

Effects of high-energy Pb-ion irradiation on critical current and flux pinning in Fe(Se,Te) thin films

*Original*

Effects of high-energy Pb-ion irradiation on critical current and flux pinning in Fe(Se,Te) thin films / Fracasso, Michela; Scuderi, Mario; Brugaletta, Elisa; Bellingeri, Emilio; Ievole, Michela; Malagoli, Andrea; Martinelli, Alberto; Manca, Nicola; Gozzelino, Laura; Gerbaldo, Roberto; Ghigo, Gianluca; Laviano, Francesco; Torsello, Daniele; Putti, Marina; Braccini, Valeria. - In: SUPERCONDUCTOR SCIENCE & TECHNOLOGY. - ISSN 0953-2048. - STAMPA. - 38:10(2025).  
[10.1088/1361-6668/ae0fc6]

*Availability:*

This version is available at: 11583/3005910 since: 2025-12-16T11:36:22Z

*Publisher:*

Institute of Physics

*Published*

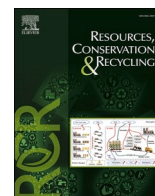
DOI:10.1088/1361-6668/ae0fc6

*Terms of use:*

This article is made available under terms and conditions as specified in the corresponding bibliographic description in the repository

*Publisher copyright*

(Article begins on next page)



## Review



## Life cycle inventories of global metal and mineral supply chains: a comprehensive data review, analysis and processing

Frédéric Lai<sup>a,\*</sup>, Stéphanie Muller<sup>a</sup>, Audrey Philippe<sup>a</sup>, Robert Istrate<sup>b</sup>,  
 Brenda Miranda Xicotencatl<sup>b</sup>, Afsoon Mansouri Aski<sup>c</sup>, Aina Mas Fons<sup>d,a</sup>,  
 Juliana Segura-Salazar<sup>e</sup>, Jair Santillán Saldivar<sup>a</sup>, Alexander Cimprich<sup>f</sup>, Stephen Northey<sup>g</sup>,  
 Lígia da Silva Lima<sup>h</sup>, Lieselot Boone<sup>h</sup>, Ryosuke Yokoi<sup>i</sup>, Kamrul Islam<sup>i</sup>, Ioanna Paschalidou<sup>j</sup>,  
 Felipe Cerdas<sup>k,l</sup>, Victor Balboa-Espinoza<sup>e</sup>, Anish Koyampambath<sup>d</sup>, Diae Hennioui<sup>a</sup>,  
 Victoire Collignon<sup>a</sup>, Aurélien Reys<sup>a</sup>, Gyslain Ngadi Sakatadi<sup>m</sup>, Jo Dewulf<sup>h</sup>,  
 Bernhard Steubing<sup>b</sup>, Christoph Helbig<sup>c</sup>, Gaétan Lefebvre<sup>a</sup>,  
 Gian Andrea Blengini<sup>n,m</sup>, Valeria Superti<sup>o</sup>, Masaharu Motoshita<sup>i</sup>,  
 Guido Sonnemann<sup>d</sup>, Kwame Awuah-Offei<sup>j</sup>, Steven B. Young<sup>f</sup>,  
 Shinsuke Murakami<sup>p</sup>, Antoine Beylot<sup>a</sup>

<sup>a</sup> BRGM, F-45060 Orléans, France

<sup>b</sup> Institute of Environmental Sciences (CML), Leiden University, Einsteinweg 2, 2333 CC Leiden, The Netherlands

<sup>c</sup> Ecological Resource Technology, University of Bayreuth, Universitätsstr. 30, 95447 Bayreuth, Germany

<sup>d</sup> Univ. Bordeaux, CNRS, Bordeaux INP, ISM, UMR 5255, F-33400 Talence, France

<sup>e</sup> Sustainable Minerals Institute, The University of Queensland, QLD, 4072, Australia

<sup>f</sup> School of Environment, Enterprise and Development, University of Waterloo, 200 University Avenue West, Waterloo, Ontario N2L 3G1, Canada

<sup>g</sup> University of Technology Sydney, Institute for Sustainable Futures, Australia

<sup>h</sup> Sustainable Systems Engineering (STEN), Department of Green Chemistry and Technology, Faculty of Bioscience Engineering, Ghent University, Coupure Links 653, 9000 Ghent, Belgium

<sup>i</sup> AIST, 305-8569 Tsukuba, Japan

<sup>j</sup> Mining & Explosives Engineering, Missouri University of Science & Technology, Rolla, MO, 65409, USA

<sup>k</sup> Institute for Sustainable Energy Systems (INSYS), Technical University of Applied Sciences Würzburg-Schweinfurt (THWS), Ignaz-Schön-Straße 11, Schweinfurt, Germany

<sup>l</sup> Fraunhofer Institute for Surface Engineering and Thin Films IST, Riedenkamp 2, Braunschweig 38108, Germany

<sup>m</sup> Department of Environment, Land and Infrastructure Engineering, Politecnico di Torino, Corso Duca degli Abruzzi, 24, 10129 Torino, Italy

<sup>n</sup> University of Turin, Earth Sciences Department (DST), Via Valperga Caluso, 35 - 10125 Torino, Italy

<sup>o</sup>ecoinvent association, Technopark, Technoparkstrasse 1, 8005 Zürich, Switzerland

<sup>p</sup> Graduate School of Engineering, The University of Tokyo, Tokyo 113-8656, Japan

## ARTICLE INFO

## Keywords:

Metals and minerals  
 Supply chains  
 Data quality  
 Life cycle assessment  
 Environmental impacts

## ABSTRACT

Reliable life cycle inventory (LCI) data are key to consistent life cycle assessment (LCA) results. This study provides a comprehensive and up-to-date overview of existing public LCI data related to metals and minerals production. It aims to deliver LCI models representing current supply chains and markets. For that purpose, this study conducts an in-depth analysis (including data quality) of 285 LCI datasets drawn from 130 different LCA studies related to metals and minerals. Following a selection process and a harmonised data compilation, processing and modelling approach, 220 individual LCI datasets were developed, covering 53 metal and mineral elements and distinguishing 163 production routes differentiated from geographical, geological, technological or material perspectives. Finally, these LCI datasets were gathered into market datasets, depicting global supply mixes. Elements such as germanium or manganese showed a limited market coverage, contrary to others such as lithium or aluminium.

\* Corresponding author.

E-mail address: [f.lai@brgm.fr](mailto:f.lai@brgm.fr) (F. Lai).

<https://doi.org/10.1016/j.resconrec.2025.108709>

Received 2 May 2025; Received in revised form 18 August 2025; Accepted 22 November 2025

Available online 29 November 2025

0921-3449/© 2025 The Authors. Published by Elsevier B.V. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

Available in open access, the high-resolution LCI datasets here developed offer key perspectives for a better modelling of metal and mineral supply chains in LCA, in turn contributing to higher quality LCAs of downstream product systems utilising these materials. At the same time, this study reveals several data gaps, paving the way for further data improvement.

## 1. Introduction

Metals and minerals are indispensable components of modern societies as key inputs to numerous applications. The demand for these materials has substantially increased over the past decades, with a more than three-fold increase in metal ores extraction between 1970 and 2020 (UNEP, 2024). Forecasts project continuous growth in metals and minerals demand, particularly driven by energy and digital transition pathways that rely on metals-intensive technologies (Carrara et al., 2023). While important for mitigating climate change, these developing technologies may be accompanied by a shift of environmental burden, compared to conventional options, from the use (e.g. impacts associated with fuel combustion in thermal vehicles) to the fabrication phase (e.g. impacts associated with raw materials production in Li-ion batteries for electric vehicles; Xu et al., 2022; Šimaitis et al., 2023; Istrate et al., 2024).

There is also growing concern about the local environmental impacts of the projected expansion in mining and refining capacity. Mining activities are notably viewed as a source of environmental threats due to potential adverse effects on e.g. biodiversity (Aska et al., 2023), land (Maus et al., 2022) or climate (Mervine et al., 2025). Life cycle assessment (LCA) is a highly relevant approach to comprehensively capture such local and global environmental impacts, and it has seen a growing implementation at industrial (Santero and Hendry, 2016) and policy levels (Sala et al., 2021) over the last decades. Specifically for metals and minerals, there have been hundreds of LCA studies published in the past years (Rachid et al., 2023; Segura-Salazar et al., 2019). Moreover, developing binding policies at European level have referenced LCA (e.g. Batteries Regulation, Critical Raw Materials Act; EC, 2023a; EC, 2024). Notably the European Union (EU) Batteries Regulation intends to set mandatory quantification and labelling of the carbon footprint performance of batteries put in the EU market, complemented by maximum life cycle carbon footprint thresholds.

These LCA studies indicate that environmental impacts of metals and minerals production may vary by several orders of magnitude from one element to another as well as for a given element, as observed in carbon footprint values of e.g. nickel (Ni), copper (Cu), manganese (Mn) or rare earths (RE) (Rachid et al., 2023; Fiorletta et al., 2020a). This variability may stem from differences in:

- Geographical coverage, i.e. with different producing countries/areas (Liu et al., 2020);
- Geological and technological characteristics, i.e. with different deposits, process chains, and output products (e.g. Li brines vs hard rock; Chordia et al., 2022; Kelly et al., 2021);
- Life cycle inventory (LCI) data sources, i.e. with different data acquisition methods that may result in varying data quality (and resulting uncertainty), and representativeness (e.g. industry-based vs process modelling data; Schenker et al., 2022; Kelly et al., 2021);
- Methodological approaches in the modelling (e.g. with application of different allocation approaches; Lai et al., 2021b).

There is thus a need to further i) differentiate the existing production routes of a given element, ii) investigate quality and representativeness of underlying LCI data (i.e. input and output flows related to e.g. material, energy, resource consumption, wastes or emissions to the environment), and iii) harmonise methodological approaches in the modelling to allow fair comparability of results. Massive efforts have been made by the scientific community, industrials in the raw materials

sector, and LCI databases providers, on the development of LCI of global metals and minerals production (e.g. Nuss and Eckelman, 2014; ecoinvent, 2025), including through reviewing published LCA studies (Rachid et al., 2023). Several studies have also pointed out gaps in some of these existing LCI data, e.g. Eltohamy et al. (2024), Fiorletta et al. (2020b), Guo et al. (2025).

Despite all these advances, a comprehensive and up-to-date overview of available LCI datasets for metal and mineral supply chains, taking benefit of the massive amount of data published in the scientific and grey literature in the last decades, is still missing. Filling this gap is critical for a more consistent and reliable modelling of these supply chains in LCA. To address this key challenge, this study provides a comprehensive review and compilation of publicly available LCI data related to existing supply chains of 63 metal and mineral elements, including assessment of LCI data quality and representativeness. This analysis then aims to result in a selection of the most relevant datasets for development of LCI models specific to the main production routes of each element under study. This process builds on a harmonised data processing and modelling approach. Finally, based on the production route-specific LCI datasets, global LCI models representative of the current global supply mix of each element are derived. The article concludes with discussing potential future use and perspectives for improving LCI datasets of metal and mineral supply chains.

## 2. Material and methods

This study follows a stepwise process (Fig. 3), starting from a literature review where a broad screening to identify the most relevant existing LCA studies is performed (see sub-sections 2.1.1 and 2.1.2). The associated LCI data are then compiled under a harmonised format, for subsequent analysis of data quality and representativeness (see supporting information (SI) document n°1 and sub-section 2.1.3), complemented by a set of additional criteria for final selection of the most relevant LCI datasets (see sub-sections 2.1.4 and 2.1.5). These datasets eventually enable the development of LCI models, at production routes level, based on a harmonised processing and modelling approach (see sub-section 2.2). Finally, global LCI models are derived to provide a representation of the market (see sub-section 2.3). Verification steps are implemented along this process to ensure robustness and consistency in the final LCI models (see SI document n°1).

