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A Quantitative Model of the transition of Electric Vehicles and Critical Mineral Supply Chains to meet Decarbonization Goals

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The contents of this dissertation reflect the views of the author, who is the main responsible for the accuracy of the information presented. The document is disseminated in the interest of transparency and accountability, and does not necessarily reflect the views of any of the funding entities.

The author declares no competing financial interest.

Statement of Contribution

The three chapters from this dissertation arise from peer-reviewed publications published in scientific journals. Each publication has colleagues and advisors appearing as co-authors. For each chapter, I served as the primary contributor and lead author of the publication. In each case I was responsible for the main tasks of the research process, including original conceptualization, data collection, data analysis, method development, model validation, figure creation (data visualization), and writing and reviewing both the initial and revised manuscripts. Faculty advisors' co-authors provided valuable assistance in methodological guidance, scope delimitation, project supervision and editorial feedback for submission. Colleagues' co-authors provided valuable support in specific data collection tasks and reviewing the initial manuscript. In all cases I lead the design, execution and final presentation of the research.

This statement is provided to ensure transparency and accountability in co-authored work, as stated in UC Davis Graduate Council Policy GC2015–01, to assist the committee in determining whether this dissertation meets the expectations of independent scholarly work.

Abstract

Major decarbonization strategies for the transport sector, such as electric vehicle (EV) adoption, depend on critical lithium-ion battery (LIB) minerals, namely lithium, nickel and cobalt. The primary objective of this dissertation is to study and model the supply chain for critical materials contained in LIBs for EVs and other sectors with energy storage needs, using up-to-date information and advanced modeling techniques.

Chapter 1 studies the supply chain stage of electric vehicle production, to reveal the link between countries that produce vehicles and countries that buy them. The chapter develops an international trade model to forecast EV production at country level, and to estimate their associated requirement of lithium-ion batteries supply, showcasing meaningful differences if battery budgets are allocated to countries where vehicles are produced, rather than sold. The model can characterize trade, production and sales data on vehicles by market segment or size, revealing heterogeneity in trade patterns by segment and the implications for the battery budget for countries that specialize in vehicle production in higher-end segments with larger battery packs. By exploring the supply aspect of the electric vehicle market under different trade development scenarios, the model informs and provides practical recommendations for original equipment manufacturers (OEMs) and policymakers in securing their battery needs for the EV transition.

Chapter 2 develops an energy transition mineral (ETM) demand estimation model using recent forecasts on-road transportation sales and grid storage needs, potential battery chemistry and technology developments, trends in vehicle and battery size, durability of batteries, and mineral intensity of battery technologies. The model estimates the future demand for lithium, nickel and cobalt at country level under different scenarios related to potential policy levers: reduction in battery size, shifting to different battery chemistries or promoting mineral recovery through global recycling mandates. Mineral demand results show a wide range of possible future mineral requirements under different policies, proving that the same

mobility benefits can be achieved with important reductions on cumulative and peak mineral demand. A considerable upscale of current mineral extraction levels will be required to meet future demand, especially for lithium. Moreover, the cumulative demand from 2022 to 2050 will require that we exhaust all known reserves for cobalt and nickel, and a considerable fraction of lithium. There will be a need to convert existing mineral resources into reserves by developing better extraction technologies and through mineral exploration, in complement with a priority to decrease primary mineral demand with smaller battery packs, technology development and circular economy mandates.

Chapter 3 studies the dynamic aspect of the lithium mining supply chain with an optimization dispatch mineral supply model based on data at deposit level, to predict the expansion and opening of lithium mines. The model satisfies future lithium demand by minimizing capital and operational costs along with non-monetary factors related to ease of doing business in each country, considering constraints in resource depletion, maximum production rates, ramp up speed and mine opening lead times. The model is tested for the different lithium demand scenarios developed in Chapter 2, showing that the best demand reduction strategies to prevent unnecessary mine expansions and openings are to reduce battery size and promote global recycling mandates. On the supply side, key technologies are crucial, such as direct lithium extraction for brines and separation technologies to extract lithium from clay deposits. Overall, the supply model shows the importance of considering mine dynamics over time and space to evaluate resource sufficiency, and that demand actions to reduce peak mineral demand have a great benefit in preventing mine openings and the creation of new frontline communities. The supply model framework developed in this chapter is applicable to analyze the future supply chain efforts for other energy transition minerals, such as nickel, cobalt, copper, graphite, among others.

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Introduction

Motivation

Society needs to reduce greenhouse gas (GHG) emissions to mitigate climate change impacts. The lead emitting sector is energy, which accounts for 73.2% of GHG emissions globally, with 11.9% of total emissions coming from on-road transport combustion (Ritchie et al., 2020). While the energy sector generates environmental impacts, it also enables modern society benefits, such as access to water, food, health, and other services, like mobility; linked to goal 7 of the United Nations Sustainable Development Goals [1] (United Nations General Assembly, 2015). Society must transition towards an energy and transportation system that maintains and extends welfare, while reducing its GHG intensity and environmental impacts.

Replacing internal combustion engine vehicles (ICEVs) with electric vehicles (EVs) is a key decarbonization strategy for the on-road transport sector (IEA, 2023c). Many regions are pursuing electrification of their vehicle fleet with ambitious targets (IEA, 2022a). For example, both the state of California and the United Kingdom have targets for 100% new vehicle sales to be EVs by 2035 (CARB, 2022; UK Department of Transport, 2023), and Japan and Germany plan to reach 100% zero emission vehicle (ZEV) sales by 2050 (Sathiyan et al., 2022). In recent years EV sales have gone from 0.7 million in 2016 to over 10 million by 2022, with forecasts that sales will surpass 55 million by 2035 (IEA, 2024).

A decarbonized energy system depends on lithium-ion batteries (LIBs), which store energy and provide traction power to EVs (Manzetti & Mariasiu, 2015), and are needed to support integration of intermittent renewables, such as solar and wind, into electricity grids (Yekini Suberu et al., 2014). Historically, LIBs were used mainly in the electronics industry (Miatto et al., 2020), to provide small storage capacities for laptops,

[1] Goal 7: “Ensure access to affordable, reliable, sustainable and modern energy for all” (United Nations General Assembly, 2015).

cellphones, and other portable electronics. However, more recently much larger LIBs, led by battery packs for EVs (25-100 kWh) have expanded rapidly, and an exponential increase in demand is expected in the next decades (Dunn et al., 2021; IEA, 2022b, 2023a).

LIBs contain minerals, including lithium, nickel and cobalt, some of which qualify as critical minerals for the United States (US)[2], due to their importance for batteries and other clean energy technologies, and potential supply risk disruption (Watari et al., 2020). While the decrease in climate impact from EVs depends on many factors, such as the carbon intensity of the electricity grids they are charged on, their manufacturing stage requires six times more minerals than the traditional ICEVs, thus shifting the sector from being fossil fuel intensive to being mineral intensive (Zhang et al., 2023), especially for critical materials contained in LIBs, such as lithium, cobalt, and nickel, among others (Dunn et al., 2021; IEA, 2023a; Xu et al., 2020; Zhang et al., 2023). Historically, demand for critical minerals has been dominated by developed nations, while extraction has occurred in a few lower income countries.

New automotive supply chains are being developed for the EV transition, including mineral extraction, mineral refining, cathode manufacturing, and battery production, vehicle assembly and end-of-life management (e.g. recycling). There has been growing interest in estimating battery requirements and mineral budgets without acknowledging that vehicles are assembled in a few specialized countries, that will require the bulk of minerals. For example, most studies estimate LIB or mineral requirements based on the country where EVs are going to be sold (Alonso et al., 2023; Baars et al., 2021; Dunn et al., 2021; Zhang et al., 2023), rather than where they are produced, despite that LIBs are required at the manufacturing location (Kannan et al., 2025). In the context of these new supply chains, countries that have reliable access to minerals, either via domestic reserves or trade relationships with countries abundant in minerals (Cheng et al., 2025), have a competitive advantage in future EV production.

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[2] United States Geological Survey (USGS) characterizes a critical mineral for the U.S. as having important uses, no viable substitutes and potential disruption in their supply chain (USGS, 2017).

Multiple studies have predicted that in the next decade the demand for these materials will scale many times (Dunn et al., 2021; IEA, 2022b, 2023b), and that circularity will not play a big role in the next 15 years (Dunn et al., 2021), so nearly all mineral supply will have to be mined extensively in the few countries that possess mineral reserves[3]. The required increase in mineral extraction will have a geopolitical risk associated with the geographical concentration of reserves, but it could also generate environmental, health and social impacts, which could translated into opposition by local communities (Kumar et al., 2021).

Multiple mineral demand models have forecasted the demand for EVs, LIBs, and their associated critical materials (Aguilar Lopez et al., 2023; Dunn et al., 2021; Egbue et al., 2022; IEA, 2022b, 2023c; Kamran et al., 2021; Miatto et al., 2021; Moreau et al., 2019; Olivetti et al., 2017; Shafique et al., 2022; Sun et al., 2017; Turcheniuk et al., 2018; Vidal et al., 2022; Xu et al., 2020), but few studies have analyzed the supply side of minerals (Alonso et al., 2023; Ambrose & Kendall, 2020; Greim et al., 2020; Hache et al., 2019; Kushnir & Sandén, 2012; Olivetti et al., 2017; Riofrancos et al., 2023; Sun et al., 2017, 2019; Vidal et al., 2022; Watari et al., 2021). To assess critical minerals supply, most studies have focused on comparing the cumulative demand against existing reserves, rather than on the timing for yearly mineral extraction upscaling[4]. A recent review on minerals modelling efforts found that only 39% (of 70 studies) addressed potential supply constraints, and 63% of them did it by simply comparing cumulative demand to reserves (Watari et al., 2021). Different modelling techniques have been deployed to model the supply for critical minerals, such as production curve[5] (Calvo et al., 2017; Vikström et al., 2013), system dynamics models like dispatch optimization (Ambrose & Kendall, 2020), linear programming (Tokimatsu et al., 2017),

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[3] Resource refers to the total amount of mineral that exists on deposits, while reserve is a subset of resources that is currently economically suitable for extraction.
[4] A useful analogy: most studies have focused on determining the size of the tank and conclude that we have enough water, but fail to consider the maximum outflow of the tank to determine if we can access that water fast enough.
[5] Also called Hubbert curves.

scheduling modelling (Northey et al., 2014) or predator-prey models (Ali et al., 2017). Each technique has advantages, drawbacks, and limitations in forecasting mineral supply. Common limitations include omission of real-world parameters such as delays in industry development or over-emphasizing the importance of extraction costs. Few studies have modelled in detail the timing and risk of shortage of critical mineral extraction (Ambrose & Kendall, 2020), even though they are necessary for the global economy to meet their decarbonization goals. A timely supply of minerals will not only guarantee the achievement of decarbonization goals but could also accelerate their deployment to reduce early GHG emissions and avoid further climatic impacts.

The upcoming global mineral demand represents an economic opportunity for the few countries that contain reserves, but extraction and mining also come with environmental impacts. If these are not considered properly, lower income countries could suffer from these decarbonization strategies, resulting in a global inequality (or regressive) trade-off with high income countries. An adequate modelling of the mineral supply chain could provide better data inputs for environmental impact assessment and life cycle assessment (LCA), which are valuable tools to reveal and reduce environmental impacts with a holistic view of the entire supply chain.

Research goals

The dissertation presented in this proposal seeks to answer the following research questions:

1. Which countries will likely produce the required EVs for on-road decarbonization?
    a. How much lithium-ion battery will each country need to secure for its automotive industry?
    b. What effects do global trade relationships have on vehicle domestic production?
2. What will be the future global demand for lithium, nickel and cobalt?
    a. Which are the most effective policies to reduce mineral demand while keeping mobility benefits?

3. Which lithium mineral deposits will require to open or expand their production capacity to meet the future lithium demand?
    a. Which countries will likely lead lithium extraction in the future?
    b. What is likely to be the major bottleneck in lithium extraction expansion?
    c. Which are the most effective supply and demand actions to reduce pressure on lithium extraction?

The format of this dissertation is:

- Chapter 1 presents a global trade model to allocate future EV production by country based on vehicle sales forecast along with vehicle market segmentation. The model is able to accurately estimate lithium-ion battery capacity requirements on the location of vehicle production.
- Chapter 2 estimates future mineral demand for key battery minerals – lithium, nickel and cobalt – and evaluates associated measures and policies to reduce demand while achieving the same level of EV adoption. The model is a dynamic material flow analysis including all mineral consuming sectors, scrappage curves that prompt battery replacements, empirical data on battery size and chemistry per country, and potential opportunity to reduce primary mineral demand by recycling and recovery.
- Chapter 3 develops a global supply dispatch optimization model for lithium, predicting which lithium deposits will need to expand their capacity or open to meet the future lithium demand. The model includes costs and non-monetary factors associated with mining projects, and shows the supply effort required in each different lithium demand scenario (modelled in Chapter 2), along with several sensitivity analysis on supply conditions.

Research contributions

The major contribution of the dissertation is the assembly of emerging data, analytical tools and modeling approaches into global models capable of answering policy-relevant questions for the EV and mineral transition, filling gaps omitted by recent literature. For each chapter, a different model is constructed to study a specific stage in the emerging energy supply chain: EV production, critical mineral demand and lithium supply (mining). The techniques used are: mixed integer optimization, computer programming for data retrieval and software development, statistical techniques for forecasting key parameters and filling data gaps, and dynamic material flow analysis to track flows and stock of EVs and minerals. Model results are tested along different policy scenarios to derive practical recommendations. Following the scientific principles of transparency and reproducibility, all the models developed (code and non-proprietary data inputs) are publicly available.

This research advances the critical mineral supply chain scientific field in the following ways:

- Provides a modelling framework to estimate the future EV production by country by using historical vehicle trade data, and generates accurate lithium-ion battery budgets useful for industrial policy planning at country or regional level. The model
- Combines conflicting vehicle trade data by using a balancing method to ensure minimal loss of information, and proposes a novel algorithm for balancing.
- The market segmentation of the trade model allows to better estimate battery requirements, as vehicle size is a big predictor of battery capacity, and to accurately represent trade flows that depend on price value of the vehicle, also positively correlated with size.
- Provides a global public tool to conduct scenarios to estimate EV production by changing relevant inputs: forecast of EV sales, consumer preferences on market segments, battery size, and global vehicle trade flows. The tool provides default data inputs from public sources.
- Estimates future battery minerals demand (lithium, nickel and cobalt) with a global and comprehensive model. The demand model expands previous efforts by:
    I. Modelling EV and LIB failure, need for battery replacements and LIB outflows for reuse, repurpose or recycling;

II. including all mineral consuming sectors beyond batteries for vehicles, such as grid storage batteries, electronics, ceramics, glass or stainless steel;

III. utilizes the most-updated data on recent battery chemistries preferences and battery capacity, which has a major influence on demand for nickel and cobalt.

- Evaluates mineral demand reduction strategies on reducing peak mineral demand, and their effect on reducing pressure on the emerging lithium extraction supply chain. The model tests eleven demand scenarios that achieve the same EV adoption goals, but with meaningful differences in battery capacity, battery chemistry and material recovery rates.
- Quantitatively evaluates the effect of demand reduction measures on reducing the pressure on the supply chain for lithium, showing that there is a non-linear effect on the supply response.
- Provides a major methodological contribution to modeling the development of mineral extraction supply chains, by combining tools for industrial ecology, engineering optimization and geology. In particular, the optimization model for lithium supply advances the field by:

  I. Considering dynamic mine constraints such as ramp up, maximum depletion rates and future available reserves;

  II. expansion of the dispatch cost curve decision-criteria by including non-monetary factors through a multi-objective optimization approach;

  III. division of resources within a deposit into stages, to model increasing extraction costs, and resource and grade ore uncertainty.

- Provides a database of existing worldwide lithium deposits for public use. The data comes from multiple sources such as government reports, company feasibility studies, industry publications and academic literate. The granular dataset will enable other authors to replicate or extend this work.

- Evaluates the resilience of the lithium global supply chain by conducting an N-1 country analysis, revealing the key regions for lithium development; and by showing the effect of emerging extraction technologies (direct lithium extraction and clay-lithium separation) on the supply chain development.
- Proposes to pursue a global industrial recycling strategy for critical minerals to reduce mine openings requirements and to provide a secure and sustainable flow of minerals for the emerging energy technologies. The latter is quantitatively informed by the demand and supply model results, which shows that the best strategy to prevent unnecessary lithium deposit openings is global recycling at scale.

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1. Chapter 1 – Future Global Production of Electric Vehicles

1.1 Scope and Purpose

The expected increase in demand for EVs will require a major shift in the global automobile industry and in their critical mineral supply chains. Recent literature has mainly focused on forecasting future EV demand (sales) at country level, and subsequent global battery and critical mineral requirements without considering which countries will actually produce these EVs. An important principle, often omitted in recent research, is that an increase in demand for EV in one country does not translate to a proportional increase in production in the same country, as vehicles are produced and assembled in global specialized supply chains. This chapter presents the development of a policy-scenario trade model that combines EV demand forecasts, light duty vehicle (LDV) global trade flows and battery characterization to allocate future EV production and battery requirements towards vehicle producing countries. The model has been published as open source[6], and allows to run scenarios with different inputs: EV sales, trade ratios, battery size and market segments.

This chapter includes some text adapted from a published article: Busch, P., Pares, F., Chandra, M., Kendall, A., & Tal, G. (2024). Future of Global Electric Vehicle Supply Chain: Exploring the Impact of Global Trade on Electric Vehicle Production and Battery Requirements. *Transportation Research Record*, *2678*(11), 1468-1482[7] (Busch et al., 2024), along with further publications of the research group (Parés Olguín et al., 2024), and with further expansions and analysis.

1.2 Introduction

Globally, the transportation sector accounts for 16.2% of greenhouse gas (GHG) emissions, and the passenger light duty for 73.5% of them (11.9% globally) (Ritchie et al., 2020). To mitigate climate change,

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[6] All the code and data inputs to run scenarios are publicly available in https://github.com/pmbusch/MONET.

[7] Authors contributions are: study conception and design: GT, PB; data collection: PB, FP, MC; analysis and interpretation of results: PB, GT, FP, MC; draft manuscript preparation: PB, GT, AK.

society is aiming to decarbonize the transport sector, while maintaining (or improving) the same level of service (mobility). Passenger transport provides multiple benefits, such as access to opportunities and services, which is a key aspect of modern society. In recent years the sector has seen a significant growth driven mostly by developing countries (IEA, 2023b). The adoption of light duty EVs arises as one of the main actions to reduce GHG emissions from the passenger transport sector, while keeping the benefits of transport to society. Many regions are pursuing electrification of their vehicle fleet with ambitious targets (IEA, 2022b). For example, the state of California established a roadmap to achieve 100% new all EV sales by 2035 (CARB, 2022). According to the international energy agency (IEA), EV sales have gone from 0.7 million in 2016 to over 10 million by 2022, with a forecast that sales will surpass 55 million units by 2035 (IEA, 2024).

This chapter is an effort to connect future spatial demand of EV with supply, and to study different trade scenarios that influence allocation of production among different countries. The model can be used to better inform trade policies and to move forward in co-locating battery production with final EV assembly. The work conducted in this chapter answers the following research questions:

- Which countries will likely produce the majority of EVs? Does vehicle trade flows differ by market segment or vehicle size? What will be battery requirements for producing countries?
- In which potential trade directions can the EV supply chain evolve? What are the implications for industrial policy?

1.3 Literature review

1.3.1 Future electric vehicle modelling efforts

Recent literature has been mostly focused on modeling the past, current and future sales, and in-use stocks of EVs (Dunn et al., 2021; Hache et al., 2019; Jones et al., 2020; OnLocation, 2023; Shafique et al., 2022; Xu et al., 2020) and their associated mineral requirement, rather than on explicitly modeling the supply chains that will produce them. In this regard, there is a gap in understanding which countries will likely be involved in the supply chain for EVs and how different policies and regional trade agreements are likely to impact the supply chain.

Table 1-1 summarizes recent global models with available EV projections found in the literature. Most models consider a time horizon up to 2050, with sales ranging from 40 to 110 million units annually; and have a global coverage with different levels of regional detail. The most detailed models focus on the whole energy sector, with a dedicated transport sub-component. Regarding EVs, the focus has been concentrated on battery requirements and their associated raw materials, rather than EVs or light duty vehicles (LDVs). Relatively few models have addressed the supply aspect of the EV market.

Key insights from the recent modelling efforts described in Table 1-1 are that in terms of value, batteries account for 30%-40% in an EV, and China completely dominates the production of lithium-ion batteries (~75%), as well as the production of the main components: cathodes and anodes (IEA, 2022c). IEA recommends to accelerate EV global uptake by ensuring secure, resilient, and sustainable supply chains (IEA, 2022c). Major worries identified for the supply chain are exponential growth of demand for EV, uneven spatial distribution in the required raw materials and market barriers that slow down the market response to the demand increase (Jones et al., 2020). Other identified challenges in the supply chain for EV batteries, besides the exponential growth on demand, are the high volume of the supply chain concentrated in East Asia, difficulty to access raw materials, and environmental and health concerns regarding the extraction of key minerals (Kumar et al., 2021). A recent IEA report states that automakers are getting involved in the critical mineral value chain to secure an adequate supply (IEA, 2023a).

Efforts have been made to model demand and supply of EV jointly, but only at national scale (Axsen et al., 2022; Bhardwaj et al., 2021, 2023). The automaker-consumer model (AUM) (Axsen et al., 2022; Bhardwaj et al., 2021, 2023) was developed to simulate the national consumer and producer interaction, using a profit maximization optimization setting to characterize the behavior of the whole automaker sector in

Canada, with no consideration of international trade. Other study focused only in Europe and USA production capacity forecasted a shortage of 6 million EV units to meet 2030 targets (Yang & Fulton, 2023).

Table 1-1. Summary of recent models/tools related to EVs or critical minerals.

Model/Article	Scope	Time resolution	Geographical resolution	Focus	EV sales projections
IEA Global Energy and Climate Model (IEA, 2022a)	Supply and Demand	Up to 2050	Global, 26 regions	All energy sectors, including EV batteries	22-34 M (in 2030)
TIAM-IFPEN (Hache et al., 2019)		Up to 2050	Global, 16 regions	EV batteries and lithium	250-1,200 M (EV stock)
CoMIT (Jones et al., 2020)	Demand	Up to 2030	Global	EV key materials	15.7 M
(Xu et al., 2020)		Up to 2050	Global	EV batteries and materials	109-211 M
(Shafique et al., 2022)		Up to 2030	China and United States only	EV batteries	18 M (batteries)
(Dunn et al., 2021)		Up to 2040	Global, 4 regions	EV batteries and materials	40-73 M
RMI (RMI, 2024)		Up to 2040	Global	Batteries (EV and grid storage)	10-14 TWh (battery)
EPPA (Ghandi & Paltsev, 2020)	Stock	Up to 2050	Global, 18 regions	All energy sectors, including LDV and EV	585-825 M (EV stock)
IEA MoMo (IEA, 2020)	Stock and demand	Up to 2050	Global, 29 regions	Transport sector	142 M (LDV 2050)
MATILDA (Aguilar Lopez et al., 2023)		Up to 2050	Global	EV batteries for passenger vehicles	2,800-4,800 M (LDV stock)
Global Transportation Roadmap (ICCT, 2022)		Up to 2050	Global, 25 regions	On-road transport sector	160 M (LDV)

TIAM: Times Integrated Assessment Model. CoMIT: Cost, Macro, Infrastructure, Technology. EPPA: Economic Projection and Policy Analysis. IEA: International Energy Agency. MoMo: Mobility Model. MATILDA: MATerIaL Demand and Availability model. ICCT: International Council on Clean Transportation.

1.3.2 Trade models

Other studies have analyzed the dynamics of vehicle international trade flows. A recent study analyzed automotive trade networks over 1993 to 2013, using trade data at country level of automobile components (electric parts; engine; and rubber and metal parts) using methods from social theory of networks (Gorgoni et al., 2018). It was found that in the last two decades, trade in major automotive components have changed significantly: the numbers of sellers for minor components have increased while the supply for engines has become concentrated in fewer players (Gorgoni et al., 2018). This highlights the importance to model trade at country level, as many trade relationships and patterns are obscured at higher aggregated levels. A similar study analyzed international trade data on 30 vehicle components using cluster analysis over time, from 1993 to 2018 considering 42 countries (98% of the trade share) (Russo et al., 2022). Over the 25-year period studied they found a transition towards denser networks within each cluster, with significant changes in the relative size between clusters. Future research directions points towards modelling the potential change that an increased share of EV at the expense of ICEVs will cause, as the new production for EV components may not occur necessarily in the countries that are currently producing components for ICEVs (Russo et al., 2022).

Other sets of models assess global trade, analyzing the impact of trade policies and agreements on the global economy by considering various factors like tariffs, exchange rates, and economic and demographic trends. These models are used to evaluate the potential effects of trade policies on various economic outcomes, such as economic growth, employment, and trade flows. Some examples of widely used global trade models include the World Trade Organization (WTO) Global Trade Model (Aguiar et al., 2019), the Global Trade Analysis Project (GTAP) model (Corong et al., 2017) and the Trade and Environment Model (TEM) (Pant et al., 2002). These models incorporate data on trade flows, production processes, and environmental impacts to estimate the impacts of trade policies and environmental regulations on the economy and the environment. Although these global trade model provide valuable insights into the potential future of the mobility sector, there are some limitations and potential shortcomings associated with them, such as dependence on multiple assumptions regarding economic and technological development.

1.3.3 MONET – EV Trade Model novelty

The biggest limitation of all these models is the scope: focusing mostly on the demand side of transportation while providing no insights on the supply side. No study or model was found with a focus on the supply side of the EV market and with a country-level global resolution. There is a modelling research gap in the EV supply side and on the impact of LDV international trade relationships. The MOdel for interNational Ev Trade (MONET) addresses multiple gaps in the current landscape of global transportation, demand, and trade models.

1. The main innovation compared to other models is that by utilizing the existing network of international trade relationships, MONET spatially connects LDV supply and demand data, enabling the consideration of global trade relationships in EV supply scenario planning. The former allows to allocate future production using historical empirical trade flows, and test different trade scenarios. By focusing on the supply side of EVs, MONET contributes to the gap generated by most studies simply considering the demand aspect of EVs.
2. MONET is designed for LDV and EV market analysis, while other models focus on the supply chain for batteries for EVs and/or the raw materials to build them. MONET main target audience are original equipment manufacturers (OEMs), rather than other actors in the supply chain such as battery producers, mineral refining or mineral extraction companies. The reason is that most supply side regulations are best targeted at OEMs, and them as the dominant players in the supply chain they can pressure upstream for changes in their supply.
3. Available literature regarding international EV demand growth, while providing reasonable forecasts for individual countries or regions, fails consistently to account for international trade relationships. Consequently, the regional composition of market supply is not accurately understood and may lead to critical misrepresentations of future market scenarios. MONET is an effort to account for international trade flows in scenario planning for global EV demand and the necessary supply required to meet it.
4. MONET models LDVs with four market segments, recognizing the heterogeneity that exists in LDV trade flows, vehicle features, price value, battery needs, and consumer preference determined by vehicle size.

5. The realization of accurate LDV trade flows also enables the quantification and tracking of valuable EV components, including lithium-ion battery and their associated critical materials, throughout the global supply chain. In that regard, MONET help industrial planners to determine a more accurate battery requirement based on their EV production forecast.

MONET is global transportation trade model whose inputs are demand forecasts for light duty EVs in combination with global trade statistics of light duty vehicle (LDVs) flows, with the main goal to allocate future production of EVs (Busch et al., 2024; Parés Olguín, Busch, et al., 2023; Tal et al., 2023). Under the assumption that global EV sales targets are met, MONET is able to identify which countries will produce these EVs and their battery requirements based on their country of destination market characteristics. An important limitation is that MONET does not consider production capabilities upscale, nor does it explicitly model competitive market dynamics of the supply chain. MONET is able to identify which countries will likely produce the biggest share of EVs and provide policy recommendations on securing a supply of required batteries.

1.4 Data

MONET uses vehicle trade, production and sales data from 2016 to 2019. The period was chosen to get recent data, avoiding the unprecedent disruption of COVID-19 in the global vehicle supply chain, in a 4-year format to minimize year-to-year variations. Other historical years of data were used for validation purposes of the model. All data was collected at country level and aggregated to the 65 countries/regions contained in MONET (supporting information (SI) Table A-1).

1.4.1 Bilateral trade

The major input for MONET are bilateral trade data for light duty vehicle, obtained from UN Comtrade (HS (Harmonized System) code 8703) (United Nations, 2025). These bilateral trade flows were complemented with data on the Mexican Automotive Industry Association (AMIA) (AMIA, 2022), Mexico's National Institute for Geography and Statistics (INEGI) (INEGI [National Institute for Statistics and Geography of Mexico], 2023), United States International Trade Commission (USITC) (USITC, 2023), and the Canadian International Merchandise Trade (CIMT) (Statistics Canada, 2023).

1.4.2 Vehicle Sales and Production

Historical LDVs sales and production by model, propulsion technology and country were obtained from InfluenceMap (InfluenceMap, 2022). As market segment in vehicles is a major predictor of vehicle size and battery requirements, MONET includes a market segment dimension based on vehicle size: S1 for vehicles with an overall length (OAL) below 4.1 m, S2 for vehicles with an OAL between 4.1-4.6m, S3 between 4.6-4.8m and S4 for vehicles larger than 4.8m (Figure 1-1).

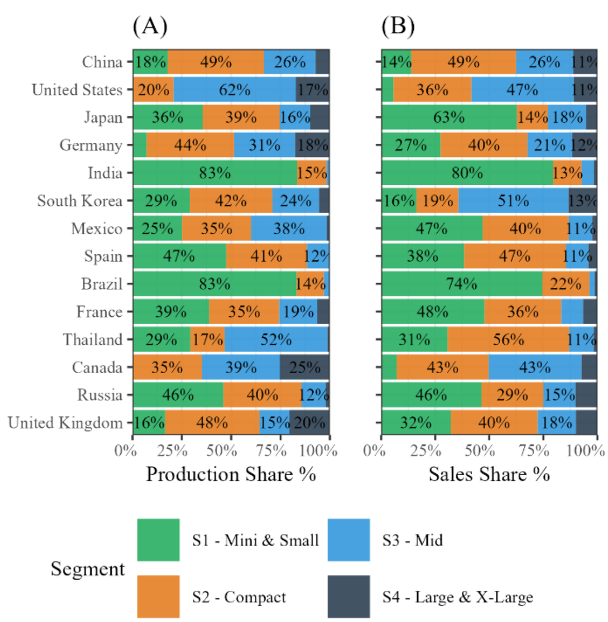

Figure 1-1. **Production (A) and Sales (B) share of LDVs by segment for top 14 buyers countries 2017-2019**. Data source: InfluenceMap (InfluenceMap, 2022) and additional extrapolation by the authors.

1.4.3 Battery capacity

An additional capability of MONET is calculating battery requirements based on the total forecasted battery powered EV production for each country. The battery capacity depends on battery size averages per segment of the country where the EV is going to be sold (demand). Battery size and chemistry characteristics come from EV Volumes historical (2010-2022) records (EV Volumes, 2022), and depends on country and market segment (Figure 1-2).

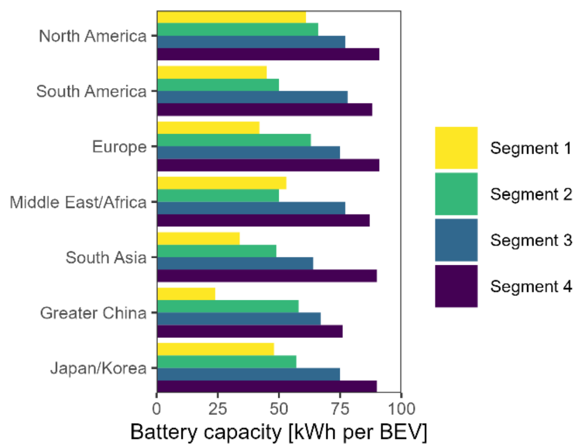

Figure 1-2. Default battery capacity (kWh) per battery EV by segment (vehicle size) and region of demand, 2022. Data source: Aggregated from EV Volumes (EV Volumes, 2022).

1.4.4 Demand forecast

Projected sales of light duty EVs from the ICCT Roadmap v2.2 forecast model (ICCT, 2022b) were used as input to allocate future vehicle production (Figure 1-3). The "Ambitious" scenario was used, which reaches 100% EV sales by 2040.

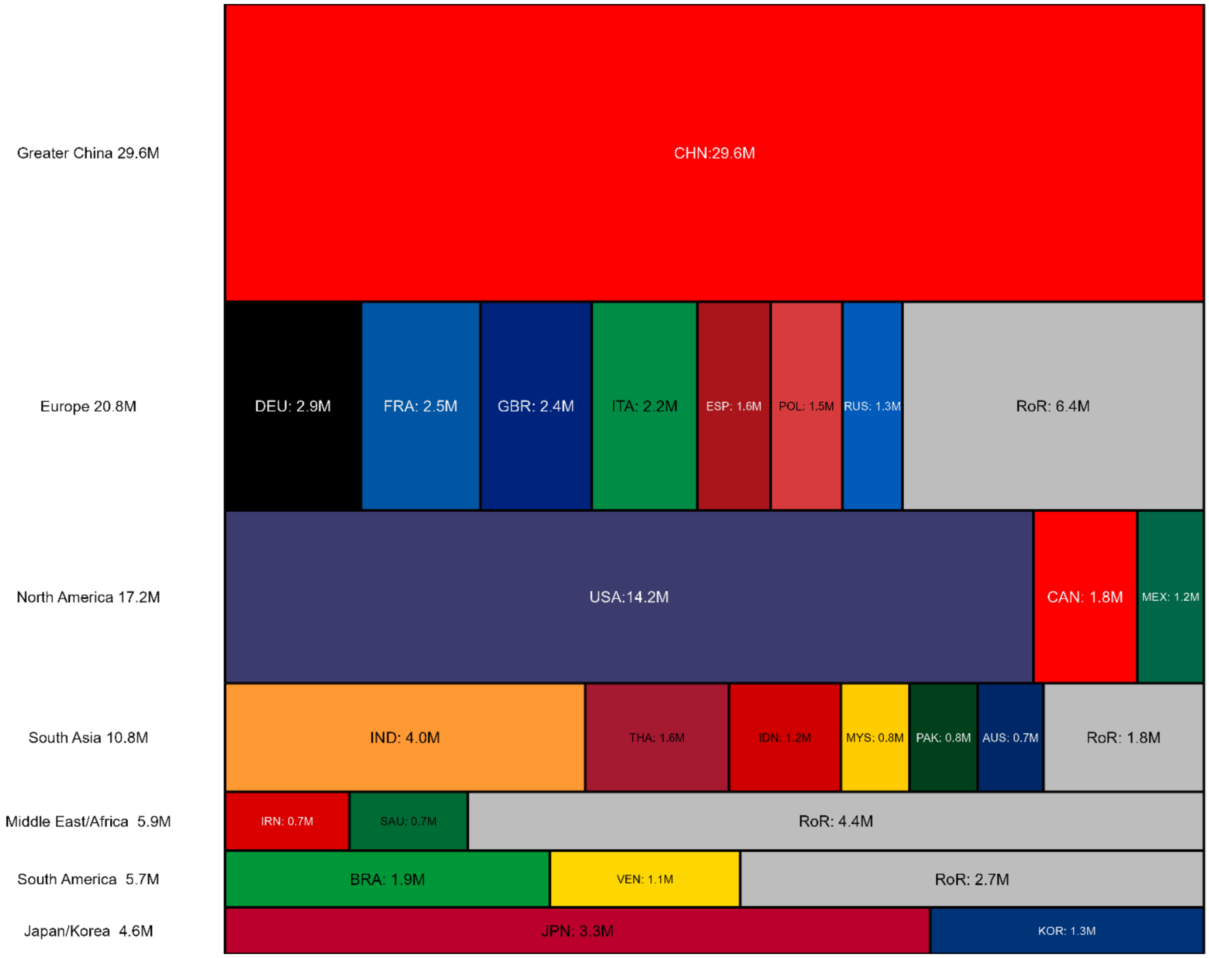

Figure 1-3. 2035 BEV Sales ICCT Roadmap forecast, ambitious scenario, for the 65 countries/regions in MONET. Total sales: 94.5 million. For relevant countries, that total sales are shown with the country ISO code. RoR: Rest of Region. Source: ICCT Roadmap Model (ICCT, 2022b).

1.5 Methods

1.5.1 Balance a trade flow matrix

If we conceptualize the vehicle bilateral trade data as a matrix, from country of production (rows) to country of sales (columns); then each entry (cell) represents a vehicle flow, the diagonal of the matrix corresponds to domestic supply (production of vehicles sold in the same country); and the sum of each row to the total production by country and the sum of each column to the total vehicle sales by country (Figure 1-4). A bilateral trade matrix provides information on total vehicle sales, production and flows between countries, allowing to model the upstream supply chain for electric vehicles.

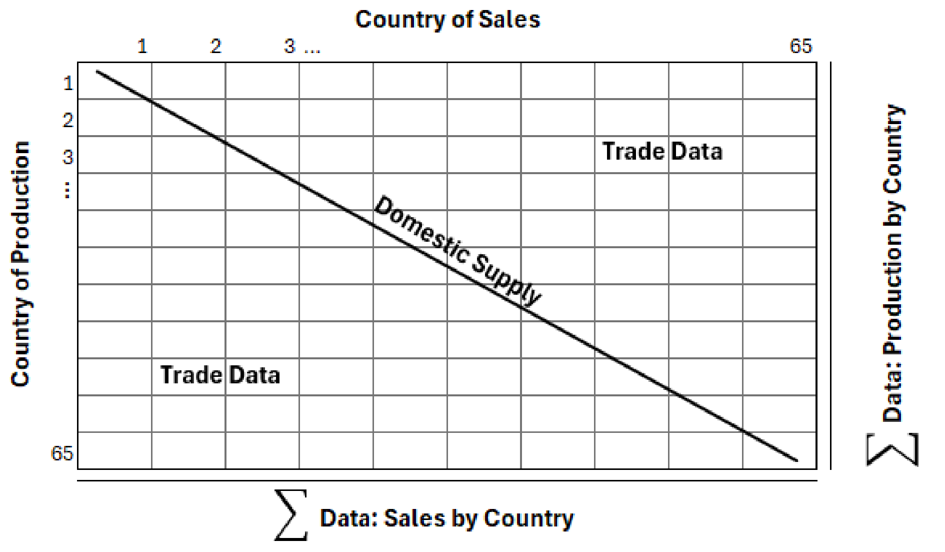

Figure 1-4. Conceptual model of MONET trade flows. The matrix shows the bilateral trade data between producers and LDV consumer countries. The total sum of columns/rows corresponds to production and sales by country. The trade ratios constructed in MONET have an additional dimension of length 4, which corresponds to market segments, thus the trade ratios become a tensor (or 3-D matrix).

