THESIS FOR THE DEGREE OF LICENTIATE OF ENGINEERING

Mapping global value chains using customs data – the case of energy storage technologies

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CHALMERS UNIVERSITY OF TECHNOLOGY

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Abstract

This thesis examines global value chains for energy storage technologies by addressing three research questions that focus on different parts of the chain: (i) the diffusion of end-use technologies, (ii) the supply of intermediate components, and (iii) the origin of raw material supply.

First, an indicator is developed to quantify the diffusion of energy storage technologies based on the temporal flexibility they provide, with the aim of enabling cross-country comparisons of ESS diffusion. Due to data limitations, the indicator was initially applied to a small sample of regions. The results indicate a general expansion of ESS in these regions and reveal technological variations across them.

Second, a methodology is developed to use customs data to map the global diffusion of a focal product and the supply of its components. The methodology is applied to lithium-ion battery (LIB) energy storage systems (ESS) as illustrative case. The results reveal the geographical diffusion of ESS, global patterns of concentration and specialisation of LIB supply, and their transformations over time.

Finally, a methodology is introduced to identify the geographic origin of raw materials using customs data. This methodology is applied to two minerals of importance to LIBs, cobalt and lithium. The results show that, compared to current practice, exemplified by the market processes in the life-cycle assessment database Ecoinvent, the proposed methodology can improve the spatial and temporal resolution of raw materials sourcing and hence the precision of environmental impact assessments.

Some general data problems are identified and addressed in this thesis. Current national databases do not support global monitoring of technological diffusion, which motivates the development of the customs-data-based methodology. However, customs data introduces its own data challenges, including inconsistencies in data reporting, variations between databases and difficulties to distinguish producing and consuming countries from intermediate countries merely involved in re-trading of goods. These issues are identified and mitigated in the proposed methodologies.

Overall, this thesis demonstrates how customs data can be leveraged to quantitatively study global value chains and applies the developed methodologies to energy storage technologies. Designed to be generalisable, these methodologies are transferable to other technologies and expected to provide spatially explicit insights into global value dynamics and enhance the spatial resolution of environmental impact evaluations.

List of Publications

Paper I

Ge, C., Nordelöf, A., & Sandén, B. (2025). Monitoring long-term trends of spatial and temporal flexibility in electricity systems. Energy Conversion and Management: X, 101437. https://doi.org/10.1016/j.ecmx.2025.101437

Paper II

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Paper III

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谢谢你们, 爸爸, 妈妈. 因为有你们, 所以我无畏. 我爱你们.

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1. Introduction

Energy systems are shifting from fossil fuel-based to renewable-based sources. This transition is neither simple nor linear; rather, it unfolds as a multidimensional, co-evolutionary process in which various elements of socio-technical systems develop concurrently and influence one another (Köhler et al., 2019). Technologies, markets, user practices, cultural meanings, infrastructures, policies, industry structures as well as supply and distribution chains evolve together, collectively shaping the direction and pace of change. Within this broad transformation, the value chains of energy storage technologies are also evolving. Energy storage systems (ESS) are required to accommodate the variability of renewable energy generation. As renewable energy deployment expands, a corresponding upscaling of ESS is anticipated, placing additional demands on the value chains that supply these technologies.

This situation highlights the importance of examining global value chains for ESS from both present and future perspectives. Analysing current value chain structures provides insights into how different parts are distributed across regions, revealing dependencies and potential bottlenecks. Foreseeing how these chains may evolve helps identifying emerging risks, such as resource constraints or supply disruptions, as well as opportunities for diversification and resilience.

At the same time, rising geopolitical issues add further complexity. On the one hand, national economies are becoming more interdependent in a globalised economy (Carlsson, 2006), creating networks of trade and production with cross-border flows. On the other hand, concerns around technology sovereignty influence industrial strategies, reshape trade relationships and stress the need for secure access to critical materials (Edler et al., 2023). Recent efforts in some regions to reduce international dependencies through higher import tariffs and industrial policies do not diminish the relevance of this issue but rather highlights its significance. Understanding how these geopolitical pressures interact with the evolution of global value chains is important for supporting the diffusion of energy storage technologies by identifying potential barriers early and informing strategies to mitigate risks.

Against this backdrop, this thesis aims to examine global value chains by focusing on two specific research gaps. First, there is a lack of quantitative tools for mapping global value chains. Existing transition studies have explored the spatial dimensions of socio-technical change, such as how innovation processes interact across scales (Binz & Truffer, 2017) and how regime rationales diffuse globally (Fuenfschilling & Binz, 2018). However, these frameworks mainly address innovation dynamics rather than changes in value chains. When technologies start to diffuse and trigger spatial reconfiguration of value chains, research often relies on qualitative methods such as interviews to trace these changes. These approaches work well in the formative phase, when value chains are relatively small and localised. However, as technologies enter the growth phase and diffuse globally, qualitative methods become impractical due to the wide geographical spread and the high number of actors. In such cases, quantitative tools are required to reveal the spatial structure of global value chains and to track how they evolve over time.