### 2.1. Literature review and LCI datasets analysis

#### 2.1.1. Scope of the review

This review covers 63 mineral elements, including 29 considered key for the energy transition (e.g., as considered by Lèbre et al. (2024) and IEA (2024); Fig. 1), focusing on the main commodities associated with each element. Mineral commodities may either refer to minerals or materials derived from minerals (USGS, 2025), encompassing both raw and processed materials (Carrara et al., 2023).

In this study, the focus is more particularly set on:

- Materials resulting from processing stages (purification and refining), such as metal compounds (e.g. nickel sulphate – NiSO<sub>4</sub>) or refined metals (e.g. Ni class 1);
- Processed materials combining several materials, such as alloys (e.g. ferriobium – FeNb).

The list of commodities, as defined in the Harmonised System (HS)

trading classification (World Customs Organization, 2025), associated with each element is provided in SI document n°2.

This study applies a cradle-to-gate perspective, distinguishing primary and secondary production routes (Fig. 2). Primary routes cover four main process steps, as defined by Nuss and Eckelman (2014):

- Mining, which consists of extracting the raw material, generally an ore, from its deposit;
- Concentration, aiming at processing the raw material into a concentrate;
- Purification, which converts the concentrate into a mineral/metal compound or an intermediate product;
- Refining, resulting in a high-purity metal or an alloy.

Secondary routes (i.e. recycling) cover all unit operations from scrap collection to the production of processed material through concentration, purification or refining steps. New scraps (also referred to as pre-consumer scraps) originating from fabrication or manufacturing processes, and old scraps (post-consumer scraps) from end-of-life products are both considered as possible feedstocks to secondary production routes (UNEP, 2011).

Production routes are defined as process chains implemented over a given geographical area (e.g. site, country, continent), potentially considering specific technologies, deposits and commodities. More particularly, this study focuses on current industrially established production routes contributing to the global production of each element under study.

2.1.2. Literature search and screening approach

The first step of the review consisted of generating a comprehensive overview of available LCA studies (until mid-2024) related to each of the 63 elements under study (Fig. 3). LCA studies from scientific literature, industrial associations and technical literature were gathered using different search engines such as Google Scholar, Web of Science or Scopus. Various search strings were applied (within titles, abstracts or keywords), considering combinations of keywords related to the element name (e.g. niobium), commodity name (e.g. ferroniobium/

FeNb), life cycle assessment/LCA, or life cycle inventory/LCI.

Based on this literature search, criteria-based screening was performed to identify the most relevant references, i.e. those providing LCI data for industrial-scale production routes related to the commodities under study, with suitable geographical, technological, and temporal coverage (Table 1). Therefore, any LCA study only providing life cycle impact assessment (LCIA) results, without any LCI data, was excluded.

Each identified LCI dataset was then compiled and further scrutinised to get an overview of its scope. Several aspects were investigated as complements to the initial screening criteria: underlying data source of the LCI (i.e. data acquisition method), associated co-/by-products, and allocation method (in case of allocated dataset).

2.1.3. Data quality and representativeness assessment

To evaluate the LCI datasets identified in the screening step, data quality and representativeness were assessed using the Pedigree approach (Muller et al., 2016; Fig. 3). As outlined in the Pedigree matrix (Table S1 in SI document 1), this approach provides ordinal rankings for each LCI data point (i.e. individual input and output flow) from 1 to 5 (5 being the lowest score) according to five criteria:

- **Reliability of the data source**, focusing on the quality of the source and the data acquisition method;
- **Completeness**, considering data representativeness from a statistical perspective;
- **Temporal/geographical/technological correlation**, reflecting data representativeness with respect to the time period, area and technology under focus.

It is noteworthy that the applicability of the Pedigree approach to LCI datasets from literature depends on the level of information available in the LCA studies. In case of missing information, a default score of 5 was assigned.

2.1.4. LCI datasets selection

This data review and analysis ultimately aims to identify the most relevant LCI datasets for modelling the global supply of the commodities

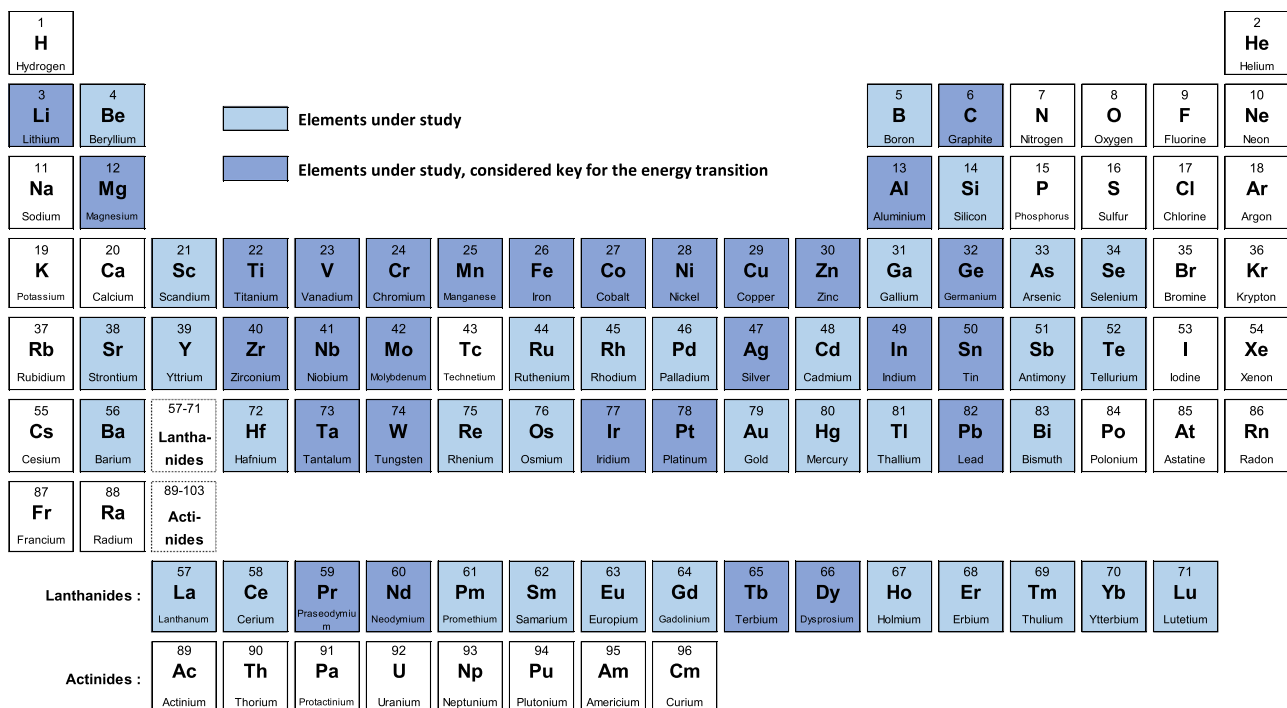


Fig. 1. Overview of the 63 mineral elements under study.

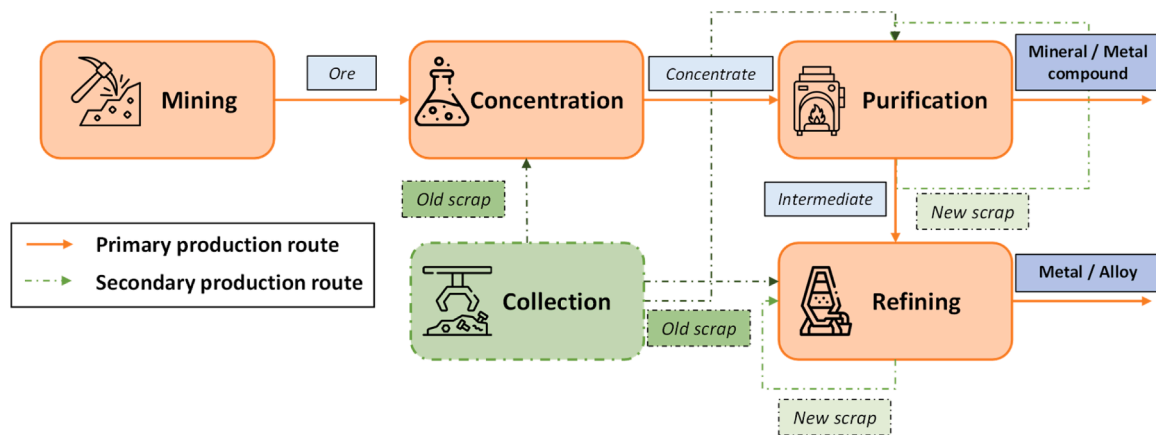


Fig. 2. Production routes as defined in this study.

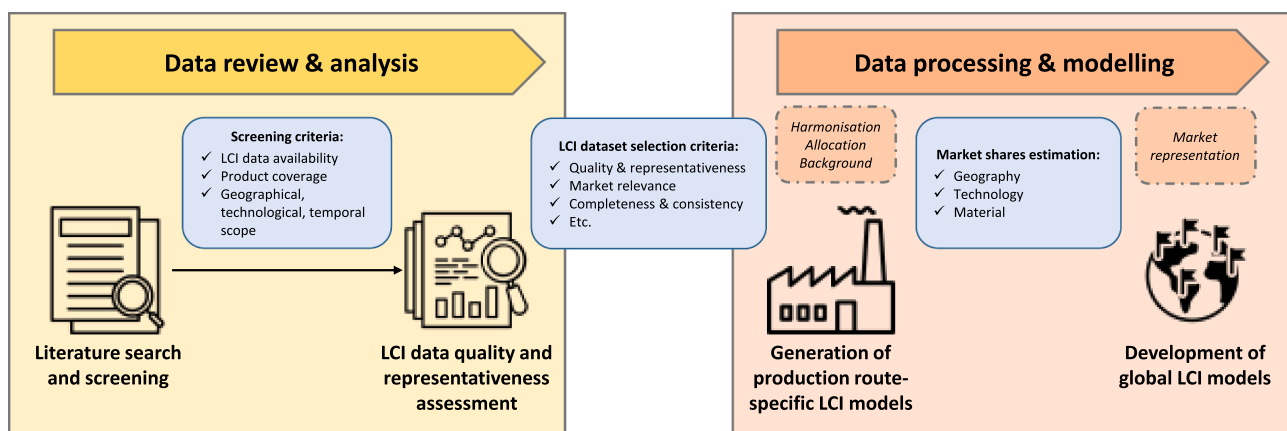


Fig. 3. Overall workflow from literature review to final LCI models developments.

Table 1

List of criteria for screening (inclusion/exclusion) of LCA studies identified in the literature search.