A major problem is that trade data is notoriously inconsistent and full of errors. Balancing a trade flow matrix requires to combine multiple conflicting data sources with a loss of information minimization procedure. UN Comtrade reports data on total exports and imports from different countries agencies, so the aggregate numbers are not consistent with each other due to multiple sources of error, such as (1) countries unwillingness to share trade information; (2) lack of agency capacity to accurately register trade volumes on either side of the transaction; (3) conflicting definitions of goods and the appropriate international HS coding across countries; (4) differences in the use of trade units across countries; (5) organizational errors in unit conversions; (6) differences in guidelines used by countries to record and report trade data; or (7) human errors. Most errors point towards an inability to accurately capture all the information, introducing a missing data or negative bias.

A major inconsistency from UN Comtrade data is that exports declared by a country do not match total imports from that country declared by other countries, due to major differences in data registration across countries. In simpler words, for each trade flow there are two sources of information often in discrepancy: what is declared as export from the country that produces the vehicle (F_E), and what is declared from the country that receives the vehicle as import (F_I). Both sources of information were combined proportional to the ratio of total exports over total exports and imports of the producing country, following the principle that countries with higher exports are likely to be better at reporting exports data.

$$Trade\ Flow = F_E(\frac{E}{E+I}) + F_I(1 - \frac{E}{E+I})$$

The resulting trade flow matrix still does not necessarily match declared country production or total sales data. To correct this trade flows inconsistency, we use data at country level of LDV production and sales Overall, a trade matrix should preserve a basic trade principle, where production and imports equal sales and exports:

$$P + I = S + E$$

The production vector (by country) corresponds to the sum of the columns of the trade matrix, and the sales vectors to the sum of the rows (Figure 1-4). We used the RAS balancing method to iteratively correct either rows or columns to match the total marginals of production and sales (EuroStat, 2014; Trinh & Viet Phong, 2013). The RAS balancing method has the main advantage to minimize the loss of information when merging conflicting data in a matrix format, and has been used extensively for trade data (Polenske, 1997; Round, 1978). The gravity model is another technique that has been extensively use to model bilateral trade (Martinez-Zarzoso, 2003; Shahriar et al., 2019), especially to estimate unknown trade flows. We choose the RAS balancing method as we have records of trade data to initialize flows, and due to the fact that the RAS method outperforms the gravity model at ensuring that the balance constraints are met (Distefano et al., 2020). The RAS method follows an iterative procedure where the matrix is collapsed into a vector by summing over one dimension (columns or rows), then a correction vector is estimated based on exogenous production or sales data, which is used to correct the trade flows of the matrix. The algorithm then iterates over the other dimension. An example of the method to adjust for sales is presented in the following equation, from iteration step *z-1* to *z* (the adjustment for production is similar, *i* and *j* are country indices):

$$\sum_j W_{i,j}^{(z)} = W_{i,j}^{(z-1)} * \frac{Sales_i}{\sum_j W_{i,j}^{(z-1)}}$$

A total of 200 iterations were run, and the simple average of the last two matrices were used as the output of the balancing method[8]. The resulting 2-dimensional matrix represents the best estimate of vehicle trade flows for the 2016-2019 period, with the sum over columns representing production by country and the sum over rows sales by country.

1.5.2 Adjusting for re-exports

A common practice in international trade is to import goods from one country and then export them to another country without changing the nature or form of the goods. This practice is known as re-exporting. Re-exporting can improve market access for certain countries by facilitating the movement of goods, but it also creates statistical discrepancies in trade data because, typically, when a country re-exports previously imported goods, these are recorded as exports even though they were not produced domestically (Lemmers & Wong, 2019). This can distort trade statistics and make it difficult to accurately track the origin and destination of goods in international trade, especially given the varying rules that different countries have for classifying and reporting re-exports.

A widely used practice in international trade analysis to resolve this issue is to apply an assumption of proportionality (Mattoo et al., 2013), in which exports are disaggregated into imports destined for re-exports (RE) and domestic production for exports (DE), using the corresponding ratio of exports over the total inputs to the country (production and imports). The following assumes that a country with relative high imports (compared to production) will have a higher proportion of re-exports.

[8] The method always matches perfectly to the last adjusted input (production or sales), thus we combine the last adjustment of sales and production to avoid a modelling preference.

$$RE = I * \frac{E}{P + I}$$

$$DE = P * \frac{E}{P + I}$$

$$E = E * \frac{P + I}{P + I} = I * \frac{E}{P + I} + P * \frac{E}{P + I} = RE + DE$$

In a similar way, sales can be disaggregated into imports for domestic consumption (FS) and domestic production destined to supply the local market (DS).

$$FS = I * \frac{S}{P + I}$$

$$DS = P * \frac{S}{P + I}$$

$$S = S * \frac{P + I}{P + I} = I * \frac{S}{P + I} + P * \frac{S}{P + I} = FS + DS$$

This process removes re-export values from the original balanced import-export matrix, effectively obtaining a new matrix in which column values represent imports destined to be sold in the final country of destiny (FS), and row values represent countries' domestic exports (DE).

1.5.3 Market segmentation balance

MONET includes an additional dimension to the bilateral trade flows matrix, converting it into a trade flows tensor (or 3-dimensional matrix). Trade flows were adjusted to capture heterogeneity among market segments, decomposing the trade flows using total sales and production data by segment (InfluenceMap, 2022). Market segmentation was modelled at the trade ratios level because different market segments have different price values and trade relationships between countries. For example, Japan is a country that produces in every segment, but mainly exports in the bigger vehicle segments, or the US produces mainly bigger vehicles and imports smaller vehicles.

The introduction of market segments generates a complex problem of data balancing, with multiple potential solutions. Overall, the tensor has the following data inputs: sales by country and market segment

($Sales_{i,k}$, n=260)[9], production by country and market segment ($Production_{i,k}$,n=260) and total LDV trade flows by country of production to country of demand ($Trade\ Flows_{i,j}$, n=4,225)[10]. The tensor has 16,900 cell entries[11] to be estimated ($W_{i,j,k}$), with the restrictions that the summation over each dimension (marginals) must match the data inputs:

$$\sum_{i} W_{i,j,k} \approx Production_{j,k}$$

$$\sum_{j} W_{i,j,k} \approx Sales_{i,k}$$

$$\sum_{k} W_{i,j,k} \approx Total\ LDV\ Trade\ Flows_{i,j}$$

Where "i" corresponds to country of origin, "j" to country of sales, "k" to market segments. The number of constraints is less than free variables, so no unique solution exists, and there is no guarantee that there is a solution that meets all the constraints. Potential ways to solve this data-matching problem are through regression analysis, optimization, market share allocation, consumer preferences, RAS balancing or simply expert allocation. We propose two techniques to balance this conflicting information inspired by the RAS balancing method.

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[9] 65 countries and 4 market segments.
[10] All combinations of flows between countries.
[11] All combinations of flows between countries for all 4 market segments.

Proportional method

The proportional allocation method is a simple way to estimate a trade flow between a pair of countries based on their relative size of sales and production, under the assumption that the trade flow should be positively correlated with both quantities (Robert A. McDougall, 1999). For each market segment a trade matrix can be calculated by multiplying the production and sales vector transposed, then normalizing by either the sum of the production or sales, which are equal (the method requires that the marginals are in perfect balance, so we slightly adjust total production to match total sales). The method allows us to estimate trade flows for each market segment with the principle of proportionality. The market segments trade flows can be used to compute the disaggregation share in segments for each trade flow relationship, that then is multiplied by the total amount of LDV in that trade flow. The method produces an initial estimate of the trade flows by market segment (tensor).

To ensure consistency for the resulting trade flows, the multidimensional RAS balancing method was used (Holý & Šafr, 2023), which is an iterative scaling process that uses the marginals (production by country and segment; sales by country and segment; and trade flows by country and country) to balance the trade flows by segment. The iterative adjustment forces the marginals of the sum of rows to be equal to the matrix of sales (country by market segment). The adjustment for production and trade flows is similar with a different index. We iterate 300 times or until convergence is reached, and use the average of the adjustment for the last value after adjustment for sales, production and trade flows. An example of the method to adjust for sales is presented in the following equation, from iteration step *z-1* to *z* (the adjustment for production or trade flows is similar):

$$\sum_j W_{i,j,k}^{(z)} = W_{i,j,k}^{(z-1)} * \frac{Sales_{i,k}}{\sum_j W_{i,j,k}^{(z-1)}}$$

Draining buckets

Another method to disaggregate the total trade flows among market segments is to follow an specific order based on market value. The method mimics a market situation where big companies get their share of vehicles first. We named this method the "Draining-buckets", as the key idea is to allocate start with buckets full of total trade flows (no market segments) and allocate them towards the different market segmentations. A full description of the algorithm is presented in Table 1-2. A key aspect is the sorting of trade flows from large to small, which allows us to accurately allocate bigger trade flows.

Table 1-2. Algorithm "Draining-Buckets". Goal is to disaggregate trade flows into market segments.

Input: Balanced LDV trade flow matrix T_{65x65}. Production P_{65x4} and sales S_{65x4} by country and segment. Empty $W_{65x65x4}$.

1) Convert T into vector of length 4225 and sort flows from bigger to smaller *(in total LDV units)*
2) For each flow f in T, with origin country "o" and destination "d" do:
    a) For each market segment M in {*S4,S3,S2,S1*} (large to small in vehicle size) do:
        i) Get origin flow amount: $X=f*\%P_M$. Note that "$\%P_M$" is the share of production of segment M of country "o".
        ii) Get destiny flow amount: $Y=f*\%S_M$. Note that "$\%S_M$" is the share of sales of segment M of country "d".
        iii) If X≤Y:
            (1) "Drain" X from production and sales buckets: P=P-X and S=S-X. Record flow $W_{o,d,M} = X$.
        iv) If X>Y:
            (1) "Drain" Y from production and sales bucket: P=P-Y and S=S-Y.
            (2) Define $Z = \sum_{i\ in\ \{S1,S2,S3,S4\}-M} S_{d,i}$ as remaining sales in other segments of country "d".
            (3) If X-Y≤Z: Allocate remaining flow Y-X into remaining segments M^C, based on proportional shares of S. Record flows $W_{o,d,M}$ = Y and $W_{o,d,Mc}$ = Y-X *(proportional).*
            (4) If X-Y>Z: Allocate Z into remaining segments M^C, based on proportional shares of S. Record flows $W_{o,d,M}$ = Y and $W_{o,d,Mc}$ = Z *(proportional).* Dismiss unallocated trade flow.
        v) Next M.
    b) Next flow f in T.

return W

The resulting trade tensor flows are balanced using the multidimensional RAS method, same as in the proportional method.

Balancing evaluation

The resulting balanced trade tensor from both methods was evaluated using the marginal input data and other metrics. The total number of trade flows captured by the resulting tensor trade flows was compared to the original matrix trade flows. The marginals (summation over one dimension) of the trade tensor were compared against the trade flows, production and sales original input data using the mean relative absolute error (MRAE). To account for errors on the tail of the distribution, the MRAE of the worst 10% mismatches between tensor marginal and accurate data (trade flows, sales and production), or the so-called super-quantile (Rockafellar & Royset, 2010) was calculated. The latter computes the average error at the worst outcomes (distribution tails), providing a more conservative assessment of the degree of mismatch.

1.5.4 Trade ratios

The resulting balanced tensor trade flows represent historical LDV data from 2016-2019. The tensor was divided by market segment, and then we normalize each resulting matrix by dividing by each country total sales. The computed trade ratios represent the proportion of vehicles in a determined segment that originates from each country. The trade ratios are the key input to allocating future vehicle production for each market segment.

To better account for the constantly changing nature of trade relationships, several trade ratio scenarios were included to forecast how the global supply chain of EVs may look in the future. Future users of MONET can create new trade scenarios, with the caveat that after a change in the trade ratios they always need to adjust them to increase/decrease participation of a certain country, and then re-balance accordingly. The proposed trade scenarios, rationale and assumptions for the global supply chain of EVs in 2035 are the following:

- **T1 - Constant LDV 2016-2019 trade ratios**. Baseline scenario assuming that the 2035 EV trade ratios will be the same as 2016-2019 LDV trade ratios. The rationale is that the current LDV flows represent the empirical equilibrium between free trade agreements and protectionism policies in the world.
- **T2 – Higher domestic supply + Free Trade USMCA & EU.** The baseline trade flows are modified under the assumption that domestic supply of EVs will grow globally by a relative increase of 40%, reducing the global exports/imports flows. The scenario considers existing trade partnership of United States-Mexico-Canada Agreement (USMCA) and European Union (EU), where the increase in domestic supply in each country is allocated proportionally among regional partnership countries. The rationale behind this scenario is a potential development of policies that could promote regional domestic production, such as the inflation reduction act (IRA) of the United States (US) that limits mineral origins for the EV batteries or the EU Carbon Border Adjustment Mechanism (CBAM) which taxes the carbon footprint of imported goods (that could include vehicles in the future). The adoption of protectionist policies may induce other countries to adopt similar policies, reducing international trade (Ahsen Demir & Sepli, 2017).
- **T3 - Global free trade**. This scenario considers an increase in the EV trade flows among countries with respect to the baseline, creating new trade relationships for the top 12 LDV producer countries. We modify the balanced trade flows by allocating 50% of future country demand supplied by imports among the 12 future EV specialist countries proportional to their current share of LDV exports. In this scenario, global trade flows are expanded while concentrating production within specialist countries. The rationale is that free trade remains a good global economic policy (Krugman, 1987; WTO, 2013) and that they led to an increase in international trade, driven by more economic competition (Ahsen Demir & Sepli, 2017).
- **T4 – China industrial focus, allocating 20% of their EV production towards exports**. China may elect to pursue an industrial export policy and allocate a higher share of their production for export by

reducing local demand. Demand forecasts indicate that China will be the biggest buyer of EVs, but right now it is an isolated player in the global market with relatively small imports and exports. In this scenario we took the assumption that the internal demand in China for segment 2 and 3 will be 20% less and allocated that production for exports to each country, based on proportional sales. Under this scenario, production in other regions will be displaced by China's exports. The rationale follows from the recent push of China towards developing their EV production market (Meckling & Nahm, 2019) and the recent increase in share of global exports of LDV from China.

1.5.5 Output: Production allocation, EV flows and battery requirements

MONET can estimate the required production for each country and market segment using the trade ratios and sales, with the following equation:

$$Production_{j,k} = Trade\ Ratios_{i,j}^{(k)`} * Sales_{i,k}$$

MONET results generate not only the production of vehicle for each country, but also detailed flows between producing countries and demand country, for each market segment. The flows then are used to calculate battery requirements based on the average battery size for each demand country and market segment.

Validation of Production Allocation

Data from 2013 to 2021 from the LDV market was used to construct historical yearly trade ratios of LDV (no market segment). The historical data on sales and production by country allows us to perform a cross-year validation. For each year with sales data the production by country was calculated using the different trade ratios matrices (from 2013 to 2021), and then it was compared to the observed historical production. The resulting comparison gives an idea on the error magnitude of the production allocation method embedded in MONET, as trade ratios naturally evolve over time. This comparison is inspired by cross-validation methods from machine learning, which uses known data, but not used on the model construction, to estimate the model accuracy.

1.6 Results

1.6.1 Trade Ratios

The resulting trade ratios reveal interesting patterns from the global LDV trade supply chain (Figure 1-5), such as : (I) many countries do not have a local car producing industry whose demand is 100% supplied by imports; (II) a high prevalence of domestic supply in LDV flows, globally domestic supply satisfies 66% of demand; (III) regional partnership clusters (Europe and North America) with important within flows regions; (IV) presence of countries with major global exports of LDV, such as Germany, Japan, South Korea and US; and (V) heterogeneity in the trade relationships by market segment (e.g. USA and Germany exports are dominated by bigger vehicles, while Japan exports focus on all segments).

Market segmentation plays a key role in trade dynamics, as production capacity differs among countries. For example, India is mostly producing and exporting smaller vehicles, with smaller batteries, thus requiring less battery capacity to meet their production. Other countries, such as Mexico, that exports mostly bigger vehicles to U.S. will need to secure higher battery capacity. The fundamental revelation of MONET is the country mismatch between demand and production, where an increase in countries demand does not necessarily translate to a proportional increase in production.

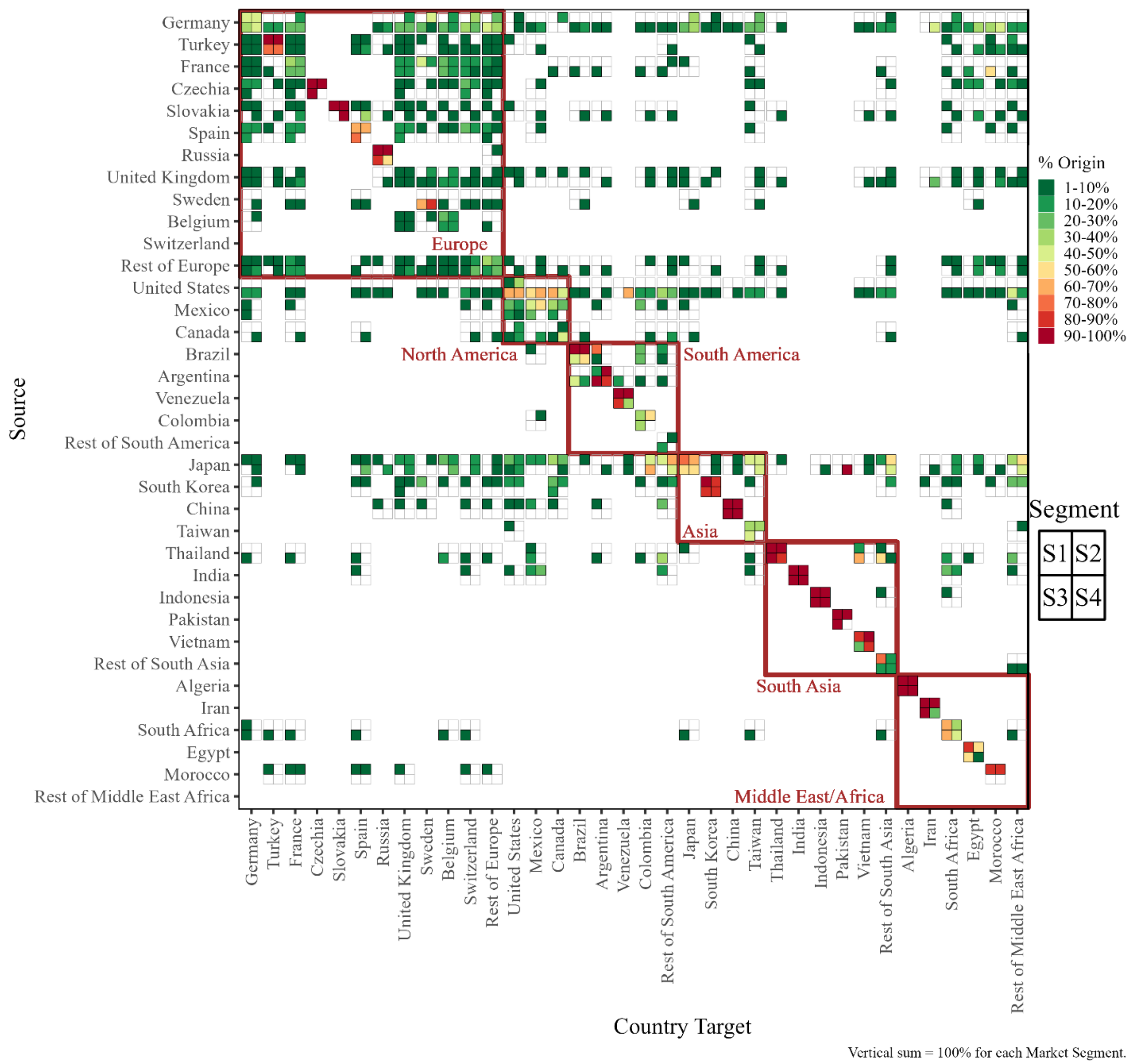

Figure 1-5 Balance trade ratios for LDVs 2016-2019 by market segment. The rows represent exports from each country, and the columns represent imports. Diagonals are named domestic supply, production in each country that goes towards satisfying domestic demand. Each square color represents the share that the origin country of LDV (*row*) is providing to the destination country (*column*). Each square is divided into 4 squares representing the trade flow for each segment. Total sum over a column is 100% for each segment (400% in total), representing the total share of origin of LDV for a given country. Blanks spaces indicates no LDV trade relationship between countries. Countries with all their row blanks simply indicate that the country does not produce any LDVs. All the 65 countries/regions in MONET were aggregated into 36 countries/region, for visualization purposes.

1.6.2 Balancing Methods Evaluation

There is a trade-off between the resulting accuracy of the tensor generated by the proposed balancing methods (Table 1-3). The “draining buckets” generates a lower error (or better matching with the more accurate production, sales and trade flows data), both at average level and for the worst outcomes (super-quantile, or average of the 10% worst cases). On the other hand, the “draining buckets” methods fail to capture a vast majority of flows, missing some small but distinctive trade relationships between countries, as the method first allocated towards the bigger flows. The trade-off can be summarized as the “draining buckets” provides a better fit overall, but fails to capture a majority of trade flows. Under this scenario, we decided to combine both tensor results at different proportions (SI Figure A-1), showcasing that a good combination is a simple average (50-50% proportion). The resulting tensor has a low error rate, and captures the majority of trade flow relationships.

Table 1-3. **Comparison of multi-dimensional balancing adjustment between the proportional and “draining buckets” method.** MRAE: Mean relative absolute error. Combination is a simple average between both method tensor output. Bold indicates best performance.

Method	MRAE with respect to marginal			MRAE Super-quantile 10%			% of Flows captured
	Prod.	Sales	Trade flows	Prod.	Sales	Trade flows	
Proportional	2.42%	**0.053%**	**0.00%**	83%	**4.25%**	**0.00%**	**83%**
“Draining buckets”	**1.37%**	0.54%	0.08%	**12%**	8.38%	0.15%	56%
Average of methods	1.66%	0.44%	0.04%	45%	6.49%	0.08%	82%

1.6.3 Production allocation cross-year validation

The production allocation method uses historical trade ratios to predict production based on sales forecast, under the main assumption that trade ratios in the future will resemble trade ratios in the past. Comparing estimated production for trade ratios years with the actual production observed by country, we found a small but increasing error rate the longer the time difference (Table 1-4). For a 3-year difference the MRAE tends to be close to 3%, and for the 8-year period difference the MRAE is around

5%, which suggests an approximate 1% error margin cause by evolving trade networks and relationship. If instead of evaluating the average relative error, we just take the worst 10% mismatch, the MRAE grows considerably up to 30% to 50% in some cases, highlighting that for some countries, especially with smaller trade flows, the allocation of production by trade ratios could have severe limitations. The latter represents just the past, and it does not guarantee that trade relationships may drastically and abruptly change due to global policies, or other major supply chain disruptions. A 1% error rate per year suggest that predictions for 2035 could have around a 30% error rate (compounded) in the production allocation, a consideration that must be considered when providing recommendable actions arising from the results of MONET.

Table 1-4. Average MRAE (A) and super-quantile for the 10% worst MRAE (B) for the prediction of global LDV production, given all combinations of yearly regional demand vectors and observed trade ratios matrices.

A: Average MRAE

Sales Year \ LDV Ratios Year	2013	2014	2015	2016	2017	2018	2019	2020	2021
2013	0.00%	1.97%	3.01%	3.12%	4.97%	3.55%	3.82%	5.00%	5.22%
2014	1.98%	0.00%	2.31%	2.45%	3.88%	2.71%	3.29%	4.16%	4.96%
2015	3.03%	2.38%	0.00%	1.19%	4.17%	3.06%	3.98%	4.93%	5.93%
2016	3.21%	2.62%	1.19%	0.00%	3.75%	2.70%	3.45%	4.31%	5.32%
2017	5.08%	3.96%	4.16%	3.72%	0.00%	2.38%	3.26%	3.90%	4.87%
2018	3.70%	2.83%	3.11%	2.67%	2.37%	0.00%	1.68%	2.56%	3.72%
2019	4.21%	3.53%	3.97%	3.41%	3.33%	1.69%	0.00%	1.56%	3.01%
2020	4.74%	4.02%	4.63%	4.03%	3.84%	2.50%	1.57%	0.00%	2.13%
2021	5.25%	5.01%	5.63%	5.07%	4.95%	3.75%	2.97%	2.22%	0.00%

B: Super Quantile 10% MRAE

Sales Year \ LDV Ratios Year	2013	2014	2015	2016	2017	2018	2019	2020	2021
2013	0%	23%	36%	33%	31%	32%	33%	40%	50%
2014	20%	0%	18%	30%	27%	41%	45%	48%	40%
2015	30%	15%	0%	20%	24%	23%	25%	29%	28%
2016	42%	48%	24%	0%	23%	30%	42%	31%	29%
2017	36%	35%	25%	19%	0%	22%	26%	35%	34%
2018	32%	32%	19%	16%	20%	0%	16%	14%	18%
2019	31%	35%	26%	21%	23%	17%	0%	11%	14%
2020	34%	27%	26%	22%	26%	13%	7%	0%	12%
2021	42%	36%	26%	25%	23%	23%	19%	12%	0%

1.6.4 Future EV Supply

Using the 2035 ICCT roadmap forecasts for light duty EV sales globally (Figure 1-3), MONET can estimate detailed EV flows between countries for major regions. The 2035 EV supply chain is dominated by regional trade relationships (see Figure 1-6 and the caption for directions on Sankey diagrams interpretation). We can observe interesting insights into the supply side of EVs based on market segmentation and global trades:

- **North America is a major producer and buyer of large EVs** – US produces a big share of bigger segment vehicles, almost entirely for domestic supply. Their domestic partners, Mexico and Canada, have adjusted their production for the US consumer preference of larger vehicles, producing mostly in these segments. Most of the small vehicle supply for US come from Japan and Korea.
- **Europe is a big producer itself –** The majority of trade flows of Europe are concentrated inside the region, with important exports towards North America and Japan & Korea.
- **Japan and South Korea are major exporters of small-medium vehicles** – The majority of production in the region goes towards exports for the entire world: North America, South America, Europe, Middle East, Africa and South Asia. Japan produces small vehicles (S1) mostly for domestic supply and Europe, large vehicles (S3) for North America and mid vehicles (S2) for all other regions.
- **China produces vehicles mostly to independently satisfy their domestic supply –** The Chinese market shows diversification in vehicle size, with most of their production going towards domestic supply. Based on historical LDV ratios, China is not a major importer or exporter of vehicles, a situation that is already changing and may dramatically influence trade ratios in the future.

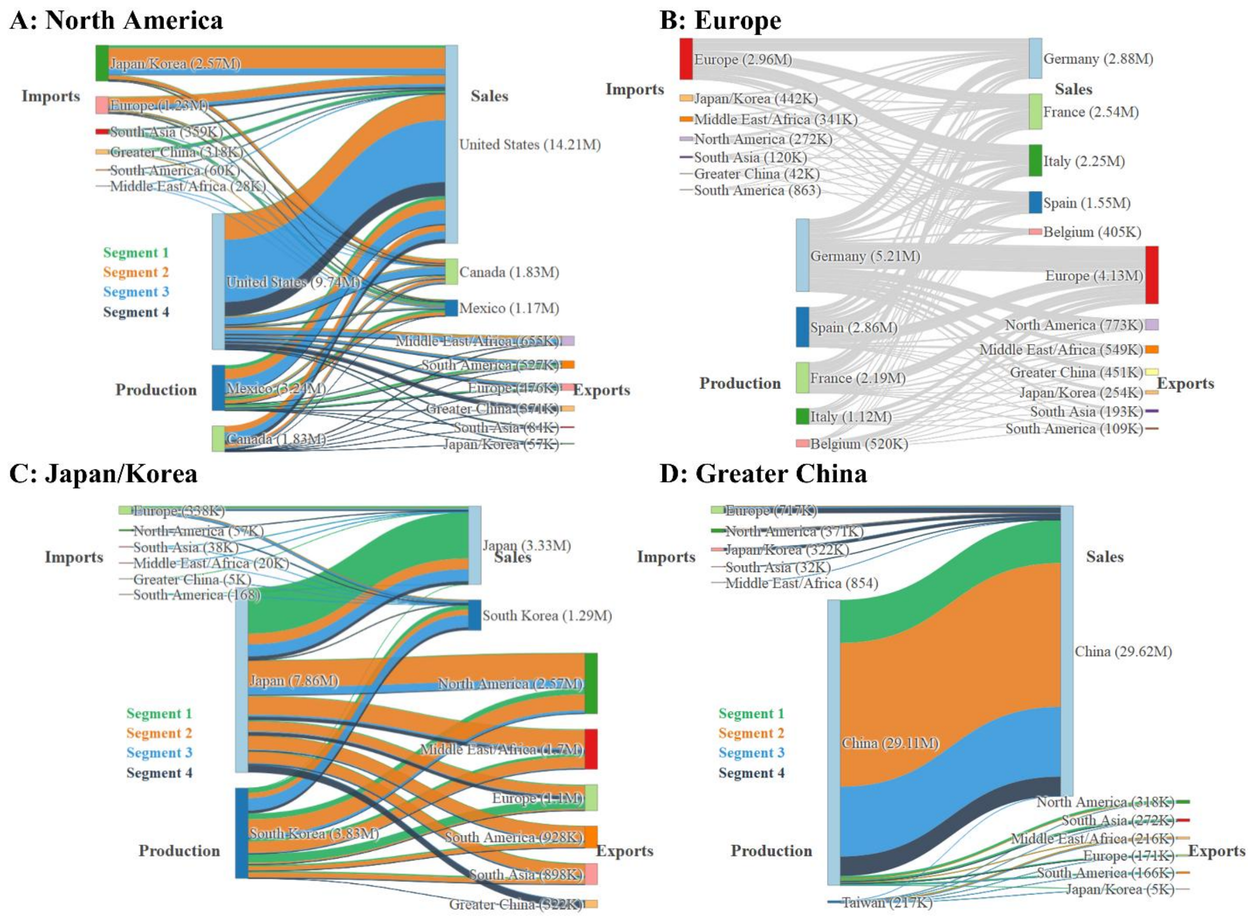

Figure 1-6. 2035 Light Duty EV Supply chain dynamics under baseline trade scenario (T1 –LDV 2016-2019 trade ratios) for major automobile producing regions: (A) North America, (B) Europe, (C) Japan & South Korea and (D) Greater China. Each Sankey diagram shows the EV dynamics inside each region, in the left side all the inputs are shown (imports and production), and on the right side all the outputs (sales and exports). Color shows market segmentation into S1 to S4 (width of the flow represents units of vehicles). Europe does not show segment details to simplify the figure.

The future global EV supply chain changes with respect to different trade scenarios. Figure 1-7 shows the EV supply chain dynamics for the Japan & Korea region under the different trade scenarios. This region was chosen as it is the major exporter region of vehicles in the world. Current LDV ratios show a similar pattern as the global free trade scenario, with slightly more production in the region under free trade. In the scenarios with higher domestic supply chain and China exporting a share of their production, an important decline in production occurs in the region. In terms of market segments, the region is mostly dominant in the small and medium vehicle sizes, where less competition is likely to occur due to the lower relative value per vehicle. Other assumptions will also change the results of the future EV production, such as vehicle sales per country or battery capacity per vehicle.

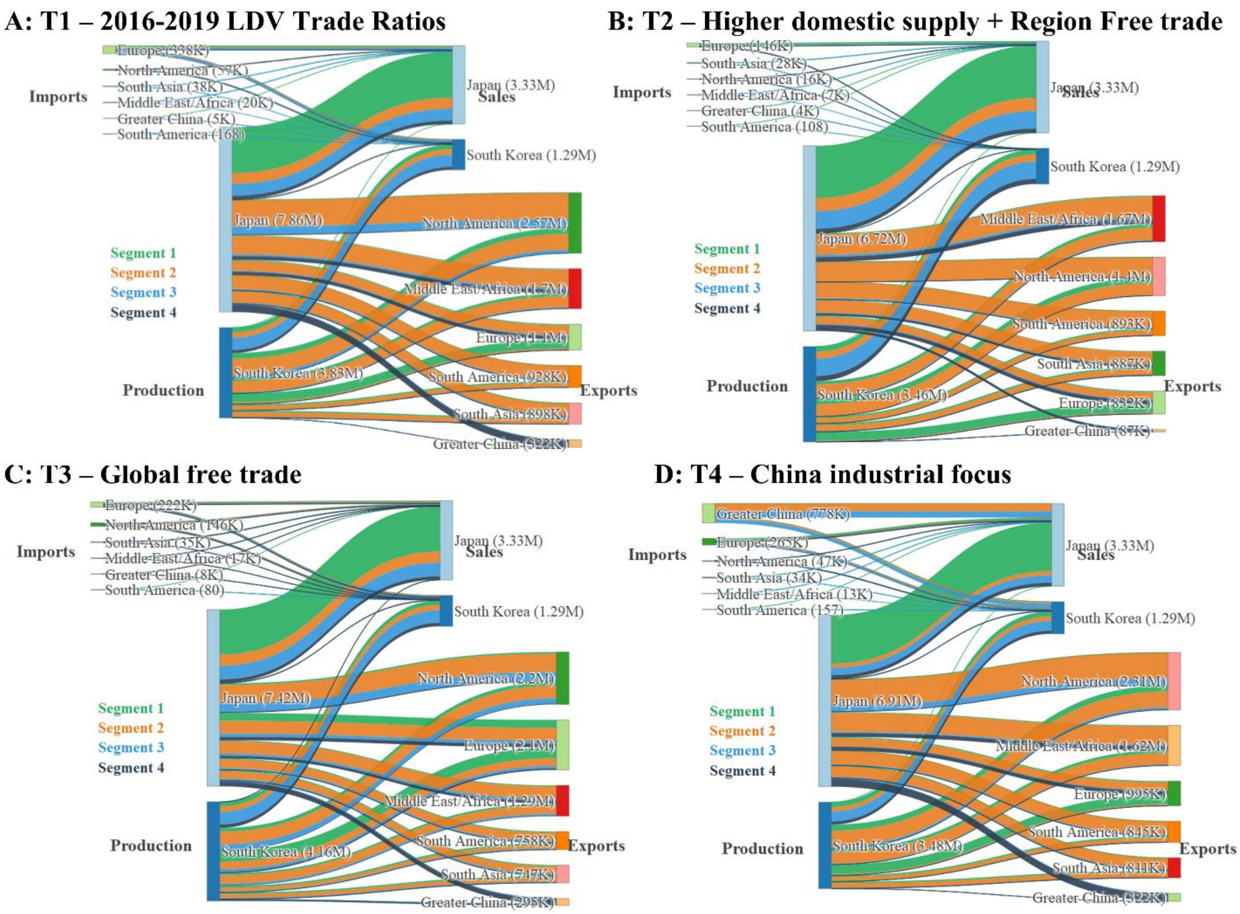

Figure 1-7. 2035 Light Duty EV Supply chain dynamics for the Japan & Korea region under different trade scenarios. (A) Baseline scenario, (B) Higher domestic supply scenario with regional free trade, (C) Global free trade scenario and (D) China industrial focus scenario (allocating 20% of demand towards exports). Each Sankey diagram shows the EV dynamics inside each region, in the left side all the inputs are shown (imports and production), and on the right side all the outputs (sales and exports). Color shows market segmentation into S1 to S4 (width of the flow represents units of vehicles).

1.6.5 Battery requirements

A major contribution of MONET is to be able to estimate EV production upscale for industrial countries that actually participate in the vehicle supply chain, and thus assess their battery requirements based on the battery size per segment and country of destination of their production.

Figure 1-8 shows a comparison of the spatial distribution of battery requirements under two different modelling assumptions. The first is allocating battery requirements to countries where the demand of EV will take place, as most critical materials studies have done (Alonso et al., 2023; Baars et al., 2021; Dunn et al., 2021; Zhang et al., 2023). The second is using results of MONET to allocate battery requirements towards the producer country. The difference is contrasting for major exporter countries, such as Japan, Mexico, Spain and Germany. For example, taking the forecasted demand for Spain gives the inaccurate battery requirement of 89 thousand MWh, while the country will require 155 thousand MWh to produce EV destinated towards domestic supply and exports. The opposite case can be made for the US, using the demand to estimate battery requirements results in an overestimation, as an important share of vehicles sold in the US are produced elsewhere. The distinction matters less for countries with less vehicle global trade activity, such as China.

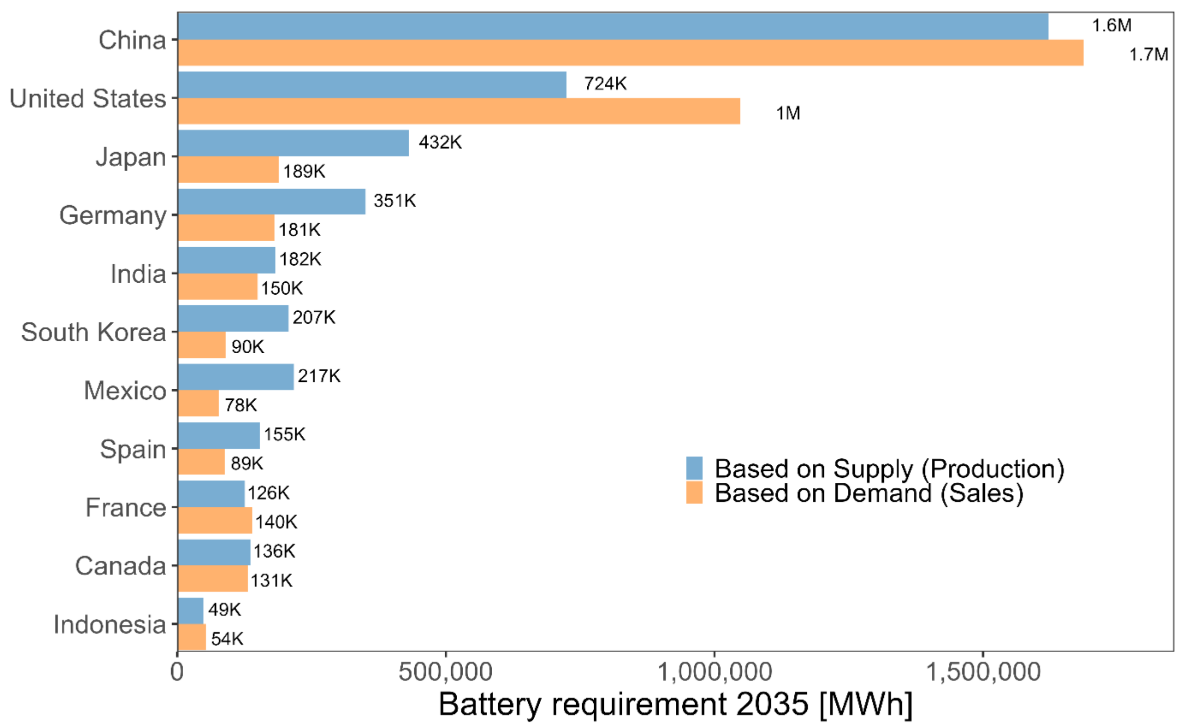

Figure 1-8. 2035 Battery supply requirements for light duty EV if considering the location where the car is sold (demand) or where it will be produced (supply). Top 11 producer countries are shown. Trade scenarios for supply is simply the baseline (T1 –LDV 2016-2019 trade ratios). Battery requirements were calculated taking into account different battery sizes per segment and type of vehicle (BEV and PHEV).