Second, there is a lack of tools for identifying raw material origins. Raw material origins influence environmental impacts of products through variations in energy mixes as well as extraction and processing conditions. These influences accumulate along the chain, as each step involves additional materials and processes. Consequently, identifying raw material origins is particularly critical for life cycle assessment (LCA), which evaluates the entire life cycle rather than isolated stages. However, current LCA databases do not provide sufficient spatial resolution to support this consideration of country of origin in assessments. A widely used database that includes country of origin data is Ecoinvent, in which such country of origin data is represented as “market processes” in market activities (Ruiz, 2023; Wernet et al., 2016). Despite its widespread use, the country of origin data in Ecoinvent suffers from limitations regarding temporal sensitivity, spatial variability, and the non-transparent data derivation methodology.

These two gaps together limit the understanding of global value chains from a spatially explicit perspective and the ability to evaluate the environmental implications of geographically dispersed supply networks.

Given these challenges, a data source capable of describing cross-border product flows with global coverage is required. Customs data offer such a potential and therefore form the basis of the methodologies developed in this thesis. Previous studies have used customs data to support technology diffusion and material flow analysis, such as estimating the installation of solar panels in countries without official statistical agencies (Westerberg, 2020), and tracking critical metal flows (Nansai et al., 2014; Sun et al., 2017, 2018, 2019). These studies, however, have not developed a generalised methodology of leveraging customs data to analyse international value chains. Nor have they systematically addressed the inherent challenges in customs data, including common data inconsistencies, variation across databases and the complex interdependences introduced through re-exports and re-imports.

2. Research questions

To fill the research gaps discussed above, this study aims to develop quantitative methodologies for mapping global value chains. The focus is on depicting different parts of the chains, from end-use diffusion to intermediate component supply and the origin of raw material provision. Based on this aim, three research questions are formulated, each having specific parts of the value chain in focus. An overview of these research questions is presented in Figure 1.

RQ1: How can the spatial and temporal diffusion of ESS, as flexibility enhancing technologies, be quantitatively indicated?

This question concentrates on the end stage of global value chains, where technologies are deployed. It aims to develop a quantitative indicator for monitoring the diffusion of ESS, which in this thesis refers to their deployment. By focusing on this stage, the question targets at providing an initial understanding of how energy system transformation progresses across countries.

As ESS provide temporal flexibility to electricity systems, the constructed indicator assesses their diffusion through the amount of flexibility delivered. The indicator is also designed to enable comparability between countries and between ESS technologies, as such comparisons reveal differences in how ESS are demanded and contribute to different national energy systems.

An additional goal of this question is to examine the availability of public data necessary for constructing and updating diffusion monitoring indicators. This goal paves the way for the next research question which aims to monitor the diffusion of ESS at the global level.

RQ2: How can customs data be used to map the global diffusion of lithium-ion battery ESS and trace the supply of their main component, lithium-ion batteries?

The initial purpose of this question is to address the data limitations identified in Paper I, where publicly available data were found to be insufficient for updating the developed indicator and expanding its applications. Customs data is applied for global-level analysis because it captures cross-border product flows with comprehensive coverage, forming the basis of this research question.

By mapping the global diffusion of LIB-based ESS and the supply of their main component lithium-ion batteries, this question focuses on the global scale and the intermediate stage of value chains.

However, this research question does not necessarily connect countries of final use to countries of origin of raw materials. This stage, which concerns the beginning of value chains, is addressed in the next research question.

RQ 3: How can the country of origin of raw materials be identified using customs data to improve market processes in LCA databases?

This question focuses on the initial stage of global value chains, namely the supply of raw materials. It investigates how customs data can be used to trace the geographic origin of raw materials. The geographical location of suppliers can greatly influence LCA results through variations in energy mixes, extraction and processing technologies, and supply routes, particularly for material intensive products, for instance, lithium-ion batteries.

By identifying the geographic origin of raw materials, this analysis aims to improve the temporal and spatial resolution of market processes in LCA databases and to support more accurate and spatially explicit evaluations of environmental impacts. To illustrate its usefulness, the methodology is applied to cobalt and lithium, two resources of particular importance for lithium-ion batteries.

Overall, these three questions together contribute to the central aim of the thesis: developing a customs data-driven approach for mapping global value chains. We aim to provide an overview of different parts of the chains: the diffusion of end-use technologies, the supply of intermediate components, and the provision of raw materials.

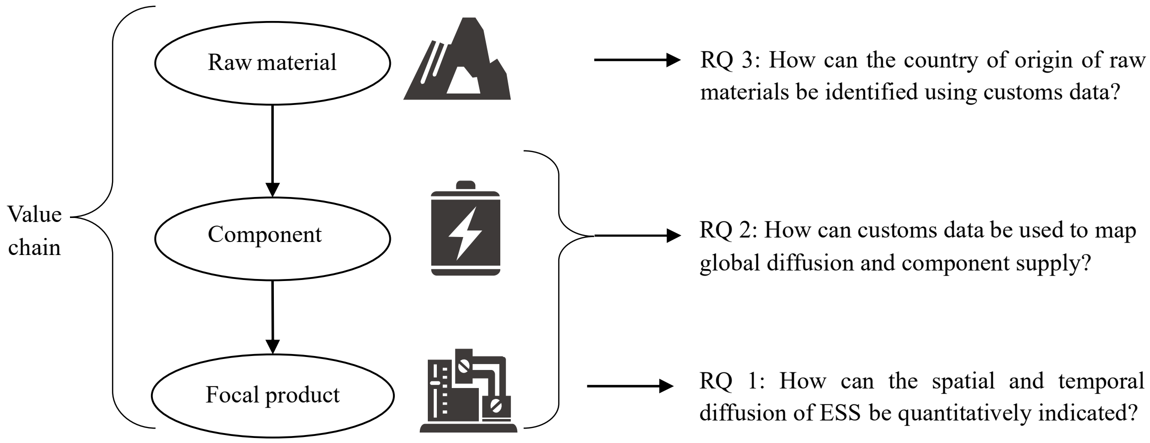


Figure 1. Overview of research questions.

