavailable, but they may obscure variability and site-specific impacts. This limitation is particularly relevant for battery assessments, as reliance on aggregated data can underestimate the environmental consequences of sourcing from regions with higher-impact production routes.

However, reliance on average data also introduces significant drawbacks as it obscures technological variability, regional differences, and site- or process-specific operational characteristics, potentially leading to oversimplified or misleading conclusions. Lastly, the lithium production datasets in Ecoinvent are found to be particularly insufficient, lacking key energy-intensive processing steps and failing to represent the final product quality used in battery cells accurately. This knowledge gap hindered a deeper understanding of the LIB supply chain and directly motivated the research questions explored in Article 2, which focuses exclusively on the lithium supply chain. Furthermore, as production scales from laboratory to pilot and eventually to industrial levels, the underlying processes also evolve to accommodate larger material flows. While it is often assumed that technologies used at small-scale can be directly scaled up, precise information about individual processes is required to validate this assumption. Such process-specific comparison is not possible for Article 1 due to unavailability of the production data for the small-scale production facility at such granular level. However, since the publication of Article 1, additional data on how specific processes may scale has become available and is analyzed in this thesis under Section 6.1.1.

Resource use impacts, as assessed using both the CSI and the SOP method, consistently indicate the scarcity of key active materials such as nickel, cobalt, and lithium (Figure 6-3). In addition, CSI highlights long-term scarcity risks associated with copper – an especially important finding given copper's critical role across multiple industrial sectors. Metal mining typically involves the co-extraction of several elements, depending on ore composition. This introduces a methodological challenge in LCA, as the environmental burdens associated with extraction and refining must be allocated across all co-products derived from the same ore. In attributional LCA, this challenge is addressed through partitioning, where inputs and emissions, such as energy use, raw material consumption, chemical inputs, waste, and emissions, are allocated to co-products based on defined criteria, most commonly mass or economic value (Ekvall, 2019). Consequently, environmental burdens are shared across all outputs of a process, often obscuring the true resource intensity of individual metals. A practical example of this issue is found in the production of nickel sulfate, which also yields cobalt as a co-product. As a result, a portion of the environmental burdens associated with cobalt extraction – including the depletion of in-ground resources – is attributed to nickel sulfate, and vice versa. Since cobalt has a significantly higher crustal scarcity potential (CSP) than nickel, the burdens transferred to nickel sulfate raise its apparent resource impact. Conversely, cobalt appears to have lower resource use impacts due to the partial attribution of burdens to nickel, which carries a lower CSP. Thus, the choice of allocation method complicates the interpretation of LCA results, particularly in the context of mineral extraction.

A similar issue arises with copper, widely used in battery components such as foils, and often co-mined with cobalt and nickel (CDI, 2016). As a result, components rich in nickel and copper tend to exhibit elevated resource use impacts, while cobalt-containing components may appear to have lower-than-expected impacts due to the influence of allocation rules. These patterns underscore the limitations of attributional modeling in capturing long-term scarcity risks especially for copper which has signifiance beyond battery applications (Kerr, 2014).

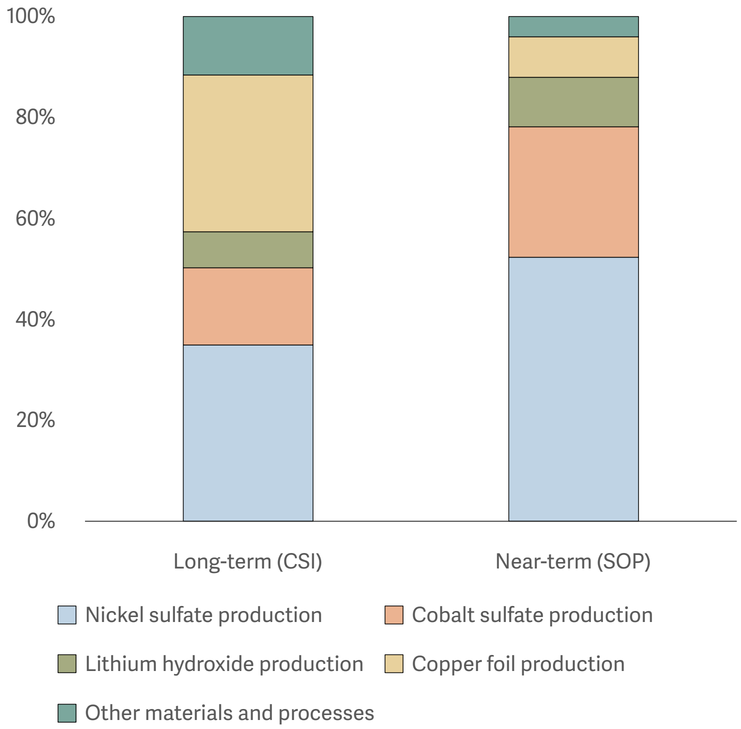

Figure 6-3: Long-term and near-term resource scarcity impacts from LIB production. CSI (crustal scarcity indicator), SOP (surplus ore potential).

6.1.1 Comparison of energy demand at various scale of production

Table 6-1 presents energy consumption data for LIB cell production across, lab-, pilot-, and industrial-scale. The lab-scale data is originally reported by Erakca et al. (2021), the pilot-scale data by Thomitzek et al. (2019), and the industrial-scale data is based on Article 4. The table compares energy consumption across various cell production processes and normalizes total energy consumption per kilowatt-hour (kWh) of theoretical cell storage capacity. This comparison clearly illustrates the efficiency gains achieved through production scale-up.

Several trends emerge from the data summarized in the table. First, dry room operation as well as electrode coating and drying process consistently ranks among the most energy-intensive processes, regardless of production scale. Cell formation, aging, and testing also exhibit high energy demands. However, comparing this step across studies is challenging due to variations in scope of how the formation process is defined. For example, how many charge-discharge cycles are included, whether cell testing is included, whether the energy is recovered from the discharge cycles or not, etc. Without detailed process specifications, direct comparisons remain limited at this point. At smaller scales, usually dry rooms tend to be oversized, which explains their disproportionately high energy consumption. This inefficiency diminishes considerably at the industrial scale, where dry room operations are more optimized and operated at higher throughput.

Table 6-1: Energy consumption at different scales of LIB production. The color coding is per column.

Cell production process	Lab Electricity	Pilot Electricity	Industrial Electricity	Industrial Cooling
NMC hydroxide production	-	-	0.7	1.9
CAM production, calcination	-	-	3.8	0.3
CAM production, other processes	-	-	4.8	0.4
Electrode production, slurry mixing	-	11.3	2.7	2.2
Electrode production, NMP refining	-	-	0.03	0.2
Electrode production, coating &drying	32.6	142.3	15.5	11.9
Electrode production, calendaring	11.8	22.1	2.0	0.3
Electrode production, slitting/notching	-	0.1	0.7	0.1
Electrode production, vacuum drying	7.0	6.4	0.7	1.3
Cell container manufacturing	-	-	0.7	-
Electrolyte mixing	-	-	0.1	-
Cell assembly, electrolyte feeding	5.5	9.2	0.01	0.04
Cell assembly, winding/stacking	-	1.3	3.0	-
Cell assembly, housing	9.3	0.7	3.4	-
Cell formation, aging and testing	42.8	120.5	9.4	-
Dry room	1360.4	448.7	5.8	5.2
Wastewater treatment	-	-	3.1	3.0
Factory operations and utilities	-	-	5.8	2.9
Total (kWh/kWh_{cell})	1469	763	62	30

Another important observation from Table 6-1 concerns the overall scope of production included at each scale. Processes such as PAM production, NMP recovery and refining, cell container manufacturing, and electrolyte mixing are typically excluded at lab- and pilot-scales. This likely reflects differences in operational requirements for smaller facilities compared to industrial-scale facilities that often integrate raw material processing on-site. It is quite likely that smaller facilities procure pre-processed materials such as NMC precursors, electrolytes, and cell containers directly from suppliers. NMP is an expensive chemical and also toxic and cannot be released into the atmosphere. At large-scale production, its waste is avoided through recovery and refining systems are installed to ensure the least possible leakages of NMP into air. At the industrial-scale, support functions such as wastewater treatment and facility operations also contribute notably to total energy consumption. These are generally omitted at smaller scales, yet their inclusion at scale provides valuable insights for the optimal design of large-scale production systems and their share in the overall energy consumption in the facility. Finally, energy use during electrode production varies across scales, but limited data on equipment and methods makes it difficult to attribute these differences. Likely factors include equipment type, process integration, and efficiency, though these are not explicit in the table.

6.2 Article 2: Lithium supply chain

The results presented from Article 2 address RQ2 of this thesis. The primary objective of the article is to investigate various supply routes for lithium, and to understand how the choice of different supply routes could influence the environmental impacts of large-scale LIB production. Lithium is typically sourced from spodumene or brine-based deposits. Among these, brine-based lithium production has been associated with freshwater stress in the regions where extraction occurs (Flexer et al., 2018; Giglio, 2021). Therefore, a secondary objective of Article 2 is to examine the water use implications of brine-based supply routes.

Due to limited availability of unique data sources in the literature on lithium extraction, the first step involved collecting data that represented different supply routes. Building on the approach used in Article 1, where data for large-scale LIB production was obtained from environmental permit applications and technical reports, a similar strategy was adopted for Article 2. The key difference was that the focus shifted to lithium mining and production sites. This effort resulted in the development of four unique datasets, two each for brine and spodumene-based supply routes, representing both current and upcoming (future) lithium production supply routes. Each of these newly developed datasets was integrated into the large-scale LIB production model from Article 1 to assess how the source of lithium affects the overall environmental impacts. In addition, various water use indicators were applied to evaluate water stress, particularly for brine-based routes, given the concerns outlined earlier. For water use results see Article 2.

To enable meaningful comparisons with existing datasets, several preparatory steps are undertaken. First, the most recent Ecoinvent dataset for lithium extraction and production was adapted by removing market processes and directly linking supply chains, thereby aligning it methodologically with the other modeled supply routes for which site-specific data was collected. A detailed description of these modifications is provided in the supporting information of Article 2 (Sections 2.1.1 and 2.2.1). In addition, the brine- and spodumene-based lithium supply datasets from Kelly et al. (2021) were re-modeled using Ecoinvent v3.8 to ensure consistency across all modeled datasets. Figure 6-4 presents the climate change impacts for all assessed lithium supply routes. Among the brine-based pathways, lower-quality brines exhibited higher environmental impacts. This can be attributed to the increased energy demand required to extract the same quantity of LiOH from aquifers with lower lithium concentrations. In contrast, the spodumene-based supply routes did not display a clear correlation between ore grade and environmental impact. Notably, two Australian sites with relatively high ore grades (1.9% and 0.8%) showed significantly higher impacts compared to sites in Canada and Finland with lower ore grades (0.7% and 0.6%, respectively). The primary driver of these differences was the reliance on diesel-based electricity generation at the Australian sites, whereas the Canadian and Finnish sites benefitted from electricity mixes with high shares of renewable energy. This observation highlights the importance of site-specific energy supply in the environmental impacts of lithium extraction.