1.7 Discussion

The results from MONET indicate a future EV global trade dominated by trade within world regions. The four major regions show distinct trade needs: North America is a big producer that still requires imports to meet their demand, Europe is a big trade region within itself, Japan & Korea are the big exporters of EVs and China's current production goes almost entirely to domestic supply. The above relationship holds for market segments, where North America produces and buys big cars, while Japan & Korea produces and buys smaller cars. The current trend of preferences towards larger vehicles is being replicated in EVs (IEA, 2023b), which could play a determinant role in production allocation.

The future global EV trade relationships will be shaped by economic and geopolitical factors, evolving from the current LDV global market. A major assumption in MONET is to start with present LDV trade flows to forecast future EV flows, under the assumption that countries will shift from ICE to EV production. Several trade scenarios show contrasting supply chain dynamics and different trade relationships evolutions. Countries that rely heavily on exporting their EV production are more exposed to exogenous trade shocks. The emergence of the developing world could play a major role in changing trade dynamics, for now Brazil and India are big producers of smaller car segments and in a similar situation as China: producing almost entirely for domestic supply. The development of the industry in these countries could have major implications for exporter countries, like Japan, Germany or Mexico, among others. The supremacy of North America in producing large vehicles may be especially challenged by China, which is also an important producer in those segments, or another country interested in the higher margin of profit provided by bigger vehicles. Other trade scenarios based on upcoming policy and geopolitical developments could be modelled using MONET as a baseline.

Battery requirements differ greatly for countries where the vehicle will be sold or produced. MONET is a novel attempt to close this research gap between supply and demand of future EV and battery material. Battery requirement per country also depends on adequately characterizing market segments. MONET results of battery requirements are especially important for country and OEMs to plan and secure battery and mineral supply in the location of production. Moving towards co-location of battery and final EV assembly has many potential benefits, such as reducing shipping costs, reducing the carbon footprint of shipping parts, sharing of knowledge and integration of the supply chain. MONET results inform countries to plan for producing batteries near vehicle production.

1.7.1 Novelty

The development of MONET main input, the historical vehicle trade ratios, includes multiple data sources, often inconsistent. This empirical data was combined with the RAS balancing method to ensure internal consistency and to minimize the loss of information, under the main assumption that aggregated production and sales data at country level is more accurate than reported trade flows. By including market segments by vehicle size, MONET captures important heterogeneity in the trade flows network and battery needs per vehicle. The tensor balancing methods produce a high accuracy result, which captures the majority of existing trade relationships. The resulting trade tensor represents a good estimation of the current trade structure for the LDV global market.

Using historical data for trade ratios, MONET can allocate production to estimate vehicle production by country. While trade ratios evolve over time due to changing economic, technical and political circumstances, there is a substantial degree of inertia in them. Nevertheless, due to changing trade ratios over time the error rate in the predictions grows over time, as all forecast methods are less precise in longer periods of time.

MONET main strengths are that it models trade flows at a detailed level, including 65 countries and aggregated regions trade relationships and market segmentation. MONET geographical scope includes the whole world, revealing the vehicle origin for many countries that do not have a domestic vehicle industry, and the likely vehicle flows around the globe. The market segmentation of MONET allows to better estimate battery requirements, as vehicle size is a big predictor of battery capacity, and to accurately represent trade flows that depend on price value of the vehicle, also positively correlated with size. In that regard, a key feature of MONET for industrial policy planning is that it predicts battery requirements for the countries that will produce the EVs.

1.7.2 Limitations

MONET has major limitations. All sources of error in the data sources collected point towards a potential missing information bias, so the trade ratios depend on the accuracy of reporting agencies regarding their trade flows. Nevertheless, by including global aggregate data for production and vehicle sales this bias is partly mitigated. The production allocation method relies heavily in the assumptions that future trade ratios will resemble their historical behavior, and all the trade scenarios use the current trade ratios, with no tendency, as a starting input. This limitation has two implications: MONET reliability as a production forecasting tool grows in uncertainty for large periods; and that major and abrupt world events, such as a pandemic or trade war, will likely produce major changes in the vehicle trade ratios not captured by MONET trade scenarios. MONET also does not include technological changes that may affect the supply chain, nor a detailed modelling of the effect of protectionism policies, and no consideration of country limiting production factor is embedded in the model.

1.8 Conclusion

The present chapter shows the importance of accounting for future EV global trade. Demand for EV in each country does not translate into a proportional production, as sales are supplied by multiple countries. In this regard, there is a mismatch between buyers of EVs and producers of EVs, even as the literature has used the country of demand to allocate battery and critical mineral requirements. This mismatch is even more pronounced when considering vehicle market segments and their different battery requirements per vehicle. MONET presents a method to close this research gap, and to accurately estimate which countries will likely produce the EVs for the global transition. The battery requirement picture changes drastically when considering country of production. The results presented should help to inform policymakers and OEMs in moving towards co-location of battery production and final EV assembly, to avoid additional costs and environmental impacts associated with shipping and to consolidate their supply chain. Forecasts on producing countries could also help to inform environmental impact analysis, as location is a key determinant of damage. The transition to EVs could generate impact burden-shifted towards producing countries. Ultimately, MONET shows the importance of characterizing not just the future demand for EVs, but the supply side as well.

1.9 Data availability

All the default data inputs, code to balance the trade ratios, and code to run new MONET scenarios are publicly available in https://github.com/pmbusch/MONET.

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2. Chapter 2 - Demand for Critical Minerals

2.1 Scope and Purpose

Achieving electric mobility targets is crucial for meeting decarbonization goals. Electric vehicles (EVs) depend on lithium-ion batteries (LIBs), which require lithium, nickel, cobalt, manganese and phosphorus, among other minerals, for their production. A higher share of renewable and intermittent energy in the electricity grid will also require forms of energy storage, which could be provided by LIBs. The minerals contained on LIBs have been classified as critical given their importance in decarbonization technologies, limited viable substitutes, and risk of supply disruption driven the geographical concentration of reserves. Multiple models have forecasted an exponential increase in mineral demand, mainly driven by EV and LIB adoption. However, no demand model has included all mineral consuming sectors globally and incorporated the dynamics of battery replacement and mineral recovery through recycling.

The following chapter presents a mineral demand model for lithium, nickel and cobalt based on the most-updated EV sales forecasts, battery technology and LIB requirements for grid storage. The model conceptualization allows to test for multiple parameters scenarios that are directly linked to policy actions to reduce mineral demand while achieving the same level of EV and grid level penetration. Additionally, the demand model is the key input for the supply modeling of Chapter 3, which directly connects and reveals how mineral demand reduction actions have important and significant implications to reduce pressure on the mineral supply chain, and avoid unnecessary mine openings.

This chapter includes some text adapted from a published article: Busch, P., Chen, Y., Ogbonna, P., Kendall, A. (2025). Effects of Demand and Recycling on the When and Where of Lithium Extraction. *Nature*

Sustainability, 1-11 (Busch et al., 2025)[12], with further expansions and analysis. The text is reproduced with permission from Springer Nature.

2.2 Introduction

Demand for minerals like lithium, nickel and cobalt is expected to scale multiple times in the upcoming decades (Dunn et al., 2021; IEA, 2022, 2023a), driven mainly by an increase in sales of EVs, which are powered by LIBs to store energy and provide traction power (Manzetti & Mariasiu, 2015). Global EV sales have gone from 700,000 in 2016 to over 10 million in 2022, with a forecast that sales will surpass 40 million units by 2030 (IEA, 2023b), and 55 million units by 2035 (IEA, 2024b). Historically, LIBs have been used mainly in the electronics industry, to provide small storage capacities for laptops, cellphones, and other portable electronics. However, more recently much larger LIBs, led by battery packs for EVs (25-100 kWh), have expanded rapidly leading to an exponential increase in demand. LIBs are also needed for other decarbonization actions, such as in stationary source power storage (SSPS) systems to support integration of high levels of intermittent renewables, like solar and wind, into electricity grids (Yekini Suberu et al., 2014). The key minerals contained in the LIB cathode (lithium, nickel, and cobalt) are called "critical", due to their importance for clean energy technologies, no viable substitutes and potential risk of supply disruption given their reserve geographical concentration (USGS, 2017; Watari et al., 2020).

Multiple models have been developed to forecast the total amount of mineral that will be required in the next three decades to achieve our decarbonization goals. A main result of these efforts is an estimation of the "mineral budget" required. This budget is useful for policy planning as it provides a roadmap for the emerging mineral supply chain. Any shortcomings on the mineral supply chain will delay decarbonization actions and potentially jeopardize our climate goals, a topic that is explored in more

[12] Authors contributions are: AK and PB designed the research, conceptualization and methodology. PB, YC and PO collected the data. PB and AK performed the research, analyzed the data and created the figures. PB and AK wrote the paper.

detail in Chapter 3. Mineral budgets are also useful to conduct a first resource sufficiency analysis, which compares future cumulative demand against known resources on the ground.

Demand models provide insights into the main parameters that determine mineral demand, such as EV adoption rates, battery size or mineral content per battery chemistry. Policies can benefit from this knowledge by prioritizing actions to reduce mineral dependence, such as reducing the average battery size (for example through an energy efficiency standard), or by promoting circular economy strategies, like recycling. However, recycling is not going to have a big role for critical minerals in the short-term (15 years) (Dunn et al., 2021), thus requiring that intensive mining for the battery minerals to build an initial stock.

The major gaps in mineral demand modelling efforts that this chapter seeks to overcome are (i) the inclusion of LIBs derived from other sectors, besides light-duty EVs, and the inclusion of mineral demand from other end-use sectors, like stainless steel; (ii) the forecasting of emerging battery chemistries given recent industry trends favoring batteries with less cobalt; and (iii) the inclusion of end-of-life dynamics, such as battery reuse, repurpose and recycling. The work conducted in this chapter answers the following research questions:

- What will be the global demand from 2022 to 2050 for lithium, nickel and cobalt?
- Which are the main drivers of these mineral demands? Which sectors? Which countries?
- Which are the most effective policies to reduce critical mineral demand while keeping the same level of mobility benefits and climate change mitigation?

2.3 Literature review

Multiple studies have forecasted mineral demand due to EV and renewable electricity adoption (Aguilar Lopez et al., 2023; Dunn et al., 2021; Egbue et al., 2022; IEA, 2022, 2023b; Kamran et al., 2021; Miatto et al., 2021; Moreau et al., 2019; Olivetti et al., 2017; Shafique et al., 2022; Sun et al., 2017; Turcheniuk et al., 2018; Vidal et al., 2022; Xu et al., 2020), with different assumptions, and geographical and temporal scope. A recent summary review on material flow analysis (MFA) studies found that EVs will consume six times more critical minerals than ICEVs (Zhang et al., 2023). The most common minerals forecasted have been lithium, nickel and cobalt, with some recent emphasis on graphite and manganese (Table 2-1). Most studies have taken a global scope with a forecast up to 2050. In mineral demand studies there has been a lack of emphasis on the spatial divergence of producing and consuming countries of minerals (Watari et al., 2020). Regarding end-use of lithium, 60-70% is for batteries (Egbue et al., 2022; Tabelin et al., 2021), and one third was ultimately destined for EV production (Hache et al., 2019).

Table 2-1. Scope of recent mineral demand models.

Sector	Li	Ni	Co	Other Minerals	Geographical Resolution	Temporal resolution	Reference
50 technologies of transportation, construction, and energy	✓	✓	✓	Cu	Global, 9 regions	1950-2100	(Vidal et al., 2022)
EV, SSPS, Solar, Wind, Hydrogen, Electricity, Nuclear, Oil, Hydro	✓	✓	✓	Cu, Gr, REE	Global	2023-2050	(IEA, 2024a)
EV, SSPS, small electronics, other Li uses	✓				US	2016-2050	(Miatto et al., 2021)
EV, end-use (e.g., portable electronics)	✓	✓	✓	Mn, Gr	Global	2016-2025	(Olivetti et al., 2017),
EV, Electric buses, SSPS, Electronics	✓				Global, 21 countries	2014	(Sun et al., 2017)
EV (light duty)	✓	✓	✓	Mn	Global, 4 regions	2020-2040	(Dunn et al., 2021)
EV (light duty)	✓	✓	✓	Cu, Gr	China, US	2012-2030	(19)
EV (light duty)	✓	✓	✓		Global	2020-2050	(Xu et al., 2020)
EV (light duty), SSPS	✓	✓	✓	Mn	UK	2020-2050	(Kamran et al., 2021)
EV (light duty)	✓	✓	✓	Mn,P,Gr,Al,Si	Global	2020-2050	(Aguilar Lopez et al., 2023a)
EV (light duty)	✓				Global	2020-2050	(Egbue et al., 2022)
EV (light duty and buses), SSPS, Electronics			✓		Global	2020-2050	(Zeng et al., 2022)
EV (light duty)			✓		EU	2017-2050	(Baars et al., 2021)
EV (light duty)	✓	✓	✓		EU	2020-2050	(Ginster et al., 2024)
EV (light duty), SSPS, Electronics	✓	✓	✓		EU	2010-2050	(H. Zhou et al., 2024)
EV (light duty), SSPS, Electronics	✓				China	2021-2050	(Liu & Domenech Aparisi, 2025)
EV (light duty)	✓	✓	✓		China	2020-2060	(Jiang et al., 2025)
Solar, Wind, SSPS, Biomass	✓	✓	✓	Multiple	Global	2010-2050	(Moreau et al., 2019)

SSPS: stationary source power storage. Gr: Graphite, REE: Rare Earth Elements.

Major parameters in mineral demand modelling are EV sales, battery size per vehicle, battery lifetime and chemistry (Calderon et al., 2024; Kamran et al., 2021). Vehicles are composed of multiple materials. Lithium, nickel and cobalt are mostly used in electronic components and batteries (Iglesias-Émbil et al., 2020), with most studies only tracking mineral content in batteries[13]. Forecasts indicate that EV sales are

[13] In an ICEV nickel is contained mostly in the engine and fuel tank & exhaust, shifting to be almost completely contained in the electronics components, such as batteries, in an EV (Iglesias-Émbil et al., 2020). Lithium and cobalt

going to reach 55 million units globally by 2035 (IEA, 2024b), driven by a replacement of ICEV and an increase in car ownership levels of developing countries. Regarding battery size, there is some evidence of EVs following a trend toward larger vehicles, like the ICEVs, which will further increase mineral requirements (IEA, 2023a).

A major uncertain parameter in mineral demand from LIBs is the future market share of different chemistries (anode, cathode and electrolyte) (Olivetti et al., 2017), with no clear consensus in the recent scientific literature. A LIB consists of a cathode (positive electrode), anode (negative electrode) and an electrolyte (where current flows). The cathode normally stores the majority of critical minerals, and the anode is mostly composed of graphite, but research points towards emerging chemistries with silicon-based anodes (Dunn et al., 2023). Trends in battery chemistry point towards a crossroads or product differentiation: there is an active development of higher energy density batteries to enhance the performance of EVs and extend their range (Kamran et al., 2021), and there is also active development of cheaper and lower energy density batteries. In the high energy density batteries, there is a clear shift towards reducing cobalt content due to its price and supply chain issues[14], in favor of increasing the nickel content (NMC 811 development is a good example[15]). Solid state electrolyte batteries replace the liquid electrolyte with a solid electrolyte, thus increasing the performance, energy density and safety of LIBs, but at a potential higher cost (Li-Air or Li-S (Albertus et al., 2021)). In terms of battery costs, materials present 50-80% of it, providing strong incentives in favor of cheap materials (Houache et al., 2022; Olivetti et al., 2017) despite lower energy densities. There is an ongoing trend towards cheaper and safer

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are used in other components of a vehicle in a relative small order of magnitude (grams) compared to batteries (kilograms) (Iglesias-Émbil et al., 2020).

[14] The Democratic Republic of Congo has the highest share of cobalt production (USGS, 2025a), with major issues regarding environmental and social impacts of the mining operations, including artisanal mining (Banza Lubaba Nkulu et al., 2018).

[15] In NMC batteries, the numbers represent the stoichiometry ratios of Ni, Mn and Co, respectively. For example, the chemical composition of an NMC 811 cathode is $LiNi_{0.8}Mn_{0.1}Co_{0.1}O_2$, and for NMC 111 is $LiNi_{0.33}Mn_{0.33}Co_{0.33}O_2$.

chemistries with lower energy density, such as lithium iron phosphate (LFP), for heavy-duty vehicles (Houache et al., 2022; Turcheniuk et al., 2018) and stationary applications (OnLocation, 2023), and a recent resurgence in light duty applications (IEA, 2023b). . There are non-lithium-based batteries on the frontier, such as sodium-ion batteries (SIBs), but they are still maturing (Zhao et al., 2023), and given energy density differences, may not be suitable for most EV LIB applications (Abraham, 2020). Nevertheless, they could play an important role for heavy-duty applications or grid storage in the medium term. Most likely a diversified battery chemistry share is expected, as in the case for U.S., the Inflation Reduction Act (IRA) goal that 80% of mineral supply coming from U.S. or free-trade partners will be challenging to meet only with NMC and LFP (Trost & Dunn, 2023). As summary, battery chemistries have different characteristics, such as energy density, safety, duration and price, that differentiate them for distinct end-uses adoption.

An important component of MFA models are end-of-life battery dynamics, which has been incorporated in multiple models (Aguilar Lopez et al., 2023, 2024; Dunn et al., 2021). Depending on the battery state of health (SOH) at the end of the EV life, several options are available for a LIB: (i) reuse as a second-hand battery in an old EV to extend its lifetime; (ii) repurpose the LIB for SSPS where performance and energy density are relatively much less important; (iii) recycling to recover key cathode materials and reduce primary mineral demand; or (iv) inadequate disposal in a landfill that could led to environmental and health hazards (Winslow et al., 2018). The above end-of-life paths are non-exclusive, meaning that a battery can potentially be reused, then repurposed and finally recycled, preventing the damage caused by inadequate disposal. To accurately quantify outflows of LIBs a product-component framework has been proposed to model separately the failure rates for EVs and LIBs, like the method pioneer by the MATILDA (MATerIaL Demand and Availability) model (Aguilar Lopez et al., 2023). The latter requires major assumptions on the future failure rates for EVs, LIBs and destination for the outflow of LIBs. Under ideal conditions it has been shown that recycling could supply about half of new demand by 2040 for battery minerals (Dunn et al., 2021), or that a strategy to repurpose a majority of LIB could meet the requirements for grid storage (Aguilar Lopez et al., 2024).

The focus on mineral demand models has led to a similar focus on demand reduction strategies being evaluated, relative to mineral supply measures. Demand policy actions can be classified into transportation, battery chemistry and end-of-life material recovery. The most common transportation policy for reducing mineral demand is reducing car dependency (Aguilar Lopez et al., 2023; Greim et al., 2020; Riofrancos et al., 2023) via provision of robust public transport systems, better urban planning or promoting higher occupancy in vehicles. Other studies propose a shift to LIB chemistries with lower contents of critical minerals (Aguilar Lopez et al., 2023; Greim et al., 2020; Turcheniuk et al., 2018). In terms of material efficiency, some policies point toward reducing battery size (Aguilar Lopez et al., 2023; Lal & You, 2023; Riofrancos et al., 2023; Watari et al., 2021) and increasing the overall lifetime of batteries (Aguilar Lopez et al., 2023; Greim et al., 2020; Riofrancos et al., 2023; Watari et al., 2021). There is a strong bias to favor recycling strategies, a review found that 74% of studies include them (Watari et al., 2021), even though recycling cannot play a large role in providing raw materials for new batteries in the next 20 years (Dunn et al., 2021), as it is unable to provide any mineral demand in the fleet turnover period (from ICEV to EV) (Kushnir & Sandén, 2012).

2.4 Data and Methods

The term “demand” through this dissertation refers to a total mineral quantity that is needed to satisfy climate goals associated with EV adoption and grid storage, among others. In chapter 3 (supply model) the demand derived from this model becomes the main constraint that the mining capacity expansion needs to satisfy.

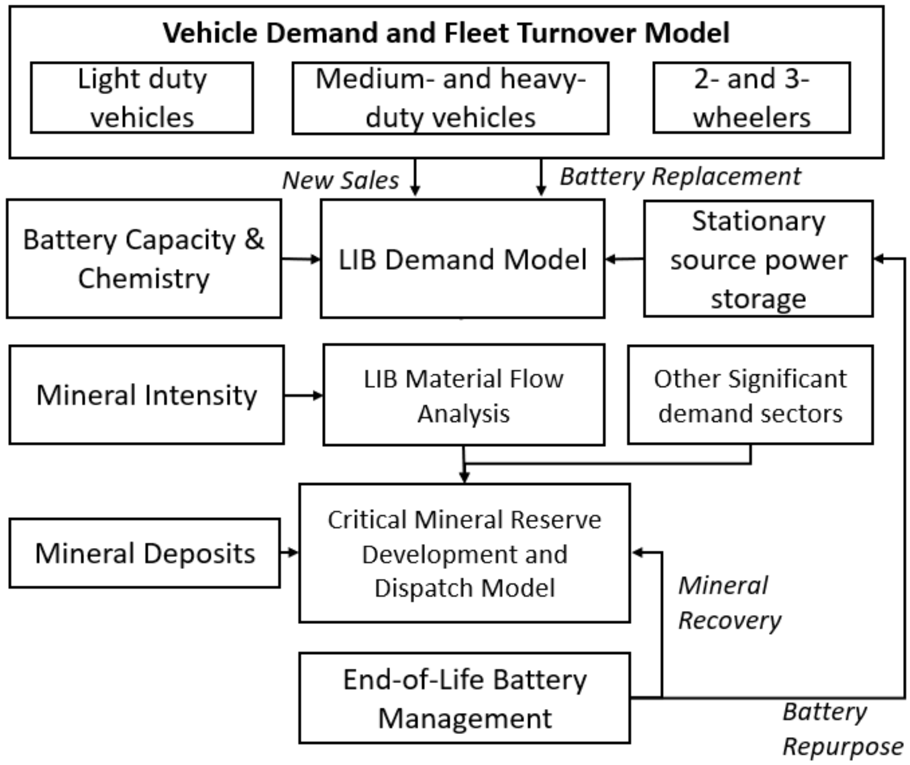

Figure 2-1. Model diagram overview. The mineral deposits and dispatch model are a component of Chapter 3, which was co-developed to the critical mineral demand model. Material from: 'Busch et al., Effects of demand and recycling on the when and where of lithium extraction, Nature Sustainability, published 2025, Springer Nature', with permission from Springer Nature.

The demand model corresponds to a dynamic material flow analysis (dMFA) to estimate global lithium, nickel and cobalt demand at country level from 2022 to 2050; based on (i) a forecast of global sales of EVs, LIBs used as SSPS, and mineral sales in other sectors, (ii) dynamics of EV and LIB failures and availability of LIBs for reuse, repurpose or recycling, (iii) likely LIB chemistry and battery capacity developments, and (iv) mineral content estimates based on battery chemistry (Figure 2-1 provides a diagram and supporting information (SI) Table B-1 indicates all data sources). These four demand drivers are also points of entry for policy levers to reduce primary mineral demand (Calderon et al., 2024; Kamran et al., 2021). The following equation summarizes the demand model conceptualization:

$$Mineral\ demand_t \left[\frac{kg}{year}\right] = Vehicles\ sales_t \left[\frac{veh}{year}\right] \mathrm{x} \sum_{k=1}^{EoL} \left(LIB\ Replacements_{k,t}\right) \left[\frac{bat}{veh}\right]$$

$$\mathrm{x\ LIB\ Size_t} \left[\frac{\mathrm{kWh}}{bat}\right] \mathrm{x\ Mineral\ intensity} \left[\frac{\mathrm{kg}}{kWh}\right]$$

2.4.1 Vehicle Sales

Yearly on-road vehicle sales projections by country were obtained from the International Council on Clean Transportation (ICCT) Roadmap v2.2 model (ICCT, 2022), with details of powertrain type (pure battery EV (BEV) or plug-in hybrid EV (PHEV)) and vehicle type: including 2-3 wheelers, cars, vans, medium-duty vehicles (MDV), buses and other heavy-duty vehicles (HDV) (Figure 2-2). The ICCT Roadmap presents a variety of alternative scenarios with respect to vehicle electrification. The ICCT "Ambitious" scenario was selected as the reference scenario, which reaches 100% ZEV sales for LDVs by 2040 and for HDVs by 2045 (ICCT, 2022). The regions with the higher number of vehicles sales are China, Europe and the United States (US); with some differences by vehicle type such as India being a relevant consumer of 2-3 wheelers.

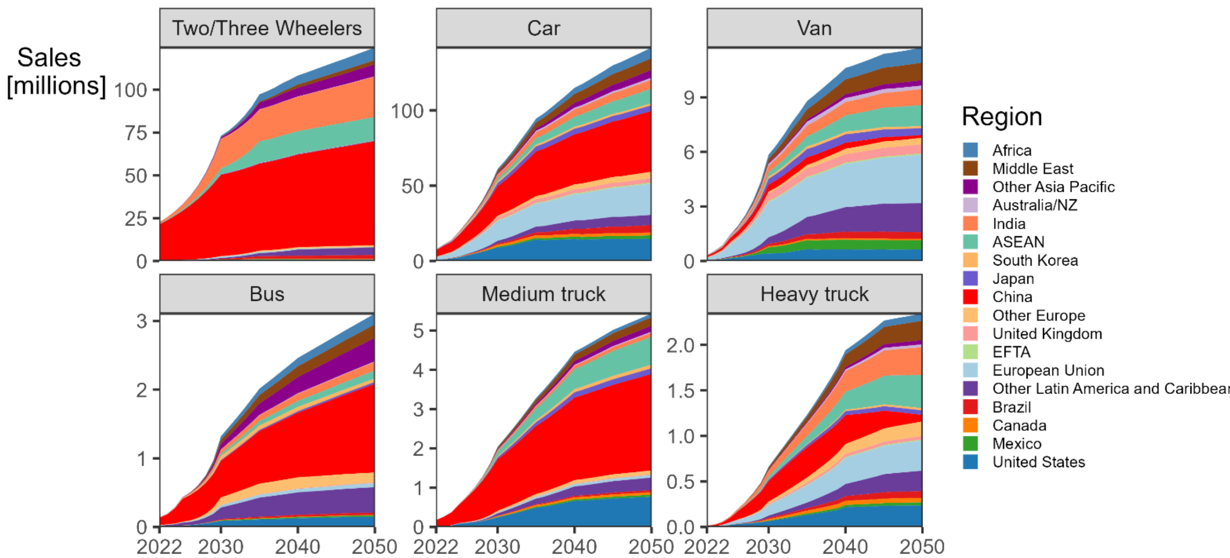

Figure 2-2. BEV Sales forecast by vehicle type from 2022 to 2050 for the Ambitious Scenario. Source: ICCT Roadmap v2.2(ICCT, 2022). Note that each panel has a different Y-axis scale. Material from: 'Busch et al., Effects of demand and recycling on the when and where of lithium extraction, Nature Sustainability, published 2025, Springer Nature', with permission from Springer Nature.

2.4.2 Battery replacement

On average, an EV will require more than 1 battery during its lifetime. Battery replacement may be prompted due to regular battery degradation processes during the use phase leading to reduced capacity (and thus lower vehicle range) and reduced power output, or battery replacement may be hastened by catastrophic failures, whether internal to the battery or caused by vehicle accidents. The demand model follows the proposed method by the MATILDA model to estimate EV and LIB replacements using product-component failure rates (Aguilar Lopez et al., 2022, 2023). The lifetime of both EVs and LIBs are modelled independently, keeping track of model year and calendar year separately. We assume failure rates follows a logistic distribution, as it provides a better fit for LDV survival curves than the Normal distribution (Greene & Leard, 2024), assuming a mean lifetime for BEVs and PHEVs of: 12 years for 2-3 wheelers, 17 years for cars and trucks, 16 years for buses and 18 for vans with a common 4 year standard deviation and maximum life of 30 years; and a mean lifetime for the LIB of 15 years for all light duty applications and 8 for heavy-duty and 2-3 wheelers application due to more intense usage, with a common 4 year standard deviation and maximum life of 30 years. The lifetime parameters roughly follow ICCT roadmap survival parameters (ICCT, 2022). Under these assumptions, less than 4% of LIBs in cars fail before age 8, which corresponds to the warranty period where the original equipment manufacturer (OEM) covers the cost of replacement of a new LIB in most markets. While battery cycle life can vary by chemistry, we did not consider different LIB lifetimes as a function of chemistry.

The product-component failure framework distinguish 3 cases that result in outflows of vehicles or batteries from the EV stock: (i) both EV and LIB fail; (ii) only the LIB fails, and (iii) only the EV fails (Aguilar Lopez et al., 2022, 2023) (Figure 2-3). In case (i) the LIB outflow of failed batteries would go straight to recycling. Case (iii) generates an outflow of LIBs that can be reused in an EV, repurposed in an SSPS application, or go towards recycling. Reuse refers to the installation of a battery in the same application as its first life, in other words, a vehicle. To estimate potential reuse cases, surviving LIBs were matched with surviving EVs by oldest-to-oldest and with the assumptions that a maximum of 50% LIBs are suitable to be reused in an EV within each country; that only an EV younger than 20 years will get a second-hand LIB or new LIB, the rest will be decommissioned at the point of battery failure; and that only LIBs younger than 12 years will be suitable for EV reuse. The remaining outflow of LIBs, including those with no match for reuse in EVs, were disaggregated equally for SSPS second life repurpose or towards recycling. For the case of SSPS use, a 2% degradation per year in the capacity for the repurposed battery was used, in line with some empirical evidence and on the warranty to maintain 80% of state of health (SOH) by year 8 (Gasper et al., 2022; Geotab, 2024). For case (ii), there is an additional requirement of a new battery for the EV if it is under the warranty period age of 8 years or no second-hand LIB is available in that country at that year. The model uses the assumption of no outflows between vehicle types, powertrains, or countries. Historical data on car BEV and PHEV sales from 2015 was used to initialize the existing stock at the start of our modeling period (2022) (EV Volumes, 2022). For other vehicles, such as heavy-duty applications and 2-3 wheelers, there are no reliable historical sales data, but as the numbers are small, they are unlikely to play a major role in the results, so their EV stock was built starting in year 2022.

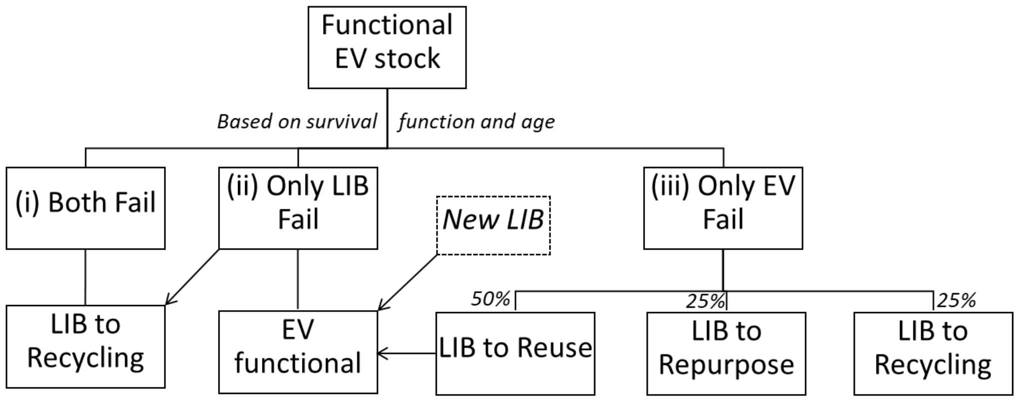

Figure 2-3. End of life dynamics for EVs and LIBs. (i) If both components (LIB and EV) fail, the LIB goes to recycling. (ii) If thse LIB fails it goes to recycling and the EV could get a new or second-hand LIB. (iii) If the EV fails, the available LIB can be reuse in an EV (case ii), repurpose for grid-storage or directed towards recycling. Material outflows from recycling depend on the recovery rate and have a 1-year delay to displace primary demand. Based on the product-component failure by MATILDA (Aguilar Lopez et al., 2022, 2023). Material from: 'Busch et al., Effects of demand and recycling on the when and where of lithium extraction, Nature Sustainability, published 2025, Springer Nature', with permission from Springer Nature.

One important omission from this model is the trade of used EVs or LIBs between countries. There are significant flows of used vehicles from the EU, Japan, the US and increasingly China, to largely Global South countries. These vehicles will increasingly become EVs, and their batteries will be retired in countries that may not have the infrastructure or policies for collecting and recycling batteries, and this could reduce the amount of recovered material available for new batteries, not to mention could present environmental hazards in countries without adequate LIB end-of-life infrastructure (ITF, 2023; Kendall et al., 2023; Parés Olguín, Iskakov, et al., 2023).

2.4.3 Battery Size and Chemistry

Historical LDV battery capacities and chemistries were obtained from EV Volumes (EV Volumes, 2022), with a region-level resolution for year 2022 (Figure 2-4). Benchmark Mineral Intelligence provides a forecast for car battery chemistry mixes at regional level (Benchmark Mineral Intelligence, 2023). The model extends their regional chemistry share forecast from 2040, the final year of their forecast, up to 2050 by using the last 5-year average (2035-2040) chemistry share growth (Figure 2-5). Data for battery size and chemistry of on-road transport vehicles besides LDVs were obtained from multiple model catalogues (SI Table B-2). The following battery sizes, in kWh, were obtained as the average between the models found: 2.6 for 2-wheelers, 6.9 for 3-wheelers, 163 for van, 407 for bus, 210 for medium truck and 470 for heavy truck. Regarding battery chemistry for other on-road transport vehicles, the model assumes that the 2-3 wheelers will use NMC811 ($LiNi_{0.8}Mn_{0.1}Co_{0.1}O_2$), a high energy density battery, and the rest will use LFP ($LiFePO_4$), a cheaper battery with lower energy density.

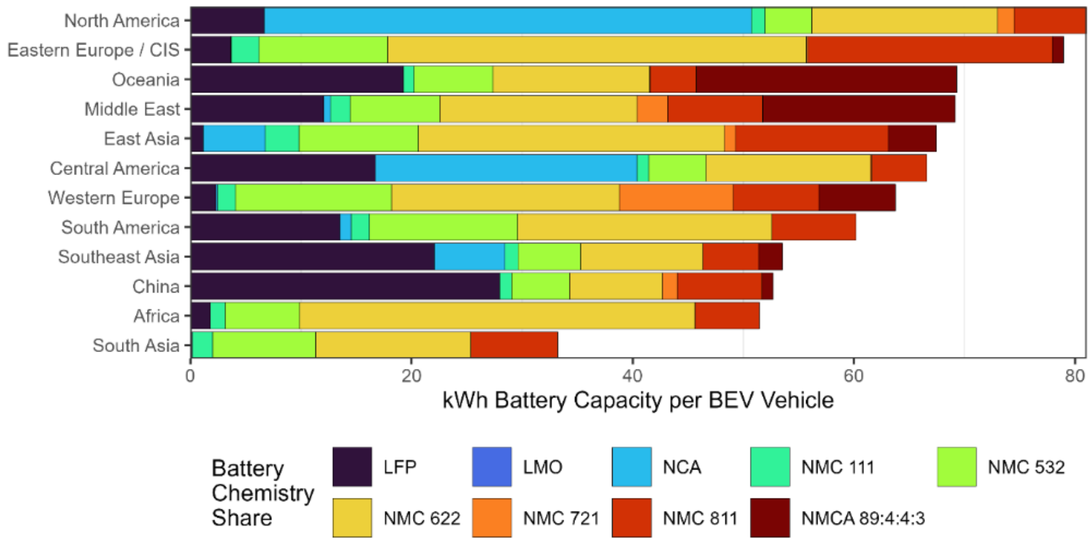

Figure 2-4. 2022 average car BEV battery size, in kWh, and chemistry for key countries/regions. Source: EV Volumes(EV Volumes, 2022). Material from: 'Busch et al., Effects of demand and recycling on the when and where of lithium extraction, Nature Sustainability, published 2025, Springer Nature', with permission from Springer Nature.

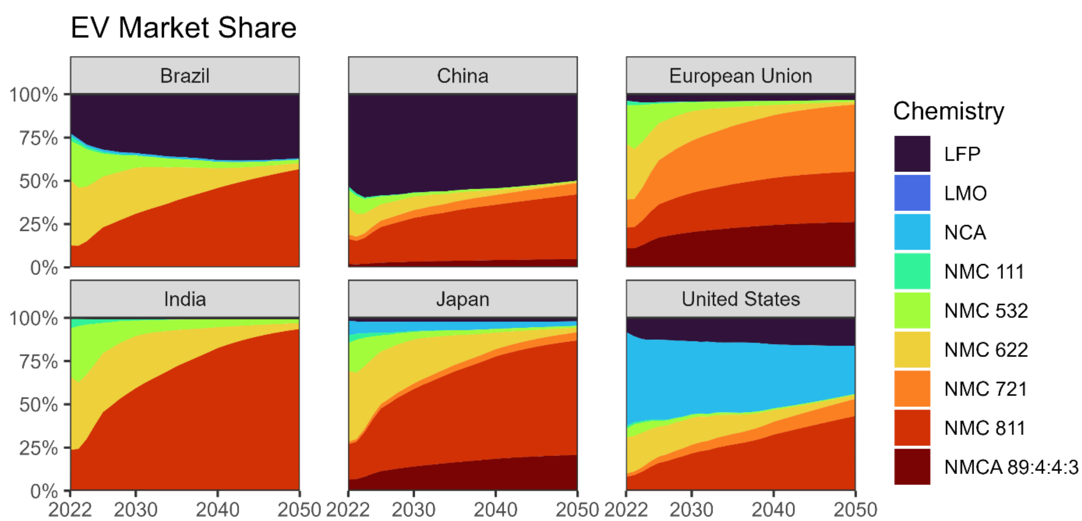

Figure 2-5. Car BEV LIB chemistry forecast mix by major world region. Source: Calculated based on EV Volumes(EV Volumes, 2022) and Benchmark Minerals' forecast(Benchmark Mineral Intelligence, 2023). Material from: 'Busch et al., Effects of demand and recycling on the when and where of lithium extraction, Nature Sustainability, published 2025, Springer Nature', with permission from Springer Nature.