Screening criteria	Condition to be met by the LCA study
Availability and singularity of LCI data	Provides an original LCI dataset (i.e. that has not been previously published).
Commodity coverage	Covers one of the main commodities available on the global market or an intermediate product within the supply chain of one of the main commodities (e.g. concentrates).
Geographical coverage	Focuses on one or several of the main producing countries. A cut-off is set at 1 % of the global production, i.e. production routes related to countries accounting for <1 % of the global production are disregarded.
Technological coverage	Covers a process chain that is implemented at an industrial scale, i.e. processes at lower technology readiness level – TRL (e.g. laboratory or pilot scale) are disregarded.
Temporal coverage	If two or more LCI datasets are available for a given production route, those developed prior to 2010 are disregarded.

under study. Accordingly, LCI datasets were selected based on quantitative and qualitative criteria, complemented with expert judgement, considering by order of priority:

- LCI data quality and representativeness, as rated through the Pedigree approach;

- Market relevance of the modelled production route (i.e. contribution to the global production of the element), building on market information compiled for each element under study (see sub-section 2.3.1);
- Level of aggregation of the dataset, in terms of unit operations or geographical coverage;
- Availability of other LCI datasets for the same production route, with better completeness and data quality/representativeness.

This multi-criteria selection approach potentially implies that LCI datasets with limited data quality and representativeness (i.e. Pedigree scores of 4 or 5) could still be selected if, from a market perspective, they cover a highly relevant production route.

In case several LCI datasets covering the same production route were deemed equally relevant according to the defined criteria and complementary in terms of reported flows, distinct input and output flows from the different datasets were combined to result in a new dataset with improved completeness.

2.1.5. Co-/by-products mapping and selection

Many metal elements are accompanied by other co- or by-products (also referred to as companion elements, Nassar et al., 2015), which may be of metal, mineral or other nature. Some metal elements are exclusively produced as co- or by-products (e.g. Ge or Ga). It is noteworthy that the distinction between co- and by-products is not further explored in this study, as differences in their definitions primarily stem from economic dynamics, which are not necessarily captured in LCI data (Afflerbach et al., 2014).

To cover these companion elements in this study, a comprehensive mapping of all co-/by-products reported in each compiled LCI dataset was first performed. However, details about co-/by-products were not always provided, which hindered the identification of these companions in some datasets. Building on this mapping, a selection of the relevant co-/by-products to consider in each multi-output LCI dataset was performed by investigating their consistency with global co-/by-production patterns (see [sub-section 2.3.1](#)). That is, co-/by-products of one given LCI dataset were selected and specific LCI was generated (see [sub-section 2.2.2](#)) only if corresponding to the identified global patterns. Otherwise, the co-/by-products were still accounted for in the overall multifunctionality solving-approach, but no specific LCI datasets were generated for these companion elements.

## 2.2. Ensuring consistency across datasets: LCI processing and modelling framework

Once selected, the LCI datasets went through different processing and modelling steps to result in “production route-specific” LCI models ([Fig. 3](#)). This included particular attention to the harmonisation of all LCI datasets (see [sub-section 2.2.1](#)), especially regarding key modelling aspects (see [sub-sections 2.2.2, 2.2.3, 2.2.4](#)) that may influence subsequent impact assessment results (out of the scope of this paper).

### 2.2.1. Datasets harmonisation

LCI datasets originating from different literature sources exhibit methodological heterogeneity. In generating the final LCI datasets from this study, efforts were made to harmonise the following key methodological aspects:

- **System boundaries:** regarding incomplete LCI datasets only covering part of the production routes as considered in this study ([Fig. 2](#)), e.g. solely focusing on mining or refining processes, LCI data relative to omitted upstream or downstream unit operations were integrated to ensure equivalent boundaries in all datasets of a given commodity. Data drawn from other LCI datasets compiled in this study or from the ecoinvent database were used to fill these data gaps. Notably, country/region-specific activities were used when information about the full production route was available, while market activities were considered otherwise;
- **Reference flows:** LCI datasets may be expressed with respect to different reference flows from one dataset to another. For consistency, harmonisation of reference flows was performed at the unit process level, when allowed by available data (i.e. mass balance data) in the original LCA studies to express LCI data of each unit operation with respect to 1 kg of output product;
- **Unit processes nomenclature:** to develop a harmonised nomenclature of unit processes across all datasets, each unit operation as modelled in each LCI dataset was associated with one of the four process steps of the classification as defined in this study ([Fig. 2](#)). It may, however, be noted that some datasets were provided considering aggregated unit processes (e.g. from mining to refining);
- **LCI modelling approach:** common rules were set and applied to all datasets regarding allocation approaches (in case of multi-outputs LCI datasets; see [sub-section 2.2.2](#)), end-of-life modelling (regarding secondary production routes; see [sub-section 2.2.3](#)) and background system modelling (see [sub-section 2.2.4](#));
- **Datasets format:** all LCI datasets are ultimately provided in two different formats, respectively Brightway- and SimaPro-based. These formats allow direct import of the inventories within both LCA softwares. Moreover, each LCI dataset is presented in a granular and transparent way, with details of all intermediate and elementary flows of each unit operation thus affording flexibility for future adjustments, e.g. regarding background modelling rules. Finally, though all inventories are provided in an allocated format (see [sub-](#)

[section 2.2.2](#)), allocation factors are provided as metadata in each dataset, allowing retracing all unallocated flows.

### 2.2.2. Co- and by-products modelling

Multifunctionality is a common issue in the case of metal and mineral production systems. From an LCA perspective, this calls for specific data processing at the inventory level to generate mono-output LCI datasets. To this end, several approaches are possible with varying hierarchy depending on the situation.

In this study, subdivision was prioritised wherever fully or partially applicable. Economic allocation was then used as a second option to account for metal co-products, and applied considering market prices of metal commodities averaged over 10 years (primarily drawn from [Argus Media \(2024\)](#)), to limit the effect of price volatility over time as recommended by [Santero and Hendry \(2016\)](#), provided that such averages are available (which may not be the case for all commodities). Finally, regarding non-metal co-products (e.g. sulfuric acid), substitution was used if alternative production routes were available. If not, mass allocation was used (see full rationale in SI document n°1).

Importantly, the approach here defined only applies to unallocated LCI datasets. Regarding already-allocated LCI datasets, two situations were encountered:

- Studies for which the applied allocation keys were provided. In these cases, the unallocated LCI dataset was recovered by recalculating the unallocated flows;
- Studies for which, instead, information regarding allocation keys was not available, preventing the application of the multifunctionality-solving approach as defined in this study.

LCI datasets for which allocation could be reversed were prioritised. However, exceptions were made for LCI datasets whose allocation details could not be found, when other selection criteria such as data quality and market relevance were satisfied, in order not to miss any highly relevant production route.

### 2.2.3. End-of-Life modelling

Recycling processes are inherently multifunctional systems as they encompass at least two functions: firstly, the production of a material/product; and secondly, waste management.

Among the existing approaches for modelling end-of-life (EoL) multifunctionality, “the cut-off approach [...] is applied when the second function of the recycled product is not included in the analysis and only the products and processes directly related to the functional unit are responsible for environmental burdens” ([Schrijvers et al., 2016](#)).

Given the scope of this study, which focuses on the production of mineral commodities, the cut-off approach is relevant for application to secondary (i.e. recycling) production routes. This approach implies that no environmental impacts are considered for waste management. The material enters the recycling system free of any burden from its first life cycle, i.e. the recycled material only carries the environmental burden of recycling activity.

This cut-off approach similarly applies to any individual recycled input flow that may enter any unit process of a primary or secondary production route.

### 2.2.4. Background system modelling

The modelling of the background system was based on ecoinvent v3.10, considering the cut-off system model, in line with the defined EoL modelling approach (see [sub-section 2.2.3](#)).

To harmonise the LCI modelling as far as possible, a set of common modelling rules was defined and applied to all selected datasets for developing production route-specific LCI models ([Fig. 3](#)).

Specific rules were notably defined for mapping i) key intermediate exchanges, modelled considering ecoinvent activities (e.g. regarding energy, chemicals, raw materials, and waste disposal), and ii)

elementary exchanges, associated with elementary flows (e.g. water, mineral resource, land use, and emissions to air/water/soil). For several of these exchanges, specific and default options were defined to cover various possibilities depending on the varying level of information provided in each LCI dataset (see details in SI document n°1).

For example, regarding electricity, the specific source was to be modelled if details were available in the LCI dataset (e.g. electricity from diesel generators or from renewable sources). If no specific details were available, the country medium voltage mix was applied. Regarding water, any flow was to be associated with an elementary flow corresponding to the source indicated in the LCI dataset or from unspecified natural origin if no indication was provided in the inventory. If the LCI dataset indicated a water supply from a production/treatment activity, then the correspondingecoinvent activity was to be used (e.g. tap water).

### 2.3. Market modelling: from production route-specific to global LCI models

The final step of this work consisted of developing global LCI models based on the production route-specific LCI models generated for each element under study (Fig. 3). These global LCI models intend to depict the global market of each element by representing global supply mixes.

#### 2.3.1. Market data compilation

In parallel to LCI data, market data were gathered for two main purposes: i) to support the LCI datasets selection by providing information as to the market relevance of each production route (which is considered as one of the key selection criteria; see sub-section 2.1.4); and ii) to provide quantitative information that enables deriving market-representative global LCI models based on production route-specific LCI models.

Accordingly, a large set of market-related data was compiled for each metal and mineral element under study (see data in SI document n°2), from various data sources:

- List of end uses, considering data from the European Commission (EC, 2023b) complemented with SCRREEN raw materials factsheets (SCRREEN, 2023);
- Main commodities associated with each element, considering commodities as defined in the HS nomenclature (World Customs Organization, 2025). Correlations between commodities and end uses were established based on SCRREEN factsheets (SCRREEN, 2023) as well as expert-based assumptions;
- Global annual production per country, at mine stage, considering World Mining Data (WMD, 2023);
- Global annual production per country, at processing stage (i.e. purification and refining), considering global processing data from the European Commission (EC, 2023b) and WMD (WMD, 2023);
- Global EoL recycling input rate (RIR), expressing the share of secondary production from old scraps within the global production of a given element. Data were essentially drawn from Talens Peiro et al. (2018), which mainly builds on UNEP (2011) data, complemented with material system analysis (MSA) data at the European level (Passarini et al., 2018);
- Global co-/by-production patterns, consisting of associations of host/companion elements, e.g. Al/Ga or Zn/Ge. These patterns are based on data from Nassar et al. (2015) complemented with information from BRGM criticality factsheets (Mineralinfo, 2025);
- Market prices of commodities averaged over 10 years (2013–2023). Data were primarily drawn from Argus Media (2024), complemented with other sources when necessary (e.g. as described in Miranda Xicotencatl (2025) for RE). Shorter averages or proxies based on other commodities were used in case of data gaps for a given commodity.

For the sake of consistency, data were drawn from the same sources as far as possible, although additional sources were also used to fill data gaps or correct inconsistencies when identified. This variety of sources from one type of data to another, however, necessarily implies a certain heterogeneity in data regarding aspects such as geographical resolution (i.e. country-level vs global data) and temporal coverage. While this study aims to provide a realistic view of the global market in 2023, the reference years of underlying data may sometimes date back to prior years in the absence of more recent data (e.g. EoL RIR data date back to 2011, production data at processing stage to 2020).

#### 2.3.2. Market shares estimation approach

The development of a global LCI model (also referred to as market dataset) for a given element  $i$  requires attributing a weight, consisting of an estimated “market share”, to each of the  $n$  individual production route-specific LCI datasets (as shown by Eq. 1).

$$LCI_{Market_i} = \sum_{x=1}^n \left( LCI_{PR_{x,i,j}} \times \frac{\%_{PR_{x,i,j}}}{\sum_{x=1}^n \%_{PR_{x,i,j}}} \right) \quad (1)$$

Where:

- $LCI_{Market_i}$  denotes the market LCI dataset of element  $i$ ;
- $LCI_{PR_{x,i,j}}$  the LCI dataset of production route  $x$  associated with element  $i$  in country/area  $j$ ;
- $\%_{PR_{x,i,j}}$  the market share of production route  $x$  associated with element  $i$  in country/area  $j$ .