3. Methodology

This section summarises the methodologies used in the papers. Section 3.1 introduces the indicator developed in Paper I for assessing flexibility in electricity systems. Section 3.3 presents the customs data, which serves as the foundation for Paper II and III. Section 3.4 and 3.4 briefly describe the methodologies of these two papers, respectively, both of which combine customs data and production data to identify international product flows.

3.1. Assessing flexibility in electricity systems

To quantify temporal flexibility in electricity systems and thereby assessing the diffusion of ESS across countries, the gross temporal flexibility (GTF) indicator was developed in Paper I. This indicator is also applied in Paper II to investigate the global diffusion of LIB-based ESS. GTF measures how much electricity consumption can be temporally shifted. It is calculated by dividing the total energy storage capacity $E_{i,t}$ (GWh) of country j in a given year t by the average annual power demand $P_{j,t}$ (GW), where $P_{j,t}$ is derived from annual electricity consumption divided by 8760 hours/year, as shown in Equation 3.1.

$$GTF_{j,t} = \frac{1}{P_{j,t}} \sum_{i=1}^{m_t} E_{i,t} \qquad \text{(h)} \qquad \textit{Equation 3.1}$$

This ratio reflects the theoretical duration for which a country's electricity consumption can be postponed if all energy storage facilities are fully charged and connected as a massive energy pool in the country. A larger value of GTF indicates a higher temporal flexibility enabled by ESS.

3.2. Introduction to customs data

Customs data refers to official trade statistics compiled by the United Nations Statistic Division (UNSD) from national authorities of nearly 200 countries or regions. These data are made publicly available through the UN Comtrade database, which is updated on both annual and monthly bases and freely accessible. This database provides essential trade information including product classifications, trading partners, and trade volumes in both monetary and physical terms, enabling the analysis of cross-border flows of materials and products (UNSD, 2024).

To ensure consistency in product classification, UN Comtrade uses the Harmonised Commodity Description and Coding System (HS), a globally standardised framework developed by the World Customs Organization (WCO). Each HS code consists of six digits, structured hierarchically into chapters (2 digits), headings (4 digits), and subheadings (6 digits). While all goods are incorporated at the heading level, not every product is assigned a unique 6-digit code. To allow for more granular classification, countries apply National Tariff Line (NTL) codes by adding two or four digits to the standard HS codes. However, UN Comtrade only includes data up to the 6-digit HS level.

Several complementary databases have been developed to enhance the comprehensiveness, accuracy and specificity of trade data. The Trade Map, created by the International Trade Centre (ITC), extends coverage to approximately 220 countries and territories by incorporating both reported and mirror statistics (ITC, 2025a). It also provides NTL-level data from over 150 national sources. The BACI database, developed by CEPII, focuses on resolving discrepancies between reported imports and exports (Gaulier & Zignago, 2010). These differences often arise due to valuation methods, with imports recorded as CIF (cost, insurance and freight) and exports as FOB (free on board), as well as inconsistencies in product classification and partner attribution. BACI is freely accessible, updated annually, but limited to the six-digit HS level.

3.3. Using customs data to map global value chain

The methodology of mapping global value chains is based on a premise that a country's total output equals its total input. [1] In other words, for a given product, the sum of production (*P*) and import (*M*) equals the sum of its consumption (*C*) and export (*E*)[2], as expressed in Equation 3.2.

$$P + M = C + E \qquad \textit{Equation 3.2}$$

Import (*M*) and export (*E*) data can be obtained from customs data once the relevant HS codes are identified (see section 3.2). Using these data, Equation 3.2 can be applied to individual parts of global value chains to estimate production when consumption is known, or vice versa. By extending this approach to every part of global value chains and linking them together, a global value chain can be mapped.

However, certain difficulties exist in acquiring production and consumption data. Given the vast diversity of products worldwide, there is no comprehensive database that provides global national-level production data of any product, nor consumption data. The UN Industrial Commodity Statistics Database records the production of major industrial commodities by country (UNSD, 2023), but its resolution is limited and is not updated on a regular basis. As a result, the main difficulty in mapping global value chains lies in addressing this lack of production and consumption data at each stage.

To overcome this, the methodology estimates production and consumption at each stage based on data from preceding stages. Specifically, production of a product is inferred from its upstream stage that contributes to its manufacture. Consumption is then calculated using Equation 3.3:

$$C = P + M - E \qquad \textit{Equation 3.3}$$

To connect different parts of value chains together, two additional datasets are required: the *end use distribution,* which indicates the proportion of a product that flows into the next stage, and the *mass fraction*, which reflects the proportion of a component within its subsequent product stage and enables accurate mass conversion. These datasets allow estimation of downstream consumption from upstream flows. For different products, additional data collection for these datasets may be necessary. Common sources include industry reports and consultancy studies.