2.4.4 Stationary Source Power Storage

Benchmark Mineral Intelligence (Benchmark Mineral Intelligence, 2023) provides a forecast for SSPS battery storage needs in kWh by chemistry and region. As with vehicle batteries, the forecast ends in 2040. To extend it to 2050, the 10-year average growth from the 2030-2040 period was used with the assumption of a similar yearly growth for the 2040-2050 period. To geographically disaggregate the global forecast, country level data on 2022 electricity generation, the key demand sector for SSPS, was used (EMBER, 2023).

2.4.5 Mineral Intensity

Mineral intensity per battery chemistry for commercially available LIBs was obtained from Argonne National Laboratory's Battery Performance and Cost (BatPaC) Model Software version 5.1 (Kubal et al., 2023). Mineral intensity (Table 2-2) is reported in mass (grams) per kWh for each mineral of interest for the following chemistries: NMC333 ($LiNi_{0.33}Mn_{0.33}Co_{0.33}O_2$), NMC532 ($LiNi_{0.5}Mn_{0.3}Co_{0.2}O_2$), NMC622 ($LiNi_{0.6}Mn_{0.2}Co_{0.2}O_2$), NMC 721 ($LiNi_{0.7}Mn_{0.2}Co_{0.1}O_2$), NMC811, NMCA 89:4:4:3 ($LiNi_{0.89}Mn_{0.04}Co_{0.04}Al_{0.03}O_2$), NCA ($LiNi_{0.8}Co_{0.15}Al_{0.05}O_2$), LFP, and LMO ($Li_{1.1}Mn_{1.9}O_4$). All default inputs were utilized, including graphite anodes for each chemistry. To obtain the mineral intensities for NMC721 and NMCA 89:4:4:3, chemistries not included by default in BatPaC, the chemical stoichiometry of the default NMC 811 battery was modified accordingly to match the new chemical formula.

Two emerging battery technologies are expected to be important in the future market: solid state (SS) LIBs and SIBs. Solid state batteries are likely to be important as they could potentially provide much higher energy density than current batteries, thus having a market advantage; and SIBs could provide battery functionality without requiring any lithium at all. For SS LIBs, results from SolidPac (Dixit et al., 2022) were used to manually calculate mineral intensities based on cathode, electrolyte and anode mass and the chemical formulas stoichiometry, similar to the method used by BatPaC. An assumption was that all SS batteries use an NMC cathode, an LPS ($Li_7P_3S_{11}$) electrolyte and lithium metal as the anode, and a size of

98 kWh, comparable to BatPaC battery defaults. Another assumption in the calculations was that the whole mass of the separator corresponds to the electrolyte. For sodium-based batteries, the lithium, nickel and cobalt content is zero, assuming a cathode of $NaCu_{0.33}Fe_{0.33}Mn_{0.33}O_2$, a sodium based electrolyte and a hard carbon anode (Y. Zhao et al., 2023).

Table 2-2. Mineral Intensity, in grams of lithium per kWh, for different battery chemistries. Source: BatPaC 5.1 (Kubal et al., 2023) for batteries with liquid electrolyte, SolidPac (Dixit et al., 2022) for batteries with solid state electrolyte, and other sources for sodium-based batteries (Y. Zhao et al., 2023). Material from: 'Busch et al., Effects of demand and recycling on the when and where of lithium extraction, Nature Sustainability, published 2025, Springer Nature', with permission from Springer Nature.

Electrolyte	Cathode	Cathode Chemical Formula	Lithium	Nickel	Cobalt
Lithium liquid	NMC 111	$LiNi_{0.33}Mn_{0.33}Co_{0.33}O_2$	123.5	340.1	341.4
	NMC 532	$LiNi_{0.5}Mn_{0.3}Co_{0.2}O_2$	112.5	464.9	186.6
	NMC 622	$LiNi_{0.6}Mn_{0.2}Co_{0.2}O_2$	110.2	546.3	182.8
	NMC 721	$LiNi_{0.7}Mn_{0.2}Co_{0.1}O_2$	100.2	578.3	82.9
	NMC 811	$LiNi_{0.8}Mn_{0.1}Co_{0.1}O_2$	99.8	658.4	82.6
	NMCA 89:4:4:3	$LiNi_{0.89}Mn_{0.04}Co_{0.04}Al_{0.03}O_2$	100.5	738.0	33.3
	NCA	$LiNi_{0.8}Co_{0.15}Al_{0.05}O_2$	107.5	710.0	133.6
	LFP	$LiFePO_4$	91.5	0.0	0.0
	LMO	$Li_{1.1}Mn_{1.9}O_4$	101.5	0.0	0.0
Solid State	SS NMC 811	$LiNi_{0.8}Mn_{0.1}Co_{0.1}O_2$	189.4	658.4	82.6
Sodium liquid	SIB	$NaCu_{0.33}Fe_{0.33}Mn_{0.33}O_2$	0.0	0.0	0.0

Manufacturing losses are embedded in the material demand estimates. A 4% manufacturing loss was used, based on a 2030 target proposed by Yu et al.(Yu et al., 2024), and add this to the material intensity estimates for production. Recycling of this scrap does occur and is described in the next section.

2.4.6 Recycling

Recycling serves to reduce net primary lithium demand. There are two sources of material available for recycling. One is scrap generated during manufacturing, and the other is from end-of-life LIBs. When LIBs are sent to recycling, the model assumes a low baseline level of mineral recovery, just 5%, unless there exists a specific regulation or mandate with mineral recovery targets, such as in the EU (80% by end of

2031 for lithium and 95% for nickel and cobalt) (European Parlament, 2023) or China (85% for lithium and 98% for nickel and cobalt) (Recycling of Traction Battery Used in Electric Vehicle–Recycling–Part 2 : Materials Recycling Requirements, 2020). All material (whether scrap or EOL LIBs) that goes to recycling is assumed to generate secondary material one year later, thus affecting the quantity and timing of required primary mineral demand.

2.4.7 Other significant mineral demand sectors

To complete the global mineral demand, the model includes demand for lithium, nickel and cobalt from other sectors (SI Table B-3, Table B-4 and Table B-5). Historical mineral consumption for each sector was obtained from the US Geological Survey (USGS, 2022, 2023a) or other reports (Cobalt Institute, 2023). Then either Gross Domestic Product (GDP) (Goldman Sachs, 2022; World Bank, 2023) or population (United Nations, 2022) forecasts were used to scale up mineral demand from these sectors (Miatto et al., 2021). The main assumption is that none of these sectors will experience an exponential growth in lithium consumption like the large format LIB sector, which serves EV and SSPS applications.

2.4.8 Scenarios

The model includes eleven representative scenarios with different assumptions for the main variables that determine mineral demand. The eleven scenarios achieve the same EV adoption[16], based on the ICCT Ambitious scenario, with meaningful differences in other major demand parameters, such as battery capacity, battery chemistry and material recovery rates (Table 2-3).

Table 2-3. Demand Scenarios included in main analysis. All scenarios are built with the same parameters as the Reference scenario, unless otherwise indicated.

Scenario	Description
(1) Reference	- Sales: ICCT Roadmap "Ambitious" scenario, 100% ZEV sales by 2040 (LDV) and 2045 (HDV) at the latest w/some markets achieving targets earlier - Battery size: 2022 avg. battery size (59kWh), with regional differentiation. - Battery chemistry: Benchmark EV battery chemistry regional forecast.

[16] Assume the same number of electric vehicles sales.

Scenario	Description
	- Mean Lifetime: EV 17 years, LIB 15 years. Standard deviation of 4 years. - End of life: A max of 50% of LIB are considered suitable for reuse, the fraction with no match is divided equally into SSPS and recycling. 25% of LIB outflow goes to recycling with a 5% recovery rate (except for EU and China), and the remaining 25% of LIB outflow goes towards SSPS.
(2) Large Capacity LIB	- Battery size: Transition linearly until 2035 to an average battery size, in kWh, of 90 for cars, 4.3 for 2-wheelers, 11.2 for 3-wheelers, 199 for van, 582 for bus, 310 for medium truck and 694 for heavy truck. The rationale is that the world will continue with the ongoing trend towards large vehicles with higher range. The upper limit for car comes from the current battery capacity of certain countries, and for the rest of vehicles we took the 95th percentile of all model catalogues found (SI Table B-2).
(3) Small Capacity LIB	- Battery size: Transition linearly until 2035 to an average battery size, in kWh, of 45 for cars, 1.2 for 2-wheelers, 3.7 for 3-wheelers, 134 for van, 239 for bus, 168 for medium truck and 375 for heavy truck. The rationale is to move forward to reducing battery capacity through gains in energy efficiency, reductions in vehicle size and/or reduced range due to a robust charging infrastructure. The lower limit for car comes from the current battery capacity of certain countries in the lower end, and for the rest of vehicles we took the 5th percentile of all model catalogues found (SI Table B-2).
(4) NMC811 Dominant Chemistry	- Battery chemistry: The share of NMC811 doubles by 2050. NMC811 is a high energy density battery that has been growing in share and significantly reduces cobalt content relative to other NMC chemistries and NCA batteries.
(5) LFP Dominant Chemistry	- Battery chemistry: The share of LFP doubles by 2050. LFP adoption has been growing rapidly due to their lower cost and lack of nickel and cobalt content, which are costly, and particularly for cobalt, have significant environmental, social, and governance issues.
(6) Solid State Adoption	- Battery chemistry: Half of the share of NMC and NCA chemistry go towards solid state LIBs. The adoption starts in 2030 and reaches half by 2040.
(7) SIB Adoption	- Battery chemistry: Half of the share of LFP goes towards SIB, both in cars and SSPS. The adoption starts in 2030 and reaches half the share by 2040. SIBs are low energy density batteries with sodium playing the role of lithium.
(8) Enhanced Repurposing	- End of life: 50% to reuse (depends on match), 15% of LIB outflow to recycling with 5% lithium recovery rates (except for EU and China which regulated higher recovery rates). 35% of LIB outflow goes first to SSPS, prior to recycling.
(9) Enhanced Recycling	- End of life: 50% to reuse (depends on match), 35% of LIB outflow goes to recycling, with global EU recovery targets timeline (90% for lithium by 2032). 15% of LIB outflow to SSPS.
(10) US Recycling	- End of life: United States adopt the same regulation as the EU.
(11) Medium Recycling + Small Capacity LIB	- Battery size: Same as Scenario (3) Small Capacity LIB - End of life: 50% to reuse (depends on match), 35% of LIB outflow goes to recycling, with global EU recovery targets timeline (55% for lithium by 2032). 15% of LIB outflow to SSPS.

The latter scenarios are intended to mimic potential pathways of mineral demand, along with the effect of policy actions. While not modelled explicitly here, a shift to other modes of transportation with higher occupancy could reduce the number of EV sales, and associated critical minerals demand, while providing or expanding mobility access and other benefits (Dulal et al., 2011).

A larger battery capacity gives the vehicle a higher range (SI Figure B-1 shows the relationship of EV range and battery capacity at country level). Scenario 2 illustrates the potential growing tendency of vehicle "obesity" or range anxiety, both requiring bigger LIBs and thus more minerals (Chakraborty et al., 2022; W. Zhou et al., 2023). Scenario 3 reflects the opposite with smaller LIBs, which can be achieved with smaller vehicles, lower range or energy efficiency improvements. Historically, improvements in energy intensity or efficiency has been a major driver in reducing energy-related climate impacts (Z. Chen et al., 2019; Danish et al., 2020). Currently, passenger EVs have a high battery to wheel efficiency, around 70% to 90% (Gustafsson & Johansson, 2015; Weiss et al., 2020), which translates to an overall energy consumption of 18.4 kWh/100km (Weiss et al., 2020)[17], with some EVs achieving a efficiency of 9.6 kWh/100km. Vehicle mass, including battery size, is a direct contributor of less efficient usage of energy (Stephens et al., 2016), with an estimated increased in consumption of 0.6 kWh/100km per each 100 kg of additional mass (Weiss et al., 2020). Improvements in efficiency can be achieved by maximizing the battery-to-wheel efficiency, vehicle lightweighting, improving aerodynamics and increasing energy recovery systems (Berjoza & Jurgena, 2017; Fiori et al., 2016; Gurusamy et al., 2023; Hofer et al., 2012; Jung et al., 2018). A vehicle efficiency standard could not only reduce mineral demand, but electricity consumption as well, thus contributing to the main goal to reduce GHG emissions.

Scenarios 4 to 7 reflects mineral demand under different dominant battery chemistries adoption. A major limitation of these scenarios is that they do not incorporate mineral supply effects, such as price volatility or constraints in production, in the adopted battery chemistry. In reality, supply availability is also a key factor in battery chemistry choice.

Scenarios 8 and 9 reflect two alternatives for end-of-life LIB management. Both options, repurposing batteries for SSPS or enhanced material recovery through recycling, need to be incentivized through policy

[17] Or an equivalent economy efficiency of 5.4 km/kWh.

actions, especially at earlier stages. Repurposing of end-of-life EV batteries for SSPS use can potentially extend the lifetime of LIBs and provide energy security for the electricity grid. Recycling, which can be complementary to repurpose but with a delay, has the potential to reduce primary mineral demand, but it will require industrial and waste management to enhance battery collection, processing and mineral recovery. Scenario 10 focus on the overall effect of a robust recycling mandate in the US, which will complement the existing mandates in China and the European Union (these regions represent the majority of future EV demand, see Figure 2-2). Finally, scenario 11 combines the mineral reduction achieved by shifting to smaller vehicles with a medium global recycling mandate, acknowledging that demand reduction measures can be bundled together.

2.5 Results

2.5.1 Mineral demand

The eleven illustrative scenarios reveal that primary[18] mineral demand in 2050 will be between 1,000-2,400 ktons for lithium, 7,000-11,000 ktons for nickel and 400-1,000 ktons for cobalt, which represents an upscale in demand from 2022 of 9-21 times for lithium, 2.5-4 times for nickel and 2.5-6 times for cobalt (Figure 2-6). Higher demand for all minerals occurs in the scenario that assumes the adoption of higher capacity LIBs (scenario 2). Scenarios with lower primary demand assume the adoption of lower capacity LIBs over time, high rates of secondary mineral recovery via robust recycling across the world or a combination of both (scenario 3, 9 or 11). Other scenarios have a mixed effect depending on the mineral: the adoption of solid-state batteries (scenario 6) increases lithium demand, mainly due to the extra lithium required in the anode (Ahuis et al., 2024), and the adoption of SIBs (scenario 7) decreases lithium demand; a scenario with NMC 811 battery chemistry dominance (scenario 4) increases the demand for nickel and cobalt, while the scenario of LFP dominance (scenario 5) decreases their demand. An ambitious US policy

[18] Primary demand: Total mineral demand minus secondary supply from recycling.

to recycle (scenario 10), similar to the ones from Europe or China, can decrease primary mineral demand, especially for cobalt (given the high share of nickel-cobalt batteries in the US). The only scenarios that reach peak primary mineral demand during the analysis period are ones assuming global recycling policies (scenario 9 and 11).

Cumulative demand for lithium, nickel and cobalt is dominated by light duty vehicles (including LIBs in new vehicles and additional LIBs required to replace failures during vehicle life) (Figure 2-6). For lithium, heavy-duty and SSPS are also important contributors to the total demand. As these sectors rely on cheap and low energy density batteries, such as LFP, the demand for nickel and cobalt is small. Other sectors, such as stainless steel for nickel, have a higher relative importance in the demand for nickel and cobalt, thus highlighting the importance of including them in future mineral demand models. Mineral demand is generally dominated by the three largest EV markets: China, the US and Europe (SI Figure B-2).

The demand results for lithium, nickel and cobalt are on the same order of magnitude as in the often cited 2024 IEA Critical Mineral Market Review Net Zero by 2050 scenario[19] (IEA, 2024a) (SI Figure B-3). For mineral derived demand coming from EVs, the lithium results closely match, while for nickel and cobalt the model results are higher than IEA results, due to different battery chemistry forecast assumptions, which highlights the relevance of battery chemistry assumptions for nickel and cobalt demand projections. IEA projects higher lithium demand from grid battery storage, but one order of magnitude smaller than electric vehicle demand.

[19] This is comparing the ICCT Ambitious demand scenario against the IEA Net Zero by 2050 scenario.

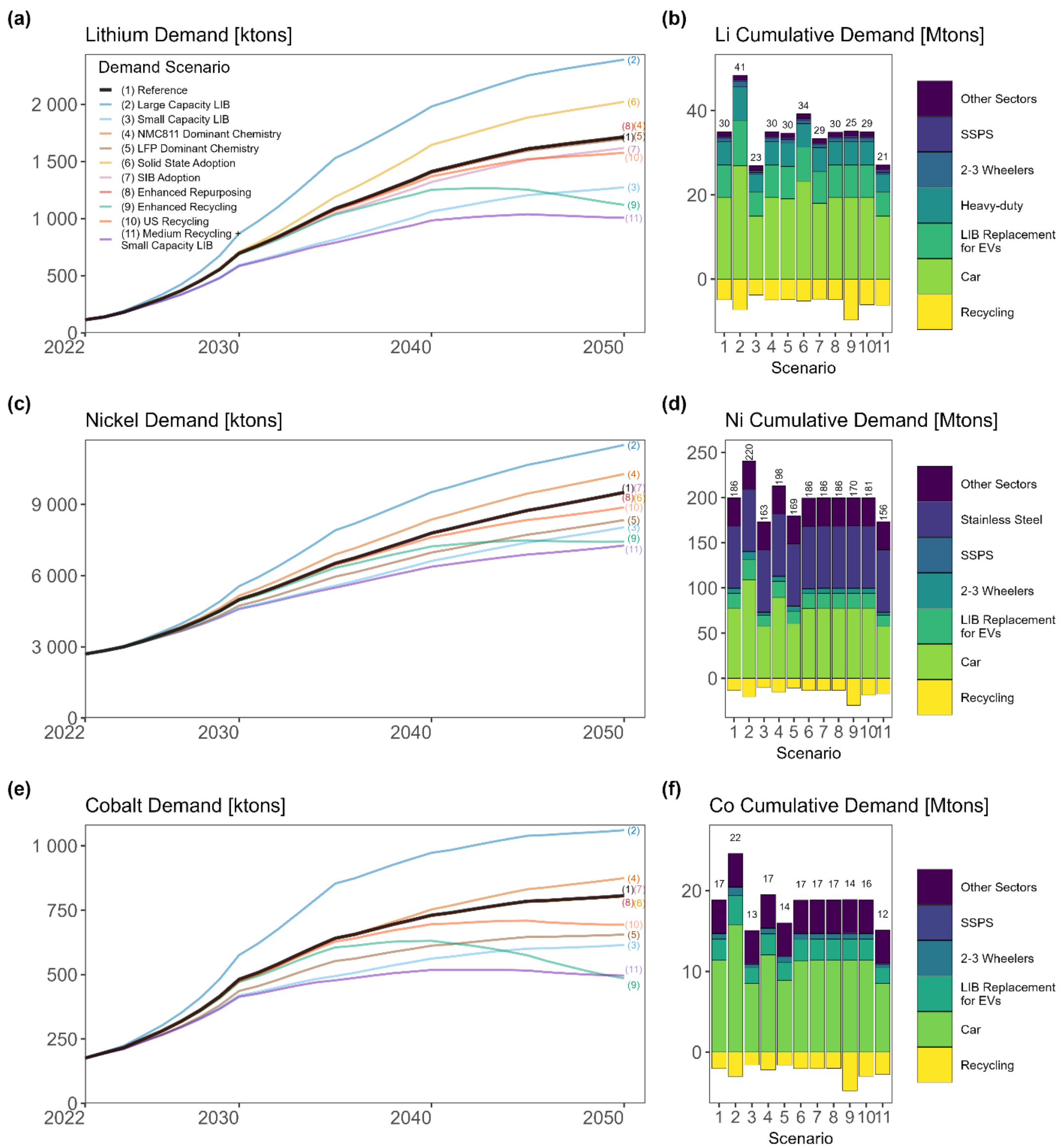

Figure 2-6. Primary mineral demand by scenario (a,c,e) and cumulative demand by sector (b,d,f) for lithium, nickel and cobalt. (**a,c,e**) Primary global mineral demand, in ktons, from 2022 to 2050. (1) Reference case, (2) Higher Capacity LIBs, (3) Lower Capacity LIBs, (4) NMC811 Dominant Chemistry, (5) LFP Dominant Chemistry, (6) Solid State Adoption, (7) SIB adoption, (8) Enhance repurposing, (9) Enhanced recycling, (10) US Recycling, (11) Medium Recycling and Small Capacity LIB (**b,d,f**) Cumulative mineral demand (2022-2050), in million tons, by demand sectors. Other sectors include ceramics, glass, lubricant greases and portable electronics, super alloys, among others. Material from: 'Busch et al., Effects of demand and recycling on the when and where of lithium extraction, Nature Sustainability, published 2025, Springer Nature', with permission from Springer Nature.

Cumulative and annual demand are necessary inputs to plan for the supply chain expansion requirements (Chapter 3). Most literature have focused on the cumulative demand aspect, comparing it to existing mineral reserves or resources (Watari et al., 2021). The latter ignores a crucial aspect, that mineral production needs to grow every year to match yearly mineral demand, with major constraints in the maximum extraction rates in mining and mine opening leading times (delays of up to 16 years from mine discovery to production (Jones, 2024)). Chapter 3 will explore the supply implications of the different mineral demand scenarios, highlighting that not only reductions in cumulative demand are needed, but also in peak demand to avoid unnecessary deposit openings.

2.5.2 Drivers of Mineral Demand

A more direct way to evaluate the differences between demand scenarios, and the effect of policy actions, is to compare the relative change with respect to the reference scenario (Table 2-4). The large capacity LIB scenario has the biggest increase in both cumulative and peak demand for lithium, nickel and cobalt, while the small capacity LIB scenarios have the biggest reduction in cumulative demand. Battery size directly determines mineral requirement, and under both scenarios the cumulative and peak demand changes in a similar proportion. Battery chemistry scenarios have mixed effects depending on the mineral. NMC 811 adoption increases nickel and cobalt demand, while LFP adoption reduces their demand (both chemistries have a marginal effect on lithium, as the content is similar (Table 2-2)). The adoption of emerging technologies, such as solid state and SIB, has a marginal effect on nickel and cobalt, as the cathode remains the same in solid state batteries, and the model has the assumption that SIB will replace low energy density LFP, which already has no nickel nor cobalt content. Emerging solid-state batteries have a solid lithium anode and a solid electrolyte with lithium, thus increasing lithium demand by more than 10%. SIB displacement of LFP batteries could reduce up to 5% lithium demand. The enhanced repurposed scenario has limited effect on reducing mineral demand, as the majority of demand comes from on-road transportation rather than grid storage. Finally, the recycling enhanced scenario shows the greatest difference between peak and cumulative demand. For example, it could reduce peak demand of lithium by about the same magnitude as lower capacity LIBs (-26%), but it has a smaller effect in reducing cumulative demand (-15% vs -23%). However, the recycling scenarios achieve peak demand before 2050, thus limiting the need for mining production capacity expansion in the long term.

Table 2-4. Relative change in peak and cumulative primary mineral demand for each scenario with respect to the Reference scenario (1). Peak mineral demand is the maximum annual demand for the period (2022 to 2050), and cumulative demand is the sum of demand from all years. Reference scenario peak demand is 1.72, 9.51 and 0.81 million tons for lithium, nickel and cobalt; and cumulative demand is 30.1, 186.2 and 16.8 million tons, respectively.

Demand	Peak Demand			Cumulative Demand		
	Li	Ni	Co	Li	Ni	Co
(1) Reference	-	-	-	-	-	-
(2) Large Capacity LIB	39%	21%	32%	37%	18%	28%
(3) Small Capacity LIB	-26%	-15%	-24%	-23%	-13%	-20%
(4) NMC811 Dominant Chemistry	0%	8%	8%	0%	6%	3%
(5) LFP Dominant Chemistry	-1%	-12%	-19%	-1%	-9%	-14%
(6) Solid State Adoption	18%	0%	0%	13%	0%	0%
(7) SIB Adoption	-6%	0%	0%	-5%	0%	0%
(8) Enhanced Repurposing	0%	0%	0%	0%	0%	0%
(9) Enhanced Recycling	-26%	-21%	-22%	-15%	-9%	-16%
(10) US Recycling	-8%	-7%	-12%	-4%	-3%	-6%
(11) Medium Recyc.+ Small Cap. LIB	-40%	-24%	-36%	-30%	-16%	-26%

2.5.3 Comparison of demand against mineral reserves and production

The forecasted model results on peak and cumulative primary mineral demand can be compared against current mineral production (extraction) and existing reserves and resources[20] (Table 2-5). Reducing peak demand reduces the need to upscale production. For example, in a high demand scenario, current lithium production needs to grow by a factor of 10 (an order of magnitude higher), which contrasts to the 4 times growth required on the lowest peak demand scenario. Notably, a reserve sufficiency analysis that

[20] Resource refers to the total amount of mineral that exists in a deposit that is potentially feasible to extract, while reserve refers to the portion of resources that meet certain physical and chemical criteria to be classified as currently economically suitable for extraction (USGS, 2023b).

compares cumulative demand against known reserves reveals that there are not enough reserves of nickel nor cobalt under any demand scenario, and a extraction of a considerable fraction of reserves is needed for lithium (surpassing them in high demand scenarios). The former analysis ignores that resources can be converted into reserves due to changing technology, such as more efficient extraction, or economic conditions, like a higher mineral price that enables higher extraction costs. The resource sufficiency[21] analysis reveals that there are enough resources on the ground for lithium, nickel and cobalt, but that a considerable fraction will need to be extracted before 2050 to meet our decarbonization goals. In summary, the sufficiency analysis (Table 2-5) reveals key points:

- The high increase in demand for these minerals will require an important upscale of current production levels.
- The cumulative mineral demand will surpass existing reserves, thus requiring that a considerable fraction of existing resources be converted into reserves.
- Even if we have enough resources on the ground, the question of how we can extract them fast enough remains unanswered. In other words, the constraints in mine openings and maximum depletion rate may be a bottleneck in the maximum production capacity for minerals worldwide. This point is addressed in detail for lithium, in Chapter 3, using a resource dispatch optimization model.

[21] This analysis ignores the quantity of future resources that could be discovered worldwide.

Table 2-5. Fraction of peak demand over current mineral production, and fraction of cumulative demand (2022-2050) over global reserves and resources. A fraction above 1 for peak demand indicates that ramp up of production is required, and a fraction above 1 for cumulative demand indicates that mineral reserve conversion or resource discovery is required. Production in 2024 was 240, 3,700 and 290 ktons for lithium, nickel and cobalt, respectively; global mineral reserves are 30, 130 and 11 million tons for lithium, nickel and cobalt, respectively; and resources are 115, 350 and 25 million tons for lithium, nickel and cobalt, respectively (USGS, 2025b, 2025c, 2025a).

Demand	Peak Demand/ Production			Cum. Demand/ Reserves			Cum. Demand/ Resources		
	Li	Ni	Co	Li	Ni	Co	Li	Ni	Co
(1) Reference	7.15	2.57	2.78	1.00	1.43	1.53	0.26	0.53	0.67
(2) Large Capacity LIB	9.97	3.11	3.66	1.37	1.69	1.96	0.36	0.63	0.86
(3) Small Capacity LIB	5.31	2.17	2.12	0.77	1.25	1.23	0.20	0.47	0.54
(4) NMC811 Dominant Chemistry	7.16	2.78	3.02	1.00	1.52	1.57	0.26	0.56	0.69
(5) LFP Dominant Chemistry	7.07	2.25	2.26	0.99	1.30	1.31	0.26	0.48	0.58
(6) Solid State Adoption	8.43	2.56	2.77	1.13	1.43	1.53	0.30	0.53	0.67
(7) SIB Adoption	6.74	2.57	2.78	0.95	1.43	1.53	0.25	0.53	0.67
(8) Enhanced Repurposing	7.13	2.57	2.78	1.00	1.43	1.53	0.26	0.53	0.67
(9) Enhanced Recycling	5.27	2.02	2.18	0.85	1.31	1.28	0.22	0.49	0.57
(10) US Recycling	6.57	2.40	2.45	0.96	1.39	1.44	0.25	0.52	0.64
(11) Medium Recyc.+ Small Cap. LIB	4.32	1.96	1.79	0.70	1.20	1.13	0.18	0.45	0.50

An important issue with supply of critical minerals is their geographical concentration (SI Table B- 6). More than half of lithium production and reserves are concentrated in Chile (Production: 21%, Reserves: 31%) and Australia (P:37%, R: 23%); Indonesia dominates nickel production and reserves (P:60%, R: 42%); and Congo dominates cobalt production and reserves (P:76%, R:56%). The concentration of production in few countries contrast with demand arising from multiple countries (Alonso et al., 2023) (SI Figure B-2). This level of concentration is likely to generate multiple geopolitical and supply chain risks, besides the environmental and health impacts caused by mineral extraction on local communities (Kumar et al., 2021), as other parts of the supply chain, such as refining and manufacturing, are dominated by China (Sun et al., 2019).

2.6 Discussion

2.6.1 Policy levers

Several actions are available to reduce primary battery mineral demand without compromising mobility or climate goals. The actions, modeled here through scenarios, are non-mutually exclusive, so further reductions can be achieved with an ambitious policy portfolio. Further research can explore the synergies between the different policy levers, such as favoring energy density batteries to reduce battery weight and increase the EV efficiency, or between grid storage development with second-hand LIB repurpose.

Each component of the demand equation can be a point of entry for regulations (Table 2-6):

- **Vehicle sales** [units per year], can be reduced by favoring other modes of passenger transportation (i.e., reduced car dependency) with higher occupancy rates, such as buses or trains, with other benefits (Dulal et al., 2011).
- **Battery replacement needs** [batteries per vehicle], can be mitigated through advancements in battery life and durability, and by promoting LIB reuse, repurpose and recycling at end-of-life. Support to right-to-repair policies could enhance the durability of batteries and reduce the need for replacement. A major challenge regarding end-of-life battery management is global trade of second-hand vehicles, which could affect countries with a high share of used vehicle export (e.g. the US or Japan). A battery passport or regulation to extend the producer responsibility could be mandated to increase recovery rates around the globe.
- **Battery size** [kWh per vehicle], which has a major effect on mineral demand, can be reduced through taxes to heavier vehicles, or even without affecting consumers by promoting EV energy efficiency standards, and by extending the charging infrastructure to mitigate range anxiety. Setting vehicle efficiency standards, much like fuel economy standards for gasoline vehicles, could lead to significant reductions in vehicle weight, battery size and mineral demand.

- **The mineral intensity** [kg per kWh] of LIBs depends on the specific cathode and anode chemistry of the battery design, resulting in differences in energy density, safety and cost. Market forces can nudge OEMs to prioritize battery chemistries with less critical mineral content, such as nickel-cobalt free chemistries; and investment can be made to support the development of novel chemistries such as solid-state batteries with higher energy density, silicon-anode chemistries or sodium-ion batteries as a substitute for lithium.

Table 2-6. Potential policy actions to reduce critical mineral demand.

Dimension	EV Sales	Battery size	Battery chemistry	Material efficiency
Economy	- Subsidies for public transport, or high-occupancy vehicle lanes.	- Incentives to shift towards EVs with smaller battery size. - Investments in a higher charging density to reduce range anxiety.	- Subsidies to produce battery chemistries with less critical mineral content.	- Recycling capacity expansion (investment). - Subsidies for battery use in grid storage as second life.
Technical	- Driving automation technologies (reduce car ownership)	- Improve battery lifetime (durability)	- Develop chemistries with less critical minerals content (e.g. sodium-based batteries).	- Improve material recovery technology. - Improve battery design for material recovery.
Regulatory	- Convert highway infrastructure into high-occupancy lanes.	- Vehicle efficiency standard (km per kWh).		- Mandates for recycling recovery goals. - Mandates for recycling content in new batteries.

Recycling is the only measure that reaches a peak primary mineral demand within the next 30 years, ensuring the long-term sustainability of the emerging energy systems even with limited mineral discovery. To achieve recycling at-scale, countries with the earliest adoption and largest markets must be first to develop industrial and waste management policies that achieve robust recycling outcomes. The EU, the second largest EV market globally (IEA, 2024b), has the most comprehensive recycling policy in the world, including collection targets, material recovery requirements for eligible recyclers, and recycled content standards to create a market pull for secondary minerals (European Parlament, 2023; Melin et al., 2021). What we see today, however, is that regions with EV LIB manufacturing capacity are where recycling facilities exist (Baum et al., 2022), because of the significant quantities of high-quality scrap generated during manufacturing. We need recycling at global scales that works for all regions, not just those that manufacture LIBs or those where the largest EV markets exist, and for this we likely need innovation in global policy and recycling technologies.

2.6.2 Novelty

Much work has been done to characterize demand for EV batteries and their constituent critical minerals. The main novelties of the demand model (presented in this chapter) are to include all mineral consuming sectors, such as battery storage needs for the electricity grid, all other on-road transport sectors besides light-duty and other traditional mineral consuming sectors, like stainless steel. LIBs and EVs are modelled through a stock model with survival lifetime parameters, which helps to account for the need for a replacement LIB during an EV lifetime and the outflows of LIB available for reuse, repurpose and recycling. Our results suggest that the mineral demand derived for replacement LIBs is significant, so other demand forecasting efforts should include this component and policy actions can be directed towards extending battery life and warranties. The outflow of LIBs generates an opportunity to recover minerals, but for recycling to happen at industrial scale policy incentives will be needed. In the next chapter (supply), the effect of recycling in reducing supply chain pressure is shown more directly.

A major novelty is analyzing demand actions across the supply chain for LIB minerals. Chapter 3 supply model tests the influence of policy in mineral demand and how this plays out in terms of shortages of minerals, the number of new mines needed and the dependency of the US on other countries' mineral deposits. The timing aspect of mineral demand is relevant, as some policies may be worth pursuing in the short-to-medium term if they allow additional time to expand mineral extraction capacities or accelerate mining operations to meet long-term goals.

2.6.3 Limitations

Like all other demand models, the results are driven by key assumptions, such as battery size and battery chemistry. The average battery capacity has a direct linear relationship with vehicle size, range and mineral content. There exist limited options to reduce lithium from battery chemistry, as roughly all chemistries have around 100 grams per kWh. SIBs are the only emerging batteries with no lithium content, but their low energy density may not be suitable for all transport applications. A shift to NMC811 will reduce cobalt needs while increasing nickel demand, and a shift towards LFP chemistry will reduce the demand for both nickel and cobalt, but it could increase it for other minerals, such as phosphorus. Not included in this model are minerals in the anode, typically graphite, which could also have an important demand upscale and supply constraints.

The main goal of the demand model is not to accurately predict demand, but rather to evaluate scenarios and policy actions. As stated wisely by George Box: “all models are wrong, but some are useful”. The usefulness of the model is to show possible mineral demand pathways and to analyze potential actions to reduce mineral demand. The mineral demand model has many limitations, and given the rapid technological innovation in the EV and LIB space, it is likely that abrupt changes may introduce big changes in the future mineral demand. These changes can come in the form of new mobility technologies, emerging battery chemistries, world trade agreements or conflicts, among others.

Known limitations of the demand model are related to the uncertainty of the parameters. Multiple factors can affect the EV sales forecast: such as economic growth, international cooperation and climate agreements, supply chain disruptions and trade wars. Battery size and chemistry are also subject to market forces and consumer preferences, with potential disruptions in the next 30 years. We model all battery chemistries with the same survival curves assumptions, only assuming a shorter mean lifetime for heavy-duty and 2-3 wheeler applications (due to more intense usage). This could be a limitation if certain battery chemistries, such as LFP, have longer cycle life, however no reliable data is yet available to estimate the differences in lifetimes.

The model does not consider the trade of second-hand EV. The latter is an assumption regarding no trade of LIB for recycling purposes, which could happen with the adequate regulations. The latter imposes new challenges on developing battery passports, strict regulations about battery end-of-life recovery across the globe and developing policies and infrastructure in countries where the EVs are most likely to be retired, to gain the benefit from mineral recovery and avoid environmental hazards associated with inadequate end-of-life management (ITF, 2023; Kendall et al., 2023; Parés Olguín, Iskakov, et al., 2023).

Demand and supply are inherently endogenous, both affecting each other. The latter is not included in the model, as both components are modelled independently (demand is an input for Chapter 3 supply model). The model then assumes several scenarios with no supply feedback. For example, if there exists scarcity of one critical mineral, OEMs may react by shifting to chemistries with cheaper minerals. Prices of minerals will also partially affect EV sales, but this feedback is not included in the demand model scope.

There are interactions between policy actions, and we did not consider all possible combinations. The ranges presented then do not cover all extreme situations, for example larger LIB size and solid-state adoption will have a higher demand for lithium.

2.7 Conclusion

The present chapter introduces a complete battery mineral demand model for clean technologies that depend on LIBs. Society can achieve the same EV adoption goals with different primary lithium, nickel and cobalt cumulative and peak demand (Aguilar Lopez et al., 2024; RMI, 2024). The entry point of each demand reduction action is different: for example, creating a future dominated by EVs with smaller-capacity LIBs will likely require nudging consumer preferences, investments in EV charging infrastructure (so that range anxiety is mitigated (W. Zhou et al., 2023)), taxing heavier vehicles (Shaffer et al., 2021) or regulations for EV efficiency standards (allowing equivalent range with smaller batteries). Achieving the enhanced recycling scenario will require rates of mineral recovery that do not occur today, meaning regulation for LIB collection and recycling coupled with requirements for high rates of mineral recovery are likely needed. Overall, multiple mineral demand futures are possible. It will depend on policies set today to ensure that the clean energy transition is done in a resource efficient way, enhancing circular economy principles.