The production routes, as covered in this study, potentially imply different types of geological deposits, processes, countries/areas of production, and feedstock (i.e. primary or secondary sources), with varying levels of granularity from one LCI dataset to another. Moreover, data availability may also vary from one element to another. In this regard, several cases, as functions of LCI data availability and granularity, were distinguished, which may accordingly translate into different approaches for estimating market shares (see equations below and details in SI document n°1). However, this “estimation approach”, along with the associated existing LCI and market data, may not fully capture the complexity in global supply chains of metal and mineral elements.

#### Case 1: one country-level LCI dataset is available for a given country and element

If a given producing country of a given element is covered by a single LCI dataset representing a widely established process chain for a common type of deposit/secondary feedstock and produced commodity (according to expert-based judgement), the market share associated with this production route may be accounted for by directly considering the total country-level production share, corrected by accounting for the share of global secondary supply (Eq. 2.1 and 2.2). Given that all global LCI models are developed for final purified or refined commodities, country-level production shares are derived based on global production data at processing stage.

Share of primary ( $p$ ) or secondary ( $s$ ) production routes, at country-level ( $j$ ) for a given element  $i$

$$\%_{PR_{x,i,j,p}} = \%_{PC_{i,j}} * (1 - \%_{RIR_{i,j}}) \quad (2.1)$$

$$\%_{PR_{x,i,j,s}} = \%_{PC_{i,j}} * \%_{RIR_{i,j}} \quad (2.2)$$

Where:

- $\%_{PC_{i,j}}$  denotes the **processing country share**, reflecting the contribution from the processing country  $j$  to the global production of the element  $i$ . In the absence of more detailed data, it is assumed that this share applies to both primary and secondary routes. In case a

production route is developed beyond country-level, i.e. at the scale of an area covering multiple countries, then a processing area share may be calculated as a sum of the processing country shares;

- $\%_{RIRi,j}$  the **EoL RIR share**, reflecting the contribution from secondary supply to the global production of the element  $i$ . In the absence of country-specific data ( $j$ ), the global EoL RIR value of element  $i$  is assumed to apply similarly to all producing countries, as a proxy.

Regarding single country-level LCI datasets that represent a marginal process chain at global scale (according to expert-based judgement), the market share is estimated based on the set of equations as described in the following (Eq. 3).

Case 2: several country-level LCI datasets are available for a given country and element

If a given producing country of a given element is covered by several LCI datasets associated with multiple production routes offering a differentiation from material, geological or technological perspectives, the associated market shares may be accounted for by considering the country-level production share along with additional parameters related to material, geology and/or technology. Moreover, some production routes may also offer a finer geographical resolution at sub-national levels, e.g. down to provincial or site-level. The following set of equations (Eq. 3) intends to provide a generic framework for the estimation of market shares in case of multi-dimensional differentiation in production routes associated with a given country and element. This set of equations is defined to be tailored on a case-by-case basis depending on the granularity of each LCI dataset.

- Share of primary ( $p$ ) production routes, at country-level ( $j$ ) for a given element  $i$ , with differentiation at provincial or site-levels

$$\%_{PR_{x,i,j,p}} = \%_{PC_{i,j}} * \%_{Provi,j} * (1 - \%_{RIRi,j}) \quad (3.1.1)$$

$$\%_{PR_{x,i,j,p}} = \%_{PC_{i,j}} * \%_{Sitei,j} * (1 - \%_{RIRi,j}) \quad (3.1.2)$$

- Share of primary ( $p$ ) production routes, at country-level ( $j$ ) for a given element  $i$ , with differentiation of geology and/or commodities

$$\%_{PR_{x,i,j,p}} = \%_{PC_{i,j}} * \%_{Geol,j} * \%_{Comm_{i,j}} * (1 - \%_{RIRi,j}) \quad (3.2)$$

- Share of primary ( $p$ ) production routes, at country-level ( $j$ ) for a given element  $i$ , with differentiation of process and/or commodities

$$\%_{PR_{x,i,j,p}} = \%_{PC_{i,j}} * \%_{Proc_{i,j}} * \%_{Comm_{i,j}} * (1 - \%_{RIRi,j}) \quad (3.3)$$

- Share of secondary ( $s$ ) production routes, at country-level ( $j$ ) for a given element  $i$ , with differentiation of waste streams

$$\%_{PR_{x,i,j,s}} = \%_{PC_{i,j}} * \%_{W_{i,j}} * \%_{RIRi,j} \quad (3.4)$$

Where:

- $\%_{Provi,j}$  and  $\%_{Sitei,j}$  respectively denote the **provincial** and **site-specific share**, reflecting the contribution from the specific province/site to the national production (country  $j$ ) of the element  $i$  (e.g. Salar de Atacama in Chile regarding Li).
- $\%_{Geol,j}$  the **geological share**, reflecting the share of production (potentially at site, national or global scale) from the specific geological deposit (e.g. lateritic or sulfidic Ni ores).

- $\%_{Comm_{i,j}}$  the **commodity share**, reflecting the share of production (potentially at site, national or global scale) under the form of the considered commodity (e.g. NiSO<sub>4</sub>, Ni class 1).
- $\%_{Proc_{i,j}}$  the **process share**, reflecting the share of production (potentially at national or global scale) from the specific process chain or technology (e.g. pyrometallurgy, hydrometallurgy).
- $\%_{W_{i,j}}$  the **waste stream share**, reflecting the share of secondary production from old scraps originating from the specific waste stream (e.g. construction and demolition wastes).

### 3. Results

#### 3.1. Overview of final selection of LCI datasets

The literature search identified a total of 308 different LCA studies related to the 63 metal and mineral elements covered in this study. 130 LCA studies were then selected based on the screening criteria and investigated in detail. 285 LCI datasets were compiled from these studies and analysed, including data quality and representativeness assessment (see details in SI document n°1 and n°3). It is noteworthy that several LCA studies were found to provide several separate LCI datasets covering different elements and production routes. 157 unallocated LCI datasets were eventually considered suitable according to the selection criteria (Fig. 4), including several multi-outputs datasets from which additional datasets specific to co-/by-products were subsequently generated (see sub-section 3.2). Moreover, several of these LCI datasets were found to cover similar production routes, which were ultimately combined to develop original LCI datasets with improved completeness (see sub-section 3.3).

Among the different elements covered in this study, the LCI datasets selection was found to be the largest for Fe, Cu, Au, Li and Al, for which >10 datasets covering various production routes were eventually selected (see SI document n°3). Elements such as B, Co, Ni, Zn and Pb also benefited from a relatively large availability of LCI datasets (from six to 10). Overall, the available data cover 53 of the 63 elements initially targeted, including 27 of the 29 key energy transition elements. Conversely, no suitable LCI datasets were found for elements such as Sn, Ta or Ga (Fig. 6). Moreover, data availability appears scarce for 11 other elements (e.g. Be, Ge or Sb) that were only covered by a single LCI dataset.

Regarding platinum group metals (PGM), two LCI datasets were compiled and selected, covering each PGM excepting Os for which no available data were found. As for RE, 10 LCI datasets were selected, covering 15 RE elements, with exceptions for Sc and Pm that were not reported in any LCI dataset.

#### 3.2. LCI datasets of co-/by-products

Several of the 157 selected LCI datasets reported different co-/by-products among which a total of 25 metal elements was identified (Fig. 5). From these, LCI datasets were specifically developed for 17 metal elements (through implementation of the multifunctionality-solving approach), in line with global co-/by-production patterns, representing a total of 26 additional LCI datasets that were not provided in the initial LCA studies (Fig. 4). These 26 LCI datasets do not account for PGM and RE datasets, which constitute specific joint production patterns for which other datasets per individual PGM and RE elements were subsequently generated (see sub-section 3.3). This selection also includes eight already-allocated datasets for which the unallocated data could not be recovered due to missing information (see SI document n°3).

Co, Se, Ag, In and Pb benefit from the largest coverage as co-/by-products identified in several LCI datasets associated with Ni, Cu or Zn production routes (Fig. 5 and SI document n°3). Notably, some of these 17 elements were exclusively found as companion elements (e.g. Co, Ge, In), while others were found both as host and companion elements (e.g.

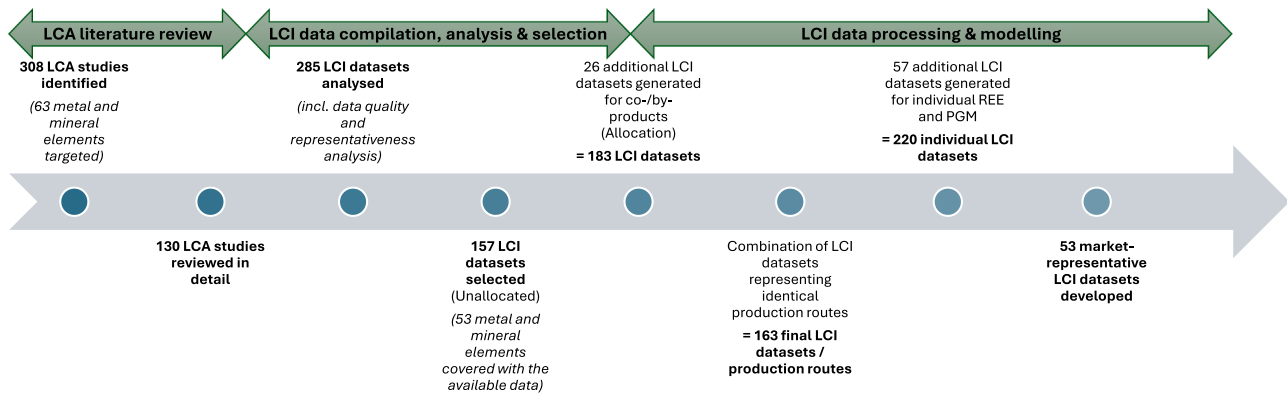


Fig. 4. Overview of the literature review and LCI datasets analysis, selection and generation.