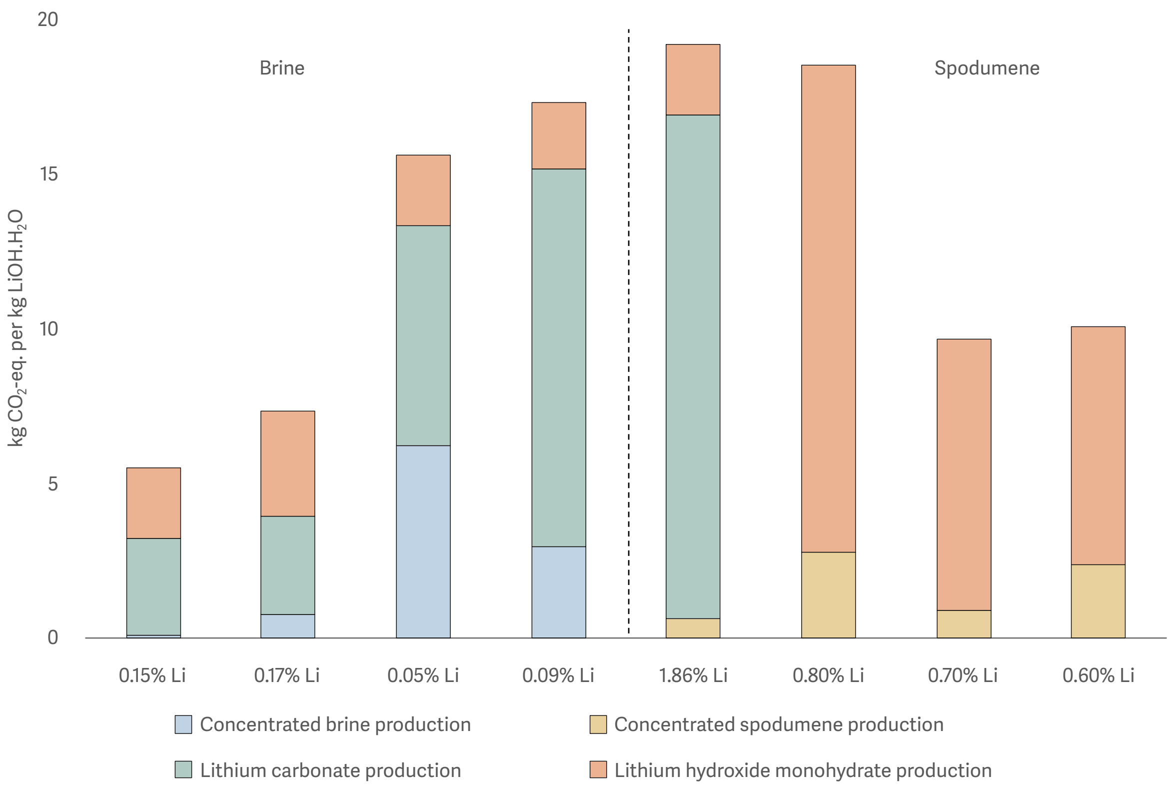

Figure 6-4: Climate impacts of producing $LiOH \cdot H_2O$ from different sources and ore grade

Overall, the most carbon-intensive supply chains are found to have climate impacts up to 3.5 times higher than those of the least impactful routes, underscoring the considerable variability in environmental performance depending on resource origin, ore grade, and energy supply characteristics. When these supply routes are coupled with the large-scale LIB production model, the choice of lithium source accounted for between 5 and 15% of the total environmental impacts. These findings are shown in Figure 6-5 and underscore the importance of supply chain considerations in the context of LIB production. The notable variation in environmental impacts due to lithium supply highlighted the need to assess other key battery materials to determine how supply chain characteristics influence the overall environmental footprint of battery production. This realization formed the basis for the research questions addressed in Article 3.

Finally, to reflect the growing body of work in the field of environmental assessment of lithium supply chains, additional literature published since Article 2 has been reviewed and summarized in Section 6.2.1.

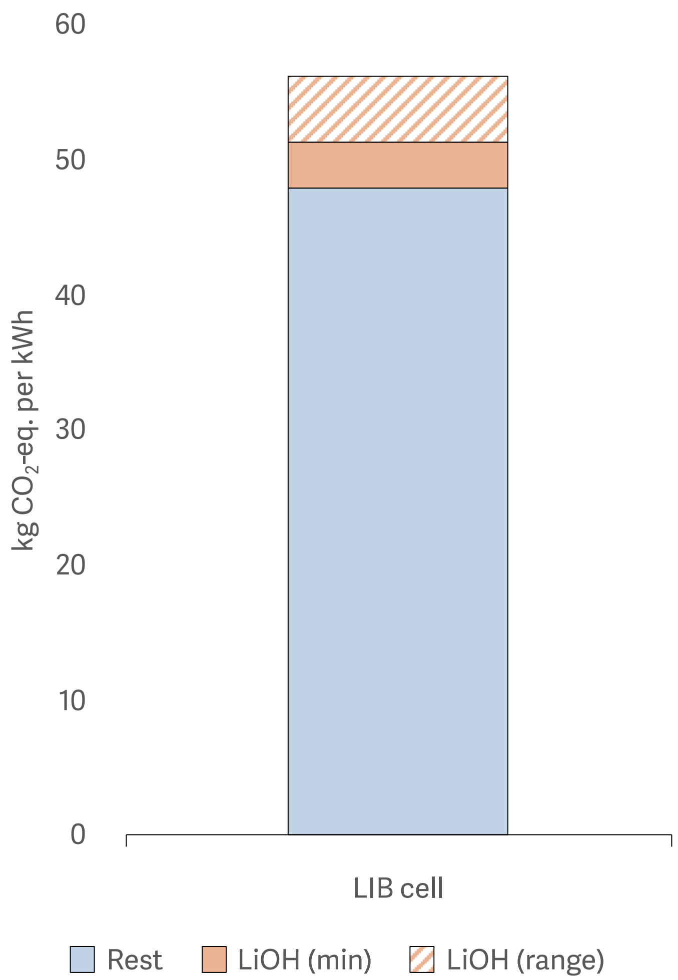

Figure 6-5: Climate impacts from LIB cell production in the context of lithium supply routes.

6.2.1 Correlation between brine grade and electricity demand

As a follow-up to Article 2 and to further investigate the relationship between brine grade and energy demand, additional literature sources (He et al., 2025; Mas-Fons et al., 2024; Mousavinezhad et al., 2024; Schenker et al., 2022; Schenker & Pfister, 2025) reporting lithium extraction from brine were analyzed. Figure 6-6 presents site-level electricity demand as a function of the initial lithium concentration in the brine. The observed trend indicates that as brine quality decreases, the on-site electricity consumption for lithium extraction and processing tends to increase. This analysis highlights two key insights. First, lower-grade brines are associated with higher energy requirements. Second, the quality of brine is likely to decline over time due to dilution from adjacent freshwater aquifers. As brine reservoirs are exploited, continued extraction may draw in surrounding freshwater, reducing lithium concentration and necessitating the processing of larger volumes of brine to yield the same amount of lithium chemical. This suggests that energy demand at individual brine extraction sites may increase over time as a consequence of declining brine quality.

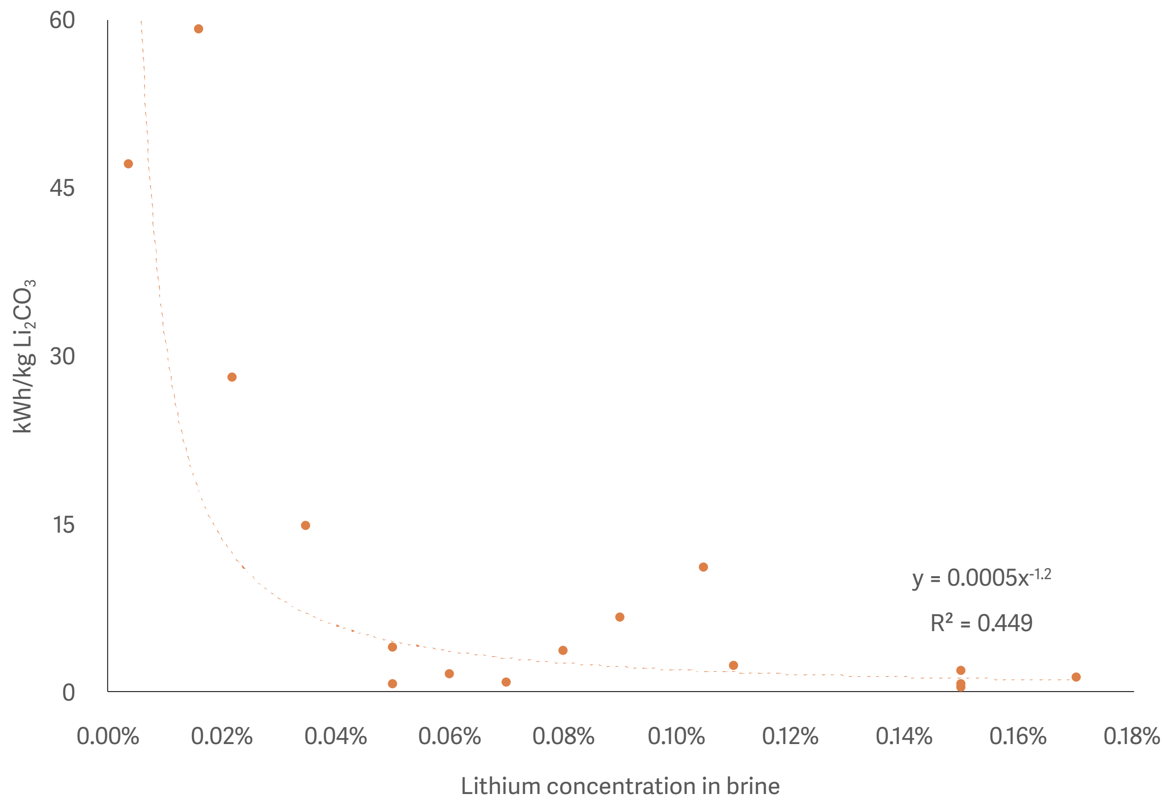

Figure 6-6: Electricity input based on the original lithium concentration in brine.

6.3 Article 3: Global LIB supply chain

The results presented from Article 3 address RQ2 of this thesis. While Article 2 focused exclusively on lithium supply routes and NMC811 chemistry, Article 3 expands the scope to include additional relevant LIB materials and other LIB chemistries. It also accounts for differences in energy requirements during cell production based on factors such as scale, cell type, and technology. For this article, data from peer-reviewed articles and gray literature on various battery materials were compiled to develop a high-level understanding of the range of environmental impacts associated with different supply chains. The heterogeneity in the climate impacts associated with the material supply chain is shown in Figure 6-7. In addition, several LCA studies on large-scale LIB production are reviewed to link supply chain impacts with reported ranges of energy consumption in large-scale LIB cell production. The findings of Article 3 reveal that the climate impacts of LIBs can vary considerably depending on material supply chain and LIB production location. For example, the cradle-to-gate emissions can differ by a factor of four due to variations in extraction methods, refining processes, and electricity grid emissions. Impacts from the upstream phase are likely to increase over time due to production from lower quality ore grades, which raises the energy and chemical expenditure per unit of product extracted or produced.

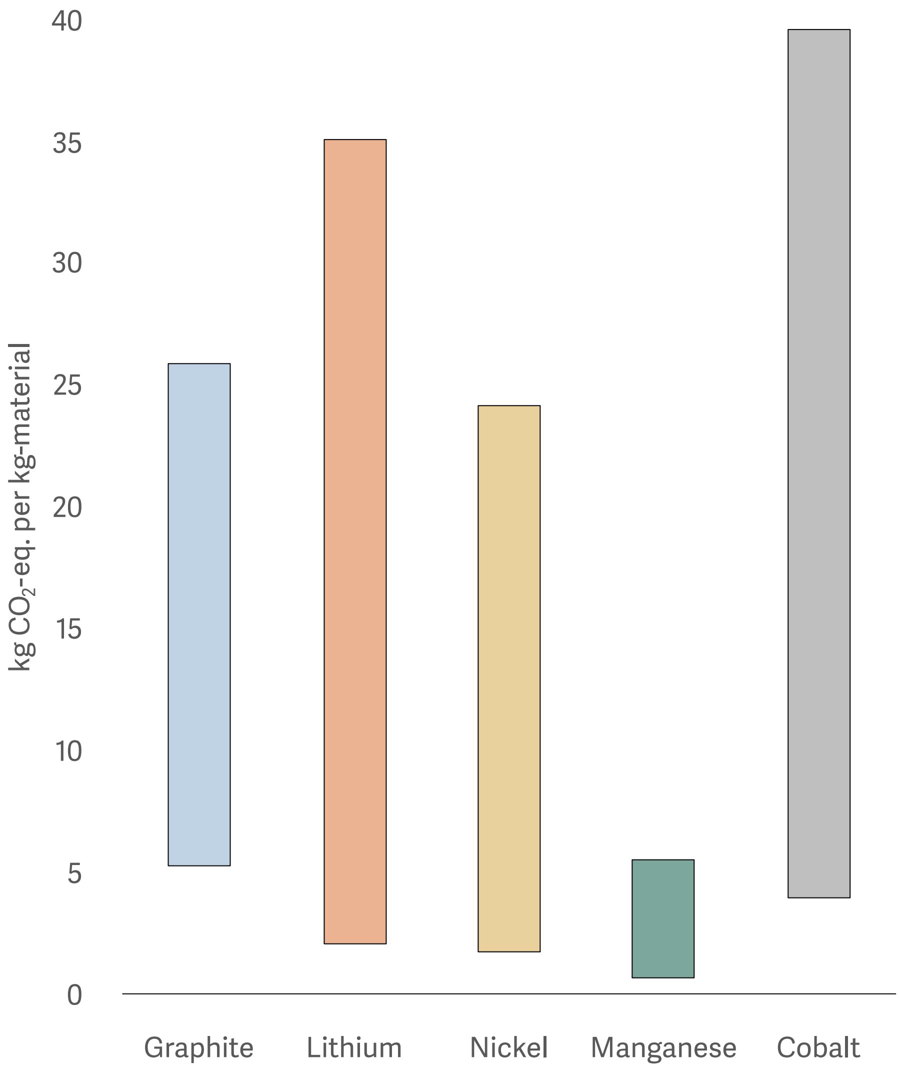

Figure 6-7: Heterogeneity in the supply chain of raw materials used in LIBs.