2.8 Data availability

All data and code required to reproduce model results is available in the supplementary materials and on GitHub: https://github.com/pmbusch/Critical-Minerals-EV.

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3. Chapter 3 - Supply for Critical Minerals – Lithium case

3.1 Scope and Purpose

As shown in Chapter 2, electric vehicle adoption at a global scale will require a considerable amount of LIB capacity with their associated critical battery minerals requirements. In recent years, use of lithium, nickel and cobalt has grown significantly (Ritchie & Rosado, 2024; USGS, 2024b); and recent forecasts indicates that demand will continue to grow rapidly in the next decades (IEA, 2024). Growth in mineral consumption will require an equivalent increase in mineral extraction. Mineral supplies will be constrained in the short, medium and long term. Most studies focus on long-term constraints, by comparing cumulative mineral demand against existing mineral reserves on ground, finding sufficiency of minerals (Calderon et al., 2024; S. Wang et al., 2023; Zhang et al., 2023). Other studies have compared announced mineral capacity extraction against demand in the short term (until 2030) (ETC, 2023; Li et al., 2024; Qiu et al., 2024). Few studies have analyzed the medium-term supply constraints, such as resources to reserve conversion, resource discovery through exploration, delays in mine opening, and maximum depletion rates allowed (Ambrose & Kendall, 2020). Medium-term constraints could slow mineral extraction and jeopardize climate efforts that rely on LIBs. Additionally, few studies deal with the geographical distribution of mineral reserves, which are concentrated in a few countries, mostly on the global south (Tyagi et al., 2023).

The following chapter presents a supply dispatch optimization model for lithium mineral extraction, which uses deposit level data. Lithium is a good candidate for a detailed bottom-up supply analysis, as (i) it has no direct substitute in LIBs; (ii) it is a recently exploited mineral, with 36 deposits currently producing (in 2022), and with over a hundred projects currently under evaluation; and (iii) it is produced commonly with no major co-products. The dispatch model is a descriptive effort to predict which lithium deposits will open or expand their capacity to meet future lithium demand, under the different scenarios developed in Chapter 2. The model is a hierarchical multi-objective optimization, minimizing total costs (investment and operational) of lithium extraction, and then within the neighborhood of the optimal cost solution it minimizes capacity development in countries with a poor business environment index. The latter setting allows to represent recent lithium mining investment decisions, where countries with suitable business environment and institutions have lead lithium production, despite being in the middle part of the cost curve (e.g. the Australia hard rock lithium case). The dispatch model can quantify the supply effort required to meet lithium cumulative and peak demand associated with decarbonization actions. It also predicts the when and where of lithium deposit expansion and openings, whose results could inform industrial policy planning and environmental impacts mitigation.

This chapter includes some text adapted from a published article: Busch, P., Chen, Y., Ogbonna, P., Kendall, A. (2025). Effects of Demand and Recycling on the When and Where of Lithium Extraction. *Nature Sustainability,* 1-11 (Busch et al., 2025)[22], with further expansions and analysis. The text is reproduced with permission from Springer Nature.

3.2 Introduction

As stated in Chapter 2, global lithium production has grown by a factor of five in the last eight years (USGS, 2022, 2024a), with forecasts indicating 7 to 17 times more will be needed by 2050. The expected dramatic growth in EV sales will require an increase in LIB demand and rapid development in the supply chains required to produce them, starting with battery mineral supply. Mineral supply poses a potential constraint on EV deployment needed to meet global decarbonization goals, and carries environmental, social and governance hazards for communities affected by mines, with attendant reputational risks for companies that supply or purchase those minerals. High demand for minerals coupled with loss of resource quality and mining productivity could also increase prices for LIBs (Bhuwalka et al., 2023),

[22] Authors contributions are: AK and PB designed the research, conceptualization and methodology. PB, YC and PO collected the data. PB and AK performed the research, analyzed the data and created the figures. PB and AK wrote the paper.

presenting an additional challenge that could slow down decarbonization actions. In the next 15 years, circularity will not likely play a big role in providing battery minerals (Dunn et al., 2021), so nearly all battery minerals will have to be newly mined.

While competitive market mechanisms, like price adjustments, may reduce mineral demand or foster innovations in energy storage solutions with less mineral intensity, they will likely play a smaller role as minerals are a small fraction of total costs of EVs. For example, LIBs accounts for around 40% of the total cost of an EV (König et al., 2021), and all minerals represent around a 40% of the total cell manufacturing costs (Philippot et al., 2019)[23], and among them lithium comprises a small fraction, so increases in its price will have small effects on total battery cell costs (Ciez & Whitacre, 2016). Nevertheless, with decreasing overall battery costs the importance of materials costs becomes more relevant, reaching up to 50-80% of total costs (Houache et al., 2022; Olivetti et al., 2017). In terms of prices signals leading to increasing supply, market equilibrium mechanisms are subject to delays or errors in mine opening or expansions, as mines need to adequately forecast mineral demand and future prices in their decision-making process.

A major gap for supply sufficiency models for lithium is that they have not considered spatial or temporal dynamics in mineral extraction. Most models have simply compared cumulative demand against static reserves (Watari et al., 2021), with no modelling of the required opening of new mines or their associated production constraints. Because of the crucial role that LIBs play in both energy and transport decarbonization strategies (IEA, 2023; IPCC, 2022; Sen & Miller, 2023), understanding mineral resource supply dynamics, potential constraints, the interplay between battery mineral demand and the timing and geography of future battery mineral supply is crucial for stakeholders to prepare for future conditions and inform policy at national and global scales (Ambrose & Kendall, 2020; Jones, 2024; Woodley et al., 2024).

[23] A major driver of mineral costs is baseline operation costs, so bigger volume of production could reduce mineral costs (on average) and their relative share on total battery manufacturing costs.

We constructed an optimization dispatch model with data at lithium deposit level. The model satisfies lithium demand requirements up to 2050 by minimizing costs, both investment and operational, considering country non-monetary factors that affect the suitability of new mining projects as well as production constraints in mineral extraction. The model predicts the number of lithium mine openings or expansions using lithium demand scenarios from Chapter 2. The work done in this chapter answers several research questions, which can provide insights for local communities, advocates and other stakeholders.

- Do we have enough lithium to meet decarbonization targets from the perspective of total resources and the production rate needed?
- Where will future lithium supplies come from and how concentrated will they be?
- How many new lithium deposits will need to open to meet future demand?
- What is likely to be the major bottleneck in lithium extraction expansion?
- What demand and supply actions will be more effective in reducing pressure on the lithium supply chain?

3.3 Literature review

While battery mineral demand has been extensively explored, far less research has been done on the supply of those minerals. A review of 70 recent metal demand and supply studies found that only 39% addressed potential mineral supply constraints, and of those, 63% simply compared cumulative demand to reserves or resources (Watari et al., 2021). This type of comparison only considers whether known reserves or resources could supply total demand, omitting an evaluation of whether production rates can keep pace with demand, and ignoring dynamics that will influence mineral availability; including the timing of opening and expanding capacity, mining dynamics and economies of scale, technological improvements (Vidal et al., 2022), discovery and development of new mines (Mudd, 2021), and non-monetary factors that affect the likelihood of mine development at a specific location and time (Fleming et al., 2024).

Many techniques have been used to model the supply for critical minerals (Watari et al., 2021) (Table 3-1). Among the resource supply models developed, most rely on Hubbert curves (Calvo et al., 2017; Greim et al., 2020; Sanginesi et al., 2023; Vikström et al., 2013), which uses a simple mathematical equation to forecast production with country-level data for total mineral resources. Other mineral supply studies use economic models based on mineral demand-elasticity (Bhuwalka et al., 2023; Ryter et al., 2022, 2024); dynamic models, such as schedule models (Northey et al., 2014) or predator-prey models (Ali et al., 2017), linear programming (optimization) (Ambrose & Kendall, 2020; Jones, 2024; Tokimatsu et al., 2017); machine learning methods based on limited historical production data (Han et al., 2023); looked at current production and project announcements (Sun et al., 2022; Woodley et al., 2024), or simply assessed supply chain risk and challenges subjectively (Kumar et al., 2021; Sun et al., 2019). Each of these techniques has advantages and limitations. Top-down models tend to omit technical constraints in the supply development, such as the omission of deposit opening constraints (e.g., delays of up to 16 years from mine discovery to production (Buarque et al., 2024; Haddad et al., 2023)) and produce broad results without major temporal or spatial resolution. Forecasting techniques adjusted by empirical data have a high dependency on limited historical data, which is key challenge for lithium, given the relatively recent and short time since rapid increases in demand have led to exploration, mine expansions and openings. The future lithium supply expansion may be vastly different from the early and recent expansion trends.

Table 3-1. **Mineral supply modelling techniques**.

Technique	Main idea	Advantages	Limitations/Assumptions	Case Studies
Hubbert curves (logistic production curves)	Resource extraction starts with a steady growth due to capacity expansion and technological development, followed by a decline due to depletion of the best resources, resulting in a Gaussian curve shape (over time) with a production peak. The area under the production curve equals the ultimately recoverable resources (URR).	Simple to fit and understand. It requires few parameters. It has been used to predict production of other resources, such as oil or copper. Production over time is equal to total resources (by design).	The functional form of the curve is a prior assumption. The model, while simple, does not capture important interactions (e.g. price, technology). It does not explicitly model deposit expansions or openings. Curve fit is based on historical production data (limited for lithium).	(Calvo et al., 2017; Greim et al., 2020; Sanginesi et al., 2023; Vikström et al., 2013)

Technique	Main idea	Advantages	Limitations/Assumptions	Case Studies
Machine Learning	Use historical data to construct a model (parametric or non-parametric) that predicts mineral production. Model design and complexity is flexible and subject to modeler's decision.	Can incorporate multiple data sources, such as GDP, price, reserves, number of mining patents, in each country, among others. It can capture non-linear interactions.	No causality or physical model of the world is used. Omits major physical or political constraints in the mining supply chain. It strongly depends on historical data. Results are hard to validate or interpret.	(Han et al., 2023)
Economic models	Summarize the historical relationship between demand, mine production and price into economic metrics (e.g. demand elasticities), which are used to forecast supply reaction and price feedback.	Includes the endogeneity between demand and supply. The feedback on price will reduce demand in high price scenarios (low supply), or vice versa.	Unrealistic market assumptions (no delays, perfect information, no market power), as well as using limited historical data. Elasticity is modelled as a static parameter, rather than a curve. No consideration of deposit level detail, so results are at aggregate level.	(Bhuwalka et al., 2023; Ryter et al., 2022, 2024)
Schedule modelling	Extension to Hubbert production curves, with additional constraints on ramp up of capacity, and modelling the order of mine openings.	Mines are open exactly to meet demand in each period, considering a ramp-up period to reach maximum capacity, fixed production and a minimum number of years of production.	Does not distinguish between types of deposit or extraction costs. Merit order criteria for mine opening are based on simplistic assumptions, like higher grade ore.	(Northey et al., 2014)
Linear programming	Model supply firm behavior as an optimization problem to minimize total costs, subject to constraints. Decision variables represent firm actions: production each year, mine opening, among others.	Includes multiple parameters: such as costs of extraction, production capacity, delays in upscaling. Results are at deposit level. Active constraints in the solution reveal areas to focus policy actions.	Unrealistic depiction of the future, with an ideal modelling behavior of a global agent. It omits non-monetary factors, such as local regulations, business environment and knowledge access. It omits the price feedback between demand and supply.	(Ambrose & Kendall, 2020; Jones, 2024; Tokimatsu et al., 2017)
Predator-prey	Models the dynamics of competition and feedback on the system. Main drivers of production are discovery of new resources with more capital investment (predator) due to wealth generation by mining; and depletion of reserves due to extraction (prey).	It models dynamically the trade off in mine operation of capital re-investment with exploitation and depletion of mineral reserves.	Parameters need to be fitted based on historical data. It generates similar results as Hubbert curves. No consideration of deposit level detail.	(Ali et al., 2017)

Among the different supply modeling techniques, linear programming (optimization) methods have the advantage of considering spatial and temporal constraints in expanding capacity, a major gap identified in the mineral supply literature. Other advantages are the consideration of investment and operational costs in decision-making, and that the optimal solution found shows potential bottlenecks in the supply chain expansion. Some limitations of previous research using linear programming methods to forecast mineral supply are the omission of uncertainty (geological, economic and geopolitical (Arief et al., 2025)), omission of other non-monetary factors that affect decision-making, assuming static reserves (no resource-to-reserve conversion), and no price feedback between demand and supply. The proposed mixed integer optimization model in this chapter advances recent models by incorporating non-monetary factors and resource-to-reserve conversion over time, along with using a comprehensive database on lithium deposit level data gathered mainly from recent company reports.

3.4 Data and Methods

The mineral supply model assumes that investments in the form of expanded mine production capacity or new deposit openings will be deployed to meet future demand and compensate the degradation of existing deposits(Bhuwalka et al., 2023; Yaksic & Tilton, 2009). Mineral deposits are dispatched based on cost (Ambrose & Kendall, 2020) and other non-monetary factors which ease or impede mineral extraction developments as a function of country-level policies and conditions. This requires a detailed database of lithium resources at the deposit level for active and potential projects. The order of lithium dispatch reflects the increasing marginal effort of extracting lithium with higher primary lithium demand. Rather than a price equilibrium model, the dispatch setting provides a descriptive global solution that meets society's primary lithium demand.

3.4.1 Lithium deposit characteristics

A comprehensive database of existing lithium deposits was constructed based on multiple sources of information, ranging from US Geological Survey mineral reports, peer-reviewed articles (Benson et al., 2023; Hocking et al., 2016; Vikström et al., 2013), company reports, and lithium project feasibility studies. The supplementary information of the peer-review published article provides a detailed list of each deposit's compiled characteristics and their sources (Data S2) (Busch et al., 2025). While deposit characteristics are constantly updated based on new discoveries or technological development, the database contains the most up-to-date information that is publicly available. The database is publicly available, with proper references to the original source of information, for transparency, replicability and research extension purposes.

The lithium database characterizes each deposit with multiple required inputs for the optimization model (Table 3-2 summarizes the main sources or assumptions used).

Table 3-2. **Supply Dispatch model parameters.**

Parameter	Source
Resources by stage (reserves, demonstrated resources and inferred resources	US Geological Survey mineral reports (USGS, 2024a), peer-reviewed articles (Benson et al., 2023; Hocking et al., 2016; Vikström et al., 2013), company reports, and lithium project feasibility studies (see Data S2 (Busch et al., 2025) for full details).
Costs (CAPEX & OPEX)	Company reports, and lithium project feasibility studies (see SI Data S2 (Busch et al., 2025)). Regression equations based on ore grade or upper quantiles were used for data filling.
Status	Chen et al (Chen et al., 2020), company report (RFC Ambrian, 2023) and lithium project feasibility studies.
Direct lithium extraction (DLE) Technology	Data collected from a report (Goldman Sachs, 2023).
Current capacity	USGS (USGS, 2024a), company reports, and lithium project feasibility studies (see Data S2 for full details).
Planned capacity	Data collected from a report (RFC Ambrian, 2023).
Costs of demand curtailment	$100,000 per ton of LCE, about 50% higher than historical maximum lithium price $68,100 per ton LCE (USGS, 2024a).
Non-Monetary Factors	Ease of Doing Business Index (World Bank, 2020).
	World Governance Index – Political Stability (World Bank, 2024).
	World Competitiveness Ranking (IMD World Competitiveness Center, 2024).
Max. Capacity	5% depletion rate of total resources for hard rock(Vikström et al., 2013), 1% for evaporation of brines and 3% for DLE brine and volcano-sedimentary.
Ramp limit	4 years at least to reach maximum capacity, based on the mine opening profile modeled in other studies (Northey et al., 2014).

Resources and reserves: The term resource refers to the total amount of mineral that exists in a deposit that is potentially feasible to extract, while reserve refers to the portion of resources that meet certain physical and chemical criteria to be classified as currently economically suitable for extraction (USGS, 2023). Resources are often classified into three categories with increasing levels of uncertainty: measured, indicated and inferred (USGS, 2023) (Supporting Information (SI) Figure C-1 shows global resources by stage). A static view of resources or reserves over time is fundamentally incorrect, as technological development or changing market conditions, like certainty in increasing future demand, will provide incentives towards exploration of new resources and conversion of known resources to reserves (Bhuwalka et al., 2023; Castillo & Eggert, 2020). Information on resource quantities does not immediately indicate the quantity of reserves, especially with uncertainty in price changes and technological development, and thus modeling is required to predict how resources convert into reserves over time. The model incorporates data on reserves and resources, both demonstrated and inferred, into the same cumulative availability curve, following the proposed method by Castillo et al. for the case of copper (2020). An important assumption is that no undiscovered ground resources or lithium in the ocean will be available for extraction during the analysis period, even if lithium has seen major resource discovery in the last 15 years (SI Figure C-2 shows historical reserve and resource estimates for lithium). The supply of lithium via end-of-life recycling is already considered in the dynamic mineral demand model (Chapter 2), with no consideration of costs. In other words, recycled supply is always used first to meet demand, so primary lithium demand reflects the net demand after recycled supply is accounted for. For each deposit we divide future extractable lithium into three stages: (1) reserves; (2) demonstrated (measured and indicated) resources, excluding reserves; and (3) inferred resources. All resources may ultimately be suitable for extraction because the average lithium concentration of known resources is higher than the normal cut-off grade used to assess reserves.

Existing and planned capacity: Some lithium deposits are currently producing lithium or under construction. Baseline extraction capacity from 2022 to 2030 was filled using historical country-level lithium production (2022 and 2023) (USGS, 2024a) with announced capacity by deposit for 2025 and 2030

(RFC Ambrian, 2023), under the assumption that the share of production of active deposits within a country remains constant and by linearly interpolating between 2023 to 2025 to 2030.

Extraction rate dynamics: Deposit openings can face long lead times – from 8 to 19 years from discovery to initial production (Buarque et al., 2024; Haddad et al., 2023), and capacity expansion faces ramp up and maximum depletion rate constraints. For hard rock deposits, the maximum capacity extraction rate was set at a 5% depletion rate of all resources (a 20-year mine life), an extraction rate that has been never been exceeded empirically (Vikström et al., 2013). For brine deposits using evaporation ponds a 1% depletion rate was used, due to the physical and land limitations of the process. For other types of lithium deposits (current brine deposits using direct lithium extraction (DLE) (Goldman Sachs, 2023) or volcano-sedimentary), the maximum capacity extraction was set at a 3% depletion rate. A constraint of four years was assumed to ramp up towards maximum capacity (Northey et al., 2014). Restrictions to avoid openings and capacity expansion were based on deposit status: no expansion or opening was allowed until 2025 for currently producing mines, until 2027 for projects under construction, until 2030 for projects in the permitting or evaluation phase, and until 2032 for all others, reflecting the delay between discovery and resource assessment to mine opening (Haddad et al., 2023). The assumption that less explored deposits could open in less than ten years is optimistic considering global mine lead time is typically around 12 to 16 years (Buarque et al., 2024; Haddad et al., 2023).

Opening and expansion costs: Opening and capacity expansion costs were derived from project evaluation data of existing lithium projects, which were adjusted for inflation. Two linear regression (ordinary least squares) models were constructed (for brine and for hard rock) to fit capital expenditures (CAPEX) based on planned production capacity, in tons per annum (tpa). The observations with complete data were weighted by reserve size.

$$CAPEX\ [M\ USD] = \beta_0 + \beta_1 \cdot Production\ Capacity\ [tpa]$$

The intercept parameter (β_0) in the regression can be interpreted as the fixed cost of opening a deposit, and the slope (β_1) as the expansion cost to build extraction capacity in the deposit (Figure C-3 for brine, Figure C-4 for hard rock). The database does not have sufficient observations (n=4) to construct a reliable model for volcano-sedimentary deposits, so the model assumes an opening cost of $250 million and expansion costs based on the ratio of production and investment required. For deposits currently producing or in the construction phase, the opening cost is $0, to reflect that the commitment to open has been already made (sunk cost).

Cost of extraction: Brine and volcano-sedimentary deposits normally produce lithium carbonate (Li_2CO_3) at 99% purity, which is an input for cathode manufacturing, while hard rock deposits produce spodumene at 6% lithium oxide (Li_2O) content, which requires further processing to be a battery grade input. Hard rock costs have a weight adjustment of lithium content required (6.74 tons of spodumene at 6% Li_2O has the same lithium content as 1 ton of Li_2CO_3) and a fixed conversion cost of $2,500 per ton of spodumene towards lithium carbonate (Atkinson, 2023). Within the operation of each deposit there are increasing marginal costs of extraction, as a normal operation will use its best quality resource first. This is modelled with a three-stage marginal cost step-function, with increasing costs for each stage: (i) reserves, (ii) demonstrated resources and (iii) inferred resources. Ordinary least squares models were fitted to explain the extraction costs or operational expenditures (OPEX) by deposit type (brine and hard rock), using lithium grade as the explanatory variable and reserve size as weights. The regression models were used to estimate extraction costs in deposits with no cost information but with available grade ore estimations, and to estimate costs in stages with decreasing ore quality.

$$OPEX\ [USD/ton\ LCE] = \alpha_0 + \alpha_1 \cdot Grade\ Ore\ [\%\ Li]$$

The slope coefficient (α_1) represent the effect of grade ore on extraction costs per ton (Figure C-5 for brine, Figure C-6 for hard rock, no model for volcano-sedimentary). For deposits with no available information of reserves or grade ore of lithium, we consider that their extraction costs should likely be in the upper range (Castillo & Eggert, 2020). For each resource type (brine, hard rock and volcano-sedimentary), the extraction costs for all missing deposits were populated using the 75th percentile of extraction cost to fill stage 1 costs, 90th percentile for stage 2 costs and 99th percentile for stage 3 costs. To avoid a tipping effect on the order criteria, a random sample was taken from a half triangular distribution, setting the *min* and *mode* parameters at the percentile, and the *max* parameter at the maximum cost value of the distribution. The latter reflects the fact that lithium resources - with less certainty in their quantity and quality - will likely have higher extraction costs than currently known reserves. Overall, 54 deposits had cost information from an external reference, 9 were estimated based on ore grade and the remaining 97 were filled based on upper quantiles. The regression equation was also used to characterize extraction costs for 13 and 44 deposits for stage 2 and stage 3, respectively. The marginal corporate tax rate and the specific royalty rate for each country was added to the extraction costs, assuming a fixed price of $20,000 US$ per ton of LCE (a common forecast for the price (Lazenby, 2024)) to estimate the revenues and profit payments (SI Table C-1 shows the rates used per country or state).

3.4.2 Non-monetary factors

Although many studies recognize the importance of non-monetary factors such as socioeconomic policies on mineral supply models (Castillo & Eggert, 2020; Fleming et al., 2024; Greim et al., 2020; Lawley et al., 2024), few have quantitatively assessed these factors. There is evidence that political, social and environmental factors play a role in the evaluation and ranking of lithium deposits worldwide (Lawley et al., 2024; C. N. Wang et al., 2022). The model minimizes (as a 2nd objective) expansion in countries with a poor ease of doing business (EDB) index (World Bank, 2020) to capture the attractiveness for companies to develop or expand projects within a country. The EDB index characterizes business accessibility in a country with data on permitting, access to electricity, credit options, registering property, contract enforcement, and insolvency resolution (World Bank, 2020). We consider the country where the deposit is located, rather than the country of the owning company, which can also play a role in capacity expansion decisions (Sun et al., 2024). When evaluating optimization results for non-monetary factors we take the average of the index weighted by the added capacity to each deposit.

3.4.3 Supply Dispatch Optimization

A dispatch multi-objective optimization model determines the timing of mineral deposit opening and expansion. The model is based on the idea that costs of extraction (OPEX) and investments (CAPEX), along with country non-monetary factors, determine which mines will be exploited sooner (Yaksic & Tilton, 2009).

The mixed integer multi-objective optimization model expands the theoretical base and capabilities of the model developed by Ambrose et al. (Ambrose & Kendall, 2020), and follows similar decision variables as previous mineral supply models (Jones, 2024), with a lithium cumulative availability curve as the main input (Fleming et al., 2024). The primary objective function is to minimize the levelized extraction costs, considering costs of opening, capacity expansion and extraction:

$$\min_{X_{i,t,s}\, Y_{i,t}\, W_{i,t}\, Z_t} \sum_t \left(\sum_i \left(CostOpen_{i,t} * \boldsymbol{W_{i,t}} + CostCapExp_{i,t} * \mathbf{Y_{i,t}} + \sum_s \left(CostExtract_{i,t,s} * \boldsymbol{X_{i,t,s}} \right) \right) + CostSlack * \boldsymbol{Z_t} \right)$$

All decision variables are indexed by deposit (i), year (t) and/or stage (s), $X_{i,t,s}$ is the extraction of lithium (in tons), with detail by stage depletion: reserve, demonstrated resources and inferred resources; $Y_{i,t}$ is the additional capacity added to the deposit that year (tons/year); $W_{i,t}$ is a binary variable that indicates the opening of the deposit; and Z_t indicates lithium demand curtailed in year (t) (tons). Transportation costs between mines and refining locations are not included. Brine deposits produce a refined 99% Li_2CO_3, so transportation costs are minor; and while currently hard rock deposits in Australia ship spodumene concentrate at 6% Li_2O to China elevating their costs, there is an active strategy to co-locate conversion facilities near mineral deposits (S&P Global Market Intelligence, 2019). An assumption to simplify the model was that there is no market power of mines to influence the commodity price of minerals and the fixed predicted global demand. Under these assumptions, the problem can be framed as minimizing costs to meet lithium demand over time.

The model minimizes total costs and non-monetary factors over the whole period, with perfect foresight of future demand and supply availability. All costs include a 7% discount rate to reflect the mining industry time-value of money and the preference to delay big investments (Ovalle, 2020). While the discount rate could vary by country due to differences in risk for long term projects (Gosson & Wood, 2013), the model handles this aspect with the non-monetary factors. The slack represents the opportunity cost of not meeting lithium demand, which was set at $100,000 US$ per ton of lithium carbonate ($LiCO_3$), about 50% higher than the historical maximum price of $68,100 reached in 2022 (USGS, 2024a). This represents the possibility that mine producers will curtail demand if short-term production costs exceed this threshold, thus causing temporary shortages in supply of lithium.

A secondary objective function is to minimize the expansion of capacity at - both currently active and new deposits in countries with non-monetary factors that are likely to make them less attractive for investment:

$$\min_{\boldsymbol{Y}_{i,t}} \sum_{i} (NonMonetary\ Factor_i * (\sum_{t} \boldsymbol{Y}_{i.t}\ ))$$

The non-monetary factor corresponds to the complement of the EDB index at country level where each deposit is located. The expansion capacity decision variable represents the non-monetary effort of developing capacity in a mine operation. The model follows a hierarchical multi-objective approach: it first finds an optimal solution (0.01% optimality gap) for the cost minimization objective function; then a second optimization routine is run to minimize the non-monetary objective function with the condition that the initial optimal cost solution does not degrade more than certain cost degradation factor (α). A 10% maximum cost degradation factor was used, but different values were tested in the sensitivity analysis of the model results. The resulting solution is in the neighborhood of the optimal cost, and favors capacity expansion in countries with better business environments. This approach is intended to represent the decision-making of companies in a real-world setting, where cost is not the sole decision criteria, and incorporates into the model the trade-off between extraction costs and the business environment where the deposit is located.

The model has the following constraints, besides non-negativity for all decision variables:

(1) Production at each mine is always equal or less than available capacity (initial production rate plus baseline expansions)

$$\sum_{s} \boldsymbol{X_{i,t,s}} \leq \sum_{k=0}^{t} \left(\boldsymbol{Y_{i,k}}\right) + \text{Planned Capacity}_{i,t},\ \forall\, i, t$$

(2) Mineral extraction surpasses demand at every period, except considering curtailed demand when cost is too high (curtailed demand moves to the next year).

$$Mineral\ Demand_t + Z_{t-1}\ \leq\ \sum_{i}\Big(\sum_{s}(\boldsymbol{X_{i,t,s}})\Big) + \boldsymbol{Z_t}\ ,\ \forall\, t$$

(3) Cumulative production at each deposit does not exceed known reserves, demonstrated resources or inferred resources (stages).

$$\sum_{k=0}^{t} \boldsymbol{X_{i,k,s}} \leq Stage\ Resources_{i,s},\ \forall\, i, s$$

(4) Upper bound on capacity (production rate) for each deposit, and capacity can only be added to open mines.

$$\sum_{k=0}^{t} (\boldsymbol{Y_{i,k}}) + \text{Planned Capacity}_{\mathrm{i,t}} \leq \sum_{\mathrm{k=0}}^{t} \boldsymbol{W_{i,k}} * Max.\ Capacity_i,\ \forall\, i, t$$

(5) Deposits can be opened only once.

$$\sum_{t} \mathbf{W_{i,t}} \leq 1,\ \forall i$$

(6) Expansion of capacity has an upper ramp limit per year.

$$\boldsymbol{Y_{i,t}} \leq Ramp\ Limit_i,\ \forall\ i, t$$

The key purpose of the model is to predict the order, timing and magnitude of the necessary deployment of global lithium deposits to meet lithium demand. In this regard, the estimated costs and non-monetary barriers need to result in ordinally correct estimates rather than precisely correct quantitative values. There is a lot of uncertainty in the model inputs, but the overall decisions of mine openings are more likely to be correct compared to particular cost predictions. Deposit expansion and opening forecast are based on the present situation of costs and non-monetary factors, which are subject to evolve over time. Rather than providing a normative forecast, the model results represent a descriptive of the likely outcome given present deposit characteristics and technological conditions.

Horizon effects occur when the model anticipates the end of the modeling period, which could lead to unrealistic outcomes, such as the opening and complete depletion of only a few deposits by 2050. To avoid this outcome, the optimization model runs for the period of 2022-2070, though only the period of 2022-2050 was considered for results and inferences. The extended time horizon ensures that by 2050 several deposits will have enough reserves left to meet ongoing demand. The following assumptions were used to extend the mineral forecast (from Chapter 2) towards 2070:

i. Battery size, chemistry share, recycling rates and lifetime parameters from 2050 remain constant to 2070, and mineral demand from other sectors grows with population or GDP forecast.
ii. Vehicle sales and SSPS remain constant (0% growth) if the five-year average growth rate in a country in 2050 is less than 1%, or 1% otherwise. This assumption reflects the uncertainty in long-term forecasts of vehicles and SSPS demand, and assumes slow growth after 2050.

To measure market concentration the Herfindahl Hirschman Index (HHI) was calculated. HHI is the sum of the squares of the market share of each country, where a higher number indicates a more concentrated supply market. Two results for HHI are provided: one omitting recycling inflows and the other by considering recycling as a supply source for the country where the battery was first sold.

3.4.4 Sensitivity analysis

To test the effect of supply constraints on the model results, several sensitivity scenarios for deposits parameters were tested. The supply parameters tested were extraction technology, depletion rate, timing of openings and expansions, resources, alternative non-monetary factors, and discount rates (Table 3-3 provides the full description of each scenario).

Table 3-3. Supply sensitivity scenarios.

Parameter	Scenario details
Extraction technology	- All brine extraction uses DLE technology, or all brine extraction uses evaporation. The DLE scenario considers an increase in CAPEX of $1,500 per ton per year LCE, and a an OPEX reduction of $900 (Goldman Sachs, 2023).
Depletion rate	- All deposits have a 5% depletion rate as their maximum production rate. - All deposits have a 2% depletion rate as maximum production rate or 100 ktons of lithium metal.
Timing for openings and expansions	- Ramp up requirements are set at 1, 2 or 8 years. - Shorter/longer lead times for capacity expansion for deposits in evaluation phase (not available until 2028/2032), and with no information (not available until 2030/2036).
Mineral resource constraints	- Volcano-sedimentary resources are unavailable. - Inferred resources are unavailable. - Country N-1 analysis: removing all deposits for a country or region to test the resilience of global supply if one country does not participate.
Non-monetary factors	- Run the model with a cost minimization only setting (single objective function - Run the multi-objective model with different cost degradation factors: 1%, 3%, 5%, 10%, 15%; and different country-level indicators related to non-monetary factors: - Ease of doing business Index (World Bank, 2020) - World governance index on political stability (World Bank, 2024) - World competitiveness ranking (IMD World Competitiveness Center, 2024) (for countries with no data we use value of 20 out of 100).
Discount rates	- Discount rates for costs of 3%, 7%, 10%, 15%, 25%. - A hyperbolic discount formulation (testing all the above discount rates).

3.5 Results

3.5.1 Global lithium deposits

Minerals are classified as either resources or reserves, with reserves referring to the portion of resources that currently can be economically extracted. Lithium resources and reserves are concentrated in a few deposits and in even fewer countries (Figure 3-1 and Figure 3-2a). Lithium resources can be found in different resource types: brines (salar, geothermal and oilfield occurrences, mostly found in South America), hard rock (pegmatites and greisen veins, found in Australia, Canada and the Democratic Republic of the Congo (DRC)) and volcano-sedimentary (adjacent to silicic volcanism, usually rich in clay, mostly found in the US and Tanzania) (Benson et al., 2023; Gardiner et al., 2024).

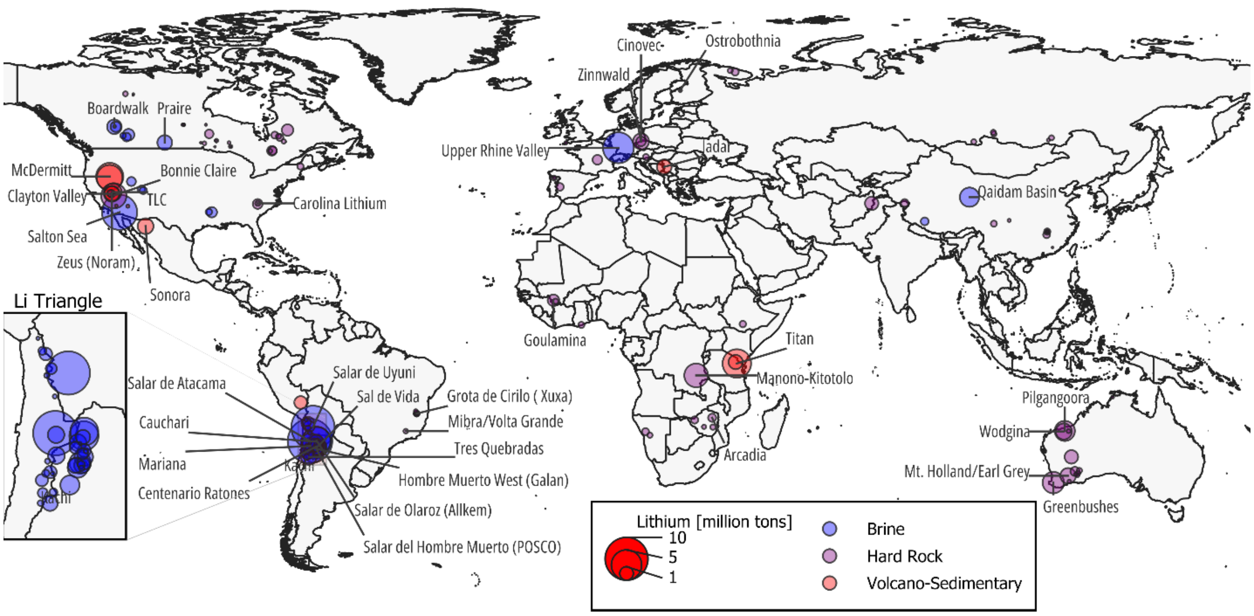

Figure 3-1. Lithium known deposits worldwide, with their resource type and size (in million metric tons of Li metal). The lithium triangle (Argentina, Bolivia and Chile) with brine deposits dominates know resources (53%). Australia dominates production in 2023 (48%) based on hard rock deposits (USGS, 2024b). 160 deposits have a lithium resource estimate, with 36 of them currently in production and 16 under construction. Source: Lithium database based on Benson et al. (Benson et al., 2023), with further additions and corrections. Material from: 'Busch et al., Effects of demand and recycling on the when and where of lithium extraction, Nature Sustainability, published 2025, Springer Nature', with permission from Springer Nature.

The lithium cumulative availability curve (Figure 3-2c) shows that brine deposits constitute the majority of resources, and that they are cheaper to exploit than hard rock or volcano-sedimentary resources, even after adjustments for different countries' royalties and tax rates. Extraction costs are not the only criteria for production, as technical, economic or political barriers may limit the maximum rate of extraction, as well as cause delays in deposit openings or expansions; and some lithium deposits faces a trade-off between costs and business environment of the country (Figure 3-2b).

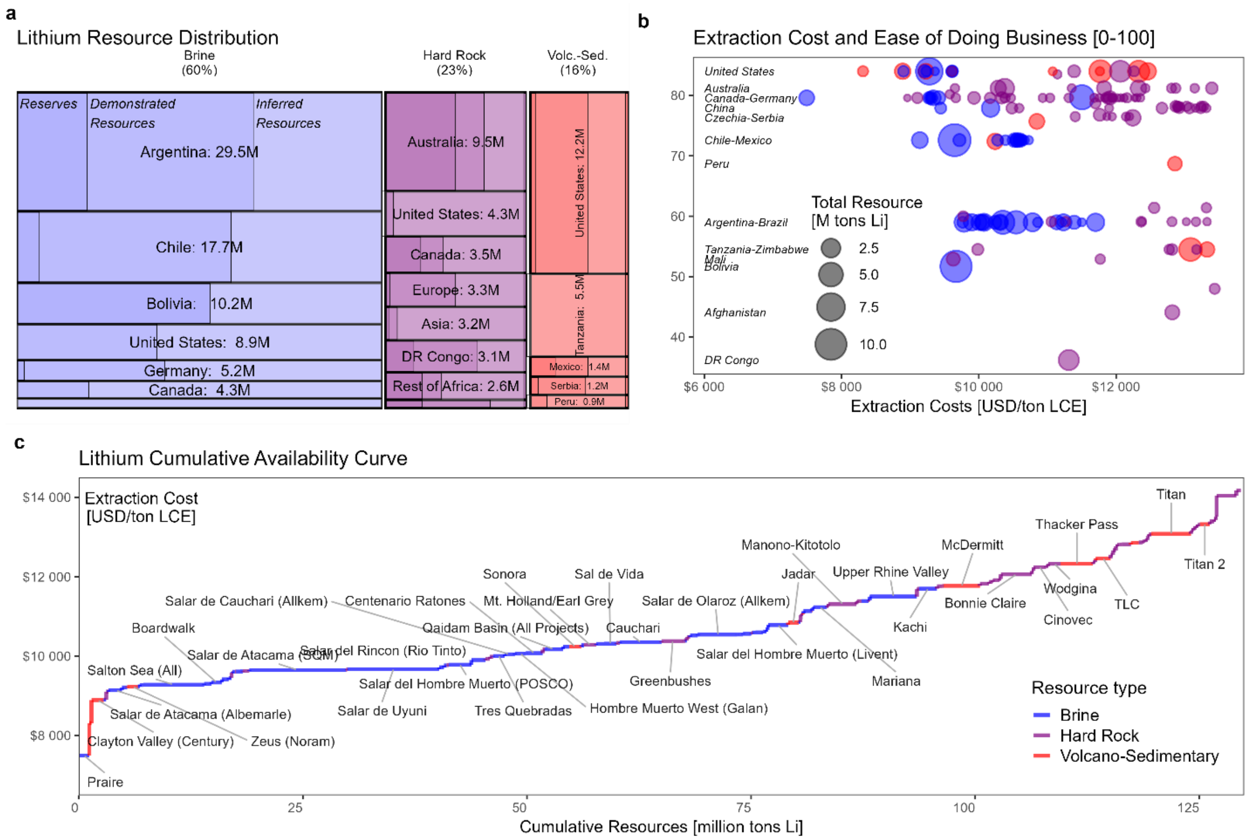

Figure 3-2. Global lithium resource distribution (a), deposit extraction costs and country ease-of-doing-business trade-off (b), and the resource cumulative availability curve (c). (a) Color indicates resource type (for all panels). Countries with the highest resources are shown in order. (**b)** Dot area indicates total resource quantity. Country label indicates the index value for that country. The upper-left quadrant shows deposits that are cheap and with a good index. The model configuration evaluates the trade-off between the lower-left and upper-right quadrants deposits, or cost against ease-of-doing business index. **(c)** Deposits are sorted by marginal extraction costs, considering royalties and tax rates, and display with their known total resources. Material from: 'Busch et al., Effects of demand and recycling on the when and where of lithium extraction, Nature Sustainability, published 2025, Springer Nature', with permission from Springer Nature.