If no data are available for any components, this methodology traces back to the starting point of value chains, where raw materials are extracted from the natural environment and entry into the technosphere. In such cases, the production at the next stage is estimated using production and trade data of raw materials together with their end-use distribution. Established data sources for mineral production includes BGS (2025) and USGS (2024), with USGS also proving global end-use distribution for many minerals.

Figure 2 is the flowchart of this methodology. It starts with a target product (*n*) and includes three types of data collection: production data, trade data, and additional datasets (end-use distribution and mass

[1] Stocks are not considered, meaning that this equation is balanced on an annual and national basis.
[2] Usually in economics export is expressed with letter *X.* Here it is referred as *E* instead since *X* has been occupied to express total input and output in section 3.4.

fraction). If both production and trade data for product *n* are available, its consumption can be obtained directly. If not, this method involves tracing back the value chain to the component level (level *n*-1) to estimate the consumption of the focal product through the consumption of one of its components. Lastly, if the production data of the component is also unavailable, it can be estimated through the consumption of signal raw material for the component.

Although in this flowchart, the value chain is presented as a three-stage hierarchy: product (*n*), component (*n*−1), and raw material (*n*−2), additional layers of sub-components may be introduced between components and raw materials if data availability permits. Besides, the distinction between products and components is relative and depends on the analytical context. For example, lithium-ion batteries can be final products themselves or components of ESS or electrical vehicles.

A single product may involve numerous components and raw materials, therefore selecting representative ones is essential. This helps streamline data collection and improves both the efficiency and accuracy of the analysis. Detailed formulae and calculations can be found in the methodology section of Paper II.

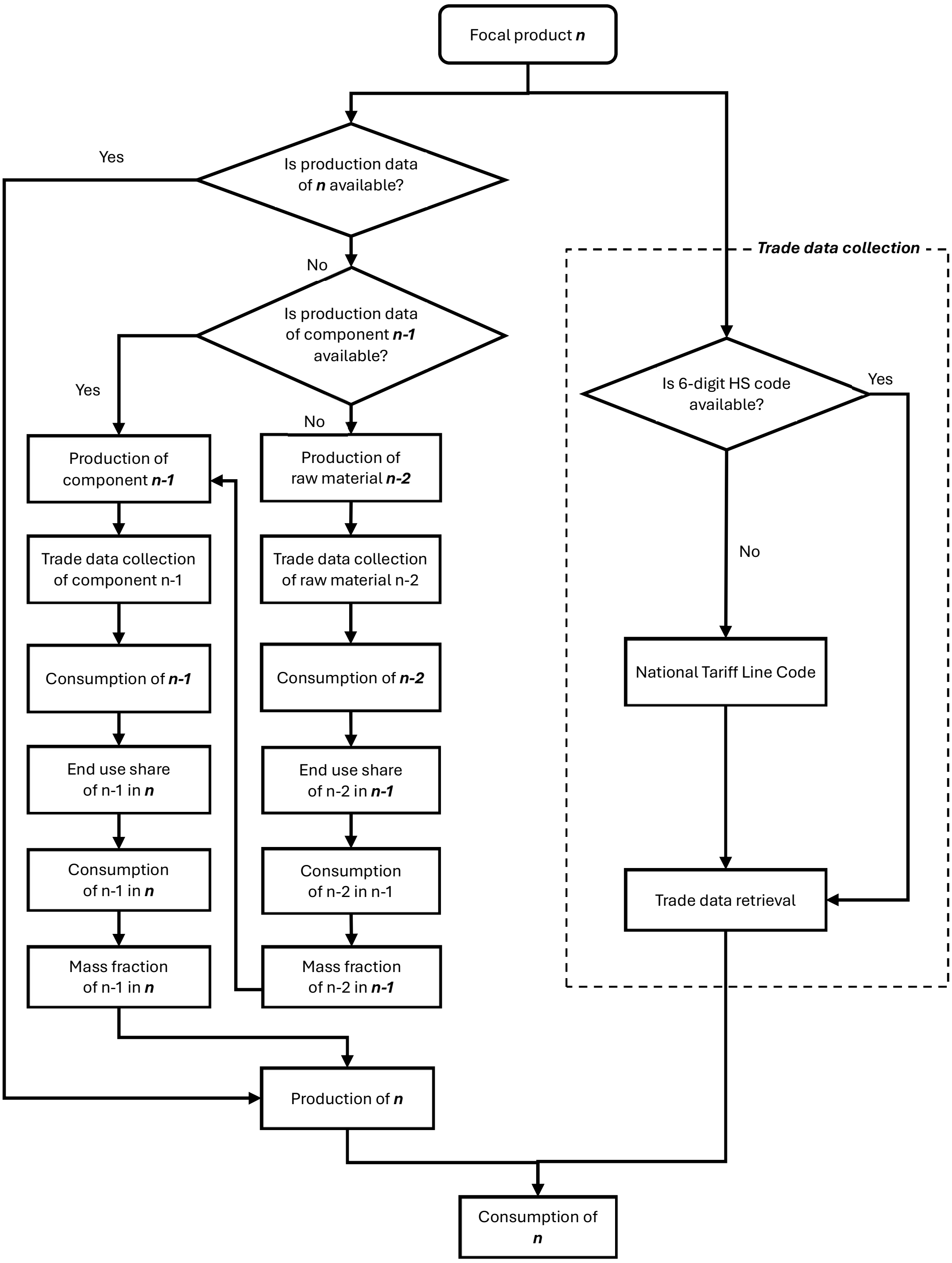


Figure 2. Flowchart for mapping global value chain using customs data.