Further, specific production routes also play a critical role, for instance Chinese provinces such as Sichuan and Yunnan demonstrate lower climate impacts from battery manufacturing than several sites in Europe and North America. This finding challenges the prevailing assumption that relocating battery production to Europe or North America inherently leads to lower greenhouse gas emissions. In fact, manufacturing in regions such as Kentucky (United States) and Poland (Europe) can result in higher carbon footprints compared to production in some Chinese provinces (Figure 6-8). This highlights the importance of prioritizing low-carbon energy sources and sustainable material sourcing, rather than relying solely on geographic relocation. Furthermore, energy consumption for LIB production varies, ranging from 40 to 80 kWh per kWh of cell capacity. These differences stem from production scale, cell technology, and geography. The wide variation highlights gaps in understanding and reporting energy use in LIB manufacturing, which motivated the research questions for Article 4.

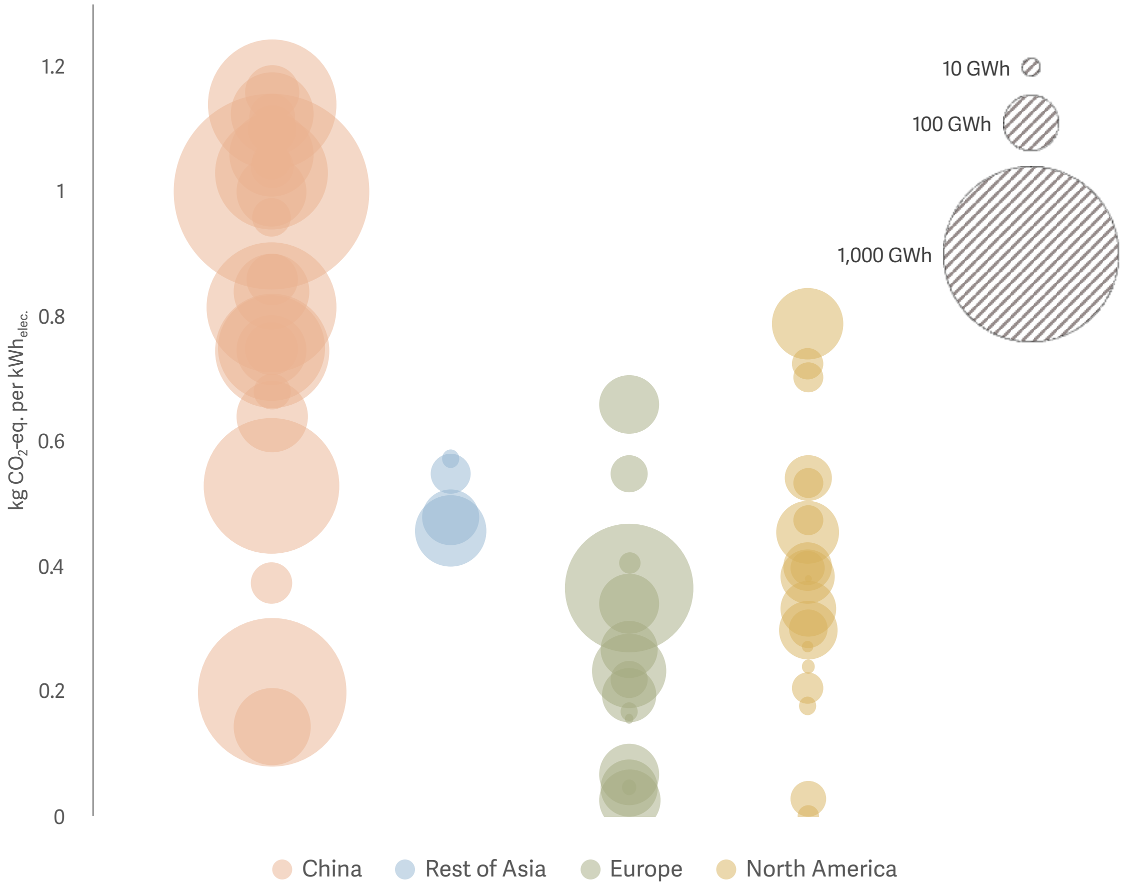

Figure 6-8: CO2-eq. emission factor and the total LIB production capacity at various locations

6.4 Article 4: Cell design and parameterization

The results from Article 4 address RQ3, focusing on how cell design influences energy use and climate impacts in LIB cell production. The analysis covered multiple cell types, capturing variations in form factor, PAM chemistry, and internal design, with both power- and energy-optimized variants examined. The article also introduces a parameterization methodology that combines bottom-up and top-down data handling for modeling the foreground system in LCA, contributing to RQ5. As outlined in Section 5.2.6, cell composition and design parameters from the CCM represent bottom-up data, while gigafactory permit data exemplify top-down inputs. Sub-section 6.4.1 presents the equations linking bottom-up and top-down data, while sub-section 6.4.2 explores the broader implications of different foreground inventory modeling approaches by comparing three gigafactories.

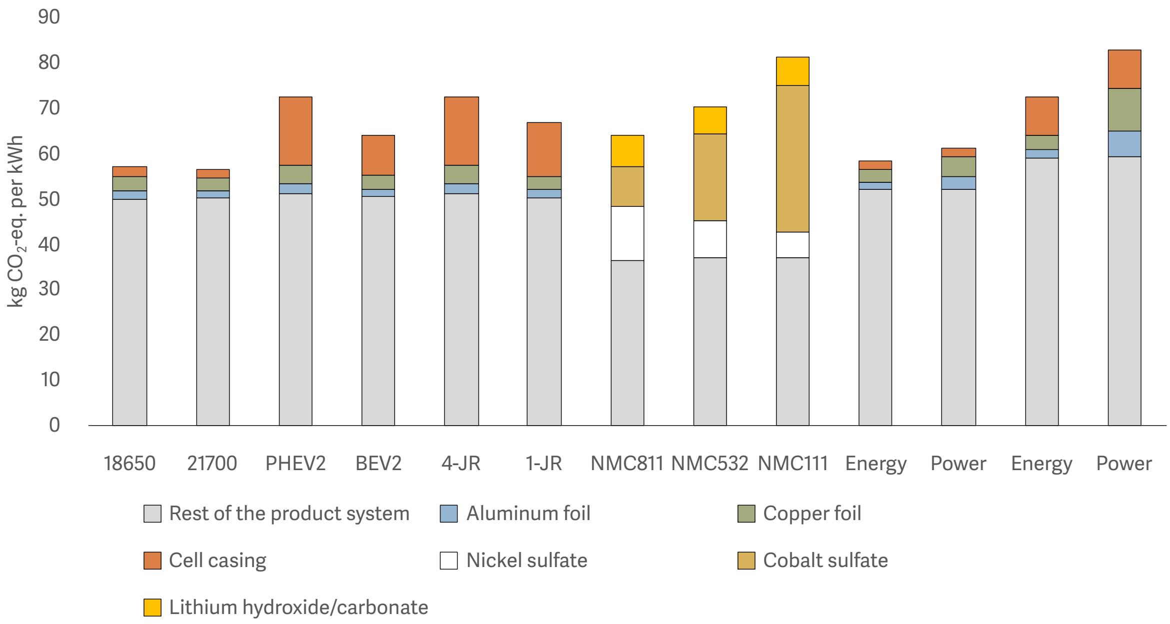

Figure 6-9: Climate impacts of cell design. The design aspects covered include, cell size, internal design (jelly rolls), PAM chemistry, and optimization (energy vs. power). The PHEV2 cell under cell size has a 4 jelly roll internal design.

When comparing the environmental impacts of producing different LIB cells, the results are normalized to a functional unit of 1 kWh of theoretical cell storage capacity (Figure 6-9). Due to its size, the PHEV2 cell exhibits the highest environmental impacts among the compared cells, linked primarily due to the production of its casing. It also has the lowest volumetric efficiency amongst the cell types analyzed. For cylindrical cells (21700 and 18650), the casing is modeled using stainless steel. Assuming typical global GHG emission factors for aluminum were used instead, the climate impacts from casing production would increase.

Internal cell design also affects climate impacts. This is evident in the comparison between single and four jelly-roll PHEV2 cells. The single jelly-roll variant has an energy density of 506 Wh/L and a total energy capacity of 180 Wh, while the four jelly-roll version delivers 390 Wh/L and 140 Wh. The single jelly-roll cell has lower production impacts, largely due to reduced casing material requirements per kWh storage capacity. Although differences in foil and active material production also contribute, their influence is less pronounced. These findings underscore the importance of volumetric efficiency in internal cell design. To assess the impact of PAM chemistry, BEV2 cells with varying compositions (NMC111, NMC532, NMC811) were compared. Results show that reducing cobalt content (or increasing the relative share of nickel) lowers climate impacts. This is attributed to the higher per-unit production impacts of battery-grade cobalt sulfate compared to nickel sulfate. Finally, the study compared cells based on its optimization type. Across all formats and chemistries, power-optimized cells exhibit higher climate impacts than energy-optimized cells, despite similar production energy demands. Power-optimized cells are designed for higher power density and therefore use thinner electrodes and larger electrode surface areas to achieve comparable capacity. This design requires more current collector material, i.e., aluminum for PE and copper for NE, thus resulting in greater climate impacts. The article presents a wide range of energy demands at the cell level, with electricity consumption varying from 1 to 30 kWh per cell and cooling energy requirements ranging from 1.6 to 49 MJ per cell, depending on the specific cell design. This variability is primarily due to differences in cell size and internal components. Notably, energy and power-optimized versions of the same cell type exhibit similar production energy demands. When normalized by storage capacity (per kWh), electricity demand during production is approximately 65 kWh/kWh, while cooling energy demand is around 107 MJ/kWh across all cell types.

6.4.1 Combining bottom-up and top-down approaches to model foreground system

A representation of the parameterization methodology linking bottom-up modeling to top-down modeling is presented in Article 4. The following steps present the data and the calculation steps used to develop the foreground inventory model.

Data:

- Adjusted normal running power of the machine (P_N), from the environmental permit report.
- Annual production capacity of the factory (S) (GWh/year), from the environmental permit report.
- Cell energy (E_{Cell}) (Wh/cell), from the CCM
- Positive or negative electrode area per cell ($a_{PE/NE}$) (m^2/cell), from the CCM

Calculation steps:

Step 1: Convert adjusted normal running power to annual energy consumption

The adjusted normal running power per machine is converted to annual energy consumption by multiplying the power with the total hours the machine runs per year (t).

$$E_{Annual} = P_N \times t$$

Step 2: Calculate the number of cells produced per year

The number of cells produced per year (N_{Cell}) is calculated by dividing the total annual cell capacity produced per year by the cell energy:

$$N_{Cell} = {}^{S}/_{E_{Cell}}$$

Step 3: Link cell design parameters to process-specific energy consumption

The relationship between energy consumption and cell design is established based on expert judgement. For example, energy consumption in mixing active materials and the solvent is linked to slurry mass, and similarly the energy consumption in coating the electrode is linked to the electrode area coated. While each process depends on multiple technical parameters, these simplifications are made for building a basic unit process model.