3.5.2 Deposit openings

Known lithium deposits are specified with cost of production estimates and non-monetary factors based on their location and then run through a multi-objective optimization model under varying demand scenarios to yield a resource dispatch curve, providing information on the timing of deposit openings and expansions, as well as the amount of lithium extracted at each deposit, year and scenario (Table 3-4).

The results show that nearly half of both existing reserves and demonstrated resources will be extracted by 2050 in the highest demand scenario (scenario 2). Increases in lithium demand generate a non-linear effect on the supply response. In the high demand scenario (scenario 2) a 171% increase in capacity at current sites is required along with the opening of 90 new deposits, while in the enhanced recycling scenario (scenario 9), society will require a capacity expansion of around 44% for open deposits and the opening of just 21 new deposits (Table 3-4). In low demand futures, most of the required openings are needed before 2035, so even recent mine development announcements are not sufficient to sustain lithium production in the medium term, but after 2035 little expansion is needed. This contrasts with high demand scenarios where new deposits will continue to be required after 2035. In addition to continued capacity expansion requirements, meeting the highest demand scenario requires 46 deposits to operate at their maximum possible depletion rate, and almost all of them need to scale production as fast as possible (in just 4 years). Eventually, the added primary lithium demand is met by deposits with poor grade, small size and high extraction costs, thus increasing the total cost, due to higher marginal cost and total quantity extracted, and increasing environmental impacts of achieving global electrification targets. High demand scenarios also required the building of production capacity in countries with less favorable business environments, as shown by the lower EDB index (World Bank, 2020) (Table 3-4). On the other hand, high demand scenarios force more deposit openings across the world, leading to more diversified supply and lower (thus better) HHI results, a measure of market concentration. However, another mechanism for lowering HHI is investment in robust domestic recycling systems; they essentially create new domestic supplies of lithium, diversifying sources and reducing market concentration (HHI with recycling in Table 3-4). Lowering primary mineral lithium demand reduces overall costs by decreasing the quantity needed and by using cheaper deposits, resulting in about $60 billion in savings in scenario 9 (recycling) with respect to the reference scenario[24]. The latter are monetary resources that can be relocated towards expanding and promoting the LIB recycling market and infrastructure.

Table 3-4. Demand and supply metrics from nine demand scenarios (2022-2050). EDB: Ease of Doing Business Index. HHI: Herfindahl Hirschman Index. The number of deposit openings is additional to the currently 36 deposits under production and 16 under construction. Material from: 'Busch et al., Effects of demand and recycling on the when and where of lithium extraction, Nature Sustainability, published 2025, Springer Nature', with permission from Springer Nature.

Demand Scenario	(1) Ref.	(2) Large LIB	(3) Smal l LIB	(4) NMC 811	(5) LFP	(6) Solid State	(7) SIB	(8) Rep.	(9) Recy.	(10) US Rec.	(11) Rec.+ Small LIB
Net primary lithium demand MMT [Million metric tons]											
Cumulative	30.1	41.1	23.1	30.1	29.8	34.0	28.6	30.0	25.5	28.9	21.0
Peak (MMT/year)	1.72	2.39	1.27	1.72	1.70	2.02	1.62	1.71	1.27	1.58	1.04
Recycling capacity in 2050 (MMT/year)	0.51	0.79	0.38	0.51	0.50	0.56	0.48	0.51	1.12	0.65	0.67
Depletion [%]											
Reserves	40%	49%	38%	40%	41%	42%	41%	41%	39%	42%	36%
Demonstrated Resources	34%	52%	23%	34%	33%	41%	31%	34%	25%	30%	21%
Inferred Resources	10%	12%	8%	10%	10%	11%	10%	10%	9%	10%	7%
Increase in capacity for open deposits [%]	79%	171%	40%	79%	76%	106%	70%	79%	44%	66%	25%
Number of deposits											
Opened	62	90	35	62	62	87	58	62	21	53	15
Opened before 2035	39	51	25	36	36	51	33	37	18	36	15
Reach maximum capacity	23	46	19	23	23	39	22	23	22	20	9
Reach maximum ramp-up	74	121	41	74	74	104	69	74	24	64	17

[24] A major limitation of this analysis is that the model does not consider recycling costs.

Demand Scenario	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Ref.	Large LIB	Smal l LIB	NMC 811	LFP	Solid State	SIB	Rep.	Recy.	US Rec.	Rec.+ Small LIB
Socioeconomic and geopolitical indicators											
EDB	81.1	76.5	83.0	81.1	81.2	79.9	81.5	81.1	83.6	81.7	83.9
HHI	0.17	0.16	0.25	0.17	0.17	0.16	0.18	0.17	0.35	0.19	0.34
HHI with recycling	0.14	0.13	0.21	0.14	0.14	0.14	0.15	0.14	0.23	0.17	0.24
Total Cost [billion US$, in 2022 net present value]	$575	$768	$448	$575	$570	$634	$551	$574	$515	$558	$425

The spatiotemporal evolution of lithium extraction is different under different demand scenarios (Figure 3-3). Starting from the same baseline of 36 deposits open and 16 under construction (in 2022), the large LIB scenario ends up with 142 active deposits in 2050 (122 in 2040) with a combined capacity of extraction of 2,400 ktons; while the scenario that combines small LIB with medium recycling levels has 67 deposits active in 2050 with a combined capacity of 1,000 ktons. All demand scenarios assume the same level of EV adoption globally, and with roughly the same decarbonization benefits, but the required lithium supply expansion is different. Another interesting takeaway is that only in demand scenarios that incorporate robust recycling strategies there is no need for additional mine openings in 2050, since peak demand is reached before mid-century. However, there are more fully depleted mines in recycling scenarios, as the decreasing primary demand allows the model to plan for depletion without risking a supply shortage (or requiring new mine openings).

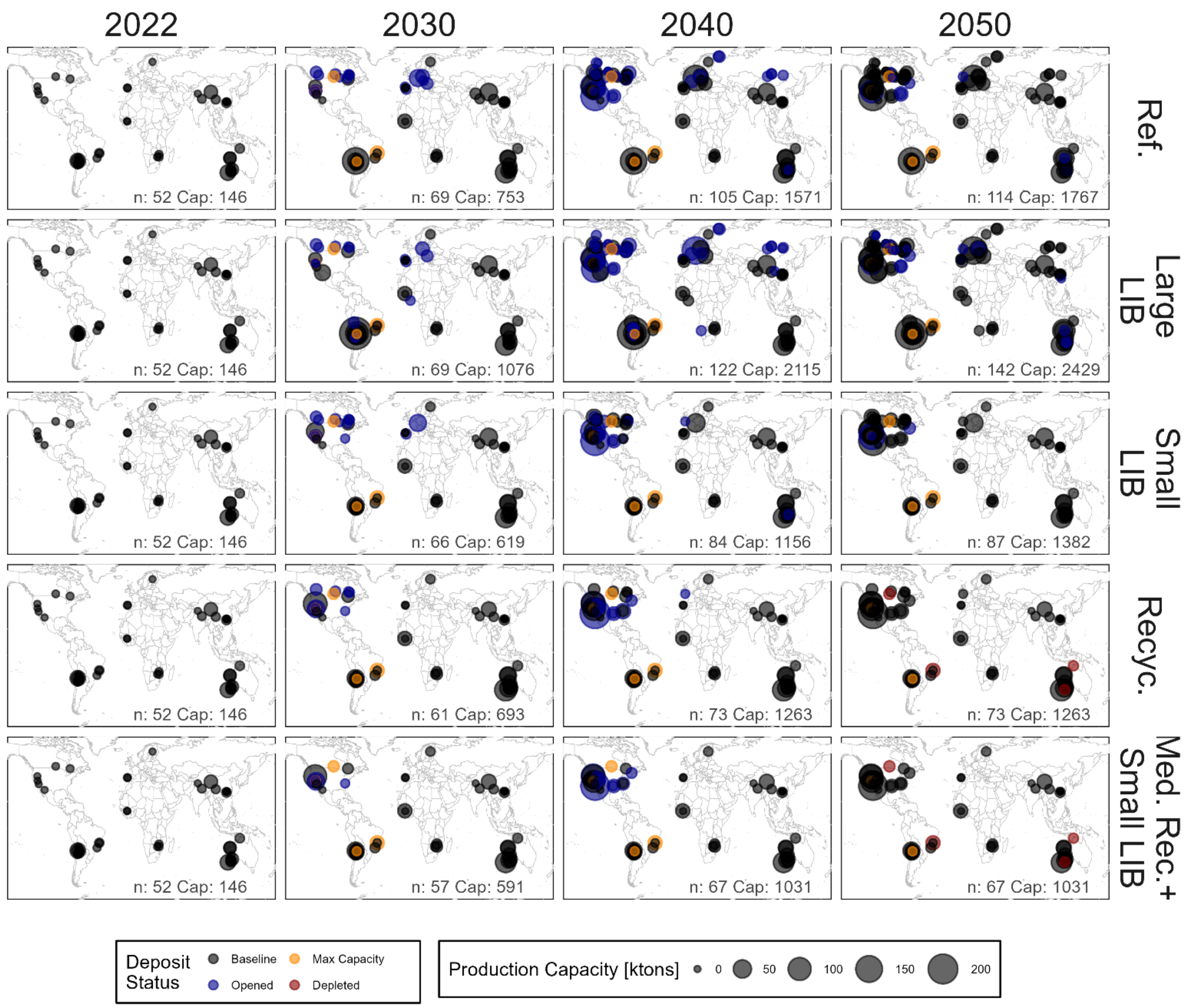

Figure 3-3. Spatial lithium deposit development until 2050 by different demand scenarios. Each dot shows a deposit that extracts lithium, with the size indicating their production capacity. Colors indicated the status of the deposit: baseline (or producing), opened in that period, with maximum capacity reached or depleted. Labels in each map indicate the number of operating mines and the combined production capacity, in ktons.

3.5.3 Lithium supply

Recycling and recovery of lithium from end-of-life LIBs plays an important role in displacing primary lithium extraction in all demand scenarios (Figure 3-4). Demand scenario 9 explores a future with high recycling and recovery rates across the world. While this scenario uses the reference scenario demand, it leads to a lower number of mine openings – just 21, as the net demand for primary lithium at the period of peak demand remains lower than every other scenario because of recycled supply (Table 3-4 and Figure 3-2). The lowest number of mine openings – just 15 – is achieved by combining a smaller battery strategy with a recycling strategy (scenario 11). Recycling also re-distributes the origin of lithium flows across the world (Figure 3-4 and SI Figure C-7). In the short term, however, recycling does not play a role in avoiding deposit openings. The relative long lifetime of EV LIBs and delays in recycling mandates means recycling cannot play a significant role until around 2040 (Dunn et al., 2021). Thus, additional deposit openings are needed in all scenarios for at least the next 15 years to introduce enough lithium into the economy, to then be able to pursue circular economy strategies.

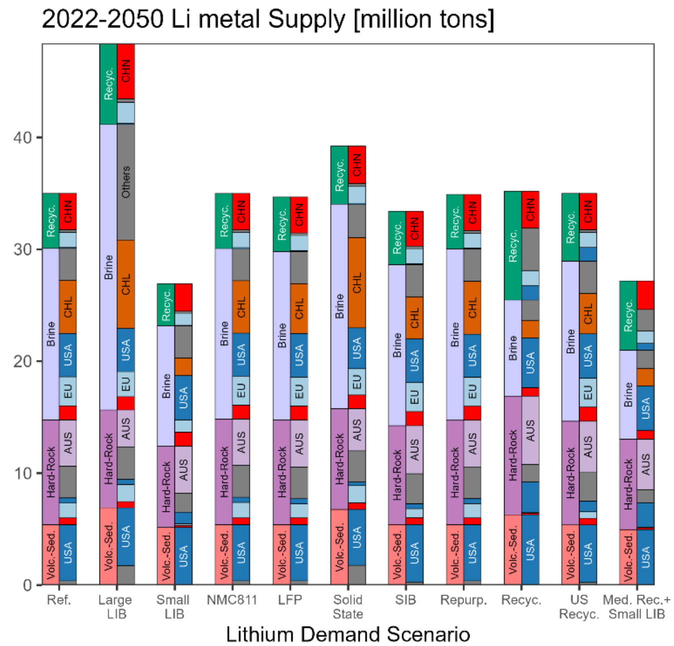

Figure 3-4. Lithium cumulative extraction by resource type and country of extraction. Lithium metal supply from primary extraction and recycling is shown for each demand scenario. Left-bars shows detail by type of resource or recycling, and right-hand bars show country distribution for each resource type (AUS: Australia, CHL: Chile, CHN: China, EU: Europe, USA: United States of America, Others: any other country not listed here). Material from: 'Busch et al., Effects of demand and recycling on the when and where of lithium extraction, Nature Sustainability, published 2025, Springer Nature', with permission from Springer Nature.

The country or region of supply is crucial to understanding the results. The lithium triangle, comprised of Chile, Argentina and Bolivia will play a pivotal role in future lithium supply, dominated by continued production from brines in Chile (Figure 3-4, and Figure 3-5 shows lithium extraction by country over time). Australia currently supplies more than half of global lithium and will continue with a steady production from hard rock deposits, but lower market shares due to entrance of new players. The US, while not currently a player in lithium supply, is expected to be a significant source of lithium starting in 2033, providing 44% of global primary supply by 2050 (Figure 3-4, Scenario 1). This is perhaps more surprising than the continued importance of Chile and Australia, given that the US supplies just a small fraction today. However, the future US lithium supply depends on technological developments to extract brine with DLE and cost-effective technology to separate lithium from clays (Fuentealba et al., 2023; Gardiner et al., 2024; Xie et al., 2024; H. Zhao et al., 2023).

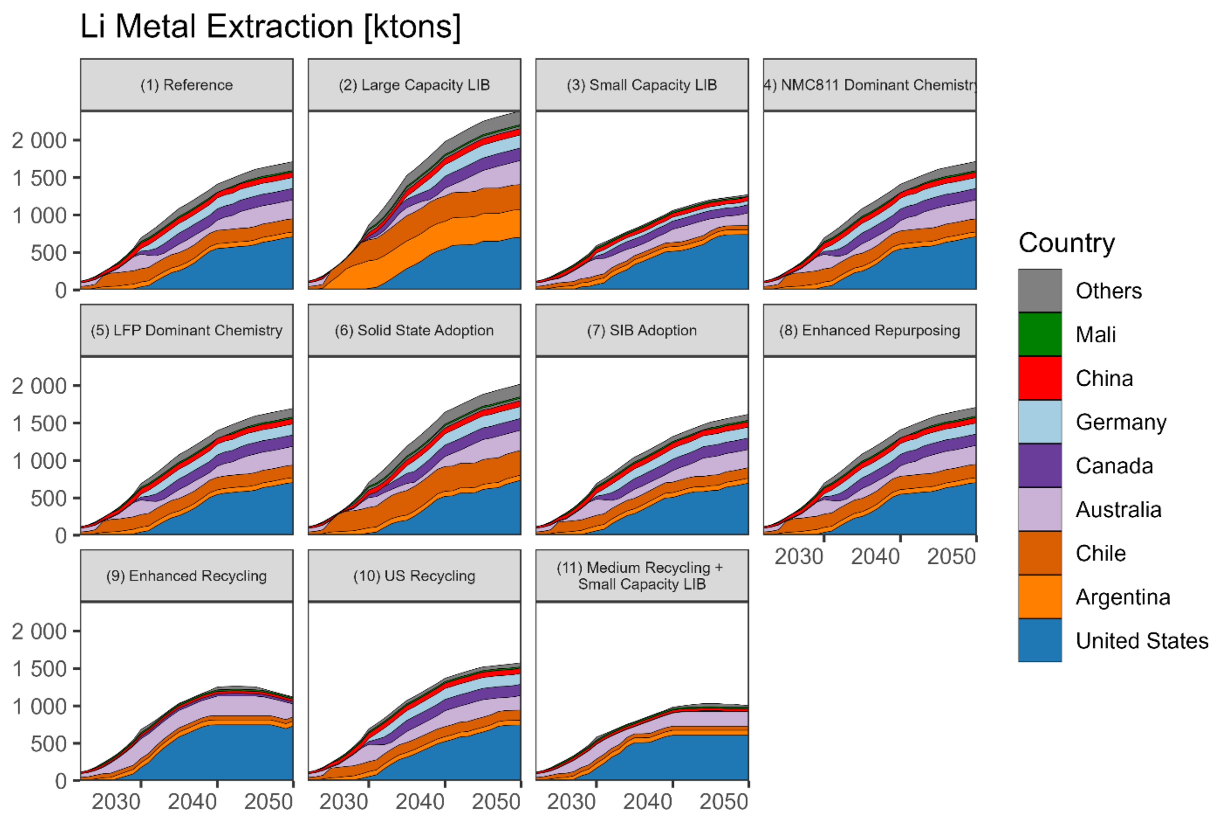

Figure 3-5. Lithium metal extraction, in ktons, by country (color) and by demand scenario (panels). Material from: 'Busch et al., Effects of demand and recycling on the when and where of lithium extraction, Nature Sustainability, published 2025, Springer Nature', with permission from Springer Nature.

Overall, the forecast of lithium production by country in the short-term (2022-2030) looks more similar to historical lithium production (2015-2021) by incorporating non-monetary factors as a second objective in the optimization (SI Figure C-8). Historical lithium production has been dominated by Australia and Chile. Results from the model using a single cost objective function predicts lower participation from Australia in the near-term, in favor of higher production in cheaper brine deposits in the lithium triangle. A model with the non-monetary factors as a 2nd objective corrects the importance of Australia as a reliable mineral supplier, increasing their production quota.

3.5.4 Recycling effect

Recycling at global scale will prevent the opening of multiple lithium deposits worldwide, while higher demand scenarios will require massive global effort to meet the lithium quota needed (Figure 3-6). While not obvious in Figure 3-6, the results show that deposits in the middle part of the cumulative availability curve may not be required, and thus those countries will not realize the benefits and not suffer the consequences associated with lithium extraction. All countries can still become suppliers via active participation in the emerging mineral recovery supply chain, though regions with the largest markets have the greatest potential in this regard.

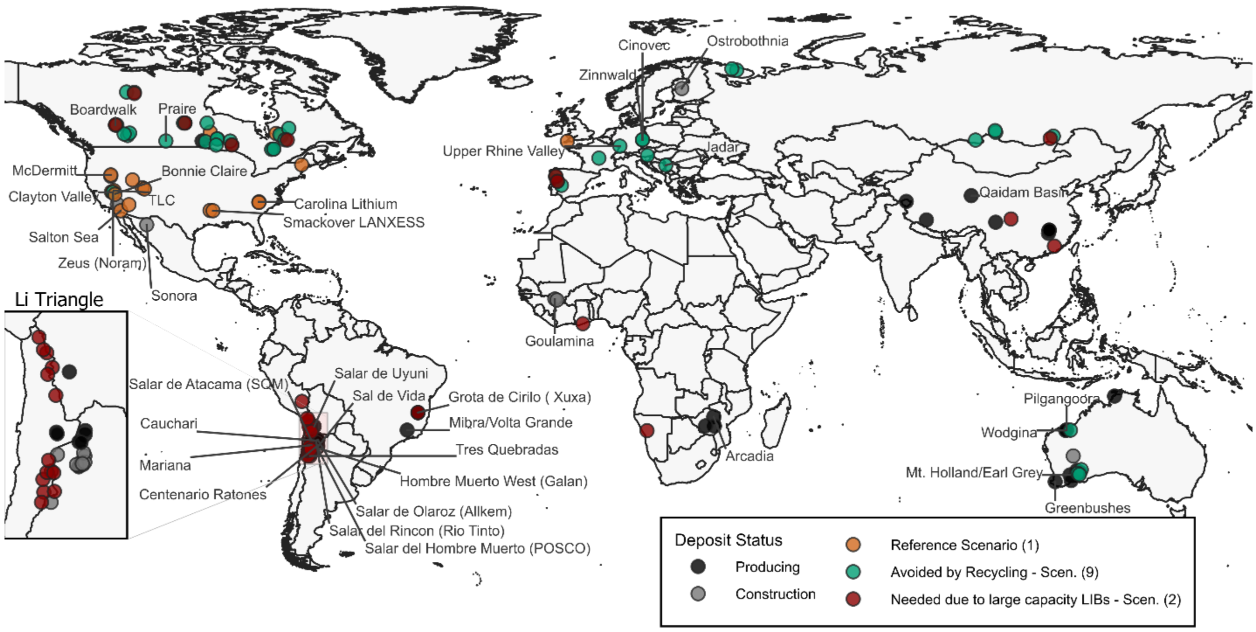

Figure 3-6. Required opening of lithium deposits by 2050. Colors indicate deposits that are currently producing (2022, n=36), in the construction stage (n=16), those that will need to open in reference case Scenario 1 (n=62), those that could be avoided in the high recycling case Scenario 9 (compared to scenario 1, n=41) and the additional deposit openings required in the high demand case Scenario 2 (compared to scenario 1, n=28). Inset: Brine deposits in the lithium triangle (Argentina, Bolivia and Chile). Material from: 'Busch et al., Effects of demand and recycling on the when and where of lithium extraction, Nature Sustainability, published 2025, Springer Nature', with permission from Springer Nature.

Any increase in the global recycling rate of lithium decreases the number of new deposits openings, and for the reference scenario a global lithium recovery rate above 45% limits the number of new openings by fewer than 40 (Figure 3-7 test deposit openings under different global recovery rates). Recycling does reduce mine openings in the large LIB capacity demand scenario, but more than 60 new openings are required even with high recycling levels.

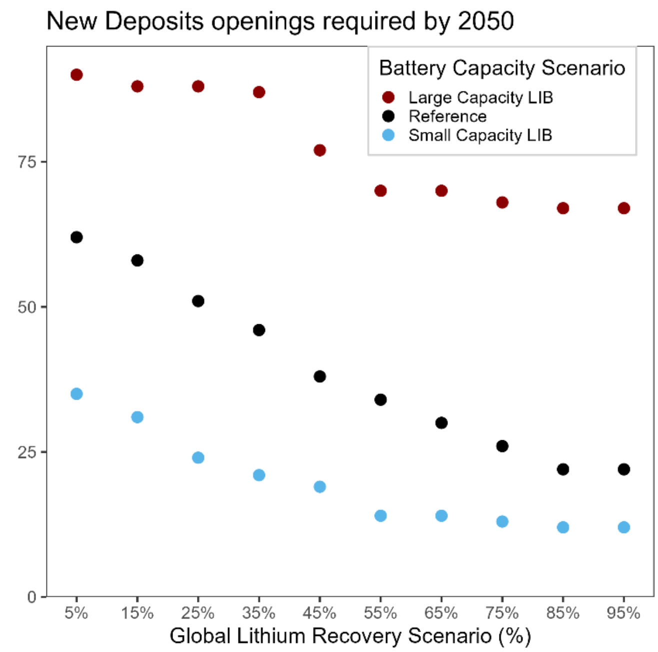

Figure 3-7. **Number of new lithium deposit openings required by 2050 under different battery capacity scenarios and global lithium recovery levels**. Recovery targets for China and the European union are modelled according to their proposed targets timeline (European Parlament, 2023; Recycling of Traction Battery Used in Electric Vehicle–Recycling–Part 2 : Materials Recycling Requirements, 2020). All other regions follow the timeline of Europe (80% by end of 2031), with the maximum attainable recovery target set by the horizontal axis levels. Material from: 'Busch et al., Effects of demand and recycling on the when and where of lithium extraction, Nature Sustainability, published 2025, Springer Nature', with permission from Springer Nature.

3.5.5 Sensitivity analysis

The sensitivity analysis seeks to reveal the key constraints in the lithium supply chain development. The optimization model was run under different parameters and deposit inputs (Figure 3-8). For the N-1 analysis, all deposits within a country or region were removed from the inputs. The latter simulates a scenario where a country does not participate in lithium extraction due to economic, political, institutional or social issues.

The N-1 analysis reveals the importance of each country in the lithium extraction supply chain. Removing the biggest future suppliers - the US, Australia and the lithium triangle, shows their share of supply will be met by multiple less efficient lithium deposits, increasing the number of mines needed (Figure 3-8b) and total cost (SI Figure C-9b). The analysis also shows that removing many of the big suppliers (particularly the lithium triangle) results in curtailed demand due to reliance on cost-prohibitive deposits (SI Figure C-10b). Demand reduction strategies, such as lower capacity LIBs or high recycling, mitigate the supply disruption caused by the unavailability of certain deposits. This reinforces the importance of circular economy and material efficiency measures to reduce pressure to access new primary lithium resource deposits and expand capacity.

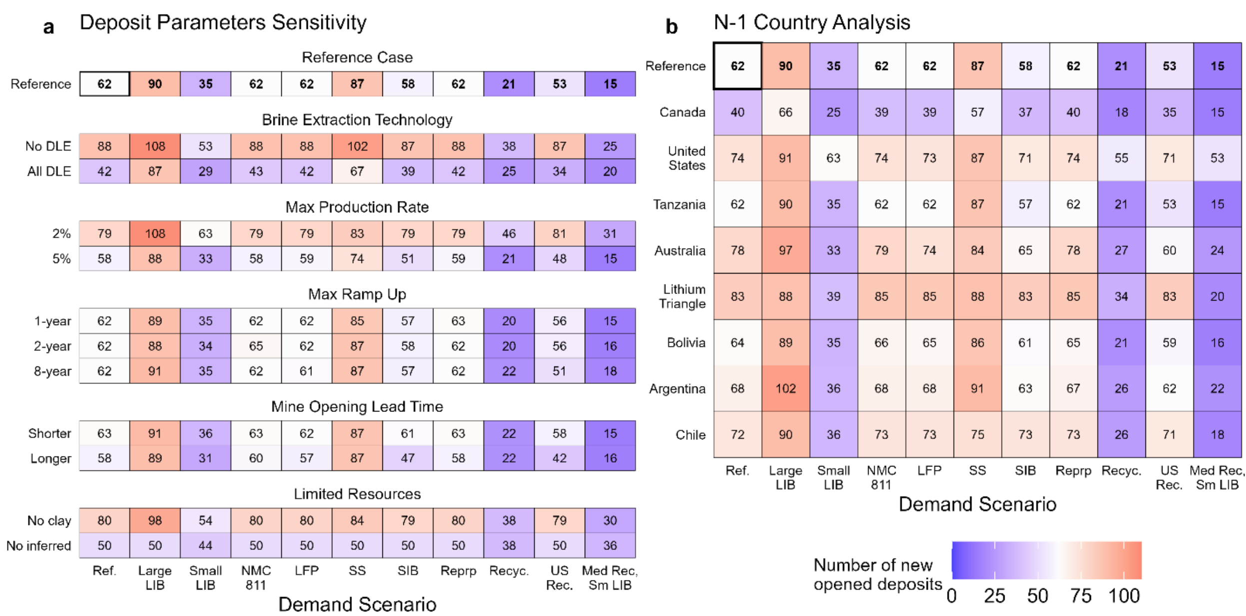

Figure 3-8. Additional lithium deposits that will require to open under different deposit parameters scenarios or by N-1 country analysis. (a) Deposit characteristics are varied by technology development of DLE for brine, maximum production rates constraints, different ramp up assumptions, longer and shorter lead times to expand deposits in the short term, and limited resources. **(b)** The model was run by removing all deposits from the country of interest from available supply. Material from: 'Busch et al., Effects of demand and recycling on the when and where of lithium extraction, Nature Sustainability, published 2025, Springer Nature', with permission from Springer Nature.

The number of required deposit openings changes in response to different supply and demand conditions (Figure 3-8a). The most important supply parameters are access to DLE (to exploit certain brine and with higher production rates), the technology to separate lithium from clay (in volcano-sedimentary deposits) and a maximum depletion rate of 5% (or 20 years mine life). If brine resources do not have access to DLE their maximum extraction rate is constrained, and the number of deposit openings required in the reference case are approximately doubled. Similar findings are evident when slower mine extraction rates and no clay resources are tested. The scenario with no access to inferred resources produces high demand curtailment, as simply the existing reserves and demonstrated resources cannot meet demand in a timely manner. These sensitivities are magnified for the reference and higher demand scenarios. The distribution of deposit openings (and total cost) to meet lithium demand is right skewed, with a long right tail of worse-outcome results that arise from combinations of limited supply and high primary demand (Figure 3-8a, SI Figure C-9a, and Figure C-10a). The supply sensitivity analysis shows that recycling is a robust solution even in bad supply conditions, though high demand scenarios still require ideal supply conditions to meet demand even with robust recycling, reinforcing the benefits of moderating demand growth for achieving a sufficient and reliable supply. Scenarios with a peak in primary demand (due to recycling) generate a small amount of curtailed demand (less than 0.15% of cumulative demand, which is met in the following period), as the model decides that it is cheaper to incur the high curtailment cost than to expand capacity for a brief period.

The supply sensitivity analysis also reveals that a less or more constrained ramp up period does not have a major effect on the lithium supply, nor does shorter or longer lead times for mine expansion and opening. The latter may reflect a key limitation of the modeling approach. The model minimizes costs with perfect certainty of future lithium demand and deposit exploitation, so it can work around and reduce the effect of ramp up periods and lead times. In reality, longer ramp up and lead times may generate unnecessary mine openings due to imperfect supply expansion driven by uncertainty and lack of global coordination. Future research could adapt the model into a stochastic optimization setting, allowing for uncertainty in demand and deposit opening lead times. Testing the model under different discount factors maintains the relative benefits of smaller battery capacity and enhanced recycling in preventing mine openings with respect to other demand scenarios (SI Figure C-11).

Figure 3-9 shows mine openings for different cost degradation factors and by using the world governance index (WGI) (World Bank, 2024) or the world competitiveness index (WCI) (IMD World Competitiveness Center, 2024). The number of new mine openings increases with a higher cost degradation factor[25], which can be interpreted as an efficiency loss due to non-monetary conditions in each deposit. In other words, a cost minimization-only model results in fewer mine openings, but it is a less realistic outcome given the importance of other factors in mining investment. Nevertheless, regardless of the cost degradation factor used, the differences across demand scenarios remains similar, showcasing the benefits of smaller capacity batteries and recycling in reducing pressure on the lithium supply chain. There is not a noticeable change in mine openings across the three different non-monetary indexes, but there could be differences in specific deposits opened worldwide. The former results are also driven by the fact that the country-level index of governance, business environment and competitiveness are correlated among themselves. The Pearson correlation among the indexes for the 28 countries with lithium deposits are 0.75 (EDB-WGI), 0.81 (EDB-WCI) and 0.69 (WGI-WCI).

[25] Which translates to a higher weight (or importance) on the non-monetary index with respect to costs in the objective minimization.

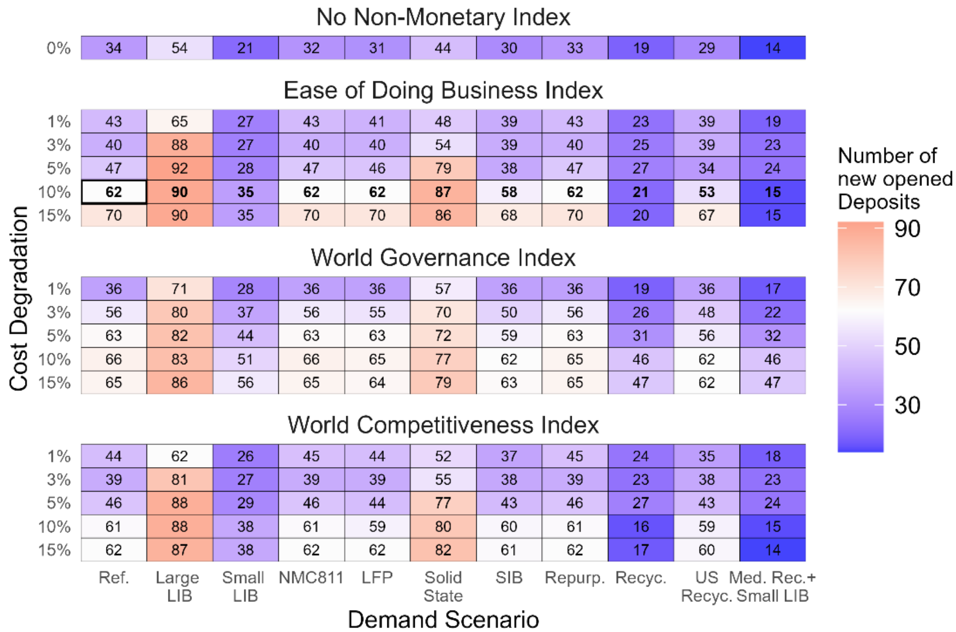

Figure 3-9. Additional lithium deposits that will require to open under different non-monetary factors minimization. The second objective function of the optimization model was to minimize country non-monetary index, such as the EDB, WGI or WCI. Rows show the maximum amount of degradation allows for the cost function (first objective). The first row indicates a model with a single cost minimization function. The reference case corresponds to using the EDB index with a 10% cost degradation. Material from: 'Busch et al., Effects of demand and recycling on the when and where of lithium extraction, Nature Sustainability, published 2025, Springer Nature', with permission from Springer Nature.

3.5.6 Lithium extraction costs

The supply optimization formulation could provide valuable insights by analyzing the active constraints of the solution, and by looking at their shadow prices[26]. The shadow price of the demand restriction can be interpreted as the marginal cost to meet the last unit of lithium demand every year, which could act as a good indicator of the future price of lithium. Unfortunately, two major issues impede getting shadow prices directly from the current model formulation:

[26] Also called Lagrange multipliers.

1. The model is a mixed integer programming setting - with binary variables – with no continuous marginal derivations.
2. The multi-objective nature of the solution implies that some constraints will no longer be active after the second objective minimization, thus making the duals (shadow prices) no longer valid.

Nevertheless, the average extraction costs per ton of lithium extracted can be calculated per year for each demand scenario (Figure 3-10). Variations are observed in the average extraction costs, as the higher average difference is around $1,000 per ton LCE (around 10%). It is important to highlight that in every scenario there is extraction from deposits that are currently open, but that are on the expensive range of the cost curve (high OPEX). The latter occurs as the model can exploit them without incurring in opening or expansion costs.

The average cost of lithium decreases in 2032, when all deposits are available to the model to exploit (including deposits under initial exploration as 2022). Average extraction costs increase over time due to the depletion of the best resources and expansion towards more expensive deposits. Across the demand scenarios there are differences in the extraction costs of lithium, the small capacity scenario has the lowest lithium extraction costs, which could translate to a decrease in price of LIBs. Recycling scenarios have a higher average extraction cost, possibly due to large extraction in deposits currently open or under construction, thus avoiding additional capital investments. Nevertheless, due to lower total primary mineral demand and savings in investments, the recycling scenarios reach the lowest total costs (Table 3-4). While the model explicitly omits price feedback loops in the mineral requirement (demand) scenarios, it is important to highlight that a decrease in extraction costs implies a higher likelihood of satisfying lithium demand requirements for decarbonization technologies adoption.

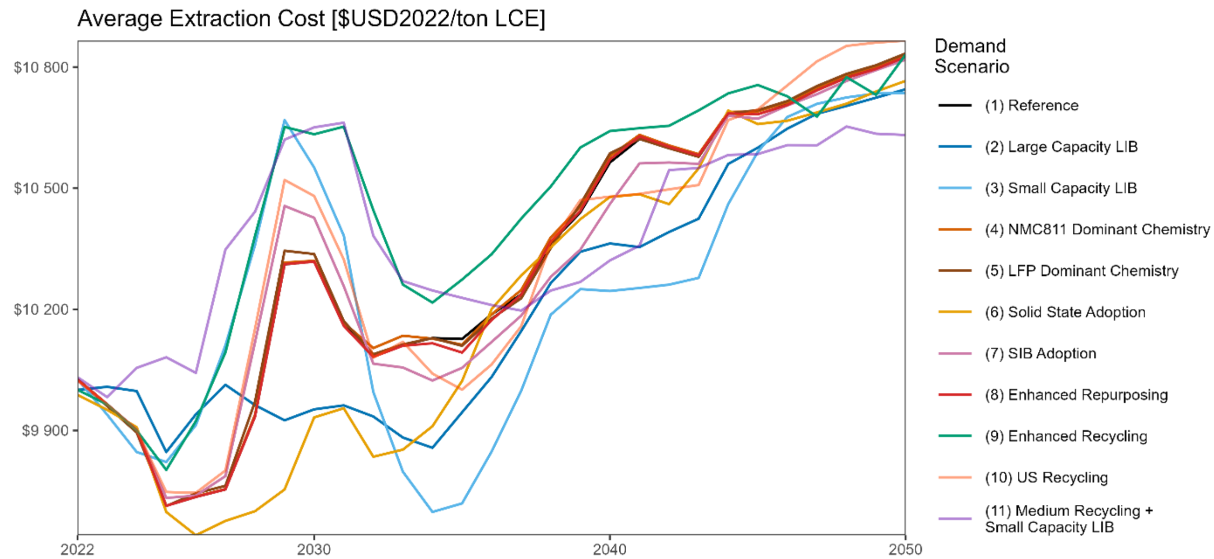

Figure 3-10. Average yearly extraction costs (OPEX, US$ per ton LCE) under different demand scenarios. All costs are in 2022$US (discounted at 7%).