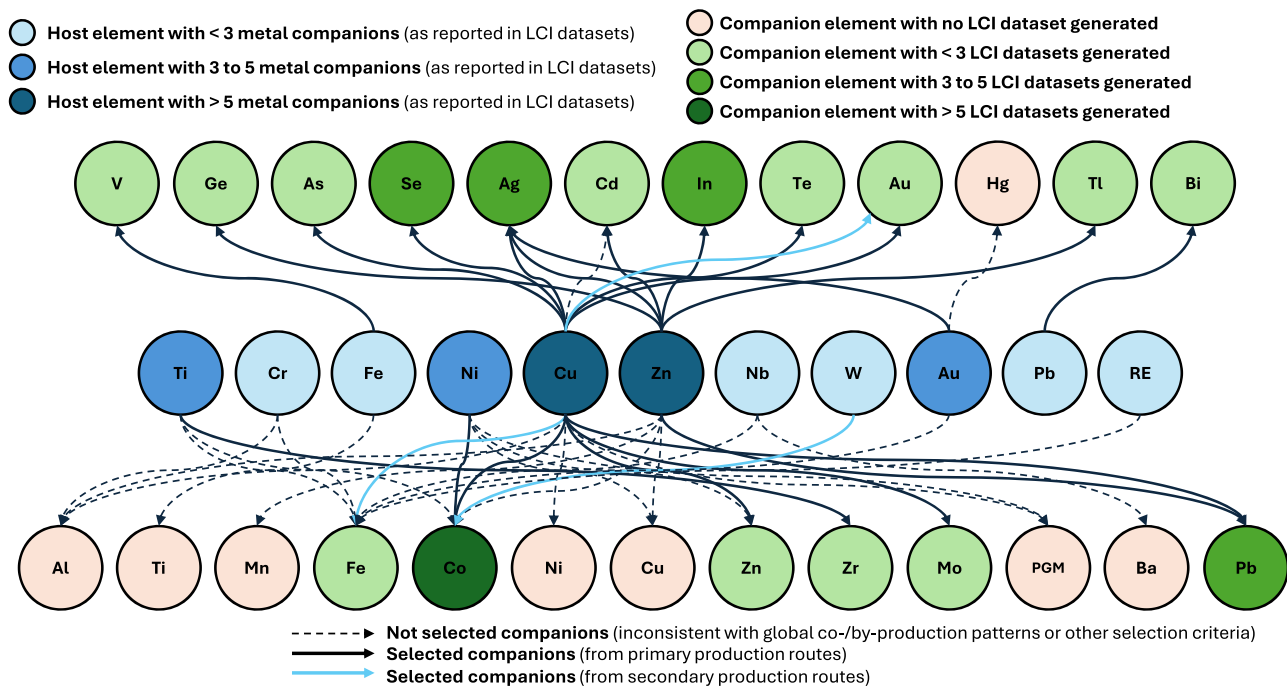


Fig. 5. Overview of co-/by-products identified in LCI datasets, including those selected for LCI generation. Individual PGM and RE are not represented here, as they represent specific joint production patterns.

Au, Pb, Zn). Regarding multi-output LCI datasets associated with recycling routes, the reference products, as defined in the original LCA study, were assumed as hosts, while other recovered products were set as companions. Following this assumption, Fe was considered as companion element of Cu recycling and Co as companion of W recycling. Eight elements (e.g. Ni, Cu, Al) were eventually disregarded as companions due to inconsistency with global co-/by-production patterns or other selection criteria (e.g. market relevance).

On the other hand, 11 metal elements were found as host elements in all compiled LCI datasets. Cu and Zn were the two host elements responsible for the most companion metal elements with respectively 13 and nine co-/by-products, e.g. Se and Te that are exclusively companions of Cu, or Ge and In exclusive companions of Zn. Regarding Cr and Nb, identified as host elements in several LCI datasets, no companion elements were eventually considered, given the limited relevance of these co-/by-production patterns at a global level. Similarly, the production of Fe as companion of RE was not further considered, as it only accounts for a limited contribution to the global Fe production.

### 3.3. Final LCI datasets and production routes coverage

After data processing (including combination of datasets related to identical production routes), 163 final LCI datasets, covering distinct production routes, were ultimately developed. Considering the disaggregation through allocation of RE and PGM datasets to each of their individual elements, 57 additional LCI datasets were generated, thus representing a total of 220 individually allocated LCI datasets (Fig. 4 and Figure 6; datasets available in an open access Zenodo repository, see Lai et al., 2025).

Overall, LCI datasets associated with Cu, Au, Fe, Al, and Ni provide the largest coverage in terms of production routes (at least 10 production routes; Fig. 6 and SI document n°4). Regarding Fe, Cu and Al, the production routes are accompanied by a large geographical differentiation with more than nine producing countries (considering both mining and processing stages) covered in the final LCI datasets. As for other elements, the final LCI datasets overall distinguish fewer than six individual producing countries (e.g. six for Au; five for Ni and Co).

As main producer of many metal and mineral elements, China stands out for being specifically considered in datasets associated with 25



**Table 2**

Examples of material, geological and technological differentiation in LCI datasets (see full table in SI document n°4). \*GFEM = Grind and Flotation Electrolytic Method; LEM = Leaching Electrowinning Method; RKEF = Rotary-Kiln Electric Furnace; HPAL = High-Pressure Acid Leaching.

Element	Commodities distinguished	Geological deposits considered	Process technology covered
Li	Li <sub>2</sub> CO <sub>3</sub> ; LiOH. H <sub>2</sub> O	Salar; Spodumene ore	/
Ti	Ti sponge; TiO <sub>2</sub>	Ilmenite ore; Rutile ore; Magnetite ore	Kroll process; Sulfate process; Chloride process
Co	CoSO <sub>4</sub> ; Co <sub>3</sub> O <sub>4</sub> ; Co (OH) <sub>2</sub> ; Co metal	Cu ore; Ni lateritic ore; Ni sulfidic ore; Hardmetal scraps	/
Ni	Ni class 1; NiO; FeNi; NPI; NiSO <sub>4</sub>	Lateritic ore; Sulfidic ore; Ni scraps	GFEM*; LEM*; Flash smelting; RKEF; Blast furnace smelting; HPAL
RE	RE oxides	Bastnaesite ore; Bastnaesite-monazite ore; Ion-adsorption clays; Monazite ore	/

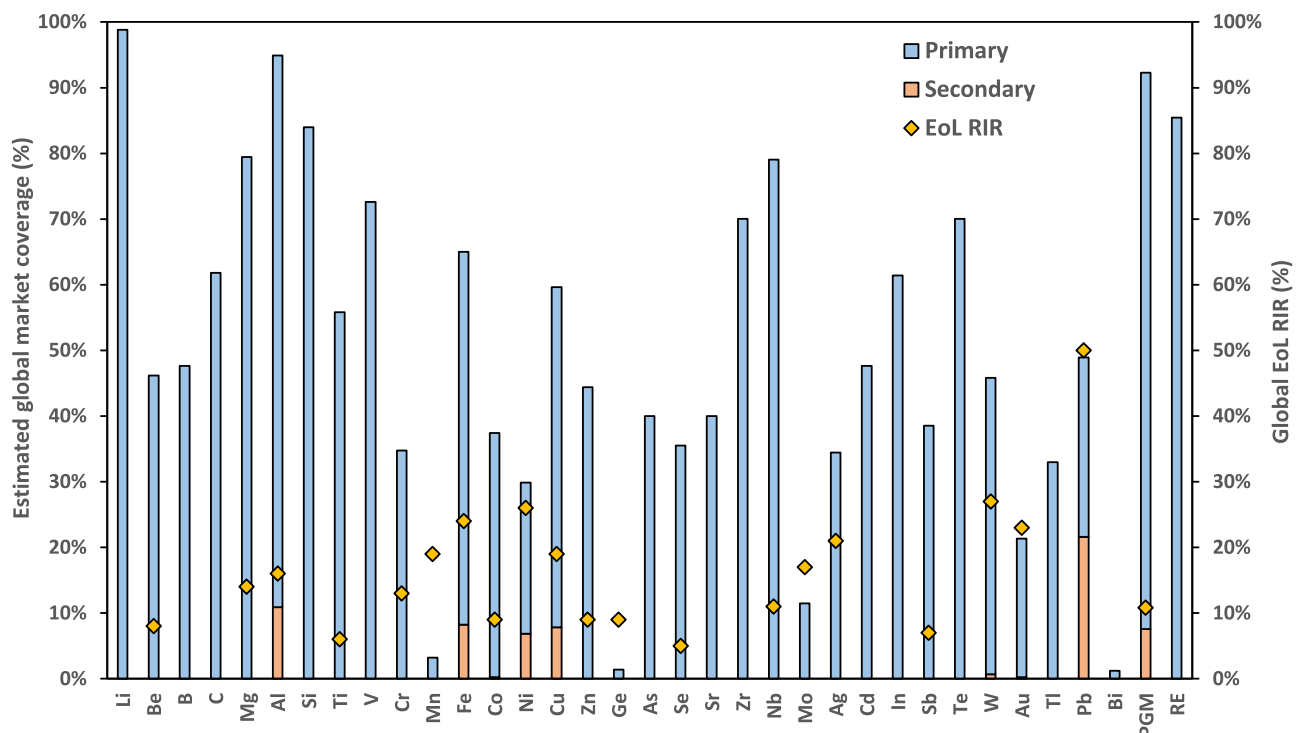
commodities (Table 2). From a geological perspective, various deposits are differentiated for several elements such as RE (four types of deposits, e.g. bastnaesite ore or ion-adsorption clays), Ni (sulfidic and lateritic ores) and Li (brines and spodumene ore). This geological differentiation may also be found in co-/by-products, with different host elements considered for some companions (e.g. Co from Cu or Ni, Ag from Zn, Au or Cu; Fig. 5). Finally, process-level differentiation is offered for several elements, either through broad distinction of processes, i.e. hydro and pyrometallurgy (e.g. as distinguished for Co, Cu or Zn), or finer distinction at a technological level. This technological granularity may notably be found in LCI datasets associated with Ni (six different technologies, e.g. HPAL or RKEF), Cu (four technologies) or Ti (three technologies).

As for secondary production routes, the coverage in the LCI datasets appears relatively limited as recycling is only covered for 11 elements (e.

g. Cu, Al or Fe; Fig. 6), while 25 elements show non-negligible EoL RIR (> 2%; Fig. 8 and SI document n°2). In particular, Cu offers the largest coverage of recycling routes (five), differentiating several types of waste streams in China and Europe: construction and demolition (C&D) wastes, end-of-life vehicles (ELV) and waste from electrical and electronic equipment (WEEE). This differentiation of waste streams is also considered for Fe, which distinguishes recycling from C&D wastes and ELV in China (see SI document n°4). Regarding Al recycling, waste streams are not specified (only referring to Al scraps), but a relatively large geographical coverage is offered (China, North America and Europe are respectively considered). About PGM, global recycling is covered for three elements: Pt, Pd and Rh (one single LCI dataset for each of these three elements).

### 3.4. Global market coverage of LCI models

Based on the 220 individual datasets, a global LCI model (depicting a proxy for the global supply mix) was developed for each of the 53 elements covered by the available data (Fig. 4), applying the approach described in sub-section 2.3.2. Building on country-level global production data for each element (at processing stage) and other market-related information (e.g. the EoL RIR described in sub-section 2.3.1), the market coverage of each global LCI model was estimated. Overall, the results show large variability between all elements, ranging from 1% to 99% (Fig. 8 and SI document n°4). The latter value is reached for Li whose nine LCI datasets cover all main production sites (e.g. Salar de Atacama, Greenbushes mine), which are assumed to be representative of the country-level productions (e.g. Chile, Australia or China). Al, PGM and RE are similarly covered with LCI datasets considered representative for a relatively large share of the global market, respectively estimated to 95%, 92% and 86%. Regarding Al, the 12 LCI datasets cover production routes in nearly all producing areas worldwide (in America, Asia, Europe, etc.), including recycling routes as well. As for RE, the five site-level LCI datasets cover all major RE production sites in China, the US and Australia/Malaysia. Moreover, several elements, such as Mg, Si, Te or Nb, benefit from a substantial estimated global market coverage (> 70%) despite a limited number of available LCI datasets (fewer than five



**Fig. 8.** Estimated market coverage of global LCI models developed for each element under study. Data points representing EoL RIR values < 2% are not displayed.

datasets). This large coverage may be explained by relatively concentrated markets dominated by a few countries (e.g. China for Mg or Brazil for Nb), as well as relatively limited diversity in process chains (i.e. limited geological, technological or material differentiation).

Conversely, very limited market coverage can be observed for Bi and Ge (1 %), whose unique LCI dataset fails to cover the main producing countries (i.e. China or Vietnam). Mn (3 %) and Mo (12 %) also show limited market coverage as the respective LCI datasets cover the main producing countries (i.e. China) but not all main associated commodities (e.g. data regarding Mn alloys or Mo oxides are missing).