Step 4: Scale material flows to annual production level

The total area of electrode foil processed per year ($A_{PE/NE}$) is calculated by multiplying electrode area per cell by the number of cells produced per year. An example is shown for positive electrode.

$$A_{PE} = a_{PE} \times N_{Cell}$$

Step 5: Normalize Flows to the Unit Process Level

Lastly, the energy consumption is normalized to the unit process, accounting for process-specific losses (L). An example is shown for the energy consumption ($\overline{E}_{PE,calendaring}$) in positive electrode calendaring step.

$$\overline{E}_{PE,calendaring} = {E_{Calendaring}}/{(A_{PE} \times L)}$$

6.4.2 Facility design and scope of large-scale LIB production

Table 6-2 presents energy consumption data from three large-scale LIB production facilities: a 7 GWh facility (Degen & Schütte, 2022), a 50 GWh facility (Knehr et al., 2024), and the 16 GWh facility analyzed in Article 4. Reported total energy consumption across the studies varies significantly, reflecting differences in facility design, energy sourcing, and process scope.

Table 6-2: Energy consumption in different large-scale LIB production facilities

Cell production process	7 GWh		50 GWh		16 GWh	
	Elec.	Heat	Elec.	Heat	Elec.	Cool.
NMC hydroxide production	-	-	-	-	0.7	1.9
PAM production, calcination	-	-	-	-	3.8	0.3
PAM production, other processes	-	-	-	-	4.8	0.4
Electrode prod., slurry mixing	0.1	-	3.0	-	2.7	2.2
Electrode prod., NMP refining	-	-	0.2	-	0.03	0.2
Electrode prod., coating & drying	0.9	10.1	3.2	4.5	15.5	11.9
Electrode prod., calendaring	0.5	-	0.3	-	2.0	0.3
Electrode prod., slitting/notching	0.2	-	0.9	-	0.7	0.1
Electrode prod., vacuum drying	0.04	1.6	1.0	-	0.7	1.3
Cell container manufacturing	-	-	-	-	0.7	-
Electrolyte mixing	-	-	-	-	0.1	-
Cell assembly, electrolyte feeding	-	-	0.2	-	0.01	0.04
Cell assembly, winding/stacking	0.3	-	0.5	-	3.0	-
Cell assembly, housing	3.6	-	0.4	-	3.4	-
Cell formation, aging and testing	10.9	0.7	10.1	-	9.4	-
Dry room	1.6	9.1	3.3	0.7	5.8	5.2
Wastewater treatment	-	-	-	-	3.1	3.0
Factory operations and utilities	2.0	-	9.7	1.1	5.8	2.9
Total (kWh/kWh_{cell})	20	21	33	6	62	30

A gigafactory typically needs electricity, heat and cooling for production. However, both heat and cooling can be generated from electricity, and cooling can be generated from heat, depending on the equipment and facility design. The 7 GWh and 50 GWh facilities both rely on a combination of electricity and natural gas to meet their energy demands. The 16 GWh facility operates mainly on electricity, including heat recovery equipment that generate the necessary heating. Cooling energy for production processes is sourced externally. The real-world factory underpinning the model has easy access to cooling water. This design choice aligns with strategies to reduce climate impacts by avoiding the use of natural gas. Despite differences in scale and design, all three facilities identify dry rooms, electrode coating and drying, and cell formation, aging, and testing as major energy-intensive processes.

The scope of included processes also varies across the facilities. For example, the 7 GWh and 50 GWh facilities do not account for PAM production in their scope, which leads to a lower estimation of the total energy demand in the respective studies. In contrast, the 16 GWh facility includes PAM production, cell container manufacturing, electrolyte mixing, and wastewater treatment. This broader scope reflects a more integrated production model and likely stems from the top-down data collection approach used in Article 4, compared to the bottom-up methods employed in the other two studies. The 16 GWh facility is also designed to integrate with a hydrometallurgical recycling process, recovering NMC hydroxide from blackmass for reuse in new cells. This forward-looking design can reduce environmental impacts across the LIB life cycle by integrating recycling at the production site.

In summary, the differences in reported energy consumption also reflect the data collection methodologies. Bottom-up approaches, as used in the 7 GWh and 50 GWh facilities, may omit certain sub-processes or support systems. In contrast, the top-down approach used in Article 4 likely capture a more comprehensive picture of facility-wide energy use, including ancillary services.

6.5 Article 5: Closed-loop recycling

The results from Article 5 address RQ4. The article primarily investigates the environmental impacts of recycling a complete LIB pack and the closed-loop recovery of transition metal hydroxide (NMC hydroxide) through hydrometallurgical processes. The system boundary encompasses raw material extraction and production, LIB cell and pack manufacturing, and recycling operations (i.e., the whole life cycle excluding the use phase). To model the LIB cell, the study adopts the integrated bottom-up and top-down approach previously applied in Article 4. For the battery pack production, it applies a bottom-up modeling strategy, as described in Section 5.2.4.

Two commonly applied approaches to modeling EoL in LCA are the EoL recycling approach (also called the avoided burden approach) and the recycled content approach (also called the cut-off approach) (Nordelöf et al., 2019). In the EoL recycling approach, recovered materials are modeled as fulfilling the same quality requirements and directly replacing an equivalent amount of primary material, either within the same or another product system. This substitution reduces the need for primary production, and the avoided impacts are credited to the product as negative impacts. A key feature is that, since crediting is based on avoided primary production, all material inputs upstream are modeled as primary. In the recycled content (cutoff) approach, recyclable materials are not traced through to their reuse in new production. Instead, modeling usually includes only collection and basic pretreatment steps. The recovery and upgrading of materials are "cut off" from the product system, so no credits are given for supplying waste streams that become secondary raw materials. Benefits appear upstream, where a share of the input is assumed to come from recycled materials and the remainder from primary extraction. Thus, secondary inputs carry only the burdens from recovery and upgrading, which overall lowers the production impacts of products with recycled content. Typically in LCA the share of recycled content reflects the average availability of secondary materials on the market, as represented in background databases such as Ecoinvent. In this thesis the recycled content represents the net results relfecting the efficiency of the recovery processes represented in this thesis, rather than an avergae market share.

The modeling of recycling and as assumed closed-loop material recovery draws on environmental permit applications for a recycling facility and is further informed by personal communication with industry experts specializing in pack and cell recycling. Results are normalized to a functional unit of 1 kWh battery pack capacity. The results are shown for two EoL modeling approaches. In the EoL recycling approach, the product system input is modeled using only primary raw materials, and the materials recovered at the end of life are credited as "avoided burdens," reflecting the environmental benefits of displacing primary material production. In the recycled content approach, the product system is generally modeled with a share of recovered materials sourced upstream from the EoL of other products. In this research, a closed-loop system is assumed in the foreground system for NMC hydroxide, lithium hydroxide, graphite, aluminum, copper and steel. The results show that energy inputs such as electricity, cooling and heat contribute nearly two-third of the total life cycle climate impacts (Figure 6-10). The remaining impacts stem from material inputs which include both the recyclable and non-recyclable product materials, and processing chemicals account for the remaining climate impacts. Hydrometallurgical recycling avoids nearly 90% of the impacts associated with recyclable materials, while non-recyclable materials and chemicals contribute about one-quarter of the overall climate impacts. These findings suggest that further reductions in climate impacts are achievable by minimizing production scrap rate, improving recycling processes to recover higher share of product materials, and optimizing the use of processing chemicals in production and recycling processes.

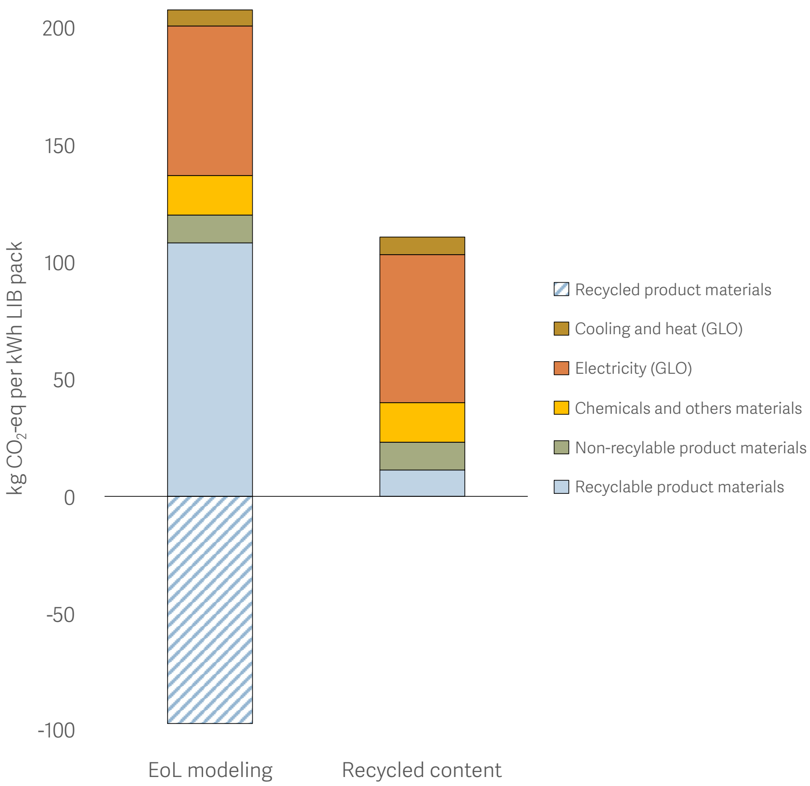

Figure 6-10: Climate impacts of production and recycling of a NMC LIB pack.

7 Discussion

7.1 Addressing research questions

RQ1: How does scale of production influence environmental impacts of LIBs?

Shift-of-burden to upstream

As highlighted in Section 6.1, scaling up LIB production reduces climate impacts, particularly through decreased energy demand in cell manufacturing. Further reductions are achievable by sourcing energy from low-carbon sources. As production scales up and energy efficiency improves, the relative contribution of upstream processes such as raw material extraction becomes more prominent in the overall environmental profile.

Shift in environmental hotspots within the factory

Section 6.1.1 presents a stepwise assessment of cell production processes at varying scales, underscoring how operating conditions influence efficiency and environmental impacts. For instance, dry rooms – among the most energy-intensive facilities in cell production – operate inefficiently at small scales, as the energy demand remains constant regardless of throughput. At industrial-scales, however, manufacturers utilize dry rooms at full capacity, thereby distributing their energy burden across much larger production volumes and lowering the per-cell impact. Similar scale effects arise in other processes: NMP, a solvent used in electrode production, remains unrecovered at small scales due to limited volumes and the cost of recovery, whereas industrial facilities recover, treat, and reuse it, motivated by both economic and environmental considerations. Wastewater provides another example, as small-scale operations often discharge it untreated, while large-scale plants treat and reuse it, reducing freshwater demand and its associated burden. Finally, industrial-scale production also optimizes the energy-intensive cell formation, testing, and aging stage by applying optimized charging profiles, reutilizing energy from discharged cells to charge others or other processes, and streamlining cell testing through sampling and diagnostics. Collectively, these cases demonstrate how scaling up enables reductions in environmental impacts by integrating material and energy recovery systems, while also showing that environmental hotspots within LIB production shift with scale.

Integrating on-site recycling

At small scales, handling production scrap and integrating it with recycling is rarely feasible, since the material volumes are too low to justify the capital and operational costs of recycling systems. In contrast, large-scale production generates sufficient volumes of production scrap to support on-site recycling infrastructure. Thus, handling of production scrap on-site and integrating with recycling processes is yet another benefit of large-scale production. On-site recycling systems, as described in Article 5 (Section 6.5), enable recovery of valuable materials from both cell production scrap and disassembled battery pack components. These materials are processed through crushing, sorting, and then via hydrometallurgical treatment recovered NMC hydroxide can be directly reused in PAM production. This approach further avoids the added chemical and energy expenditure from separating into metal salts which is still a common approach in the industry. Thus, by integrating recycling with production within the same facility, closed-loop systems can be set up that can reduce environmental impacts from the LIB life cycle.

RQ2: How does the origin and the supply chain of primary raw materials influence environmental impacts of LIBs?