3.6 Discussion

Reducing lithium demand can decrease pressure on supply in the short term, but only robust recycling has the sustained effect of limiting new deposit openings. Although this conclusion does not require the kind of analysis done here, results show a non-linear relationship between the provision of secondary lithium supply and the requirement for new deposit openings, a finding which is only possible thanks to spatially and temporally explicit modeling at the deposit level. Other circular economy strategies including repurposing also reduce primary lithium demand, but have a less noticeable effect than recycling.

The number of new lithium deposits required to meet climate mitigation goals depends on both cumulative and peak primary lithium demand (Table 3-4), and mitigating peak demand is best achieved via robust recycling and recovery across the world. Preventing the continued growth in average EV LIB capacity or reducing capacity can be a complementary measure. Promoting technologies that increase the maximum extraction rate of minerals, such as DLE or clay-lithium separation, are also effective in reducing new deposit openings to meet peak demand. A key difference between combustion engines and EVs is that the former burns gasoline in an irreversible process, while critical minerals contained in the EV batteries can be recovered and put back into the economy, closing the loop. Achieving the enhanced recycling scenario will require rates of recovery for lithium that do not occur today, meaning regulation for LIB collection and recycling coupled with requirements for high rates of lithium recovery are likely needed.

The lithium supply expansion results across scenarios show that it is possible to meet the increasing demand, but at a higher marginal cost and global effort in mine openings. Demand actions are key to reducing pressure on the supply chain and increase the feasibility of achieving our decarbonization goals. By reducing cumulative demand and peak demand there is a sharp reduction in the amount of lithium extracted from the ground, number of mines operating at maximum capacity, and number of lithium deposit openings. For example, by comparing the range of our results (Table 3-4), we observe a scenario with 90 mine openings (or roughly 3.2 per year from 2022 to 2050) and another with just 15 openings (roughly one every two years until 2050), the latter scenario is much more feasible to achieve globally. Each deposit opening requires massive effort in monetary terms (around half billion dollars of investment), evaluation studies, permitting process, community engagement; and will generate local socioenvironmental impacts in carbon emissions, water stress, land use or biodiversity. By taking proactive demand reduction measures we can avoid the opening and expansion of unnecessary lithium deposits, and prevent the creation of new frontline communities.

The optimization formulation operates under a logic of “what needs to happen” to meet lithium demand, but in reality high demand scenarios may induce supply bottlenecks or price increases that limit the rate of EV adoption. Under these circumstances the automotive market could react in negative ways by extending the lifetime of combustion engine vehicles or keep selling them (repealing EV sales mandates), or by reducing the mobility benefits in the transport sector. Under both circumstances there is a social cost in carbon emissions or less mobility benefits. Our results reveal that proactive actions can be taken to avoid these circumstances by promoting share modes of transportation, lower battery sizes, more efficient battery chemistries and enhanced mineral recovery at end-of-life.

3.6.1 Novelty

Few studies have modelled the supply of battery minerals. The main novelty of the model is understanding the mineral capacity expansion effort required to meet upcoming lithium demand, under different scenarios. Most supply modelling efforts have relied on Hubbert curves with no consideration of lead maximum production constraints or lead time associated with opening a deposit. Economic models that have used elasticity to link demand and supply, largely ignore the major disruptions in project development in the mining industry or the availability of deposits to expand. Techniques that rely on historical data to forecast the future, like machine learning, have limited data for lithium as it has just recently seen a sharp increase in their production levels spur by EV adoption. The supply model presented in this chapter is an effort to better understand the emerging lithium mineral supply chain incorporating multiple parameters to characterize each mineral deposit, such as extraction costs, mineral type and grade ore; and current project status of deposits and delays on opening and expansion.

Testing different demand and supply conditions allows prioritizing policy actions to secure lithium supply. We have shown how different demands or supply conditions affect the number of new mines needed and the total costs. The timing aspect, both in demand (e.g. reduction in LIB size) or supply (e.g. lower depletion rates), is a relevant feature of the model, and it reveals that some policies may be worth pursuing in the short-to-medium term if they allow additional time to expand mineral extraction capacities or accelerate mining operations to meet the long-term goals.

The model conceptualization provides some novel techniques to characterize the critical mineral supply chain. It incorporates non-monetary factors using a multi-objective hierarchical approach, which tries to mimic real-world decision making for mining investments. The model considers constraints not only on reserve size, but also maximum production rates and ramp up capacity. The extraction cost structure embedded on the model using stages considers the increasing degrees of uncertainty related to lithium quantity in each deposit, the decreasing ore grade quality, and the possibility to extract demonstrated and inferred resources. Exploitation of resources is driven by reserve depletion, changing economic conditions (like a high lithium demand), technological development and deposit exploration.

The model results not only inform the effect of demand actions or supply restrictions on the lithium deposits openings, but also inform the when and where of future mine developments. The latter can be used as input for environmental impact assessments or roadmap planning. The several sensitivity scenarios tests for various supply conditions, and the N-1 analysis conducted reveals the importance of countries among the lithium supply chain. In particular, it emerges that the lithium triangle, especially Chile, and USA will be key determinants of future raw lithium extraction.

The compiled database on the currently 160 lithium deposits with resource size estimates also contributes to the scientific community, by providing public and recent data gathered from multiple company reports. The database, made available to the public, is structured so every data number extracted has a specific reference to the report page where it appears, in the spirit of being verifiable by third parties and to be updated over time.

3.6.2 Limitations

The supply dispatch model results are determined heavily by the mineral deposit data used, which is incomplete and subject to frequent updates. Potential drivers of change in deposit data include: resource discovery through exploration; new extraction technologies that could change extraction costs and rates, converting resources into reserves; trade restrictions may limit the access to chemical inputs required in the extraction process; protectionism policies, such as the Inflation Reduction Act (IRA), may incentivize production in certain countries with preferential trade agreements. The model results also depend on assumptions, such as the ramp-up delays, maximum production constraints or the resource availability. By testing the model under different supply conditions we found that the conclusions remain similar, that is that demand reduction measures provide a great benefit in reducing unnecessary mine openings (Figure 3-8).

There are multiple pathways for non-monetary factors to influence mining projects development. They could impose delays in the discovery, exploration, permitting and/or construction phase. They could also affect the feasibility (or probability of occurrence) of a project; or increase costs, by imposing additional requirements on the investment and operational phases, or simply by having a higher interest rate to finance the project, due to the increased financial risk. The modelling approach used in this chapter assumes that non-monetary factors should be minimized, without explicitly modelling any of these pathways. Future research could use alternative methods to translate non-monetary factors into additional delays, project feasibility and/or extra costs.

The business environment index only captures a fraction of all non-monetary factors that could affect investment decisions in each country. While it includes metrics that could affect investment decisions, such as the permitting process or access to electricity, it is an aggregate measure. The model results are not sensitive to using other indexes related to country stability (Figure 3-9). Other local factors not captured by country-level aggregated indices could affect a project viability, such as proximity to land protected areas, indigenous communities, water scarcity or local communities that may oppose mining.

The optimization formulation assumes a central and global agent that coordinates all mining companies to minimize costs and exposure to lower business environments. The latter is not an accurate representation of the real-world market dynamics of the industry. It is reasonable to expect that companies will minimize their costs, and if the market is perfectly competitive the global optimization model should accurately describe reality. However, there are many factors that could deviate the lithium market from competitive behavior, such as asymmetries of information or geopolitical trade restrictions. Lithium extraction is dominated by a few big firms (Sun et al., 2024), which could act in a oligopolistic behavior and influence the price in their own benefit. The model also omits market interactions between agents and assumes a perfect foresight of the future demand and cost structure.

As stated in Chapter 2, demand and supply are endogenously determined through a constant feedback loop through prices. A shortage of lithium supply may induce a price increase that leads to product substitution or lower demand, while an excess of supply may lower prices down thus increasing EV adoption. While the model does not include this market interaction, it shows for a variety of demand scenarios the total effort required in the supply chain, highlighting the steep marginal efforts to extract lithium, forcing high demand scenarios to open more than 85 new deposits in the next decades.

Nevertheless, the conclusion remains clear despite all these limitations: reducing primary mineral demand can alleviate supply pressure and vastly reduce the lithium extraction capacity expansion required to meet climate goals.

3.6.3 Future research directions

The limitations listed above can be a guide towards potential improvements to the model formulation, such as updating the lithium deposit database or including other non-monetary factors. The model main parameters, like ramp up delays, can also be calibrated with historical data.

The capacity expansion model conceptualization can be used to study the supply for other critical minerals and clean energy sectors, as the whole range of clean energy technologies (solar, wind, electric vehicles) depend on mining of new materials (S. Wang et al., 2023). The lithium case presents some differences with other minerals, thus requiring some modifications of the model formulation. For LIB usage, lithium has no clear mineral substitute, so high demand scenarios need to rely on deposits towards the right side of the supply curve, no matter the high costs. The latter is different for other minerals, such as nickel and cobalt, which can be completely substituted with other battery chemistries. Lithium is produced as the main mineral in a deposit, so opening, expansion and extraction decisions depend solely on lithium. Other minerals, like cobalt, are usually a co-product of mine operations for other main minerals[27] (Turcheniuk et al., 2018; van den Brink et al., 2020). Nickel price is an order of magnitude higher than cobalt price, making cobalt supply from Ni-Co deposits dependent on nickel supply, while some Cu-Co deposits report a 40% revenue coming from cobalt (Olivetti et al., 2017). For modelling purposes, supply for cobalt will depend on market conditions for copper and nickel; and the model formulation can be adapted by either:

i. Assume a cost allocation based on mineral revenue to separate minerals in each deposit.
ii. Expand the model dimensions to include both minerals at the same time, so the model can open deposits with production of both minerals.

For minerals that have been exploited for decades, such as copper, the model can be adapted to include supply sources from retiring end-uses (by recycling), extracting mineral from mine tailings[28] or by re-opening idle deposits (previously closed due to market conditions).

The model formulation can also be applied to other stages of the supply chain: mineral refining, cathode manufacturing, battery production or electric vehicle production. A fundamental difference is that the raw mineral extraction stage requires geological reserves, which tend to be geographically concentrated. Other stages face not such restrictions, but there exist drivers that may facilitate adoption in each country, such as industry technological level, human capital, free trade agreements, access to ports, labor cost and electricity price. In this regard, a parallel can be drawn with MONET (Chapter 1). MONET has a similar goal to spatially identify future of production in a supply chain stage, but it employs a different method. The focus of Chapter 3 is on mineral extraction, while MONET focuses on EV manufacturing. Some key differences in the approach emerge from the fact that mineral extraction depends on the global availability of reserves and mining knowledge in each country, while future EV production likely depends

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[27] Roughly 70% of Co production come as by-product of cooper and 20% as by-product of nickel (van den Brink et al., 2020).

[28] Mine tailings usually have valuable minerals that were not recovered at the time due to past market or technological conditions (Drobe et al., 2021).

on the current LDV production ecosystem. MONET (chapter 1) uses empirical trade data and the assumption of inertia: vehicle trade relationships will not deviate much during the EV transition. The lithium supply model starts with available mineral deposits in each country and their extraction costs as predictors of future mineral supply expansion, rather than historical mining production.

Another possible formulation that leverages the non-monetary factors information is through a stochastic optimization setting. The business environment index can be translated into a probability of project success, to represent the uncertainty faced by mining companies when engaging in a long-term project. Mining companies may choose to invest in a more expensive project if the feasibility is higher or decide to "gamble" for lower cost projects but with less certainty. A stochastic optimization setting incorporates this probability into the model, thus representing the best actionable course of action for the medium term given the uncertainty in long-term demand and project developments. A single agent deciding all deposit projects (as the current model setting) may have a portfolio bias, where uncertainty in the expected value is mitigated by multiple choices made by the agent. The latter can be solved by using a different aggregation function instead of the expected value, such as the super-quantile (Rockafellar & Royset, 2010). The latter computes the error at the worst outcomes (e.g. expected value of the 10% worse Montecarlo samples), providing a more robust assessment of risk mitigation.

A two-stage or multi-stage stochastic can address the perfect foresight of the deterministic model formulation. The first stage can be modelled as deterministic, as it represents higher short-term certainty about deposit availability and global demand. In the first stage the model decides the opening and expansion of deposits in the short-term. The second stage is modelled by adding uncertainty to certain parameters through scenarios or sample average approximation (using Montecarlo sampling). A key feature of a two-stage model is that the first stage decisions are made in consideration of the potential uncertain scenarios of the second stage. In other words, the openings and expansions of the first stage need to be able to meet the constraints for all possible uncertain futures, thus acknowledging the effect of uncertainty in capacity planning and expansion. The latter is especially relevant for the mining industry, as it faces different kinds of uncertainty (Arief et al., 2025), which can be modelled as uncertain parameters in a second stage.

- Geological uncertainty, related to total resource size, grade ore and spatial distribution (which affects extraction costs).
- Economic uncertainty, related to future mineral demand, mineral prices, technology development or operational costs.
- Geopolitical uncertainty, related to trade policies or restrictions, environmental regulations or social acceptance of local communities.

Additionally, the mining industry has a slow ability or flexibility to adapt to changing conditions, as it has long lead times from discovery to mine production and constraints in the ramp up times. The latter affects the industry ability to adapt once the uncertainty is "cleared" in a second stage, potentially needing unnecessary mine openings in the first stage just for the worst-case outcomes. A stochastic model can provide many actionable recommendations in the form of which policies or guidelines work best to get a robust solution. Interestingly, recycling mandates can have a co-benefit[29] in reducing uncertainty in primary mineral demand forecast, as they will force industry to recover a fraction of lithium and reduce primary mineral demand.

Another potential research expansion of the model is to propose a better course of action to meet our lithium demand goals. The current formulation of the optimization model follows a descriptive (or positive) approach, it tries to predict actual behavior of mining firms (it answers the question of what companies will do). The model can be adapted to follow a prescriptive (or normative) approach, where the relevant question becomes what companies ought to do. From a social standpoint, environmental

[29] Besides reducing primary mineral demand.

impacts, like greenhouse gas (GHG) emissions or water usage, can be added to the cost function to provide a socially optimal solution. Lithium deposit types have different carbon impacts per ton extracted, with brines generating less GHG emissions than hard rock mining (Kelly et al., 2021; Lagos et al., 2024), and recycling having less impact than mining new ore (Machala et al., 2025). Adding the social cost of carbon due to lithium extraction may alter the overall supply cost curve and order of dispatch. Other environmental impacts can also be added to the cost curve, if there are pathways for them to be monetized, such as air quality effects on human health or water stress. Environmental impacts can be included in the analysis using Pareto curve principles, by providing a frontier of solutions that are optimal (in costs or environmental impacts mitigation) given a previously level of costs or environmental impacts mitigation. The latter approach ought to reveal trade-off between mining private costs and environmental impacts, and can also reveal the subset of lithium deposits that are Pareto dominant[30].

Future research can also leverage the temporal and spatial detail of the results regarding lithium deposits openings, expansion and production. Future lithium openings can be a valuable input to procure a proactive strategy to encourage sustainable mining, reduce environmental impacts and increase engagement with local communities. Results can also indicate which countries will dominate the raw lithium stage, so national plans can be made to promote trade agreements or mineral off-take agreements to secure a reliable mineral supply. The results can be spatially joined with relevant geodata, such as environmentally protected areas, water access, electricity networks or local communities to further evaluate the feasibility or impact of future lithium production. The latter should be done with consideration of the benefits, mostly in reduced GHG emissions, that lithium provides by enabling batteries, a key technology for our clean energy transition.

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[30] In simple words, the lithium deposits that are cheaper and have lower environmental impacts, thus opening in every scenario and trade-off comparison.

Other interesting research questions that the optimization model is suited to answer are regarding geopolitics and trade flows of lithium (and other critical minerals). Several regions are pursuing strategies to increase the share of domestic mineral supply, such as the IRA, which may favor the development of deposits that are not cost-effective, but serve a strategic national role. The model formulation can be extended with constraints that guarantee that a certain share of demand is met with domestic deposits, which will generate an equal or worse solution. This analysis can highlight the loss of global efficiency due to geopolitical tensions and domestic production policies, as well as the degradation trajectory with more ambitious domestic supply requirements.

3.7 Conclusion

In line with many demand and supply models for lithium, we find that sufficient mineral resources exist to meet climate goals to 2050 and many decades following. Our analysis at the deposit level shows the evolution of supply over time and its interaction with our explored demand scenarios, which result in potentially disparate supply futures characterized by non-linear relationships between primary lithium demand and the number of new deposit openings needed. Understanding these dynamics over time and space also reveals ways to reduce pressure on mineral extraction; small reductions in primary lithium demand can have disproportionate effects on new deposit openings. Preventing the continued increase in battery capacity we see in EVs dramatically reduces the number of deposits needed (from 90 to 62), recycling does more to drive down deposit openings (from 62 to 21). Recycling does not require dramatic demand reduction strategies, which could present tensions between dual priorities of rapid EV adoption by consumers and battery mineral efficiency, but instead requires policy interventions that could have co-benefits for industrial growth and innovation.

3.8 Data availability

All data and code required to reproduce model results is available in the supplementary materials and on GitHub: https://github.com/pmbusch/lithium-Supply.

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3.9 References

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Conclusion

The primary goal of this work is to quantitatively evaluate the demand and supply for critical minerals, lithium, nickel, and cobalt; mostly contained in LIBs, a key energy storage solution to meet decarbonization goals through EV adoption and electricity grid decarbonization. The results from this work inform policymakers at different stages of the emerging energy and mineral supply chains: EV production, mineral requirements and lithium mining capacity expansion.

Chapter 1 is especially relevant for original equipment manufacturers of vehicles and policy makers interested in industrial policy planning for EV production and battery requirements. Through an international vehicle trade model it is shown that battery requirements need to be quantified at the country where vehicles are produced, rather than sold.

Chapter 2, the critical mineral demand model, forecasts the likely range of future needs of lithium, nickel and cobalt, while identifying the most efficient policy options to guarantee a successful decarbonization implementation, with strategies for mineral demand reduction like battery downsizing, end-of-life mineral recovery and circular economy practices.

Chapter 3, the lithium supply capacity expansion optimization model, introduces a novel method to study the dynamic aspect of the mining supply expansion, showing that reductions in lithium peak demand have a great effect in reducing pressure on the mining effort required, thus avoiding unnecessary expansion and opening of new deposits. The optimization framework proposed can be replicated to study the supply development of other minerals and energy sectors, revealing supply bottlenecks and the effect of demand reduction actions on the extraction stage. Overall, the work shows that major actions can be taken in the supply chain to secure battery needs for the vehicle industry, reduce mineral demand while providing the same level of mobility benefits and minimizing lithium mine openings and thus preventing the creation of new frontline communities.

Supporting Information

A: Supporting Information for Chapter 1

Table A-1. Countries and regions included in MONET

Region	Countries included
Greater China	China, Taiwan
Japan/Korea	Japan, South Korea
South Asia	Australia, India, Indonesia, Malaysia, New Zealand, Pakistan, Philippines, Singapore, Thailand, Vietnam, Rest of South Asia/Oceania
Middle East/Africa	Algeria, Egypt, Ethiopia, Iran, Israel, Kenya, Morocco, Nigeria, Saudi Arabia, South Africa, United Arab Emirates, Rest of Middle East/Africa
North America	Canada, Mexico, United States
South America	Argentina, Bolivia, Brazil, Chile, Colombia, Peru, Uruguay, Venezuela, Rest of South America
Europe	Austria, Belgium, Czechia, Denmark, Eastern Europe/Central Asia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Netherlands, Norway, Poland, Portugal, Romania, Russia, Slovakia, Spain, Sweden, Switzerland, Turkey, United Kingdom, Western Europe non-EU, Rest of European Union (EU)

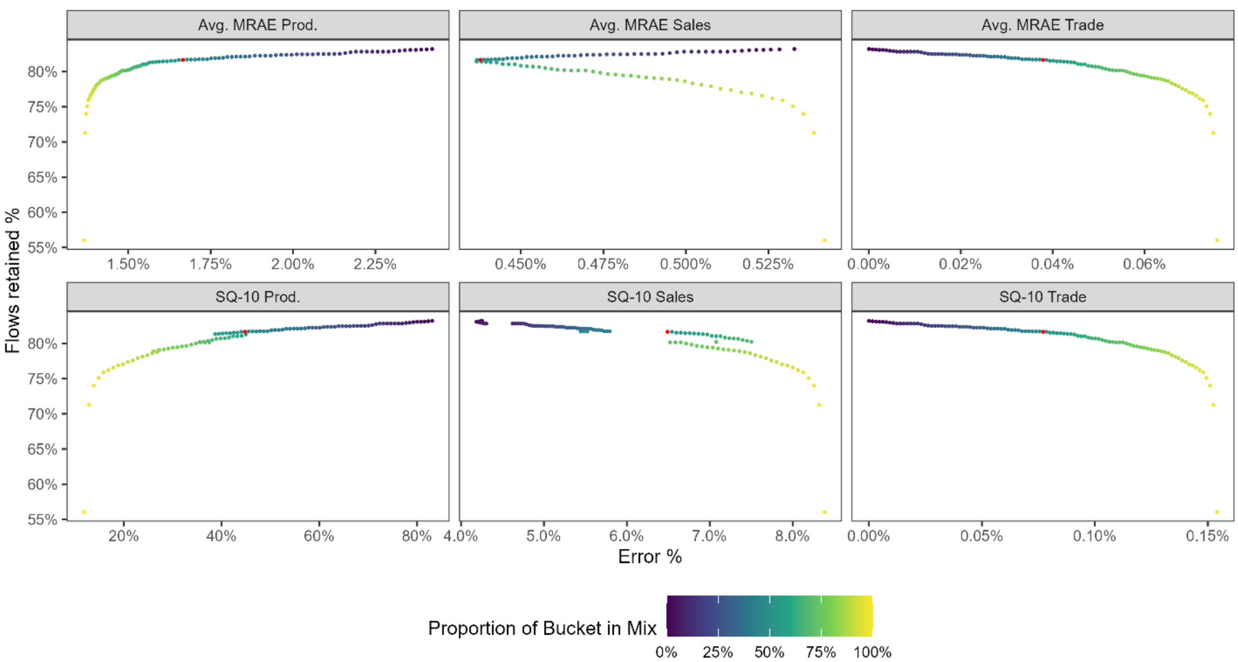


Figure A-1. Error evaluation (MRAE on X axis, and captured trade flows in Y-axis) of different combination of the tensors from the proportional method and "draining buckets" method. Red dot indicates the 50-50 combination used as the main result.

B: Supporting Information for Chapter 2

Table B-1. Data Sources for Demand Model. LDV = light duty vehicle, MDV = medium duty vehicle, HDV = heavy duty vehicle, BEV = battery electric vehicle, PHEV = plug-in hybrid electric vehicle, LCO = lithium cobalt oxide, LFP = lithium iron phosphate, NMC = lithium nickel manganese cobalt oxide (NMC111, NMC 523, NMC 622, and NMC 811), NCA = lithium nickel cobalt aluminum oxide, LMO = lithium manganese oxide. Material from: 'Busch et al., Effects of demand and recycling on the when and where of lithium extraction, Nature Sustainability, published 2025, Springer Nature', with permission from Springer Nature.

Module	Type	Source	Geographic resolution	Temporal resolution	Detail
Demand Forecast	**On-Road Vehicle fleet**	ICCT Roadmap v2.2 (ICCT, 2022)	Global (18 regions)	2022-2050, yearly	They include all on-road sector (2-3 wheelers, LDV, MDV and HDV). Disaggregated for BEV and PHEV.
	Deployed Stationary Power Storage	(Benchmark Mineral Intelligence, 2023)	Global (6 regions)	2022-2040, yearly	Grid Level Storage and Behind the Meter Storage. Cathode chemistry: LCO, LFP, NCA, NMC (with ratios), LMO.
Battery Size and Chemistry	**LDV**	(EV Volumes, 2022)	Global, with data at country level	2010-2022, yearly	Battery data by chemistry for BEV and PHEV (LDV only). Chemistries: NMC (with ratios), LFP, NCA, and others.
	Other vehicles beside LDV	Multiple sources	Global	2022	See SI Table B-2.
Mineral Intensity	**All batteries**	BatPaC 5.1 (Kubal et al., 2023) SolidPac (Dixit et al., 2022) Others (Zhao et al., 2023)	N/A	2022	Mineral content for different battery chemistries

Table B-2. List of manufacturers for battery capacity – 2-wheelers, 3-wheelers, bus and trucks. n=146 from 27 manufacturers. The list is not exhaustive of all model catalogue for electric vehicles. Material from: 'Busch et al., Effects of demand and recycling on the when and where of lithium extraction, Nature Sustainability, published 2025, Springer Nature', with permission from Springer Nature.

Manufacturer	Country	Vehicle Type	Number of Models Recorded	Min Recorded Battery Size (kWh)	Max Recorded Battery Size (kWh)	Source
Ola Electric	India	2-wheeler	4	2	4	https://olaelectric.com/
Okinawa Autotech	India	2-wheeler	9	1	3	https://okinawascooters.com/
Hero Electric	India	2-wheeler	8	2	3	https://heroelectric.in/
Ampere Vehicles	India	2-wheeler	3	2	3	https://ampere.greaveselectricmobility.com
Ather Energy	India	2-wheeler	3	3	4	https://www.atherenergy.com/
Lohia Auto	India	2-wheeler	13	1	8	https://www.lohiaauto.com/index.php
Yadea	China	2-wheeler	6	1	2	https://www.yadea.com/
Sunra	China	2-wheeler	5	1	2	https://www.sunraev.com/
Luyuan	China	2-wheeler	11	1	3	https://www.luyuanev.com/
Super Soco	China	2-wheeler	5	2	3	http://www.supersoco.com/second-phase/en/index.php
Huaihai	China	2-wheeler / 3-wheeler	13 / 3	0.96 / 3.6	4.32 / 3.84	https://www.huaihaiglobal.com/electric-scooters/
Mahindra Electric	India	3-wheeler	8	4	10	https://mahindralastmilemobility.com/
Piaggio Vehicles	India	3-wheeler	3	5	8	https://piaggio-cv.co.in/ape-e-city/
Euler Motors	India	3-wheeler	1	13	13	https://www.eulermotors.com/
Proterra	The United States	Bus	2	492	738	https://www.proterra.com/products/battery-technology/
Ebusco	Europe	Bus	2	400	500	https://www.ebusco.com/batteries-and-charging/
GILLIG Corporation		Bus	1	294	686	https://www.gillig.com/battery-electric
New Flyer of America	North America	Bus	1	160	520	https://www.newflyer.com/bus/xcelsior-charge-ng/
NOVA Bus Corporation	Canada / North America	Bus	1	564	564	https://novabus.com/buses/bus-models/
Mercedes-Benz		Bus	1	396	396	https://www.mercedes-benz-bus.com/en_de/models/ecitaro/facts/facts-ecitaro.pdf
BYD Motors	The United States	Bus / Truck	12 / 5	141 / NA	578 / NA	https://en.byd.com/
VDL Bus & Coach (VDL Groep)	Netherlands & Belgium	Bus	1	216	420	https://www.vdlbuscoach.com/en
Yutong Bus	Asia, Europe, Commonwealth of Independent States,	Bus	13	255	564	https://en.yutong.com/

Manufacturer	Country	Vehicle Type	Number of Models Recorded	Min Recorded Battery Size (kWh)	Max Recorded Battery Size (kWh)	Source
	Middle East, Latin America					
Tesla		Bus / Truck	1 / 2	300 / 500	200 / 800	https://www.tesla.com/ns_videos/tesla-master-plan-part-3.pdf
Volvo	The United States	Truck	7	375	565	https://www.volvotrucks.us/trucks/vnr-electric/
Kenworth		Truck	1	396	396	https://www.kenworth.com/trucks/t680e/
International Trucks	The United States & Canada	Truck	1	210	210	https://www.internationaltrucks.com/trucks/emv-series

Table B-3. Forecast of lithium demand for other sectors. All consumption in ktons. Source: USGS for 2018 Lithium consumption (USGS, 2022), GDP forecast (Goldman Sachs, 2022; World Bank, 2023), population forecast (United Nations, 2022).

Sector	Driver	2018 Cons.	2050 Cons.
Ceramics & Glass	GDP	10.8	22
Lubricant greases	None	2.9	2.9
Polymer production	GDP	1.96	4.06
Continuous casting mold flux powders	GDP	1.47	3.04
Air treatment	Population	0.98	1.24
Other uses	Population	2.94	3.73
Portable electronics	Population	6.98	8.85

Table B-4. **Forecast of nickel demand for other sectors**. All consumption in ktons. Source: USGS for 2018 Nickel consumption (USGS, 2023a), GDP forecast (Goldman Sachs, 2022; World Bank, 2023).

Sector	Driver	2018 Cons.	2050 Cons.
Stainless steel	GDP	1,538	3,184
Nonferrous alloys	GDP	233	482
Electroplating and other surface finishing	GDP	210	434
Alloy steels other than stainless	GDP	186	386
Foundry products	GDP	70	145

Table B-5. Forecast of cobalt demand for other sectors. All consumption in ktons. Source: Cobalt Market Report (Cobalt Institute, 2023), GDP forecast (Goldman Sachs, 2022; World Bank, 2023), population forecast (United Nations, 2022).

Sector	**Driver**	**2022 Cons.**	**2050 Cons.**
Portables	Population	56.1	68.4
Super Alloys	GDP	16.8	32.1
Air Hard Metals	GDP	9.4	17.8
Catalysts	GDP	5.6	10.7
Ceramics/Colours	GDP	5.6	10.7
Others	GDP	18.7	35.6

Table B- 6. Summary statistics for Lithium, Nickel and Cobalt. Source: USGS 2025 Mineral Commodity Summaries (USGS, 2025b, 2025c, 2025a). Production is for 2024. Based on current production levels, depletion horizon is 125 years for lithium, 36 for nickel and 37 for cobalt.

Mineral	**Metric**	**Total (MMt)**	**Share of top 3 countries**	**Top 3 Countries**
Lithium	Production	0.24	76%	Australia: 37%, Chile: 21%, China: 17%
	Reserves	30	68%	Chile: 31%, Australia: 23%, Argentina: 13%
Nickel	Production	3.7	75%	Indonesia: 60%, Philippines: 9%, Russia: 6%
	Reserves	>130	72%	Indonesia: 42%, Australia: 18%, Brazil: 12%
Cobalt	Production	0.29	89%	Congo: 76%, Indonesia: 10%, Russia: 3%
	Reserves	11	78%	Congo: 56%, Australia: 16%, Indonesia: 6%

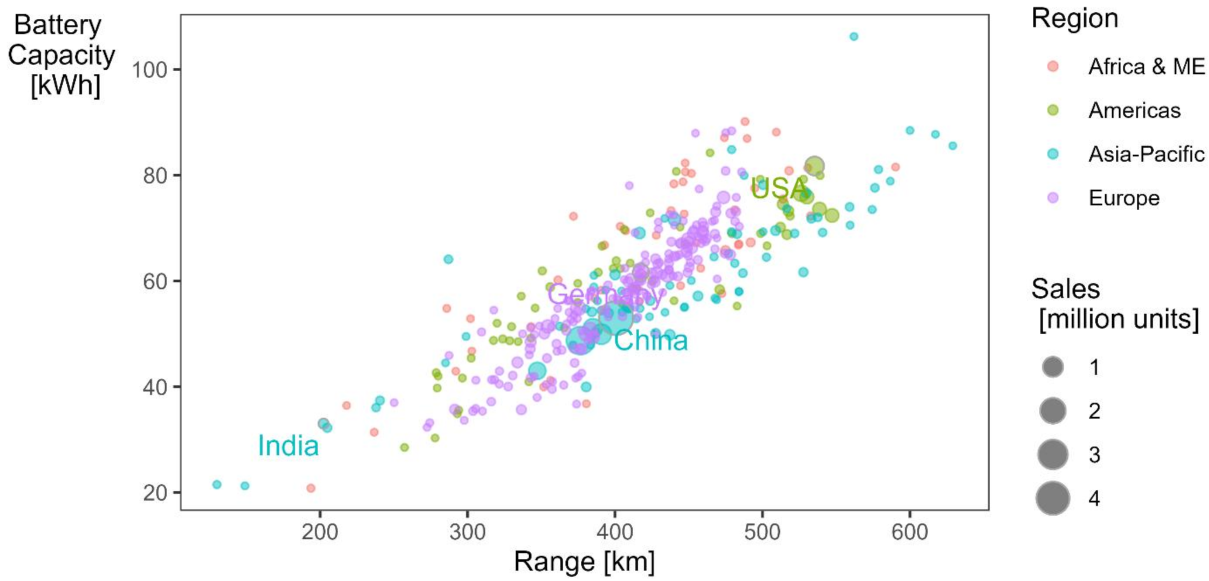


Figure B-1. Relationship between light duty EV battery capacity and nominal range for each country fleet (average by sales), 2018 to 2022. Each dot represents the country's average for range and battery capacity for a given year. Data from: EV Volumes (EV Volumes, 2022).

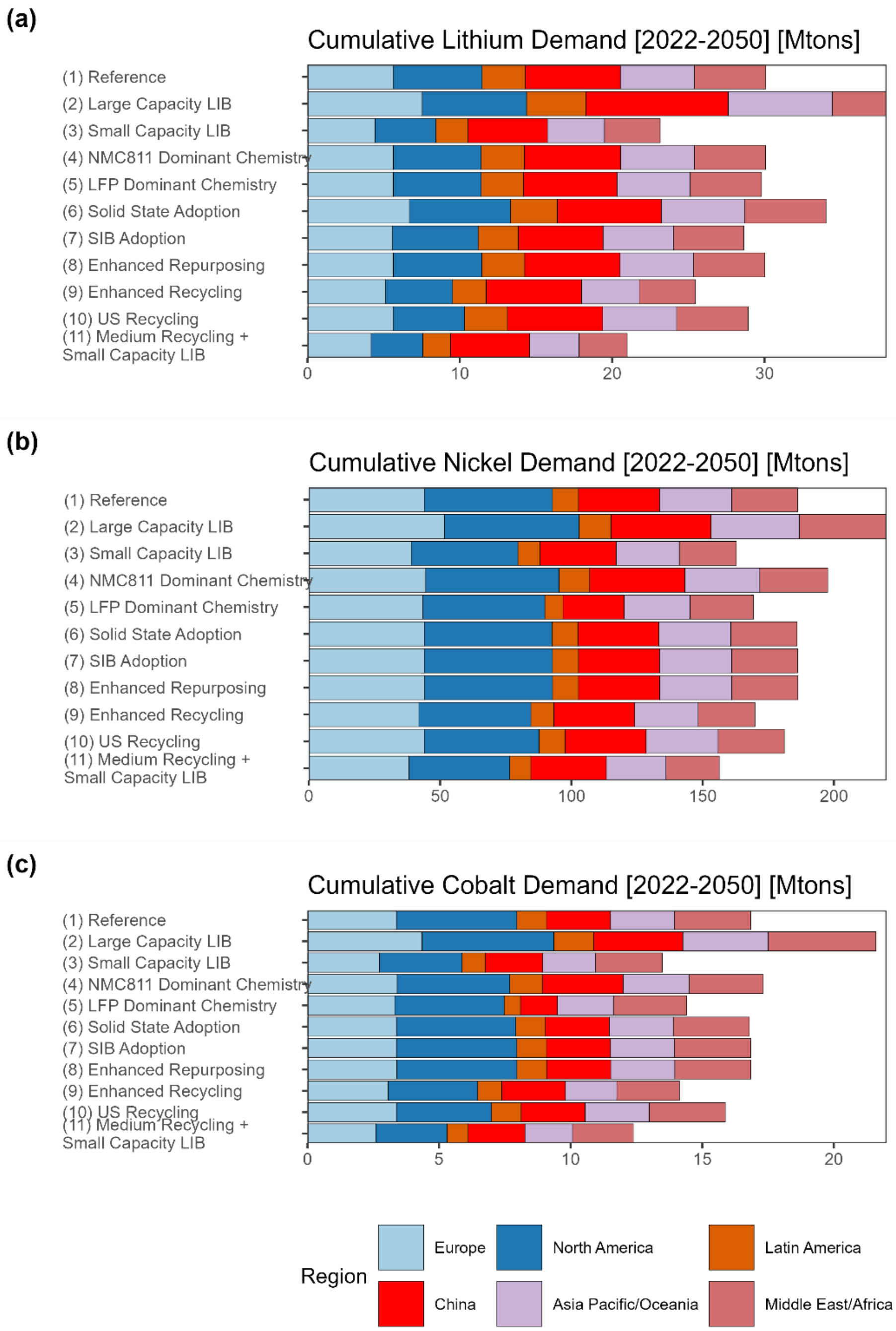


Figure B-2. Cumulative primary (a) lithium, (b) nickel, (c) cobalt demand, in million tons, by region for each demand scenario.