3.4. Using customs data to identify the country of origin

The methodology for identifying country of origins using customs data is based on import-export (IE) tables, which are constructed also based on the premise of Equation 3.2 that total output equals total input. The structure of an IE table is presented in Table 1 and comprises four elements: the intermediate trade matrix Z (z_{ij}), the final consumption vector C (c_i), the production vector P (p_i), the total output/input vector X (x_i). The intermediate trade matrix describes trade flows between countries, and the flow direction is from rows to columns. The final consumption represents the domestic demand, while production refers the domestic supply. The total input and total output are using the same vector X (x_i) based on the premise that a country's total output equals its total input.

By constructing the IE table in this way, each row shows how a country's total output is distributed between exports to other countries and to its own final consumption. Each column shows how a country's total input is sourced from other countries and supplemented by its own production. For instance, the first row represents that among the total output x_1, country N1 exports z_{12} to country N2, z_{13} to country N3, and consumes d_1 by itself; the first column represents that among the total input x_1, z_{21} is imported from country N2, z_{31} from country N3, and p_1 is from its own production. Diagonal entries, $z_{ij,\ wher\ \ i=j}$, are all zeros, as countries typically neither import from nor export to themselves.[1]

Table 1. Schematic structure of an import-export table

		Country			Final consumption (C)	Total output (X)
		N1	N2	N3		
Country	N1	z_{11}	z_{12}	z_{13}	c_1	x_1
	N2	z_{21}	z_{22}	z_{23}	c_2	x_2
	N3	z_{31}	z_{32}	z_{33}	c_3	x_3
Production (P)		p_1	p_1	p_1		
Total input (X)		x_1	x_2	x_3		

Based on the premises that total output (export plus consumption) equals total input (import plus production), we get:

$$X_i = \sum_{j=1}^{n} Z_{ij} + C_i = \sum_{i=1}^{n} Z_{ij} + P_i \qquad \textit{Equation 3.4}$$

Before used in the calculation of country specific market processes, IE tables need to be normalised first. The resulting normalised matrix, A, is called the trade coefficient matrix. It is constructed by dividing each import to a country by that country's total output, as shown in Equation 3.5. This matrix represents how much input each country requires from other countries to produce one unit of output.

$$a_{ij} = \frac{Z_{ij}}{X_j} \qquad \textit{Equation 3.5}$$

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots \\ a_{21} & a_{22} & \cdots \\ \vdots & \vdots & \ddots \end{bmatrix} = \begin{bmatrix} \frac{Z_{11}}{X_1} & \frac{Z_{12}}{X_2} & \cdots \\ \frac{Z_{21}}{X_1} & \frac{Z_{22}}{X_2} & \cdots \\ \vdots & \vdots & \ddots \end{bmatrix} \qquad \textit{Equation 3.6}$$

[1] China is an importing partner of China because goods routed through Hong Kong are re-imported as inward processing materials to benefit from the duty exemption for processing trade (ITC, 2025b)

Each country's production is also normalised with respect to its total output, as shown in Equation 3.7. The diagonal operator is applied to express this relationship in matrix form. The resulting normalised matrix, $\hat{P}$ (P_{hat}), denotes the *production coefficient matrix*, indicating how much domestic production each country requires to produce one unit of output.

$$\hat{P}_i = \frac{P_i}{X_i} \qquad \textit{Equation 3.7}$$

$$\hat{P} = diag\left(\frac{P}{X}\right) = \begin{bmatrix} \frac{P_1}{X_1} & 0 & \dots \\ 0 & \frac{P_2}{X_2} & \cdots \\ \vdots & \vdots & \ddots \end{bmatrix} \qquad \textit{Equation 3.8}$$

Therefore, for IE tables from the consumption perspective, Equation 3.4 and Equation 3.7 can be rewritten as:

$$X = AX + C \qquad \textit{Equation 3.9}$$

$$P = \hat{P}X \qquad \textit{Equation 3.10}$$

Solving Equation 3.9 gives:

$$X = (I - A)^{-1}C \qquad \textit{Equation 3.11}$$

The matrix $(I - A)^{-1}$ describes how changes in final consumption (*C*) translate into changes in total output requirements (X). Substituting Equation 3.11 into Equation 3.10 results in:

$$P = \hat{P}(I - A)^{-1}C \qquad \textit{Equation 3.12}$$

The matrix $\boldsymbol{\hat{P}(I - A)^{-1}}$ is referred to as the market matrix (*M*), which enables the description of production (*P*) as a function of final consumption (*C*). This matrix captures how a unit increase in final consumption (demand) in each country spreads through the international trade network and finally translates into production requirements in primary supply countries. By accounting for the impacts of recursively structured international trade flows with multiple rounds of reexport and reimport, the market matrix allows for tracing the actual geographic origins of goods.

4. Results

This section presents selective results from Paper I, II and III. Section 4.1 presents the results from Paper I, i.e., the diffusion of ESS in a sample of countries. This diffusion is assessed by quantifying the flexibility these systems provide. Section 4.2 and 4.3 summaries the results of Paper II, i.e., the diffusion of LIB-based ESS in all countries and the trade flows of the main component LIB. Section 4.4 presents the market processes of cobalt and lithium, the two minerals of importance for LIBs. Further details can be found in the respective papers.