Notably, a large availability of LCI datasets does not necessarily translate into a large market coverage. This is particularly the case for Au, for which the 14 LCI datasets only account for 21 % of the global market, given that Au production is scattered across >30 producing countries, with China as the largest producer accounting for 10 % of the global production (WMD, 2023). Regarding Ni, despite 11 LCI datasets covering several of the main producing countries (e.g. Indonesia or China), the global market coverage is only estimated to 30 %, as the available datasets do not comprehensively capture the diversity in global Ni supply chains, which entail various process chains (depending on the Ni deposit types) that lead to various commodities (e.g. Ni Class 1, FeNi, NiSO<sub>4</sub>). This diversity in process chains and commodities also applies to Co (37 % of market coverage), which may be co-produced along with Cu or Ni in numerous forms (e.g. Co metal, CoSO<sub>4</sub>, Co<sub>3</sub>O<sub>4</sub>; see SI document n°4).

Finally, for several elements, the global market coverage is affected by the limited coverage of secondary production routes, as e.g. for Cr, Mn, Mo, Ag whose EoL RIR exceeds 10 % (Talens Peiro et al., 2018; UNEP, 2011; Fig. 8). Regarding elements whose LCI datasets cover secondary production routes, PGM and Al account for the largest coverage of global secondary production (respectively 70 % and 68 % of total secondary production); while this coverage ranges from 26 to 43 % for Ni, Fe, Cu and Pb. Other secondary production routes in LCI datasets of Co, W and Au only account for very limited market shares (< 3 %; Fig. 8 and SI document n°4).

## 4. Discussion

### 4.1. Towards more consistent data for modelling metal and mineral supply chains in LCA

The LCI datasets developed in this study are intended to offer a high-resolution modelling of metal and mineral supply chains in LCA. On the one hand, metals and minerals production may account for a relatively important share of direct environmental impacts in the first life cycle stages of some systems (e.g. in the case of Li-ion batteries; Xu et al., 2022; Šimaitis et al., 2023). But at the same time, these materials may also be responsible for important indirect impacts potentially arising in other life cycle stages, e.g. due to energy production that may rely on metals-intensive technologies (Carrara et al., 2023). It is, therefore, key to further improve the modelling of metal and mineral supply chains not only at the foreground but also background LCI level.

While background data are usually drawn from LCI databases, the coverage of metal and mineral commodities may reveal gaps in these databases. For example, the Environmental Footprint (EF) database (in its 3.1 version), as developed by the European Commission, offers a relatively limited choice of LCI datasets related to metals and minerals as highlighted by BRGM/CEA (2023). Regarding theecoinvent database (in its 3.10 version), a large coverage of metals and minerals is offered, but with a relatively limited granularity for some elements, i.e. with limited differentiation of production routes. For instance, regarding several elements, the LCI datasets as available in the database may fail to distinguish some of the main producing countries (e.g. Indonesia for Ni, Congo for Co, Argentina for Li) as well as the main commodities (e.g. NPI for Ni, V<sub>2</sub>O<sub>5</sub> for V).

In this regard, the LCI datasets developed in this study may offer

perspectives for supporting the development and improvement of existing LCI databases. These LCI datasets were notably developed to ensure transparency and flexibility, which ultimately offers adaptability to comply with methodological and formatting requirements of any LCI database (or any LCA practitioner). This adaptability is also particularly essential in a context where different methodological guidelines for calculating the carbon/environmental footprint have been developed at sectoral level over the past years, specific to metals (e.g. for Li or Co; International Lithium Association, 2024; Cobalt Institute, 2023) or downstream sectors (e.g. for the automotive sector; Catena-X, 2024; EC, 2023a). These guidelines call for modelling raw materials supply with either primary or secondary LCI data such as those developed in this study, provided that the latter comply with the defined methodological requirements.

### 4.2. A need for additional LCI data development and improvement

#### 4.2.1. Main data gaps to address

Several of the 63 elements considered in this study showed a total absence (e.g. Sn, Ta, Ga) or limited availability (e.g. a single dataset for Ge, Sb, Bi) of LCI data in the literature. Moreover, for several other elements, the global market coverage offered by LCI datasets was estimated to be relatively low (e.g. Mn, Ni, Mo). Finally, at the level of individual production route-specific LCI dataset, the quality and representativeness of specific input or output flows may also raise issues. Further data development, therefore, remains necessary to improve data availability (especially regarding elements showing absolute data gaps, with no data currently available), quality/representativeness, as well as to extend the global market coverage.

Efforts in data development should first focus on covering the main producing countries associated with each element. China, as a major producer of most metal and mineral elements, remains the key country to focus on, regarding elements such as Sn, Ga or Ge, for which LCI datasets of Chinese production routes are indispensable. However, while China is already quite represented in many datasets, other major producing countries suffer from a limited coverage. This is notably the case for countries such as Russia (e.g. important producer of Ti, Co, Ni, Se), India (e.g. Mn, Zn), Indonesia (e.g. Sn), Vietnam (Sb, Bi), for which the few available LCI datasets do not reflect their relatively large role in the global mining and metal industry (EC, 2023b; WMD, 2023).

Regarding multi-output production routes, a key issue resides in the tracking of all metal co-/by-products resulting from the process chains, for which information may not always be available due to already-allocated LCI datasets as well as limited transparency in the allocation approach. This may consequently hinder the coverage of some elements that are produced as companions (e.g. Ga from Al, Ge from Zn). Transparency and consistency in reporting all information associated with co-/by-products, especially regarding mass balance and allocation keys, are crucial for future developments of LCI datasets for these companion elements.

Finally, another key area of improvement for LCI datasets of metals and minerals relates to secondary production routes (i.e. recycling), where data availability remains limited. While the share of secondary supply is projected to increase in the future, e.g. regarding raw materials for Li-ion batteries such as Li, Ni or Co (Husmann et al., 2025), further development of LCI data for these routes is crucial to fully capture global supply chains of metal and mineral commodities.

#### 4.2.2. Incompleteness and inconsistencies in LCI datasets

LCI datasets developed in this study may show different levels of completeness in terms of input and output flows. While key input flows related to energy, chemical, material or water are generally considered, other types of input and output flows may not be systematically reported in the datasets. Most common missing flows notably include inputs related to land use (occupation and transformation), resource (extraction from the ecosphere) or infrastructure. For example, land use is only

considered in 41 of the 163 LCI datasets (considering the aggregated RE and PGM datasets) developed in this study. Regarding output flows, completeness may sometimes be even more limited than for input flows, as emissions to the environment (e.g. emissions of metal elements to air, water or soil) and waste flows (e.g. tailings disposal) are often partly or completely lacking in the inventories.

Due to this incompleteness, inconsistencies in the LCI datasets may arise. Firstly, the discrepancy in coverage of input and output flows implies that, from a material perspective, mass balance cannot be respected as total outputs do not match inputs. Secondly, inconsistencies may also be observed with respect to water balance. While input flows representing water withdrawal from a given source are generally indicated, output flows may not necessarily be reported in LCI datasets, which may hinder the accounting of actual water consumption (i.e. water loss) e.g. as wastewater or evaporation (Northey et al., 2014).

Incompleteness and inconsistencies at LCI level may ultimately translate into inaccurate impact assessment, e.g. regarding impact categories related to land use, resource use, water scarcity or toxicity. Efforts for addressing these completeness and consistency issues therefore remain crucial for consolidating the LCA of minerals and metals, e.g. through mass balance reconciliation in LCI (Beylot et al., 2021a; Lai and Beylot, 2023), better accounting of water (Northey et al., 2014) and waste flows (Beylot et al., 2022; Rachid et al., 2023) as well as direct emissions from mining and metallurgical activities (Lai et al., 2021a).

#### 4.2.3. Limits in market modelling

The market modelling, as performed in this study, is built on an estimation approach developed to adapt to different levels of granularity in both LCI and market-related data, complemented with several assumptions necessary to fill data gaps in market data. Notably, while the calculation of market shares for each production route was performed considering country-level production shares as a starting point, country-level production statistics were only found at element-level (e.g. Ni), without any breakdown at commodity-level (e.g. Ni class 1, NiSO<sub>4</sub>, FeNi). Similarly, no specific statistics were found regarding geological and technological breakdown or EoL RIR at country-level. Moreover, some of the data used in this study date back to prior to 2015 (e.g. < 2011 data for EoL RIR or < 2015 data for global co-/by-production patterns), which may not be fully representative of 2023 supply chains as considered in this study. Consequently, uncertainty in market shares, as calculated in this study, may be relatively important for some LCI datasets, especially regarding elements for which global supply chains entail a large complexity and diversity in commodities, deposits and technologies (e.g. regarding Ni or Co). Developing more detailed and up-to-date primary and secondary production statistics (with improved commodity-level, geological or technological details), which would enable more robust estimation of market shares, is, therefore, key for future improvement of all global LCI models.

Moreover, another area of improvement of market models resides in the integration of LCI data representativeness in the estimation of market shares. Indeed, the Pedigree approach, as implemented in this study, revealed potential discrepancies in LCI data quality and representativeness (from temporal, geographical and technological perspectives) from one input/output flow to another within the same LCI dataset. In the absence of rating at LCI dataset level, data representativeness was not accounted for in the calculation of market shares, which may potentially result in an additional uncertainty in market shares stemming from limited LCI data representativeness.

Finally, some site-level LCI datasets, assumed to be representative of country-level productions (assuming that the process chains are relatively widespread), may show overestimated market shares, thus resulting in a large total market coverage at the element level (e.g. as for Li or graphite; see SI document n°4). Further improvement of the market coverage also calls for additional LCI development, ideally building on a bottom-up approach starting from individual site-level data to derive representative country- and global-level LCI models, with priority on the

main producing sites and countries (e.g. Russia, Indonesia, Vietnam, which currently suffer from a limited data availability).

#### 4.2.4. Potential data sources for future LCI developments

Future improvement and development of LCI datasets for metal and mineral supply chains requires generating new LCI data. While the generation of representative LCI data should ideally be directly based on plant-level industrial data, access to such primary data may sometimes be limited. As other options, different public sources and tools may be considered as relevant alternatives for generating relatively representative LCI data:

- Company-specific reporting, which includes different types of reports that may be source of relevant data for LCI. Sustainability/environmental reports at company-level and technical reports of mining projects/sites (e.g. NI43-101 reports) constitute potential LCI data sources, as these reports may provide data related to the consumption of energy, chemicals, water or generation of waste and emissions to the environment (see e.g. Northey et al. (2013) and Chordia et al. (2022) for examples of LCI datasets development from company reporting);
- Process modelling and simulation may also show potential for supporting the development of LCI data, as it enables deriving data related to e.g. energy, chemicals or water consumption, by modelling realistic operating conditions of a given process chain (as highlighted by Rachid et al. (2023) and exemplified by Mas-Fons et al. (2024) and Beylot et al. (2021b));
- Remote sensing imagery, using satellites, may constitute a relevant option to accurately account for land use of mining activities (as exemplified by Islam et al. (2020) in the case of Cu-Au-Ag mining or Sun et al. (2025) for Li production), in a context of poor land use accounting in current LCI datasets (as highlighted in sub-section 4.2.2).