High production impacts from low-grade ores and heterogeneity in supply chain

As global demand for raw materials continues to rise, the industry will increasingly turn to lower-grade ore deposits. Although advancements in mining technology may partially offset the additional environmental burdens associated with lower-quality ores, the overall impact remains a concern, as highlighted in Section 6.2. In particular, the exploitation of low-grade ores is likely to exacerbate regional environmental issues from future mining operations. This trend highlights the need for more responsible sourcing strategies and improved environmental governance throughout the supply chain.

Furthermore, Section 6.2 and 6.3 showed that the supply chain for raw materials used in LIBs is highly complex and globally distributed. Typically, the extraction and initial processing of ores occur in one country, further refinement in another, and final cell production in yet another. To better assess the environmental impacts across the life cycle of LIBs, it is essential to communicate the supply chain specific information about the raw materials. Although ultimately it is the goal and scope of the study that determines the applicability of average data over site- or source-specific data.

RQ3: How does cell design influence environmental impacts of LIBs?

Volumetric efficiency

The volumetric efficiency (Wh/L) is a key determinant in estimating the environmental impacts from LIB cell production. This was most obvious when the PHEV2 cells with different internal design (four jelly roll versus single jelly roll) were compared. Even though the cells have the same size, the amount of active material pack in each of them differs due to the internal design, with the 1-jelly roll version performing better from a climate impact point of view. Generally larger cells will have higher production impacts, however, when impacts are compared per kWh storage capacity, it is the volumetric efficiency that counts.

Influence of foil and casing

When cell chemistry is kept constant (in this case NMC-811) it is the impacts from electrode foils and casing that differentiate the climate impacts between cells, as shown in Figure 6-9. Further, cylindrical cells have better volumetric efficiency than prismatic cells (see cell size in the figure), hence have lower climate impacts. However, the cylindrical cells modeled in this thesis have stainless steel body. If instead a typical global average GHG emission factor for aluminum was used in cylindrical cells, then the impacts are likely to be higher due to higher per unit mass production impacts of primary aluminum compared to steel in the model. These examples highlight that keeping the cell chemistry constant, reduction in climate impacts can be achieved by optimizing the foil mass and choosing cell casing material with lower production impacts.

Influence of cell size on energy demand

As seen in Article 4, the production energy demand per cell varies considerably. This variability is closely linked to the overall size of the cell as well as its internal design. Larger cells require greater amounts of electrode material, longer coating lines, larger electrolyte filling volumes, and extended formation and testing times, all of which increase the overall production energy per cell. However, when comparing power- and energy-optimized variants of the same cell type, the total production energy per cell remains very similar, since the underlying manufacturing steps do not differ significantly between these variants. Importantly, when results are normalized per kWh, much of this variability in results disappears. Although larger or more complex cells consume more energy in absolute terms, they also deliver proportionally greater storage capacity. As a result, the production energy per kWh shows relatively little variation across different designs, reflecting the fact that the scaling of inputs and outputs in cell manufacturing tends to balance out when expressed relative to functional capacity.

RQ4: How does recycling influence environmental impacts of LIBs?

Closed-loop design

Closed-loop recycling established via the recovery from NMC hydroxide from the hydromet process and integrating with battery production offers strategic and environmental benfits. By actively recovering NMC hydroxide rather than metal salts such as nickel or cobalt sulfates as is usually the case during hydrometallurgical treatment of blackmass minimizes the demand for additional chemical reagents, energy subsequent and processing steps, thereby reducing both the environmental impact and operational complexity. The direct production of NMC hydroxide facilitates integration with the production of PAM, enhancing quality control and process efficiency. Importantly, effective crushing and sorting remain critical components of the recycling process, as they ensure the clean separation of battery constituents and the high-purity recovery of valuable metals, which is essential for maintaining the material standards required for reintegration into new battery cells.

RQ5: How does the choice of foreground data modeling approaches influence environmental impacts of LIBs?

Scope and accuracy

Section 5.2 discusses several bottom-up and top-down foreground system modeling approaches applied in LCA studies. Section 6.4.1 presents a new approach that combines the two. Typically, bottom-up approaches offer the benefit of offering higher granularity, whereas top-down approaches are able to capture system wide interactions and report a broader scope. By combining the two, usefulness of both these approaches can be obtained.

RQ6: How does background system database influence environmental impacts of LIBs?

Temporal trends and data quality

The influence of background databases on LCA results of LIBs was highlighted in Section 6.1. The LCA results obtained for a small-scale LIB production facility using ecoinvent v3.7.1 were notably higher than those calculated with v2.2. This difference arises from improvements in background system data quality, reflecting better representation of technology and greater completeness in process coverage, particularly for battery-relevant materials.

For instance, updates to datasets for electricity generation, metal refining, and chemical use incorporate more recent and geographically differentiated data, which in turn raises the environmental burdens attributed to upstream supply chains. These changes demonstrate how database updates can shift the magnitude of results without any alteration to the modeled foreground system. Consequently, consistent and transparent reporting of database versions becomes critical when comparing studies across time or between different studies.

The observed differences in results illustrates how the understanding of past impacts may evolve as background system inventories improve, introducing uncertainty in the interpretation of temporal trends. This reinforces the need for caution when contrasting “past,” “present,” and “future” impacts, as apparent changes may partly reflect evolving database quality rather than true shifts in production technology or supply chain performance. Methodologically, researchers should explicitly distinguish the contribution of background data updates from actual technological improvements in the foreground system, by parallel calculations with different database versions, to ensure that observed differences are correctly attributed.

7.2 Limitations and future work

A key limitation of this thesis is the exclusion of the use phase of LIBs. For a holistic assessment of environmental impacts across the full life cycle, it is necessary to account for burdens arising during battery operation. Including the use phase would provide a more complete understanding of overall life cycle impacts and the potential of cell design to mitigate them. Furthermore, this thesis focuses primarily on climate impacts. To gain a broader perspective on environmental pressures, particularly those linked to raw material supply chains, it is also important to consider regional pollution impacts associated with mining and extraction.

This thesis and the appended articles focus mainly on NMC LIBs. As identified in the introduction, LFP batteries are now competing with NMCs for market shares. Thus, comparing the life cycle environmental impacts of LFP batteries with that of NMC batteries in the context of the current BEV market is relevant and its assessment could provide a broader understanding of the field.

A methodological limitation of this thesis is that it relies solely on LCA, which, while capturing system-wide impacts, does not address site-specific effects of large-scale battery production. Tools such as EIA could complement LCA by highlighting local consequences at production sites, including impacts on water resources, air quality, biodiversity, and surrounding communities. In addition, Multi-Criteria Decision Analysis (MCDA) could be used alongside LCA to incorporate economic, technical, and social dimensions, enabling a more balanced evaluation of trade-offs when siting and scaling up production facilities. Together, these tools would provide a more comprehensive understanding of both global supply chain burdens and localized environmental and societal pressures linked to the industrialization of LIB technologies.

Future research should aim to address these limitations. Beyond that, it is important to investigate the environmental impacts of large-scale LIB production also on aspects such as regional pollution and biodiversity loss. There are areas that are still underrepresented in current LCA of LIBs. Furthermore, incorporating social impact assessments, including labor conditions and community effects associated with raw material extraction and battery manufacturing, would provide a more comprehensive evaluation of the LIB life cycle.

7.3 Generalization

Other battery technologies

The findings of this thesis can be extended to other competing and emerging battery technologies, such as LFP and sodium-ion batteries. Although LFP chemistries rely on fewer critical raw materials than NMC batteries, they still depend on lithium. With demand for lithium expected to rise substantially, extraction and refining are likely to impose considerable regional environmental pressures at mining and processing sites. Future reliance on lower-grade ores will further intensify impacts, irrespective of the battery chemistry. The same applies to sodium-ion batteries, even though they are based on less scarce elements, they ultimately depend on raw material extraction, which will scale in step with demand.

A common denominator across all battery technologies is the growing requirement for copper. As a geochemically scarce metal that is indispensable to both battery production and modern industrial society, copper will remain a critical material whose supply risks may constrain the scalability of battery electric vehicles and the broader energy transition.

LCA for emerging technologies

Another generalization from this thesis is the broader applicability of LCA to emerging technologies. Most technologies progress through a similar trajectory of development, beginning at laboratory scale, advancing to pilot or small-scale demonstration, and eventually reaching industrial-scale deployment. At each of these stages, LCAs are shaped by different levels of data availability, modelling assumptions, and system complexity, which can yield results that vary widely in scope and reliability. For instance, early-stage LCAs often rely on experimental data, theoretical extrapolations, or proxy datasets, while later assessments can make use of industrial data and more established process knowledge.

In addition, background systems such as electricity supply, transport logistics, supply chain efficiencies, and recycling infrastructure are not static but evolve over time. As these supporting systems decarbonize, expand, or become more efficient, the environmental profile of the same product system may change considerably, even without modifications to the core technology itself. This dynamic context highlights the importance of revisiting and updating LCAs for emerging technologies at regular intervals. Only by doing so can assessments provide robust, representative, and policy-relevant insights that accurately reflect both technological advances and systemic changes.

Finally, this perspective underlines that LCAs should not be treated as one-off exercises, but rather as iterative tools that accompany technologies throughout their development pathways. Such an approach ensures that environmental assessments remain aligned with technological realities and can better guide decision-making toward sustainable innovation and large-scale deployment.

7.4 Lessons for stakeholders

For *LCA researchers*, this work highlights several methodological considerations. First, the choice between bottom-up and top-down modeling approaches involves a trade-off between granularity and system-wide scope. Researchers should align their modeling strategy with the specific goals of the assessment while being transparent about its limitations. Second, the influence of background system databases on LCA results is non-trivial. The observed differences between Ecoinvent versions illustrate how updates in data quality, particularly for novel and developing technologies, can alter impact estimates. This underscores the importance of understanding the context, representativeness, and temporal relevance of background system data when interpreting and comparing LCA results. Lastly, LCA researchers are advised to remodel not only their older studies using updated background databases but also LCA studies they compare results to. The former helps in developing an understanding of their own models, its limitations and improvements in data quality over time the latter provides better context for comparing results.

For *industry*, the results underscore the environmental and operational advantages of scaling up LIB production. Larger facilities not only benefit from economies of scale but also enable the integration of energy-efficient technologies. They also enable the possibility of incorporating on-site closed-loop recycling that further enhance the material efficiency of the overall system. These systems, particularly when designed to recover high-value materials like NMC hydroxide, can significantly reduce the environmental impact of battery production. Moreover, the thesis highlights the importance of cell design choices, such as volumetric efficiency and material selection, which directly influence environmental impacts.

From a *policy perspective*, as the industry increasingly relies on low-grade ores and globally distributed supply networks, environmental governance should evolve to address the regional and cumulative impacts of raw material extraction and processing. Policies that incentivize the use of low-carbon energy sources in manufacturing, and mandate recycling infrastructure, are important for reducing the environmental impacts from LIB life cycle. At the same time, policymakers should recognize the preliminary nature of LCA results for emerging technologies, using them to guide the development of environmentally sound practices without prematurely constraining promising technologies based on data from immature production systems.

8 Conclusions

This thesis finds that while scaling up LIB production lowers impacts per unit, it shifts the environmental burden upstream to mining, extraction, and processing. Recycling, particularly when integrated with production sites, offers a way to mitigate these pressures through closed-loop systems. The results also show that supply chain characteristics and cell design strongly influences LCA results. Finally, the thesis underscores that both foreground and background system modelling choices significantly shape results, highlighting the need for methodological transparency and consistency in LCAs of LIBs.

Viewed through the lens of the thesis title, the *past* understanding of LIB impacts has been partial, often constrained by unrepresentative data. Assessment of the *present* state of production illustrates high variability in results originating from diverse supply chain characteristics, cell design aspects, and modelling assumptions. The *future* points to intensifying upstream pressures owing to dependence on low-grade ores unless systemic improvements in recycling, energy sourcing, and governance are pursued. Taken together, these insights underline that batteries are at a crossroads: while critical to enabling a low-carbon transition in the transport sector, their environmental friendliness cannot be assumed and must be continually reassessed.