4.1. Diffusion of energy storage systems in a sample of countries

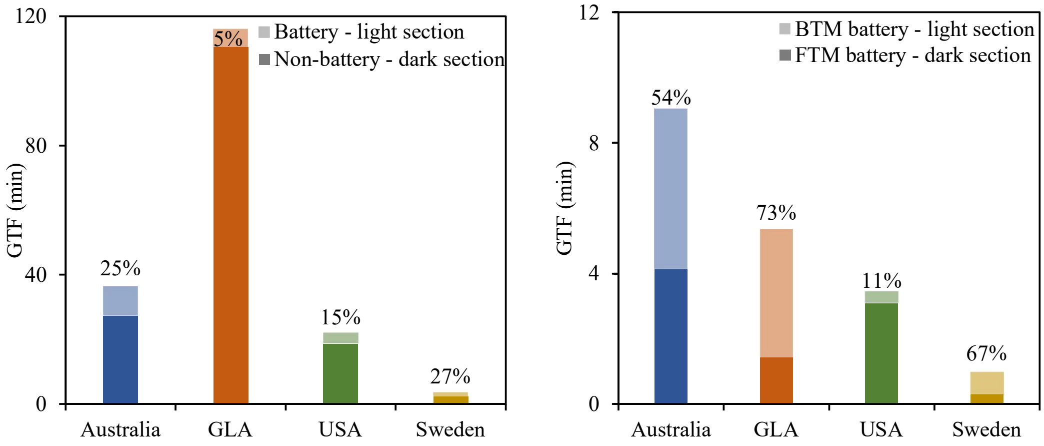
Figure 3 shows an overview of the GTF of four studied regions in 2022. The four studied regions are Australia, Germany-Luxembourg-Austria region (GLA), Sweden and the USA. Figure 3a compares battery and non-battery technologies while Figure 3b compares behind-the-meter (BTM) and front-of-the-meter (FTM) technologies. BTM refers to appliances located on the customer side of the meter while FTM refers to applications on the utility side.

As shown in Figure 3a, GLA has considerably higher temporal flexibility compared to other regions in 2022. Non-battery technologies dominate in this region due to the large energy capacity of older pumped storage hydro (PSH) systems. The GLA has the lowest share of battery technologies with a contribution factor of 5%. Comparatively, the contribution factors of battery technologies in Australia and Sweden are 25% and 27%, respectively.

Among battery technologies, the contribution of BTM and FTM batteries to temporal flexibility differs across countries, as shown in Figure 3b. GLA and Sweden had a relatively large share of temporal flexibility from BTM batteries, at 73% and 67%, respectively. While for USA, only 11% of temporal flexibility comes from BTM batteries. Australia shows a more balanced distribution, with 54% from BTM batteries and 46% from FTM batteries.

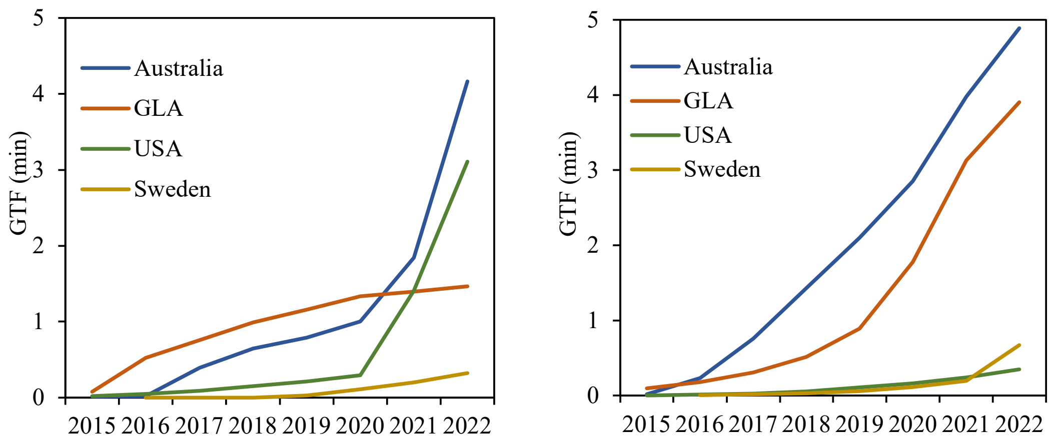
Figure 4 illustrates the historical GTF contributions from FTM and BTM batteries across the four studied regions since 2015. Both FTM and BTM battery have seen increasing deployment in all regions. In Australia, the uptake of both FTM and BTM batteries has been notable, with FTM installations accelerating from 2020 onwards and BTM adoption increasing rapidly between 2015 and 2022. Meanwhile, the USA has seen growth in FTM batteries from 2020, whereas GLA has experienced a fast deployment of BTM batteries from 2015.

These results demonstrate that this indicator can capture the diffusion of ESS across time and space while allowing for the comparison between countries. However, this monitoring of diffusion is conducted only in a sample of countries because of the availability of public data. Current public data is not sufficient to support easy indicator construction. This increases the effort required in data collection and hinder a wider range of monitoring technological diffusion.



(a) Battery and non-battery technologies (b) BTM and FTM battery technologies

Figure 3. Gross temporal flexibility (GTF) of the four regions in 2022. The percentage represents the contribution of batteries in (a) and BTM batteries in (b).