## 5. Conclusions

This study offered a comprehensive overview of available LCI data for metal and mineral elements, through a thorough review, compilation and analysis of LCI datasets originating from public LCA sources. Building on this, a total of 220 individual LCI datasets was eventually developed based on a harmonised LCI data processing and modelling approach. These datasets cover various production routes associated with 53 metal and mineral elements (including key energy transition elements), offering a large differentiation from geographical, material (i. e. commodities), geological and technological perspectives. Notably, Cu, Fe, Au, Al and Ni are the elements benefiting from the largest LCI datasets availability and differentiation in covered production routes. The market models developed from these LCI datasets ultimately reveal a varying global market coverage depending on the element, with e.g. Li, Al, PGM or RE showing a large coverage contrary to elements such as Ge or Bi.

These LCI datasets, available in open access (Lai et al., 2025), are intended to offer a high-resolution modelling of metal and mineral supply chains in LCA, which could support more robust impact assessments for these materials (which was out of the scope of this study) but also for downstream systems using them (e.g. energy transition systems). In particular, the level of granularity offered in the datasets enables capturing the key influence of geographical, geological or technological parameters on the environmental impacts of metals and minerals production. A better understanding of these environmental impacts either at production routes or global (supply mix) level is particularly crucial to support sound decision-making as to potential future implementation of decarbonisation and eco-design strategies at product, company, sectoral or policy levels (e.g. Battery Regulation at the EU level), towards mitigation of the environmental footprint.

Developed following a harmonised approach and in transparent,

disaggregated and flexible formats that can be directly imported in some LCA softwares, these LCI datasets are intended to further use in future LCA studies by any LCA practitioner. Their adaptability enables compliance with methodological requirements different from those considered in this study (e.g. regarding multifunctionality). At a larger scale, these datasets may as well support the development and improvement of standard LCI databases, with potential for further complementing the currently available secondary data, which may benefit from the large resolution in the data resulting from this study.

Future LCI data improvement and development remains necessary, as several gaps were identified in this study. Several elements showed an absence or limited availability of LCI data (e.g. Sn, Ga), and limited global market coverage (e.g. Ge, Mn, Mo or Ni). This may imply a limited representativeness in the quantification of their global environmental impacts, which may induce uncertainty in the outcomes of LCA of products and systems that would build on these secondary datasets. This may induce consequences in some regulatory contexts, e.g. in the EU Batteries Regulation that intends to set carbon footprint thresholds for EV batteries. Further development of representative LCI data calls for i) better covering the major countries producing metals and minerals (e.g. China, Russia, Indonesia), ii) comprehensively tracking co-/by-products all along process chains (e.g. Ga, Ge), with improved transparency in the applied multifunctionality-solving approaches, iii) modelling secondary production (recycling) routes, with distinction of possible waste streams and up-to-date recycling statistics. To this end, diverse data sources such as company-specific reporting, process modelling and simulation, as well as remote sensing imagery stand as possible options offering perspectives for future development of representative and up-to-date LCI data. Finally, another key area of improvement resides in improving the overall completeness and consistency of LCI datasets, e.g. regarding direct emissions from mining and metallurgical activities, market modelling, land use, or mass and water balance, so as to avoid any bias in impact assessment (e.g. regarding resource-, land- or water-related impact categories).

#### List of supporting information (SI) documents

- N°1: Additional methodological details and results (PDF file);
- N°2: Set of market-related data for each element under study (Excel file);
- N°3: Full details regarding the literature review and LCI datasets analysis (Excel file);
- N°4: Full details about the production routes covered by the LCI datasets and the market shares calculation, including data and assumptions (Excel file).

#### CRedit authorship contribution statement

**Frédéric Lai:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Project administration, Methodology, Investigation, Data curation, Conceptualization. **Stéphanie Muller:** Writing – review & editing, Methodology, Investigation, Conceptualization. **Audrey Philippe:** Writing – review & editing, Software, Investigation, Data curation. **Robert Istrate:** Writing – review & editing, Software, Investigation, Data curation. **Brenda Miranda Xicotencatl:** Writing – review & editing, Data curation, Investigation. **Afsoon Mansouri Aski:** Writing – review & editing, Investigation. **Aina Mas Fons:** Writing – review & editing, Investigation. **Juliana Segura-Salazar:** Writing – review & editing, Investigation. **Jair Santillán Saldivar:** Writing – review & editing, Investigation. **Alexander Cimprich:** Writing – review & editing, Investigation. **Stephen Northey:** Writing – review & editing, Investigation. **Lígia da Silva Lima:** Writing – review & editing, Investigation. **Lieselot Boone:** Writing – review & editing, Investigation. **Ryosuke Yokoi:** Writing – review & editing, Investigation. **Kamrul Islam:** Writing – review & editing, Investigation. **Ioanna Paschalidou:** Writing – review & editing, Investigation. **Felipe Cerdas:**

Writing – review & editing, Investigation. **Victor Balboa-Espinoza:** Writing – review & editing, Investigation. **Anish Koyampambath:** Writing – review & editing, Investigation. **Diae Hennioui:** Writing – review & editing, Investigation. **Victoire Collignon:** Writing – review & editing, Investigation. **Aurélien Reys:** Writing – review & editing, Investigation. **Gyslain Ngadi Sakatadi:** Writing – review & editing, Investigation. **Jo Dewulf:** Writing – review & editing, Supervision, Methodology. **Bernhard Steubing:** Writing – review & editing, Supervision. **Christoph Helbig:** Writing – review & editing, Supervision. **Gaëtan Lefebvre:** Writing – review & editing, Supervision, Methodology. **Gian Andrea Blengini:** Writing – review & editing, Supervision, Methodology. **Valeria Superti:** Writing – review & editing. **Masaharu Motoshita:** Writing – review & editing, Supervision, Investigation. **Guido Sonnemann:** Writing – review & editing, Supervision. **Kwame Awuah-Offei:** Writing – review & editing, Supervision. **Steven B. Young:** Writing – review & editing, Supervision. **Shinsuke Murakami:** Writing – review & editing, Supervision. **Antoine Beylot:** Writing – review & editing, Supervision, Project administration, Methodology, Conceptualization.

#### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

#### Acknowledgements

The authors of this study acknowledge the financial support from:

- The EIT RawMaterials under the HiQ-LCA (Grant Agreement (GA) n°22039) project (F. Lai, S. Muller, J. Santillán Saldivar, A. Beylot, D. Hennioui, R. Istrate, B. Steubing);
- The European Union (Horizon Europe) under the RAWCLIC (GA n°101183654) project (F. Lai, A. Beylot, D. Hennioui, R. Istrate);
- The European Union (Horizon Europe) under the METALLICO (GA n°101091682) project (G.N. Sakatadi, G.A. Blengini);
- The European Union (Horizon Europe) under the MADITRACE (GA n°101091502) project (B. Miranda Xicotencatl);
- The European Union (Horizon 2020) under the SUSMAGPRO (GA n°821114) project (B. Miranda Xicotencatl);
- The French National Research Agency (ANR) under the PEPR Recyclage – LULABAT (GA n° ANR-22-PERE-0007) project (F. Lai, A. Mas Fons);
- The Queensland Government (Tony Knight and Janelle Kerr) and The University of Queensland (Steven Micklethwaite and Anna Littleboy) through the Sustainable Minerals Institute's Resourcing Decarbonisation Strategic Program (J. Segura-Salazar).

The authors would also like to thank the BRGM experts who provided relevant insights necessary to define and validate some of the data, estimations and assumptions used in this study.

#### Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.resconrec.2025.108709](https://doi.org/10.1016/j.resconrec.2025.108709).

#### Data availability

LCI datasets are accessible in the following Zenodo repository: <https://doi.org/10.5281/zenodo.15075067>

#### References

- Afflerbach, P., Fridgen, G., Keller, R., Rathgeber, A.W., Strobel, F., 2014. The by-product effect on metal markets – New insights to the price behavior of minor metals. *Resour. Policy* 42, 35–44. <https://doi.org/10.1016/j.resourpol.2014.08.003>.
- Argus Media, 2024. Available at <https://www.argusmedia.com/en>.