References

Angel, D. P., Hamilton, T., & Huber, M. T. (2007). Global Environmental Standards for Industry. *Annual Review of Environment and Resources*, *32*(Volume 32, 2007), 295-316. https://doi.org/https://doi.org/10.1146/annurev.energy.32.031306.102415

Aramendia, E., Brockway, P. E., Taylor, P. G., & Norman, J. (2023). Global energy consumption of the mineral mining industry: Exploring the historical perspective and future pathways to 2060. *Global environmental change*, *83*, 102745. https://doi.org/https://doi.org/10.1016/j.gloenvcha.2023.102745

Arvidsson, R., Chordia, M., & Nordelöf, A. (2022). Quantifying the life-cycle health impacts of a cobalt-containing lithium-ion battery. *The International Journal of Life Cycle Assessment*, *27*(8), 1106-1118. https://doi.org/10.1007/s11367-022-02084-3

Arvidsson, R., Söderman, M. L., Sandén, B. A., Nordelöf, A., André, H., & Tillman, A.-M. (2020). A crustal scarcity indicator for long-term global elemental resource assessment in LCA. *The International Journal of Life Cycle Assessment*, *25*(9), 1805-1817. https://doi.org/10.1007/s11367-020-01781-1

AUDI. (2025). *Audi Media Center*. Retrieved 10th June from https://www.audi-mediacenter.com/en

Augustsson, O., Baburao, B., Dube, S., Bedell, S., Strunz, P., Balfe, M., & Stallmann, O. (2017). Chilled Ammonia Process Scale-up and Lessons Learned. Energy Procedia,

Ausenco. (2020). *Association for the Advancement of Cost Engineering (AACE) Class 3 Feasibility Study - First Cobalt Refinery Project, Ontario, Canada*.

Bakhtavar, E., Shahriar, K., & Osanloo, M. (2006). Old tailings rehabilitation with regard to environmental impacts at the Mooteh gold mine. 6th International Scientific Conference on Modern Management of Mine Producing, Geology and Environmental protection, SGEM 2006,

Bibin, C., Vijayaram, M., Suriya, V., Sai Ganesh, R., & Soundarraj, S. (2020). A review on thermal issues in Li-ion battery and recent advancements in battery thermal management system. *Materials Today: Proceedings*, *33*, 116-128. https://doi.org/https://doi.org/10.1016/j.matpr.2020.03.317

BMI. (2025). *How many mines are needed for the energy transition?* Retrieved May 5 from https://source.benchmarkminerals.com/article/how-many-mines-are-needed-for-the-energy-transition

Bouter, A., & Guichet, X. (2022). The greenhouse gas emissions of automotive lithium-ion batteries: a statistical review of life cycle assessment studies. *Journal of cleaner production*, *344*, 130994. https://doi.org/https://doi.org/10.1016/j.jclepro.2022.130994

Calvo, G., Mudd, G., Valero, A., & Valero, A. (2016). Decreasing Ore Grades in Global Metallic Mining: A Theoretical Issue or a Global Reality? *Resources*, *5*(4). https://doi.org/10.3390/resources5040036

Casey, M., Hamm, J., Miller, M., Ramsey, T., Schild, R., Stewart, A., & Tom, J. (2019). Kilo lab and pilot plant manufacturing. In *Chemical Engineering in the Pharmaceutical Industry* (pp. 1011-1036). https://doi.org/10.1002/9781119600800.ch46

CDI. (2016). *The Environmental Performance of Refined Cobalt*. E. R. M. Limited.

Chaouki, J., & Sotudeh-Gharebagh, R. (2021). Iterative scale-up method: Concept and basics. In *Scale-Up Processes: Iterative Methods for the Chemical, Mineral and Biological Industries* (pp. 21-56). https://doi.org/10.1515/9783110713985-002

Chen, M., Ma, X., Chen, B., Arsenault, R., Karlson, P., Simon, N., & Wang, Y. (2019). Recycling End-of-Life Electric Vehicle Lithium-Ion Batteries. *Joule*, *3*(11), 2622-2646. https://doi.org/https://doi.org/10.1016/j.joule.2019.09.014

Chordia, M., Nordelöf, A., & Ellingsen, L. A.-W. (2021). Environmental life cycle implications of upscaling lithium-ion battery production. *The International Journal of Life Cycle Assessment*, *26*(10), 2024-2039. https://doi.org/10.1007/s11367-021-01976-0

Chordia, M., Wickerts, S., Nordelöf, A., & Arvidsson, R. (2022). Life cycle environmental impacts of current and future battery-grade lithium supply from brine and spodumene. *Resources, Conservation and Recycling*, *187*, 106634. https://doi.org/https://doi.org/10.1016/j.resconrec.2022.106634

Chordia, M., Wikner, E., & Nordelöf, A. (2022). A model platform for solving lithium-ion battery cell data gaps in life cycle assessment. EVS 35 Symposium, Oslo.

da Silva-Rêgo, L. L., de Almeida, L. A., & Gasparotto, J. (2022). Toxicological effects of mining hazard elements. *Energy Geoscience*, *3*(3), 255-262. https://doi.org/https://doi.org/10.1016/j.engeos.2022.03.003

Degen, F., & Schütte, M. (2022). Life cycle assessment of the energy consumption and GHG emissions of state-of-the-art automotive battery cell production. *Journal of cleaner production*, *330*, 129798. https://doi.org/https://doi.org/10.1016/j.jclepro.2021.129798

Degen, F., Winter, M., Bendig, D., & Tübke, J. (2023). Energy consumption of current and future production of lithium-ion and post lithium-ion battery cells. *Nature Energy*, *8*(11), 1284-1295. https://doi.org/10.1038/s41560-023-01355-z

Edelen, A., & Ingwersen, W. W. (2018). The creation, management, and use of data quality information for life cycle assessment. *The International Journal of Life Cycle Assessment*, *23*(4), 759-772. https://doi.org/10.1007/s11367-017-1348-1

Ekvall, T. (2019). *Attributional and Consequential Life Cycle Assessment* (Sustainability Assessment at the 21st Century, Issue.

Ellingsen, L. A.-W., Jayne Thorne, R., Wind, J., Figenbaum, E., Romare, M., & Nordelöf, A. (2022). Life cycle assessment of battery electric buses. *Transportation Research Part D: Transport and Environment*, *112*, 103498. https://doi.org/https://doi.org/10.1016/j.trd.2022.103498

Ellingsen, L. A. W., Majeau-Bettez, G., Singh, B., Srivastava, A. K., Valøen, L. O., & Strømman, A. H. (2014). Life cycle assessment of a lithium-ion battery vehicle pack. *Journal of Industrial Ecology*, *18*(1), 113-124.

Erakca, M., Baumann, M., Bauer, W., de Biasi, L., Hofmann, J., Bold, B., & Weil, M. (2021). Energy flow analysis of laboratory scale lithium-ion battery cell production. *iScience*, *24*(5), 102437. https://doi.org/https://doi.org/10.1016/j.isci.2021.102437

Regulation (EU) 2023/1542 of the European Parliament and of the Council of 12 July 2023 concerning batteries and waste batteries, amending Directive 2008/98/EC and Regulation (EU) 2019/1020 and repealing Directive 2006/66/EC, 1-117 (2023). https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32023R1542

European Council. (2022). *Fit for 55 - Proposal for a REGULATION OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL establishing a Social Climate Fund - General approach*. (2021/0206(COD). Brussels Retrieved from https://data.consilium.europa.eu/doc/document/ST-10775-2022-INIT/en/pdf

Regulation (EU) 2023/1542 on batteries and waste batteries, 1-114 (2023). https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX%3A32023R1542

Finnveden, G., Hauschild, M. Z., Ekvall, T., Guinée, J., Heijungs, R., Hellweg, S., Koehler, A., Pennington, D., & Suh, S. (2009). Recent developments in Life Cycle Assessment. *Journal of Environmental management*, *91*(1), 1-21. https://doi.org/https://doi.org/10.1016/j.jenvman.2009.06.018

Finnveden, G., & Moberg, Å. (2005). Environmental systems analysis tools – an overview. *Journal of cleaner production*, *13*(12), 1165-1173. https://doi.org/https://doi.org/10.1016/j.jclepro.2004.06.004

Flexer, V., Baspineiro, C. F., & Galli, C. I. (2018). Lithium recovery from brines: A vital raw material for green energies with a potential environmental impact in its mining and processing. *Science of the Total Environment*, *639*, 1188-1204. https://doi.org/https://doi.org/10.1016/j.scitotenv.2018.05.223

Ford. (2024). *Ford Updates EV, Hybrid Plans, Readies Manufacturing Plants* https://media.ford.com/content/fordmedia/fna/us/en/news/2024/04/04/ford-updates-timing-for-next-gen-evs--readies-manufacturing-plan.html

Friel, D. D. (2014). Electronic Options for Lithium-Ion Batteries. In *Lithium-Ion Batteries: Advances and Applications* (pp. 361-386). https://doi.org/10.1016/B978-0-444-59513-3.00016-9

Frischknecht, R., Jungbluth, N., Althaus, H.-J., Doka, G., Dones, R., Heck, T., Hellweg, S., Hischier, R., Nemecek, T., Rebitzer, G., & Spielmann, M. (2005). The ecoinvent Database: Overview and Methodological Framework (7 pp). *The International Journal of Life Cycle Assessment*, *10*(1), 3-9. https://doi.org/10.1065/lca2004.10.181.1

Frith, J. T., Lacey, M. J., & Ulissi, U. (2023). A non-academic perspective on the future of lithium-based batteries. *Nature Communications*, *14*(1), 420. https://doi.org/10.1038/s41467-023-35933-2

Ghebreigziabiher, A. M., & Lohmeier, S. (2024). Tailings – Environmental Risks or Future Raw Material Resources? [Article]. *Mining Report*, *160*(6), 588-600. https://www.scopus.com/inward/record.uri?eid=2-s2.0-85213542729&partnerID=40&md5=adf90cc99a940e760052460ed8056978

Giglio, E. (2021). Extractivism and its socio-environmental impact in South America. Overview of the "lithium triangle". *América Crítica*, *5*(1), 47-53.

Ginster, R., Blömeke, S., Popien, J.-L., Scheller, C., Cerdas, F., Herrmann, C., & Spengler, T. S. (2024). Circular battery production in the EU: Insights from integrating life cycle assessment into system dynamics modeling on recycled content and environmental impacts. *Journal of Industrial Ecology*, *28*(5), 1165-1182. https://doi.org/https://doi.org/10.1111/jiec.13527

Gortych, J. E. (2006). Rules of disclosure: The ABCs of NDAs [Article]. *Optics and Photonics News*, *17*(9), 14-15. https://www.scopus.com/inward/record.uri?eid=2-s2.0-33750682671&partnerID=40&md5=df3959dc0d492a5347609640fa349000

Gregory, P. (2015). *Battery Management Systems, Volume I: Battery Modeling*. Artech. http://ieeexplore.ieee.org/document/9100168

Guinée, J. B., Heijungs, R., Huppes, G., Zamagni, A., Masoni, P., Buonamici, R., Ekvall, T., & Rydberg, T. (2011). Life cycle assessment: past, present, and future. *Environ Sci Technol*, *45*(1), 90-96. https://doi.org/10.1021/es101316v

Guo, J., Li, R., Zhang, R., Qi, J., Li, N., Xu, C., Chiu, A. S. F., Wang, Y., Tanikawa, H., & Xu, M. (2025). Shedding light on the shadows: Transparency challenge in background life cycle inventory data [Article]. *Journal of Industrial Ecology*. https://doi.org/10.1111/jiec.70010

Harper, G., Sommerville, R., Kendrick, E., Driscoll, L., Slater, P., Stolkin, R., Walton, A., Christensen, P., Heidrich, O., Lambert, S., Abbott, A., Ryder, K., Gaines, L., & Anderson, P. (2019). Recycling lithium-ion batteries from electric vehicles. *Nature*, *575*(7781), 75-86. https://doi.org/10.1038/s41586-019-1682-5

He, Z., Korre, A., Kelsall, G., Nie, Z., & Colet Lagrille, M. (2025). Environmental and life cycle assessment of lithium carbonate production from Chilean Atacama brines [10.1039/D4SU00223G]. *RSC Sustainability*, *3*(1), 275-290. https://doi.org/10.1039/D4SU00223G

Huijbregts, M., Steinmann, Z., Elshout, P., Stam, G., Verones, F., Vieira, M., Hollander, A., Zijp, M., & van Zelm, R. (2016). *ReCiPe 2016 : A harmonized life cycle impact assessment method at midpoint and endpoint level Report I: Characterization* (ReCiPe 2016 : Een geharmoniseerde levenscyclus impact assessment methode op 'midpoint' en 'endpoint' niveau Rapport 1: karakterisatie, Issue. http://hdl.handle.net/10029/620793

IEA. (2023). *Global EV Outlook 2023*. IEA. Retrieved May 5 from https://www.iea.org/reports/global-ev-outlook-2023

IEA. (2024). *Global EV Outlook 2024*. IEA. Retrieved May 5 from https://www.iea.org/reports/global-ev-outlook-2024

IEA. (2025a). *The battery industry has entered a new phase*. IEA. Retrieved May 5 from https://www.iea.org/commentaries/the-battery-industry-has-entered-a-new-phase

IEA. (2025b). *Global EV Outlook 2025*. https://www.iea.org/reports/global-ev-outlook-2025

IPCC. (2023a). *Climate Change 2021 – The Physical Science Basis: Working Group I Contribution to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press. https://doi.org/DOI: 10.1017/9781009157896

IPCC. (2023b). *Climate Change 2023: Synthesis Report. Contribution of Working Groups I, II and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, H. Lee and J. Romero (eds.)]*.