(a) FTM battery (b) BTM battery

Figure 4. Gross temporal flexibility provided by FTM and BTM batteries from 2015 to 2022.

4.2. Diffusion of lithium-ion battery energy storage systems

This section supplements the results in section 4.1 by monitoring diffusion of ESS at the global level. To be more specific, we limit ESS to LIB-based ESS. Figure 5 maps the diffusion of LIB-based ESS across all countries in 2012 and 2022, alongside their total electricity generation. This comparison follows the GTF rationale that higher electricity demand generally requires greater storage capacity.

Overall, cumulative ESS installations increased by 2022 compared to 2012. China, the USA, and Germany exhibit the most installation, with installations growing by nearly two orders of magnitude. The number of countries adopting LIB-based ESS also rises during this period, as indicated by more blue than red dots. However, installation levels vary across countries with similar electricity generation. For instance, Togo and Aruba have the similar electricity generation but their ESS installation varies by nearly a factor of 100, resulting in different degree of temporal flexibility. A comparable contrast is observed between Germany and Saudi Arabia.

In Section 4.1, the GTF was initially calculated for a limited set of countries due to limited availability of national data and the large effort required to collect data for individual countries separately. Using the results shown in Figure 5, it becomes possible to estimate the GTF for all countries. Figure 6 presents the top twenty countries by temporal flexibility indicator in 2022, with Togo, Slovakia and Djibouti ranking highest. This indicator is derived by normalising energy storage capacity against electricity demand (Equation 3.1). Consequently, countries with lower electricity demand can achieve high temporal flexibility with relatively modest ESS installations, whereas countries with larger electricity demand such as China and Germany require substantially greater ESS capacity to reach comparable flexibility levels.

4.3. Supply of lithium-ion batteries

This section maps the supply of lithium-ion batteries as the core component of ESS. Their trade flows in 2012 and 2022 are illustrated in Figure 7. In both years, LIB supply is highly concentrated. In 2012, most exports originated from Asian countries, particularly China, Japan and the Republic of Korea. China, Vietnam and India also receive substantial volumes, reflecting their roles as major original equipment manufacturers of consumer electronics at that time.

By 2022, the number of countries importing LIB has increased, with many new importers being European countries. This suggests a growing diversity of market players and a geographical diffusion of LIB. The entry of these countries is likely linked to the rise of new LIB applications, including electric vehicles and ESS. Meanwhile, a diversification of supply chains can be observed when comparing 2022 to 2012, although China's dominance in the supply of LIB remains. In 2012, many countries relied on only one or two supplying countries, often including China, whereas in 2022 more countries, including Germany and the USA, import LIB from a wider range of countries. This trend may be driven by the increasingly challenging geopolitics and growing attention to supply chain risk management.

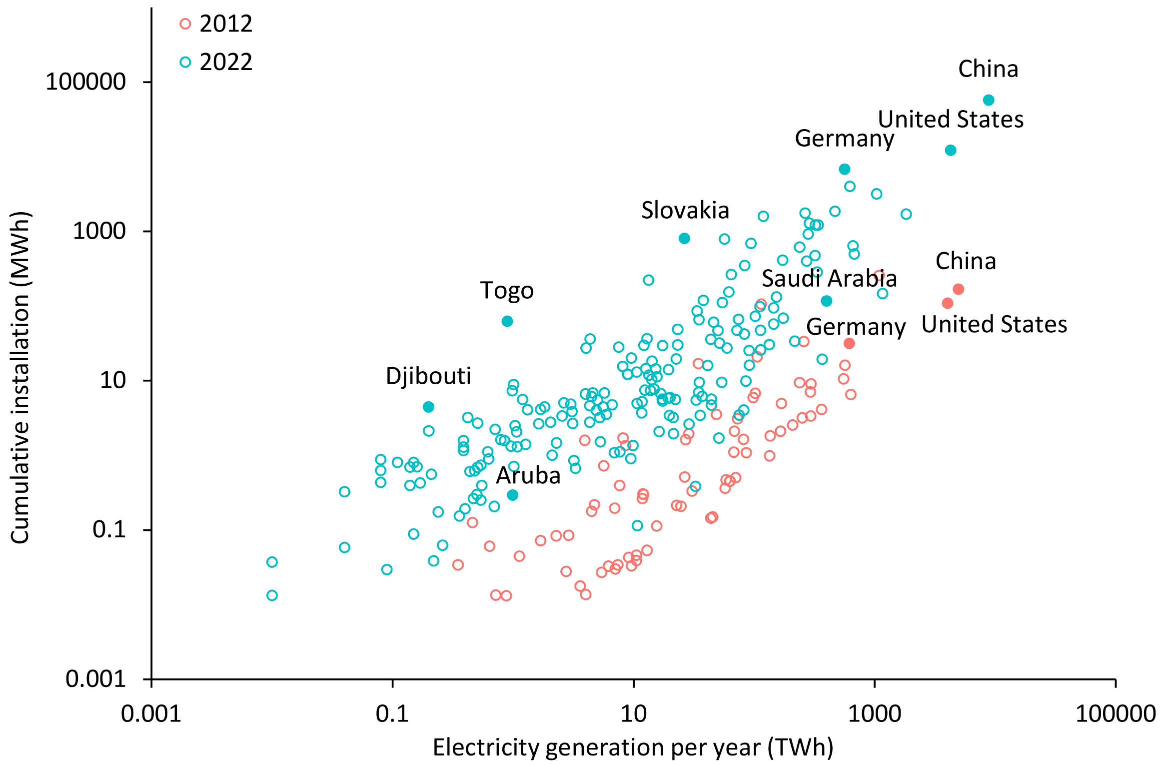


Figure 5. Cumulative installation of lithium-ion battery energy storage systems in 2012 and 2022.