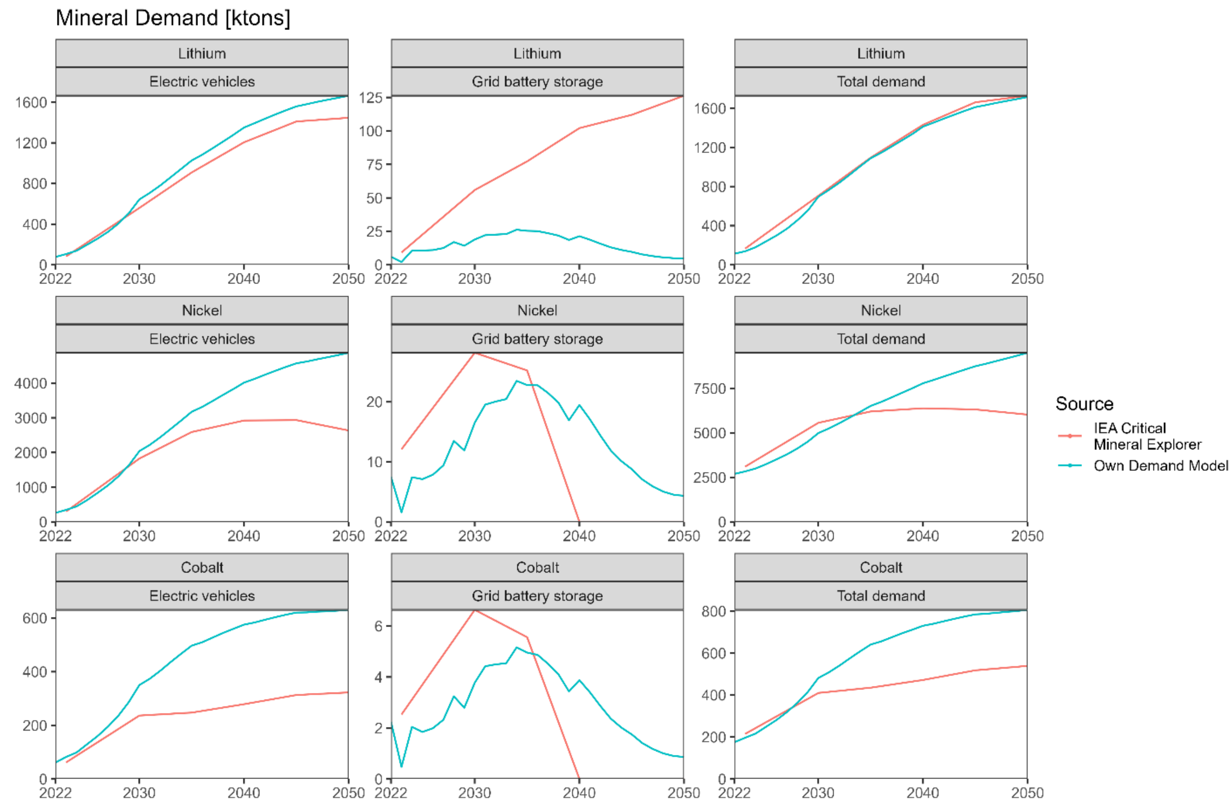


Figure B-3. Mineral demand comparison to IEA Critical Mineral Data Explorer 2024 (IEA, 2024a). Own Demand model uses EV sales from ICCT Roadmap "Ambitious" scenario, while IEA mineral demand comes from the "Net Zero Emissions by 2050" scenario. Note that the Y-axis scale is different in every panel. For reference, IEA predicts an upscale in annual demand from 2023 to 2050 of 11.9x for lithium, 2.27x for nickel and 2.84x for cobalt.

C: Supporting Information for Chapter 3

Table C-1. Royalty Rate, Royalty Base, and Corporate Tax Rate by Country or U.S. State. Material from: 'Busch et al., Effects of demand and recycling on the when and where of lithium extraction, Nature Sustainability, published 2025, Springer Nature', with permission from Springer Nature.

Countries or States	Corporate Tax Rate[a]	Royalty Rates[b]	Royalty Based[c]	Source Royalty
France	25%	\$66.9/ton $Li2O$[d]	Unit	Française Légifrance République. (2024). *A : Redevance communale des mines (Article 1519)*. https://www.legifrance.gouv.fr/codes/section_lc/LEGITEXT000006069577/LEGISCTA000006191913/
United Kingdom	25%	\$2.57/ ton ore rock[e]	Unit	PwC. (n.d.). *United Kingdom - Corporate - Other taxes*. https://taxsummaries.pwc.com/united-kingdom/corporate/other-taxes
Spain	25%	Not found	-	Nicoletopolous, V. (2013). *Spanish Mining Taxation and Regulation*.

Countries or States	Corporate Tax Rate[a]	Royalty Rates[b]	Royalty Based[c]	Source Royalty
Czech Republic	19%	10.0%	Revenue	Chris, J. (2017). *Greenpeace calls for hike in Czech lithium mining royalties as row continues*. Radio Prague International. https://english.radio.cz/greenpeace-calls-hike-czech-lithium-mining-royalties-row-continues-8179746
Germany	30%	10.0%	Revenue	Federal Republic of Germany. (n.d.). *Federal Mining Act (BBergG)*. Retrieved July 6, 2024, from https://www.gesetze-im-internet.de/englisch_bbergg/englisch_bbergg.html
Chile	27%	8.0%	Profit	Fabian, C. (2023). *Focus: Chile miners, facing higher taxes, seek faster permits, lower energy costs | Reuters*. Reuters. https://www.reuters.com/markets/commodities/chile-miners-facing-higher-taxes-seek-faster-permits-lower-energy-costs-2023-07-13/ Vásquez, P. I. (2023). Lithium Production in Chile and Argentina: Inverted Roles. *Wilson Center*.
Afghanistan	20%	7.5%	Revenue	Afghanistan. (2019). *Mining Regulations*.
Mexico	30%	7.5%	Profit	Bazel, P., Mintz, J. M., & Reyes-Tagle, G. (2023). *Taxation of the Mining Industry in Latin America and the Caribbean: Analysis and Policy*. https://doi.org/10.18235/0004957
Russia	25%	6.0%	Revenue	Reuters. (2021). *Russia submits proposed mining tax changes to the Parliament*. https://www.miningweekly.com/article/russia-submits-proposed-mining-tax-changes-to-the-parliament-2021-09-30
Australia	30%	5.0%	Revenue	MinterEllison. (2020). *New lithium royalty regime commences in Western Australia*. https://www.lexology.com/library/detail.aspx?g=a584f963-7b9b-4f81-b910-d36755561d95
China	25%	5.0%	Revenue	People's Republic of China. (2019). *The Resource Tax Law of the People's Republic of China*. https://www.mee.gov.cn/ywgz/fgbz/fl/202303/t20230314_1019553.shtml
Ethiopia	30%	5.0%	Revenue	Ministry of Mines. (n.d.). *Ethiopia's Mining Legislation and Regulations*. http://www.mom.gov.et/index.php/mining/legislation-and-regulations/
Ghana	25%	5.0%	Revenue	Ghana Minerals Commission. (2021). *The Minerals and Mining Act,2006*.
Serbia	15%	5.0%	Revenue	Nikola, Đ. (2021). *As Serbia prepares to mine lithium, activists warn of environmental cost*. https://emerging-europe.com/news/as-serbia-prepares-to-mine-lithium-activists-warn-of-high-environmental-cost/
Zimbabwe	25%	5.0%	Revenue	Reuters. (2022). *Zimbabwe's new mineral royalty policy comes into force Reuters*. https://www.reuters.com/markets/commodities/zimbabwes-new-mineral-royalty-policy-comes-into-force-2022-11-08/
Bolivia	25%	4.5%	Revenue	Enrique, B. (2022). *Dentons - Dentons Global Mining Guide: Bolivia*. https://www.dentons.com/en/insights/newsletters/2022/january/17/dentons-global-mining-guide/dentons-global-mining-guide-2022/bolivia
Peru	30%	4.0%	Profit	BizLatin Hub. (2023). *How Does the Peruvian Fiscal System Function for Mining Companies?* https://www.bizlatinhub.com/peru-mining-fiscal-system/#peruvian-fiscal-system-–-mining-taxes
DR Congo	30%	3.5%	Revenue	Thomas R. Yager. (2019). The Mineral Industry of Congo (Kinshasa)in 2019. *USGS 2019 Minerals Yearbook*, 11.1.
Argentina	35%	3.0%	Revenue	Eri, S. (2023). *Argentina's lithium incentives push industry prospects above neighbors | S&P Global Market Intelligence*. S&P Global. https://www.spglobal.com/marketintelligence/en/news-insights/latest-news-headlines/argentina-s-lithium-incentives-push-industry-prospects-above-neighbors-73972022
Mali	27%	3.0%	Revenue	Ousman, G., Emelly, M., & Guirane, N. (2012). *Royalty Rates in African Mining Revisited: Evidence from Gold Mining*. https://www.afdb.org/fileadmin/uploads/afdb/Documents/Publications/AEB%20VOL%203%20Issue%206%20avril%202012%20Bis_AEB%20VOL%203%20Issue%206%20avril%202012%20bis_01.pdf
Portugal	21%	3.0%	Revenue	José, P. A., & Branco, A. (2021). *Spotlight: Mining law in Portugal - Lexology*. Lexology. https://www.lexology.com/library/detail.aspx?g=aa59a994-40fa-4eaf-96eb-7149be70dc17
Tanzania	30%	3.0%	Revenue	Thomas, S. (2022). *Dentons - Dentons Global Mining Guide: Tanzania*. Dentons. https://www.dentons.com/en/insights/newsletters/2022/january/17/dentons-global-mining-guide/dentons-global-mining-guide-2022/tanzania
Brazil	34%	2.25%	Revenue	Bazel, P., Mintz, J. M., & Reyes-Tagle, G. (2023). *Taxation of the Mining Industry in Latin America and the Caribbean: Analysis and Policy*. https://doi.org/10.18235/0004957
Namibia	32%	2.0%	Revenue	Chamber of Mines of Namibia. (n.d.). *Mining tax regime*. Retrieved July 1, 2024, from https://chamberofmines.org.na/mining-tax-regime/
Austria	24%	1.0%	Revenue	Adam, D. (2023). *European Lithium nearly doubles footprint at Wolfsberg Lithium Project in Austria*. Mining.Com.Au. https://mining.com.au/european-lithium-nearly-doubles-footprint-at-wolfsberg-lithium-project-in-austria/
Finland	20%	0.6%	Revenue	Reuters. (2022). *Finland plans new tax on mining | Reuters*. Reuters. https://www.reuters.com/markets/europe/finland-plans-new-tax-mining-2022-09-27/

Countries or States	**Corporate Tax Rate[a]**	**Royalty Rates[b]**	**Royalty Based[c]**	**Source Royalty**
Canada	27%	0.0%	Revenue	Department of Finance Canada. (2024). *Government extending support for mineral exploration in Canada - Canada.ca*. https://www.canada.ca/en/department-finance/news/2024/03/government-extending-support-for-mineral-exploration-in-canada.html Mineral Tax Act (2024). https://www.bclaws.gov.bc.ca/civix/document/id/complete/statreg/96291_01#section1.2 Nunavut Mining Regulations (2021). https://laws-lois.justice.gc.ca/eng/regulations/SOR-2014-69/page-5.html#h-813547
United States	25%	*State specific*	*State specific*	
Alaska		5.0%	Profit	California Department of Tax and Fee Administration. (2023). *California Lithium Extraction Tax Study Report*. www.watereducation.org/western-water/long-troubled-salton-sea-may-finally-be-getting-what-it-most-needs-action-and-money.
Arizona		2.5%	Revenue	Arizona Department of Revenue. (2024). *Rate and Code Updates*. https://azdor.gov/business/transaction-privilege-tax/model-city-tax-code/rate-and-code-updates
Arkansas		$0.0000173/ Liter	Unit	Arkansas Administration of Finance Department. (n.d.). *Miscellaneous tax Brine*. https://www.dfa.arkansas.gov/excise-tax/miscellaneous-tax/brine
California		$400/ton LCE	Unit	California Department of Tax and Fee Administration. (2023). *New Lithium Extraction Excise Tax*.
Maine		2.2%	Revenue	Maine Department of Administrative and Financial Services. (2024). *Maine's Taxation of Metallic Mineral Mining Business Activity Report Prepared for the Joint Standing Committee on Taxation*.
Nevada		1.96%	Revenue	California Department of Tax and Fee Administration. (2023). *California Lithium Extraction Tax Study Report*. www.watereducation.org/western-water/long-troubled-salton-sea-may-finally-be-getting-what-it-most-needs-action-and-money.
North Carolina		0.0%	N/A	North Carolina Department of Revenue. (2015). *Important Notice: Tax on Severance of Energy Minerals Effective*. www.dornc.com
South Dakota		0.0%	N/A	South Dakota Legislature. (2023). *Taxation of Precious Metals and Other Extracted Materials*.
Utah		2.60%	Revenue	Utah Code Part 2 Mining Severance Tax (2023).
Wyoming		7.0%	Revenue	Susan, D. S. (2019). *Specific examples of mining tax provisions in western states*.

[a] Source: Damodaran, A. Country Default Spreads and Risk Premiums. https://pages.stern.nyu.edu/~adamodar/New_Home_Page/datafile/ctryprem.html, last updated: January 2024.

[b] Some countries present royalty rates as a range. We have determined fixed rates based on actual transactions or reasonable estimates for local mines.

[c] Four countries without specified royalty bases, we used a revenue-based rate as it is the most common.

[d] Conversion rate used: 1 EUR = 1.07 USD.

[e] Conversion rate used: 1 GBP = 1.266 USD.

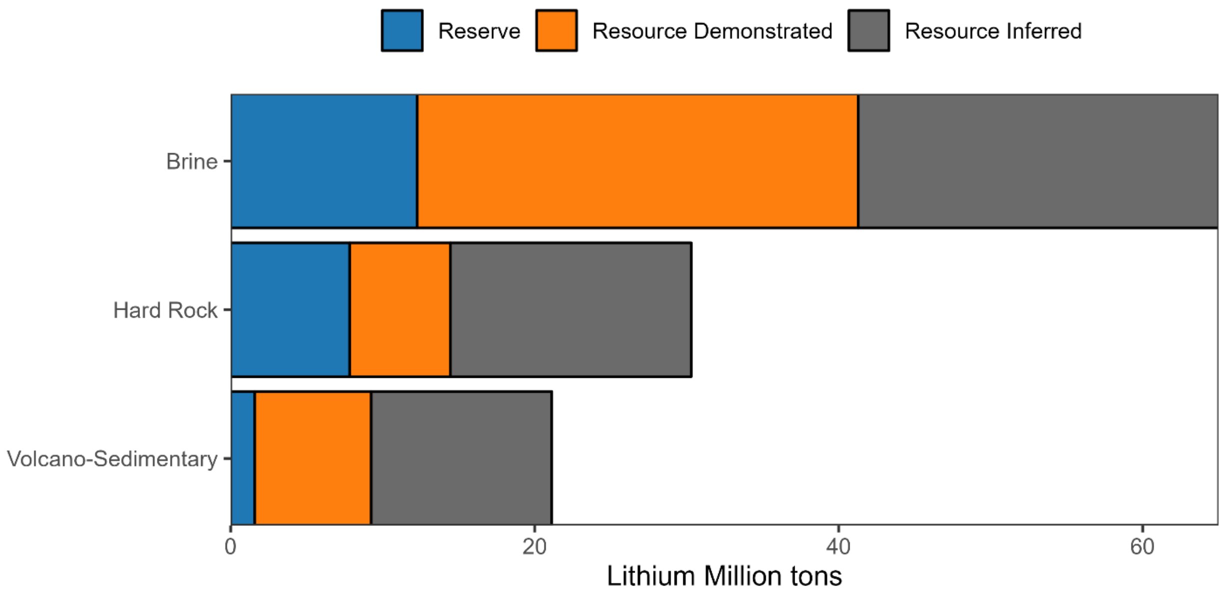


Figure C-1. Resources by stage (reserve, demonstrated resources and inferred resources) and lithium resource type. Material from: 'Busch et al., Effects of demand and recycling on the when and where of lithium extraction, Nature Sustainability, published 2025, Springer Nature', with permission from Springer Nature.

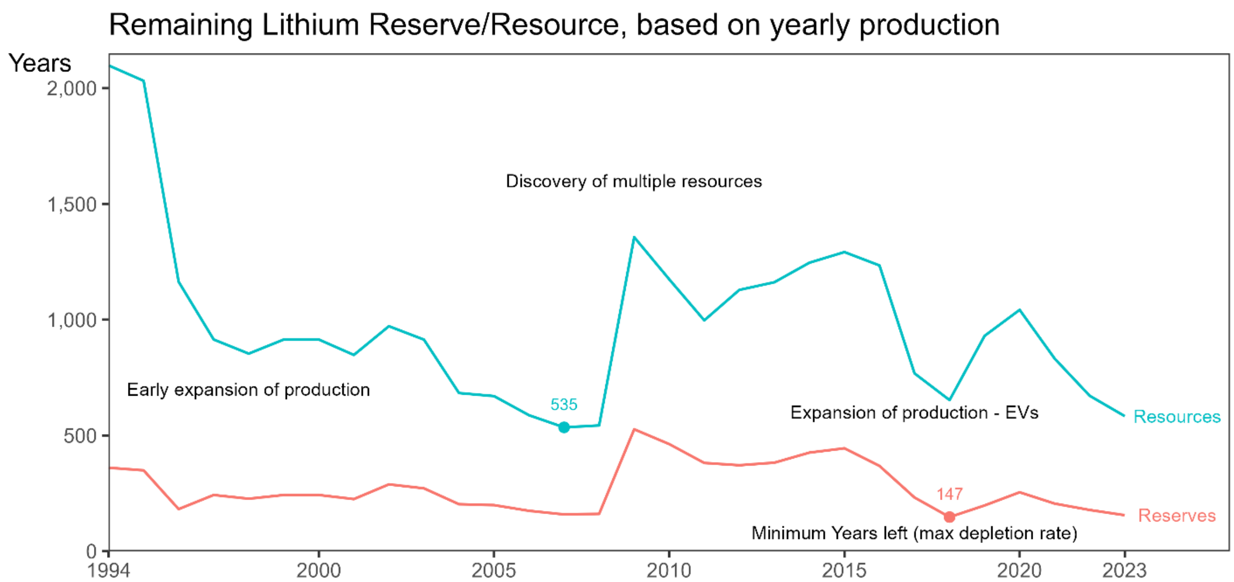


Figure C-2. Ratio of reserves and resources over annual production, which represents remaining years. Data from USGS Mineral Commodity Summaries (USGS, 2025). Historical production of lithium has never been below a 100-year reserve depletion horizon, but production of lithium has been historically low.

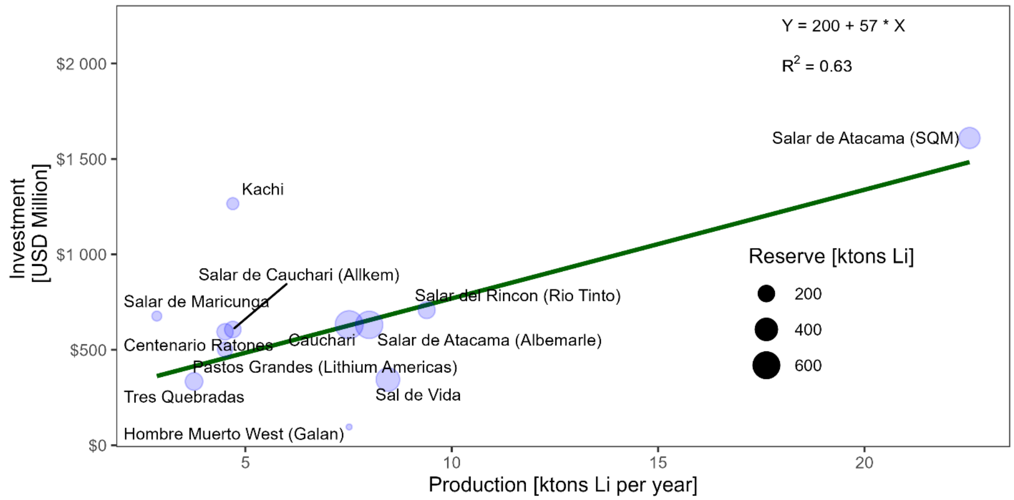


Figure C-3. Linear regression model between CAPEX (in million US$) and production capacity targets (tonnes per year), for brine projects. n=12. Regression is weighted by reserve size. Material from: 'Busch et al., Effects of demand and recycling on the when and where of lithium extraction, Nature Sustainability, published 2025, Springer Nature', with permission from Springer Nature.

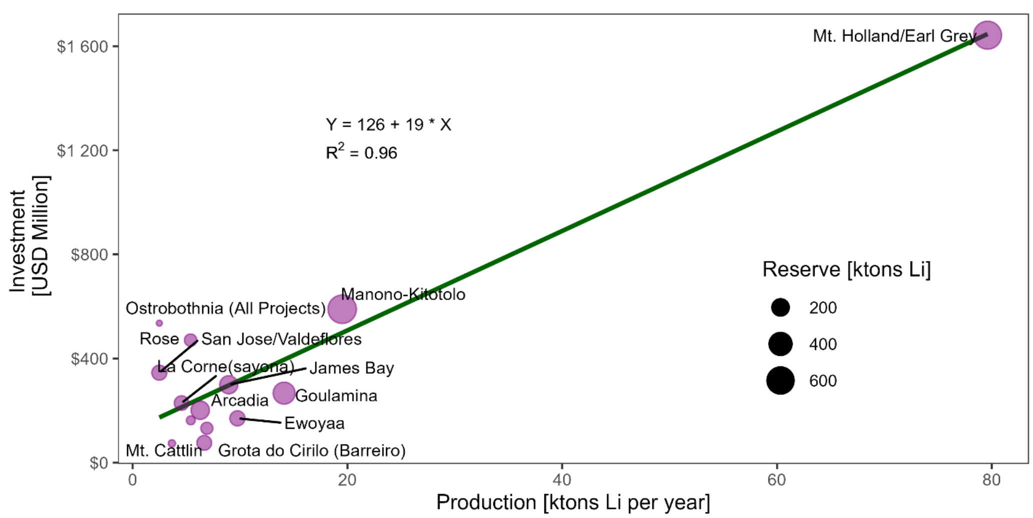


Figure C-4. Linear regression model between CAPEX (in million US$) and production capacity targets (tonnes per year), for hard-rock projects. n=14. Regression is weighted by reserve size. Material from: 'Busch et al., Effects of demand and recycling on the when and where of lithium extraction, Nature Sustainability, published 2025, Springer Nature', with permission from Springer Nature.

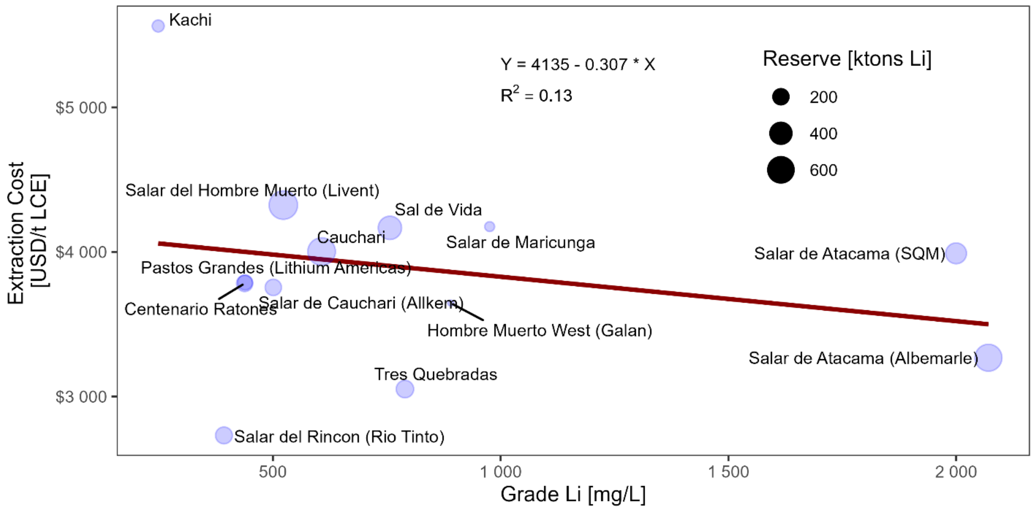


Figure C-5. Linear regression model between OPEX (in US$ per ton of LCE extracted, no royalties or taxes) and grade of lithium (in mg/L), for brine projects. n=13. Regression is weighted by reserve size. Material from: 'Busch et al., Effects of demand and recycling on the when and where of lithium extraction, Nature Sustainability, published 2025, Springer Nature', with permission from Springer Nature.

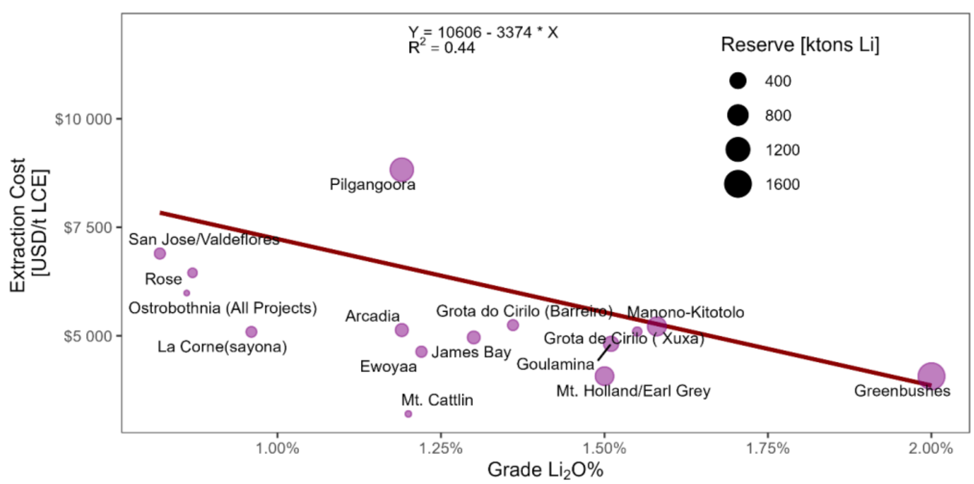


Figure C-6. Linear regression model between OPEX (in US$ per ton of LCE extracted, no royalties or taxes) and grade of lithium (in Li_2O %), for hard rock projects. n=15. Regression is weighted by reserve size. Material from: 'Busch et al., Effects of demand and recycling on the when and where of lithium extraction, Nature Sustainability, published 2025, Springer Nature', with permission from Springer Nature.

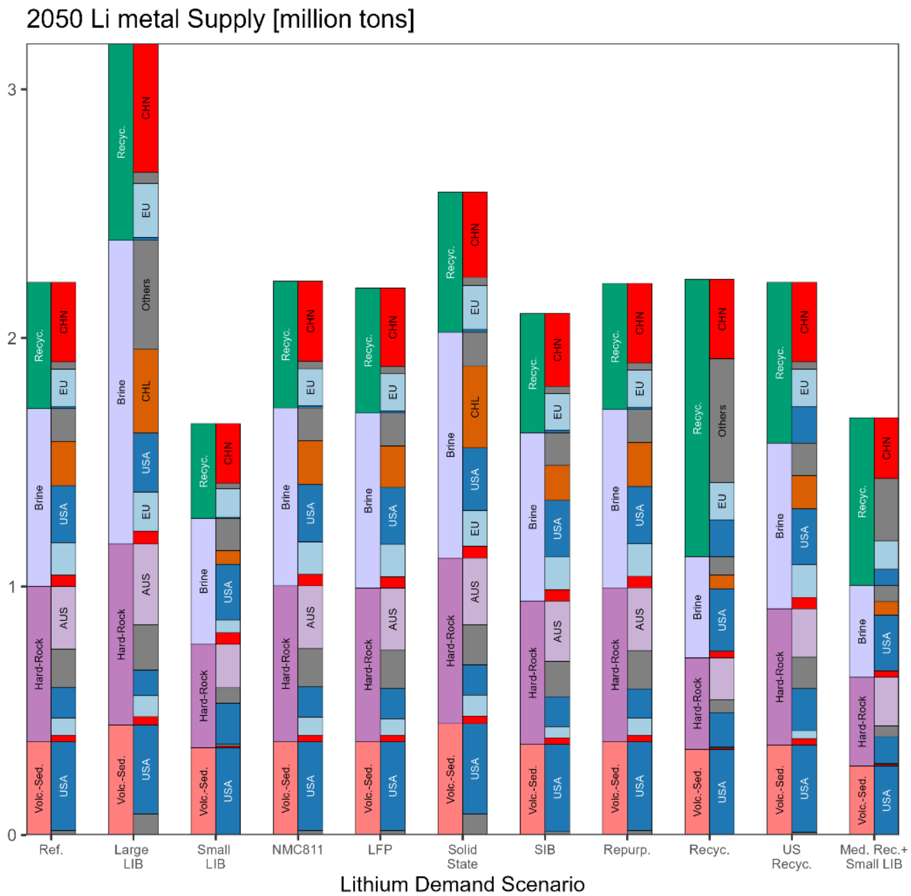


Figure C-7. 2050 Lithium extraction by resource type and country of extraction. Lithium metal supply from primary extraction and recycling is shown for each demand scenario. Left-bars shows detail by type of resource or recycling, and right-hand bars show country distribution for each resource type (AUS: Australia, CHL: Chile, CHN: China, EU: Europe, USA: United States of America, Others: any other country not listed here). Material from: 'Busch et al., Effects of demand and recycling on the when and where of lithium extraction, Nature Sustainability, published 2025, Springer Nature', with permission from Springer Nature.

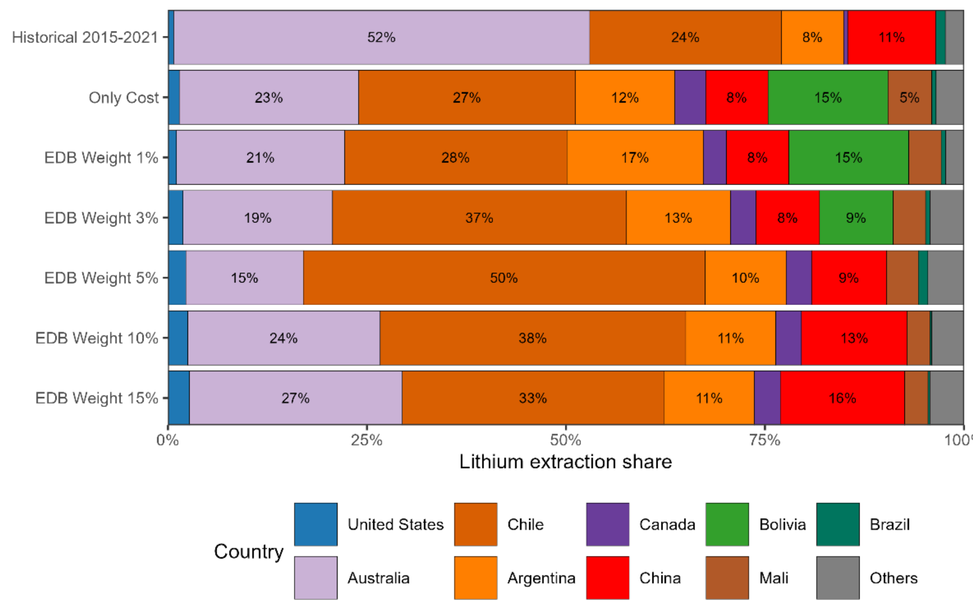


Figure C-8. **Country lithium extraction share (2022-2030)**, by different levels of cost degradation factors (using the ease of doing business index as the non-monetary factor). Results are for the Reference demand scenario. Historical extraction by country is shown for the period 2015-2021, according to USGS (USGS, 2024b).

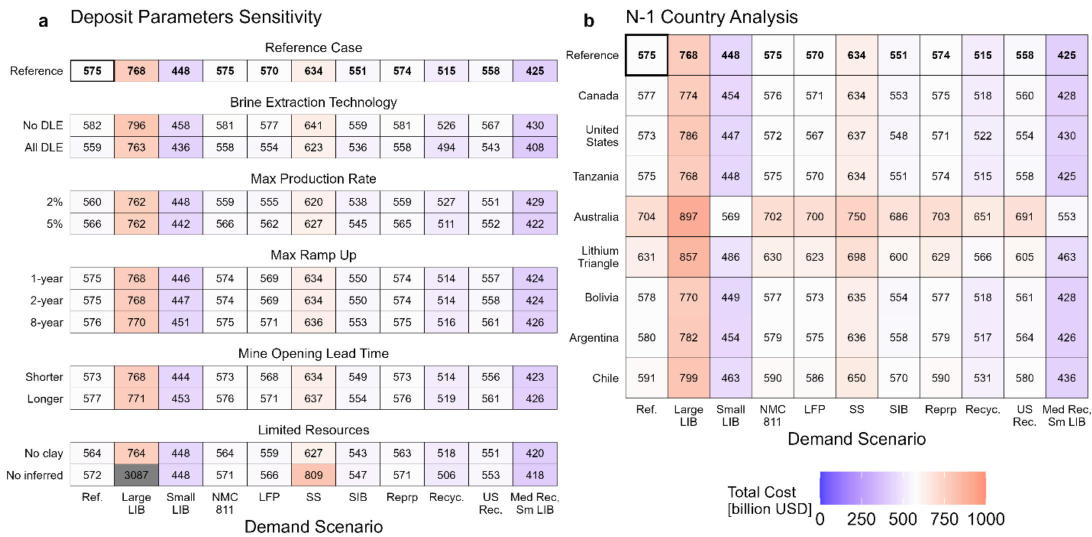


Figure C-9. Total cost (trillions US$, in 2022 present value) to meet lithium demand requirements by scenario under different deposit parameters (**a**) or (**b**) by N-1 country analysis. In both figures colors indicate the demand scenario, and the vertical line marks the reference case for the sensitivity analysis. Material from: 'Busch et al., Effects of demand and recycling on the when and where of lithium extraction, Nature Sustainability, published 2025, Springer Nature', with permission from Springer Nature.

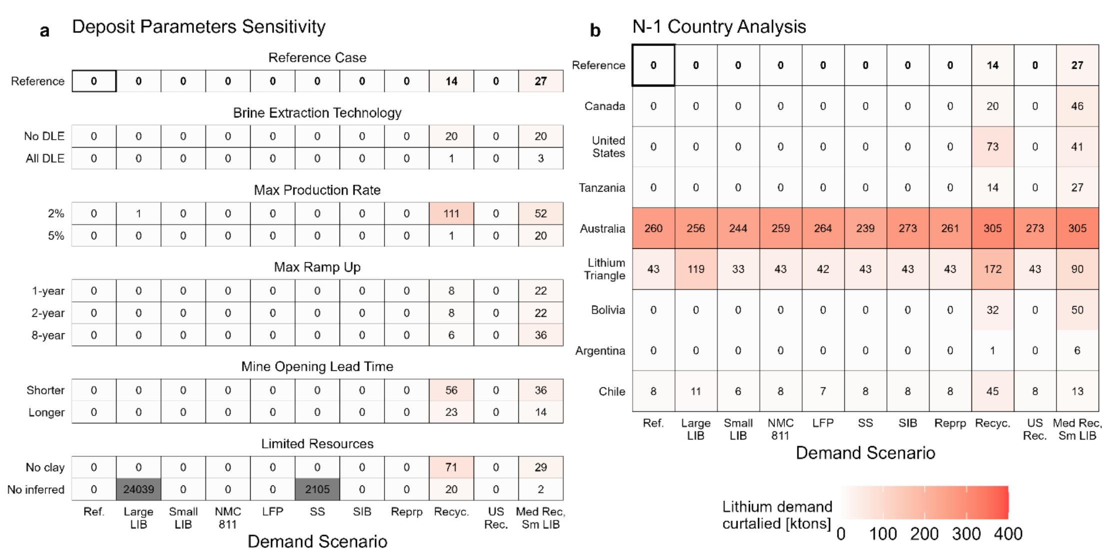
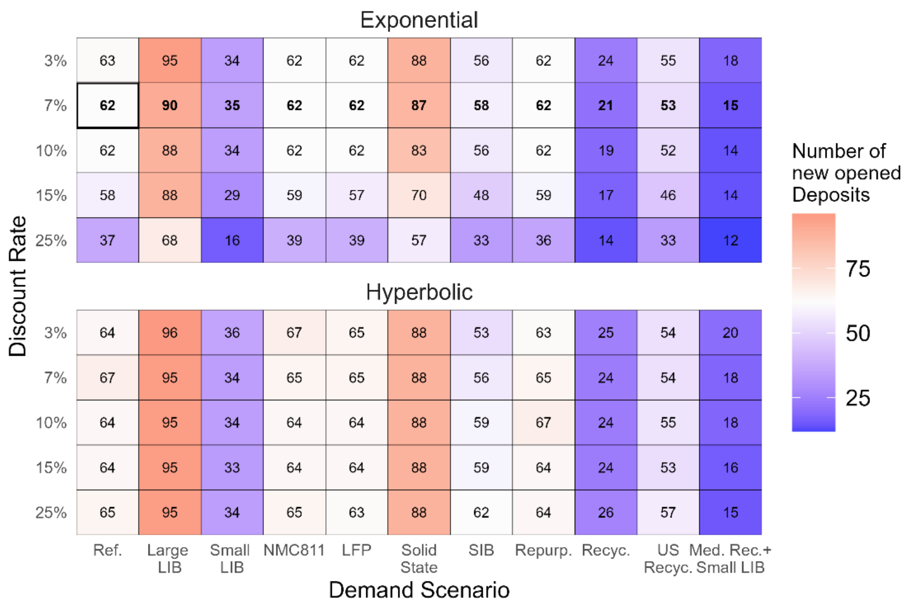


Figure C-10. Total demand curtailed (in ktons lithium) due to cost exceeding slack price threshold, under different deposit parameters (**a**) or (**b**) by N-1 country analysis. In both figures colors indicate the demand scenario, and the vertical line marks the reference case for the sensitivity analysis. Material from: 'Busch et al., Effects of demand and recycling on the when and where of lithium extraction, Nature Sustainability, published 2025, Springer Nature', with permission from Springer Nature.



Exponential	Ref.	Large LIB	Small LIB	NMC811	LFP	Solid State	SIB	Repurp.	Recyc.	US Recyc.	Med. Rec.+ Small LIB
3%	63	95	34	62	62	88	56	62	24	55	18
7%	**62**	**90**	**35**	**62**	**62**	**87**	**58**	**62**	**21**	**53**	**15**
10%	62	88	34	62	62	83	56	62	19	52	14
15%	58	88	29	59	57	70	48	59	17	46	14
25%	37	68	16	39	39	57	33	36	14	33	12

Hyperbolic	Ref.	Large LIB	Small LIB	NMC811	LFP	Solid State	SIB	Repurp.	Recyc.	US Recyc.	Med. Rec.+ Small LIB
3%	64	96	36	67	65	88	53	63	25	54	20
7%	67	95	34	65	65	88	56	65	24	54	18
10%	64	95	34	64	64	88	59	67	24	55	18
15%	64	95	33	64	64	88	59	64	24	53	16
25%	65	95	34	65	63	88	62	64	26	57	15

Figure C-11. Additional lithium deposits will require to open under different discount rates. Rows indicate different assumptions of discount rate utilized for all costs parameters. Hyperbolic refers to the usage of a hyperbolic discount rate, instead of the exponential formula. The hyperbolic discount rate mitigates the extreme discount in periods over 30 years. Material from: 'Busch et al., Effects of demand and recycling on the when and where of lithium extraction, Nature Sustainability, published 2025, Springer Nature', with permission from Springer Nature.