Istrate, R., Mas-Fons, A., Beylot, A., Northey, S., Vaidya, K., Sonnemann, G., Kleijn, R., & Steubing, B. (2024). Decarbonizing lithium-ion battery primary raw materials supply chain. *Joule*. https://doi.org/10.1016/j.joule.2024.10.003

Jannesar Niri, A., Poelzer, G. A., Zhang, S. E., Rosenkranz, J., Pettersson, M., & Ghorbani, Y. (2024). Sustainability challenges throughout the electric vehicle battery value chain. *Renewable and Sustainable Energy Reviews*, *191*, 114176. https://doi.org/https://doi.org/10.1016/j.rser.2023.114176

Jinasena, A., Burheim, O. S., & Strømman, A. H. (2021). A Flexible Model for Benchmarking the Energy Usage of Automotive Lithium-Ion Battery Cell Manufacturing. *Batteries*, *7*(1). https://doi.org/10.3390/batteries7010014

Johnson, N. (2022). Lithium-ion cells, batteries, and other emerging storage technologies. In *Alternative Fuels and Advanced Vehicle Technologies for Improved Environmental Performance: Towards Zero Carbon Transportation* (pp. 613-636). https://doi.org/10.1016/B978-0-323-90979-2.00022-6

Kallitsis, E., Lindsay, J. J., Chordia, M., Wu, B., Offer, G. J., & Edge, J. S. (2024). Think global act local: The dependency of global lithium-ion battery emissions on production location and material sources. *Journal of cleaner production*, *449*, 141725. https://doi.org/https://doi.org/10.1016/j.jclepro.2024.141725

Kelly, J. C., Wang, M., Dai, Q., & Winjobi, O. (2021). Energy, greenhouse gas, and water life cycle analysis of lithium carbonate and lithium hydroxide monohydrate from brine and ore resources and their use in lithium ion battery cathodes and lithium ion batteries. *Resources, Conservation and Recycling*, *174*, 105762. https://doi.org/https://doi.org/10.1016/j.resconrec.2021.105762

Keppeler, M., Tran, H. Y., & Braunwarth, W. (2021). The Role of Pilot Lines in Bridging the Gap Between Fundamental Research and Industrial Production for Lithium-Ion Battery Cells Relevant to Sustainable Electromobility: A Review [Review]. *Energy Technology*, *9*(8), Article 2100132. https://doi.org/10.1002/ente.202100132

Kerr, R. A. (2014). The Coming Copper Peak. *Science*, *343*(6172), 722. https://doi.org/10.1126/science.343.6172.722

Knehr, K. W., Kubal, J. J., Yoon, S., Jeon, H., Roh, W. J., & Ahmed, S. (2024). Energy consumption of lithium-ion pouch cell manufacturing plants. *Journal of cleaner production*, *468*, 143050. https://doi.org/https://doi.org/10.1016/j.jclepro.2024.143050

Kuczenski, B., Sahin, C., & El Abbadi, A. (2017). Privacy-preserving aggregation in life cycle assessment [Article]. *Environment Systems and Decisions*, *37*(1), 13-21. https://doi.org/10.1007/s10669-016-9620-7

Kumar, P., Tadikonda, N., Kumari, P., Kumar, D., & Kumar, N. (2024). Estimation of State of Charge for Lithium-Ion EV Battery Packs Using Passive Cell Balancing. Lecture Notes in Electrical Engineering,

Kumar, R. (2024). Lithium-Ion Battery for Electric Transportation: Types, Components, Pack Design, and Technology. In *Energy Efficient Vehicles: Technologies and Challenges* (pp. 156-172). https://doi.org/10.1201/9781003464556-8

Kwade, A., Haselrieder, W., Leithoff, R., Modlinger, A., Dietrich, F., & Droeder, K. (2018). Current status and challenges for automotive battery production technologies. *Nature Energy*, *3*(4), 290-300. https://doi.org/10.1038/s41560-018-0130-3

Lagos, G., Peters, D., Videla, A., & Jara, J. J. (2018). The effect of mine aging on the evolution of environmental footprint indicators in the Chilean copper mining industry 2001–2015. *Journal of cleaner production*, *174*, 389-400. https://doi.org/https://doi.org/10.1016/j.jclepro.2017.10.290

Laker, M. C. (2023). Environmental Impacts of Gold Mining—With Special Reference to South Africa [Review]. *Mining*, *3*(2), 205-220. https://doi.org/10.3390/mining3020012

Lappalainen, H., Rinne, M., Elomaa, H., Aromaa, J., & Lundström, M. (2024). Environmental impacts of lithium hydroxide monohydrate production from spodumene concentrate – A simulation-based life cycle assessment. *Minerals Engineering*, *209*, 108632. https://doi.org/https://doi.org/10.1016/j.mineng.2024.108632

Li, W., Erickson, E. M., & Manthiram, A. (2020). High-nickel layered oxide cathodes for lithium-based automotive batteries. *Nature Energy*, *5*(1), 26-34. https://doi.org/10.1038/s41560-019-0513-0

Lottermoser, B. G. (2007). *Mine wastes (second edition): Characterization, treatment, environmental impacts* [Book]. https://doi.org/10.1007/978-3-540-48630-5

Maisel, F., Neef, C., Marscheider-Weidemann, F., & Nissen, N. F. (2023). A forecast on future raw material demand and recycling potential of lithium-ion batteries in electric vehicles. *Resources, Conservation and Recycling*, *192*, 106920. https://doi.org/https://doi.org/10.1016/j.resconrec.2023.106920

Majeau-Bettez, G., Hawkins, T. R., & Strømman, A. H. (2011). Life cycle environmental assessment of lithium-ion and nickel metal hydride batteries for plug-in hybrid and battery electric vehicles. *Environmental science & technology*, *45*(10), 4548-4554.

Makuza, B., Tian, Q., Guo, X., Chattopadhyay, K., & Yu, D. (2021). Pyrometallurgical options for recycling spent lithium-ion batteries: A comprehensive review. *Journal of Power Sources*, *491*, 229622. https://doi.org/https://doi.org/10.1016/j.jpowsour.2021.229622

Manthiram, A. (2017). An Outlook on Lithium Ion Battery Technology. *ACS Central Science*, *3*(10), 1063-1069. https://doi.org/10.1021/acscentsci.7b00288

Maranghi, S., Parisi, M. L., Basosi, R., & Sinicropi, A. (2020). LCA as a support tool for the evaluation of industrial scale-up. In *Life Cycle Assessment in the Chemical Product Chain: Challenges, Methodological Approaches and Applications* (pp. 125-143). https://doi.org/10.1007/978-3-030-34424-5_6

Mas-Fons, A., Horta Arduin, R., Loubet, P., Pereira, T., Parvez, A. M., & Sonnemann, G. (2024). Carbon and water footprint of battery-grade lithium from brine and spodumene: A simulation-based LCA. *Journal of cleaner production*, *452*, 142108. https://doi.org/https://doi.org/10.1016/j.jclepro.2024.142108

Mehlig, D., ApSimon, H., & Staffell, I. (2022). Emissions from charging electric vehicles in the UK. *Transportation Research Part D: Transport and Environment*, *110*, 103430. https://doi.org/https://doi.org/10.1016/j.trd.2022.103430

Mekonnen, Y., Sundararajan, A., & Sarwat, A. I. (2016, 30 March-3 April 2016). A review of cathode and anode materials for lithium-ion batteries. SoutheastCon 2016,

Merrow, E. W. (2011). *Industrial megaprojects: Concepts, strategies, and practices for success* [Book]. https://doi.org/10.1002/9781119201045

Miranda Xicotencatl, B., Kleijn, R., van Nielen, S., Donati, F., Sprecher, B., & Tukker, A. (2023). Data implementation matters: Effect of software choice and LCI database evolution on a comparative LCA study of permanent magnets [Article]. *Journal of Industrial Ecology*, *27*(5), 1252-1265. https://doi.org/10.1111/jiec.13410

Mousavinezhad, S., Nili, S., Fahimi, A., & Vahidi, E. (2024). Environmental impact assessment of direct lithium extraction from brine resources: Global warming potential, land use, water consumption, and charting sustainable scenarios. *Resources, Conservation and Recycling*, *205*, 107583. https://doi.org/https://doi.org/10.1016/j.resconrec.2024.107583

Mudd, G. M. (2012). Key trends in the resource sustainability of platinum group elements. *Ore Geology Reviews*, *46*, 106-117. https://doi.org/https://doi.org/10.1016/j.oregeorev.2012.02.005

Mueller, K. G., Lampérth, M. U., & Kimura, F. (2004). Parameterised inventories for life cycle assessment. *The International Journal of Life Cycle Assessment*, *9*(4), 227-235. https://doi.org/10.1007/BF02978598

Muratori, M., Alexander, M., Arent, D., Bazilian, M., Cazzola, P., Dede, E. M., Farrell, J., Gearhart, C., Greene, D., Jenn, A., Keyser, M., Lipman, T., Narumanchi, S., Pesaran, A., Sioshansi, R., Suomalainen, E., Tal, G., Walkowicz, K., & Ward, J. (2021). The rise of electric vehicles—2020 status and future expectations. *Progress in Energy*, *3*(2), 022002. https://doi.org/10.1088/2516-1083/abe0ad

Naumann, G., Famiglietti, J., Schropp, E., Motta, M., & Gaderer, M. (2024). Dynamic life cycle assessment of European electricity generation based on a retrospective approach. *Energy Conversion and Management*, *311*, 118520. https://doi.org/https://doi.org/10.1016/j.enconman.2024.118520

Newman, J., & Thomas-Aleya, K. (2004). *Electrochemical systems*. Wiley-Blackwell.

Noh, H.-J., Youn, S., Yoon, C. S., & Sun, Y.-K. (2013). Comparison of the structural and electrochemical properties of layered Li[NixCoyMnz]O2 (x = 1/3, 0.5, 0.6, 0.7, 0.8 and 0.85) cathode material for lithium-ion batteries. *Journal of Power Sources*, *233*, 121-130. https://doi.org/https://doi.org/10.1016/j.jpowsour.2013.01.063

Nordelöf, A., Messagie, M., Tillman, A.-M., Söderman, M. L., & Van Mierlo, J. (2014). Environmental impacts of hybrid, plug-in hybrid, and battery electric vehicles—what can we learn from life cycle assessment? *The International Journal of Life Cycle Assessment*, *19*(11), 1866-1890.

Nordelöf, A., Poulikidou, S., Chordia, M., Bitencourt de Oliveira, F., Tivander, J., & Arvidsson, R. (2019). Methodological Approaches to End-Of-Life Modelling in Life Cycle Assessments of Lithium-Ion Batteries. *Batteries*, *5*(3), 51.