- Aska, B., Franks, D.M., Stringer, M., Sonter, L.J., 2023. Biodiversity conservation threatened by global mining wastes. *Nat. Sustain.* 7, 23–30. <https://doi.org/10.1038/s41893-023-01251-0>.
- Beylot, A., Ardenete, F., Sala, S., Zampori, L., 2021a. Mineral resource dissipation in life cycle inventories. *Int. J. Life Cycle Assess.* <https://doi.org/10.1007/s11367-021-01875-4>.
- Beylot, A., Bodéan, F., Guezennec, A.-G., Muller, S., 2022. LCA as a support to more sustainable tailings management: critical review, lessons learnt and potential way forward. *Resour. Conserv. Recycl.* 183, 106347. <https://doi.org/10.1016/j.resconrec.2022.106347>.
- Beylot, A., Muller, S., Segura-Salazar, J., Brito-Parada, P., Paneri, A., Yan, X., Lai, F., Roethe, R., Thomas, G., Goettmann, F., Braun, M., Moradi, S., Fitzpatrick, R., Moore, K., Bodin, J., 2021b. Switch on-switch off small-scale mining: environmental performance in a life cycle perspective. *J. Clean. Prod.* 312, 127647. <https://doi.org/10.1016/j.jclepro.2021.127647>.
- BRGM/CEA, 2023. Analysis of the JRC harmonized rules for the calculation of carbon footprint of electric vehicle batteries. Available at <https://liten.cea.fr/cea-tech/liten/english/Pages/Medias/News/Batteries/CEA-and-BRGM-recommendations-to-the-European-regulation-on-the-carbon-footprint-of-batteries.aspx>.
- Carrara, S., Bobba, S., Blagoeva, D., Alves Dias, P., Cavalli, A., Georgitzikis, K., Grohol, M., Itul, A., Kuzov, T., Latunussa, C., Lyons, L., Malano, G., Maury, T., Prior Arce, A., Somers, J., Telsnig, T., Veeh, C., Wittmer, D., Black, C., Pennington, D., Christou, M., 2023. Supply Chain Analysis and Material Demand Forecast in Strategic Technologies and Sectors in the EU – A foresight Study. Publications Office of the European Union, Luxembourg, p. 2023. <https://doi.org/10.2760/386650.JRC132889>.
- Catena-X, 2024. Product carbon footprint rulebook. Available at <https://catenax-ev.github.io/assets/files/CX-NFR-PCF-Rulebook.v.3.0-04874a80a6d27511df06e07ae3049278.pdf>.
- Chordia, I., Wickerts, S., Nordelöf, A., Arvidsson, R., 2022. Life cycle environmental impacts of current and future battery-grade lithium supply from brine and spodumene. *Resour. Conserv. Recycl.* 187, 106634. <https://doi.org/10.1016/j.resconrec.2022.106634>.
- Cobalt Institute, 2023. Determining the global warming potential of cobalt. Available at <https://www.cobaltinstitute.org/sustainability/determining-the-global-warming-potential-of-cobalt/>.
- EC (European Commission), 2024. Regulation (EU) 2024/1252 of the European Parliament and of the Council of 11 April 2024 establishing a framework for ensuring a secure and sustainable supply of critical raw materials and amending Regulations (EU) No 168/2013, (EU) 2018/858, (EU) 2018/1724 and (EU) 2019/1020.
- EC (European Commission), 2023a. Regulation (EU) 2023/1542 of the European Parliament and of the Council of 12 July 2023 concerning batteries and waste batteries, amending Directive 2008/98/EC and Regulation (EU) 2019/1020 and repealing Directive 2006/66/EC.
- EC (European Commission), 2023b. Study on the Critical Raw Materials for the EU 2023 - Final report. Available at <https://ecoinvent.org/>.
- Eltohamy, H., Van Oers, L., Lindholm, J., Raugel, M., Lokesh, K., Baars, J., Husmann, J., Hill, N., Istrate, R., Jose, D., Tegstedt, F., Beylot, A., Menegazzi, P., Guinée, J., Steubing, B., 2024. Review of current practices of life cycle assessment in electric mobility: a first step towards method harmonization. *Sustain. Prod. Consum.* 52, 299–313. <https://doi.org/10.1016/j.spc.2024.10.026>.
- Fiorletta, M., Tomasetta, C., Bonnemaïson, M., Lai, F., 2020a. Impacts environnementaux des activités minières pour quelques matières premières (In French).
- Fiorletta, M., Tomasetta, C., Bonnemaïson, M., Lai, F., 2020b. Environmental impacts of mining activities for some raw materials - Executive summary.
- Guo, J., Li, R., Zhang, R., Qi, J., Li, N., Xu, C., Chiu, A.S.F., Wang, Y., Tanikawa, H., Xu, M., 2025. Shedding light on the shadows: transparency challenge in background life cycle inventory data. *J. Ind. Ecol.* <https://doi.org/10.1111/jiec.70010> n/a.
- Husmann, J., Beylot, A., Ginster, R., Marie, A., Muller, S., Philippe, A., Monfort, D., Blömeke, S., Spengler, T.S., Herrmann, C., 2025. Determining the key drivers of the potential secondary battery raw materials supply from the urban mine in the European Union. *Resour. Conserv. Recycl.* 218, 108246. <https://doi.org/10.1016/j.resconrec.2025.108246>.
- IEA, 2024. Global Critical Minerals Outlook 2024. Available at <https://www.iea.org/reports/global-critical-minerals-outlook-2024>.
- International Lithium Association, (ILiA), 2024. Determining the Product Carbon Footprint of Lithium Products. Available at <https://lithium.org/guidance/>.
- Islam, K., Vilaysouk, X., Murakami, S., 2020. Integrating remote sensing and life cycle assessment to quantify the environmental impacts of copper-silver-gold mining: a case study from Laos. *Resour. Conserv. Recycl.* 154, 104630. <https://doi.org/10.1016/j.resconrec.2019.104630>.
- Istrate, R., Mas-Fons, A., Beylot, A., Northey, S., Vaidya, K., Sonnemann, G., Kleijn, R., Steubing, B., 2024. Decarbonizing lithium-ion battery primary raw materials supply chain. *Joule* 8, 2992–3016. <https://doi.org/10.1016/j.joule.2024.10.003>.
- Kelly, J.C., Wang, M., Dai, Q., Winjobi, O., 2021. Energy, greenhouse gas, and water life cycle analysis of lithium carbonate and lithium hydroxide monohydrate from brine and ore resources and their use in lithium ion battery cathodes and lithium ion batteries. *Resour. Conserv. Recycl.* 174, 105762. <https://doi.org/10.1016/j.resconrec.2021.105762>.
- Lai, F., Beylot, A., 2023. Loss of mineral resource value in LCA: application of the JRC-LCI method to multiple case studies combined with inaccessibility and value-based impact assessment. *Int. J. Life Cycle Assess.* 28, 38–52. <https://doi.org/10.1007/s11367-022-02110-4>.
- Lai, F., Beylot, A., Navarro, R., Schimek, P., Hartlieb, P., Johansson, D., Segarra, P., Amor, C., Villeneuve, J., 2021a. The environmental performance of mining operations: comparison of alternative mining solutions in a life cycle perspective. *J. Clean. Prod.* 315, 128030. <https://doi.org/10.1016/j.jclepro.2021.128030>.
- Lai, F., Laurent, F., Beylot, A., Villeneuve, J., 2021b. Solving multifunctionality in the carbon footprint assessment of primary metals production: comparison of different approaches. *Miner. Eng.* 170, 107053. <https://doi.org/10.1016/j.mineng.2021.107053>.
- Lèbre, E., Sharma, V., Corzo Remigio, A., 2024. Extracting minerals for the energy transition – Local data for global decision making. *J. Clean. Prod.* 474, 143563. <https://doi.org/10.1016/j.jclepro.2024.143563>.
- Liu, Y., Li, H., Huang, S., An, H., Santagata, R., Ulgati, S., 2020. Environmental and economic-related impact assessment of iron and steel production. A call for shared responsibility in global trade. *J. Clean. Prod.* 269, 122239. <https://doi.org/10.1016/j.jclepro.2020.122239>.
- Mas-Fons, A., Horta Arduin, R., Loubet, P., Pereira, T., Parvez, A.M., Sonnemann, G., 2024. Carbon and water footprint of battery-grade lithium from brine and spodumene: a simulation-based LCA. *J. Clean. Prod.* 452, 142108. <https://doi.org/10.1016/j.jclepro.2024.142108>.
- Maus, V., Giljum, S., Da Silva, D.M., Gutschlofer, J., Da Rosa, R.P., Luckeneder, S., Gass, S.L.B., Lieber, M., McCallum, I., 2022. An update on global mining land use. *Sci. Data* 9, 433. <https://doi.org/10.1038/s41597-022-01547-4>.
- Mervine, E.M., Valenta, R.K., Paterson, J.S., Mudd, G.M., Werner, T.T., Nursamsi, I., Sonter, L.J., 2025. Biomass carbon emissions from nickel mining have significant implications for climate action. *Nat. Commun.* 16, 481. <https://doi.org/10.1038/s41467-024-55703-y>.
- Minéralinfo, 2025. Substances critiques et stratégiques (In French). Available at <https://www.mineralinfo.fr/fr/securite-des-approvisionnements-pour-leconomie/substances-critiques-strategiques>.
- Miranda Xicotencat, B., 2025. Compilation of historic prices of rare earth oxides and their co-products. Zenodo, v1. <https://zenodo.org/records/15806631>. </Dataset>.
- Muller, S., Lesage, P., Samson, R., 2016. Giving a scientific basis for uncertainty factors used in global life cycle inventory databases: an algorithm to update factors using new information. *Int. J. Life Cycle Assess.* 21, 1185–1196. <https://doi.org/10.1007/s11367-016-1098-5>.
- Nassar, N.T., Graedel, T.E., Harper, E.M., 2015. By-product metals are technologically essential but have problematic supply. *Sci. Adv.* 1, e1400180. <https://doi.org/10.1126/sciadv.1400180>.
- Northey, S., Haque, N., Mudd, G., 2013. Using sustainability reporting to assess the environmental footprint of copper mining. *J. Clean. Prod.* 40, 118–128. <https://doi.org/10.1016/j.jclepro.2012.09.027>.
- Northey, S.A., Haque, N., Lovel, R., Cooksey, M.A., 2014. Evaluating the application of water footprint methods to primary metal production systems. *Miner. Eng.* 69, 65–80. <https://doi.org/10.1016/j.mineng.2014.07.006>.
- Nuss, P., Eckelman, M.J., 2014. Life cycle assessment of metals: a scientific synthesis. *PLOS ONE* 9, e101298. <https://doi.org/10.1371/journal.pone.0101298>.
- Passarini, F., Ciacci, L., Nuss, P., Manfredi, S., 2018. Material Flow Analysis of Aluminium, Copper, and Iron in the EU-28, EUR 29220 EN. Publications Office of the European Union, Luxembourg. <https://doi.org/10.2760/1079>, 2018, ISBN 978-92-79-85744-7/JRC 111643.
- Rachid, S., Taha, Y., Benzaazoua, M., 2023. Environmental evaluation of metals and minerals production based on a life cycle assessment approach: a systematic review. *Miner. Eng.* 198, 108076. <https://doi.org/10.1016/j.mineng.2023.108076>.
- Sala, S., Amadei, A.M., Beylot, A., Ardenete, F., 2021. The evolution of life cycle assessment in European policies over three decades. *Int. J. Life Cycle Assess.* 26, 2295–2314. <https://doi.org/10.1007/s11367-021-01893-2>.
- Santero, N., Hendry, J., 2016. Harmonization of LCA methodologies for the metal and mining industry. *Int. J. Life Cycle Assess.* 21, 1543–1553. <https://doi.org/10.1007/s11367-015-1022-4>.
- Schenker, V., Oberschelp, C., Pfister, S., 2022. Regionalized life cycle assessment of present and future lithium production for Li-ion batteries. *Resour. Conserv. Recycl.* 187, 106611. <https://doi.org/10.1016/j.resconrec.2022.106611>.
- Schrijvers, D.L., Loubet, P., Sonnemann, G., 2016. Developing a systematic framework for consistent allocation in LCA. *Int. J. Life Cycle Assess.* 21, 976–993. <https://doi.org/10.1007/s11367-016-1063-3>.
- SCRREEN, 2023. SCRREEN raw materials factsheets. Available at <https://screen.eu/crms-2023/>.
- Segura-Salazar, J., Lima, F.M., Tavares, L.M., 2019. Life Cycle Assessment in the minerals industry: current practice, harmonization efforts, and potential improvement through the integration with process simulation. *J. Clean. Prod.* 232, 174–192. <https://doi.org/10.1016/j.jclepro.2019.05.318>.
- Šimaitis, J., Allen, S., Vagg, C., 2023. Are future recycling benefits misleading? Prospective life cycle assessment of lithium-ion batteries. *J. Ind. Ecol.* 27, 1291–1303. <https://doi.org/10.1111/jiec.13413>.
- Sun, X., Giljum, S., Maus, V., Schomberg, A., Zhang, S., You, F., 2025. Robust assessments of lithium mining impacts embodied in global supply chain require spatially explicit analyses. *Environ. Sci. Technol.* 59, 7081–7094. <https://doi.org/10.1021/acs.est.4c12749>.
- Talens Peiro, L., Nuss, P., Mathieux, F., Blengini, G., 2018. Towards Recycling Indicators Based On EU Flows and Raw Materials System Analysis data, EUR 29435 EN. Publications Office of the European Union, Luxembourg. <https://doi.org/10.2760/092885>, 2018, ISBN 978-92-79-97247-8 (online)(online), JRC112720.
- UNEP (United Nations Environment Programme), 2024. Global Resources Outlook 2024: bend the trend – Pathways to a liveable planet as resource use spikes. International Resource Panel. Nairobi. <https://wedocs.unep.org/20.500.11822/44901>.

- Lai et al., 2025. LCI datasets associated with the “Life cycle inventories of global metal and mineral supply chains: a comprehensive data review, analysis and processing” article. Zenodo. <https://doi.org/10.5281/zenodo.15075067>.
- UNEP (United Nations Environment Programme), 2011. Recycling Rates of Metals - A Status Report, A Report of the Working Group on the Global Metal Flows to the International Resource Panel.
- USGS, 2025. Mineral commodities. Available at <https://www.usgs.gov/science/science-explorer/minerals/mineral-commodities>.
- World Customs Organization, 2025. Harmonized System. Available at <https://www.wcotradetools.org/en/harmonized-system>.
- WMD, 2023. World Mining Data 2023. Available at: [https://www.world-mining-data.info/?World\\_Mining\\_Data\\_PDF-Files](https://www.world-mining-data.info/?World_Mining_Data_PDF-Files).
- Xu, C., Steubing, B., Hu, M., Harpprecht, C., van der Meide, M., Tukker, A., 2022. Future greenhouse gas emissions of automotive lithium-ion battery cell production. Resour. Conserv. Recycl. 187, 106606. <https://doi.org/10.1016/j.resconrec.2022.106606>.