Norgate, T. E., Jahanshahi, S., & Rankin, W. J. (2007). Assessing the environmental impact of metal production processes. *Journal of cleaner production*, *15*(8), 838-848. https://doi.org/https://doi.org/10.1016/j.jclepro.2006.06.018

Northey, S., Mohr, S., Mudd, G. M., Weng, Z., & Giurco, D. (2014). Modelling future copper ore grade decline based on a detailed assessment of copper resources and mining. *Resources, Conservation and Recycling*, *83*, 190-201. https://doi.org/https://doi.org/10.1016/j.resconrec.2013.10.005

Northvolt. (2017a). *MKB Anläggning för tillverkning av litiumjonbatterier, Northvolt, Skellefteå kommun*.

Northvolt. (2017b). *Northvolt Ett – Anläggning för storskalig produktion av litiumjonbatterier*. Northvolt.

Northvolt. (2018). *Teknisk beskrivning Northvolt Ett – Utökad anläggning för storskalig produktion av litiumjonbatterier*.

Northvolt. (2019). *Teknisk beskrivning Northvolt Ett – Utbyggnad av anläggning för storskalig tillverkning av batterier och ny anläggning för återvinning av litiumjonbatterier, samt uttag av vatten från Skellefteälv*. N. AB.

Northvolt. (2020). *Energieffektivisering enligt utredningsvillkor U4*.

Nsude, C. C., Wimhurst, J. J., & Debnath, R. (2024). A global fairtrade partnership needed to address injustices in the supply chains of clean energy technology materials. *MRS Energy & Sustainability*, *11*(2), 401-408. https://doi.org/10.1557/s43581-024-00113-2

OICA. (2025). *Motorization rate 2020 - Worldwide*. Retrieved May 5 from https://www.oica.net/category/vehicles-in-use/

Olivetti, E. A., Ceder, G., Gaustad, G. G., & Fu, X. (2017). Lithium-Ion Battery Supply Chain Considerations: Analysis of Potential Bottlenecks in Critical Metals [Review]. *Joule*, *1*(2), 229-243. https://doi.org/10.1016/j.joule.2017.08.019

Orangi, S., Manjong, N. B., Clos, D. P., Usai, L., Stokke Burheim, O., & Strømman, A. H. (2023). Trajectories for Lithium-Ion Battery Cost Production: Can Metal Prices Hamper the Deployment of Lithium-Ion Batteries? [Article]. *Batteries and Supercaps*, *6*(12), Article e202300346. https://doi.org/10.1002/batt.202300346

Pauer, E., Wohner, B., & Tacker, M. (2020). The influence of database selection on environmental impact results. Life cycle assessment of packaging using gabi, ecoinvent 3.6, and the environmental footprint database [Article]. *Sustainability (Switzerland)*, *12*(23), 1-15, Article 9948. https://doi.org/10.3390/su12239948

Peiseler, L., Schenker, V., Schatzmann, K., Pfister, S., Wood, V., & Schmidt, T. (2024). Carbon footprint distributions of lithium-ion batteries and their materials. *Nature Communications*, *15*(1), 10301. https://doi.org/10.1038/s41467-024-54634-y

Perez Clos, D., Ventura Silva, G., Cerdas, F., Burheim, O., Herrmann, C., & Stromman, A. (2025). Development and Validation of Scalable Energy Models for Battery Cell Production Processes. *Energy Technology*, *n/a*(n/a), 2402114. https://doi.org/https://doi.org/10.1002/ente.202402114

Peters, J. F. (2023). Best practices for life cycle assessment of batteries. *Nature Sustainability*, *6*(6), 614-616. https://doi.org/10.1038/s41893-023-01067-y

Piccinno, F., Hischier, R., Seeger, S., & Som, C. (2016). From laboratory to industrial scale: a scale-up framework for chemical processes in life cycle assessment studies. *Journal of cleaner production*, *135*, 1085-1097. https://doi.org/https://doi.org/10.1016/j.jclepro.2016.06.164

Priester, M., Ericsson, M., Dolega, P., & Löf, O. (2019). Mineral grades: an important indicator for environmental impact of mineral exploitation. *Mineral Economics*, *32*(1), 49-73. https://doi.org/10.1007/s13563-018-00168-x

Pryshlakivsky, J., & Searcy, C. (2021). Life Cycle Assessment as a decision-making tool: Practitioner and managerial considerations. *Journal of cleaner production*, *309*, 127344. https://doi.org/https://doi.org/10.1016/j.jclepro.2021.127344

Ram, R. (2016). Conceptual idea, test work, design, commissioning, and troubleshooting. In *Innovative Process Development in Metallurgical Industry: Concept to Commission* (pp. 179-199). https://doi.org/10.1007/978-3-319-21599-0_10

Rehman, S., Al-Greer, M., Burn, A. S., Short, M., & Cui, X. (2025). High-Volume Battery Recycling: Technical Review of Challenges and Future Directions [Review]. *Batteries*, *11*(3), Article 94. https://doi.org/10.3390/batteries11030094

Renner, T. (2007). *Quantities, units and symbols in physical chemistry*. The Royal Society of Chemistry. https://doi.org/10.1039/9781847557889

Rinne, M., Elomaa, H., Porvali, A., & Lundström, M. (2021). Simulation-based life cycle assessment for hydrometallurgical recycling of mixed LIB and NiMH waste. *Resources, Conservation and Recycling*, *170*, 105586. https://doi.org/https://doi.org/10.1016/j.resconrec.2021.105586

Sacchi, R., Bauer, C., Cox, B., & Mutel, C. (2022). When, where and how can the electrification of passenger cars reduce greenhouse gas emissions? *Renewable and Sustainable Energy Reviews*, *162*, 112475. https://doi.org/https://doi.org/10.1016/j.rser.2022.112475

Salomaa, E., & Watkins, G. (2011). Environmental performance and compliance costs for industrial wastewater treatment – an international comparison. *Sustainable Development*, *19*(5), 325-336. https://doi.org/https://doi.org/10.1002/sd.440

Schenker, V., Oberschelp, C., & Pfister, S. (2022). Regionalized life cycle assessment of present and future lithium production for Li-ion batteries. *Resources, Conservation and Recycling*, *187*, 106611. https://doi.org/https://doi.org/10.1016/j.resconrec.2022.106611

Schenker, V., & Pfister, S. (2025). Current and Future Impacts of Lithium Carbonate from Brines: A Global Regionalized Life Cycle Assessment Model. *Environ Sci Technol*, *59*(13), 6543–6555. https://doi.org/https://doi.org/10.1021/acs.est.4c12619

Sengupta, M. (2021). *Environmental Impacts of Mining - Monitoring, Restoration, and Control* (2nd ed.). https://doi.org/https://doi.org/10.1201/9781003164012

Shafique, M., & Luo, X. (2022). Environmental life cycle assessment of battery electric vehicles from the current and future energy mix perspective. *Journal of Environmental management*, *303*, 114050. https://doi.org/https://doi.org/10.1016/j.jenvman.2021.114050

Sinigaglia, T., Eduardo Santos Martins, M., & Cezar Mairesse Siluk, J. (2022). Technological evolution of internal combustion engine vehicle: A patent data analysis. *Applied energy*, *306*, 118003. https://doi.org/https://doi.org/10.1016/j.apenergy.2021.118003

Sommer, A., Bazlen, S., Tran, H. Y., Leeb, M., Wachter, J., Braunwarth, W., & Daub, R. (2024). Integration of an Electrode-Sheet-Based Traceability System into the Manufacturing Process of Lithium-Ion Battery Cells [Article]. *Energy Technology*, *12*(6), Article 2301221. https://doi.org/10.1002/ente.202301221

Sommerville, R., Zhu, P., Rajaeifar, M. A., Heidrich, O., Goodship, V., & Kendrick, E. (2021). A qualitative assessment of lithium ion battery recycling processes. *Resources, Conservation and Recycling*, *165*, 105219. https://doi.org/https://doi.org/10.1016/j.resconrec.2020.105219

Sun, X., Giljum, S., Maus, V., Schomberg, A., Zhang, S., & You, F. (2025). Robust assessments of lithium mining impacts embodied in global supply chain require spatially explicit analyses. *Environmental science & technology*, *59*(14), 7081-7094.

Taub, A. I., Krajewski, P. E., Luo, A. A., & Owens, J. N. (2007). Yesterday, today and tomorrow: The evolution of technology for materials processing over the last 50 years: The automotive example [Review]. *Jom*, *59*(2), 48-57. https://doi.org/10.1007/s11837-007-0022-7

Thomitzek, M., Cerdas, F., Thiede, S., & Herrmann, C. (2019). Cradle-to-Gate Analysis of the Embodied Energy in Lithium Ion Batteries. *Procedia CIRP*, *80*, 304-309. https://doi.org/https://doi.org/10.1016/j.procir.2019.01.099

Torabian, M. M., Jafari, M., & Bazargan, A. (2022). Discharge of lithium-ion batteries in salt solutions for safer storage, transport, and resource recovery. *Waste Manag Res*, *40*(4), 402-409. https://doi.org/10.1177/0734242x211022658

H.R.5376 - Inflation Reduction Act of 2022 (2022). https://www.congress.gov/bill/117th-congress/house-bill/5376

Volkswagen. (2025). *Accelerate* https://www.volkswagen-newsroom.com/en/strategy-3912

Volvo Cars. (2024). *Volvo Cars adjusts electrification ambitions, remains committed to fully electric future* https://www.media.volvocars.com/global/en-gb/media/pressreleases/333213/volvo-cars-adjusts-electrification-ambitions-remains-committed-to-fully-electric-future

Wesselkämper, J., Dahrendorf, L., Mauler, L., Lux, S., & von Delft, S. (2024). Towards circular battery supply chains: Strategies to reduce material demand and the impact on mining and recycling. *Resources Policy*, *95*, 105160. https://doi.org/https://doi.org/10.1016/j.resourpol.2024.105160

West, J. (2011). Decreasing Metal Ore Grades. *Journal of Industrial Ecology*, *15*(2), 165-168. https://doi.org/https://doi.org/10.1111/j.1530-9290.2011.00334.x

Witman, P. D., & Johnson, K. L. (2008). A guide to non-disclosure agreements for researchers. In *Handbook of Research on Information Security and Assurance* (pp. 347-359). https://doi.org/10.4018/978-1-59904-855-0.ch030

Xia, X., & Li, P. (2022). A review of the life cycle assessment of electric vehicles: Considering the influence of batteries. *Science of the Total Environment*, *814*, 152870. https://doi.org/https://doi.org/10.1016/j.scitotenv.2021.152870

Xu, C., Dai, Q., Gaines, L., Hu, M., Tukker, A., & Steubing, B. (2020). Future material demand for automotive lithium-based batteries. *Communications Materials*, *1*(1), 99. https://doi.org/10.1038/s43246-020-00095-x

Yao, Y., Zhu, M., Zhao, Z., Tong, B., Fan, Y., & Hua, Z. (2018). Hydrometallurgical Processes for Recycling Spent Lithium-Ion Batteries: A Critical Review [Review]. *ACS Sustainable Chemistry and Engineering*, *6*(11), 13611-13627. https://doi.org/10.1021/acssuschemeng.8b03545

Zargar, S., Yao, Y., & Tu, Q. (2022). A review of inventory modeling methods for missing data in life cycle assessment. *Journal of Industrial Ecology*, *26*(5), 1676-1689. https://doi.org/https://doi.org/10.1111/jiec.13305

Zimmermann, P., Frischknecht, R., & Ménard, M. (1996). Background Inventory Data. In S. Schaltegger, A. Braunschweig, K. Büchel, F. Dinkel, R. Frischknecht, C. Maillefer, M. Ménard, D. Peter, C. Pohl, M. Ros, A. Sturm, B. Waldeck, & P. Zimmermann (Eds.), *Life Cycle Assessment (LCA) — Quo vadis?* (pp. 39-49). Birkhäuser Basel. https://doi.org/10.1007/978-3-0348-9022-9_4

Zwissler, B. E., Vitton, S. J., Oommen, T., & Seagren, E. A. (2024). The Development of a Laboratory-Based Method to Simulate Cold-Weather Dusting on Mine Tailings Impoundments [Article]. *Journal of Cold Regions Engineering*, *38*(4), Article 04024033. https://doi.org/10.1061/JCRGEI.CRENG-757