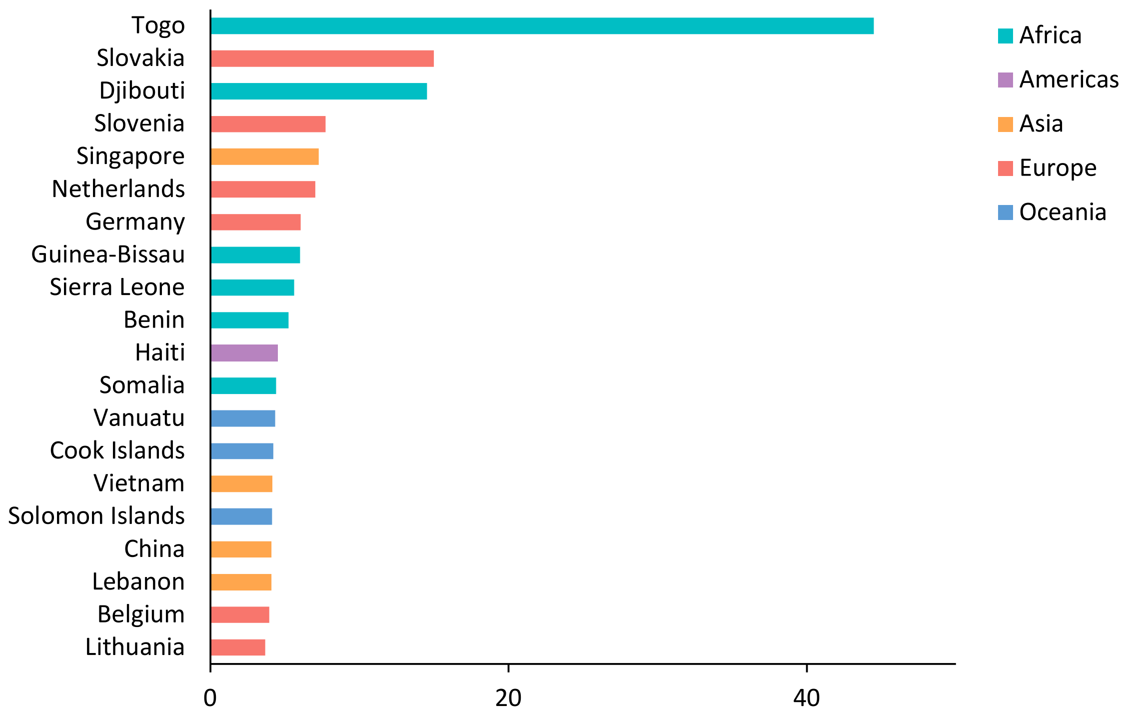
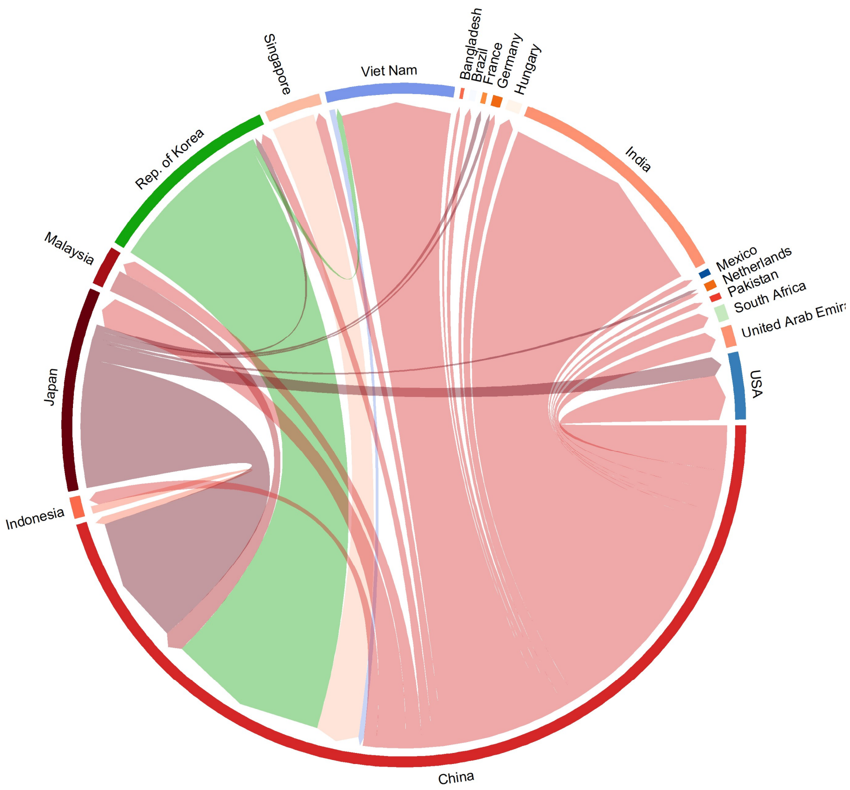
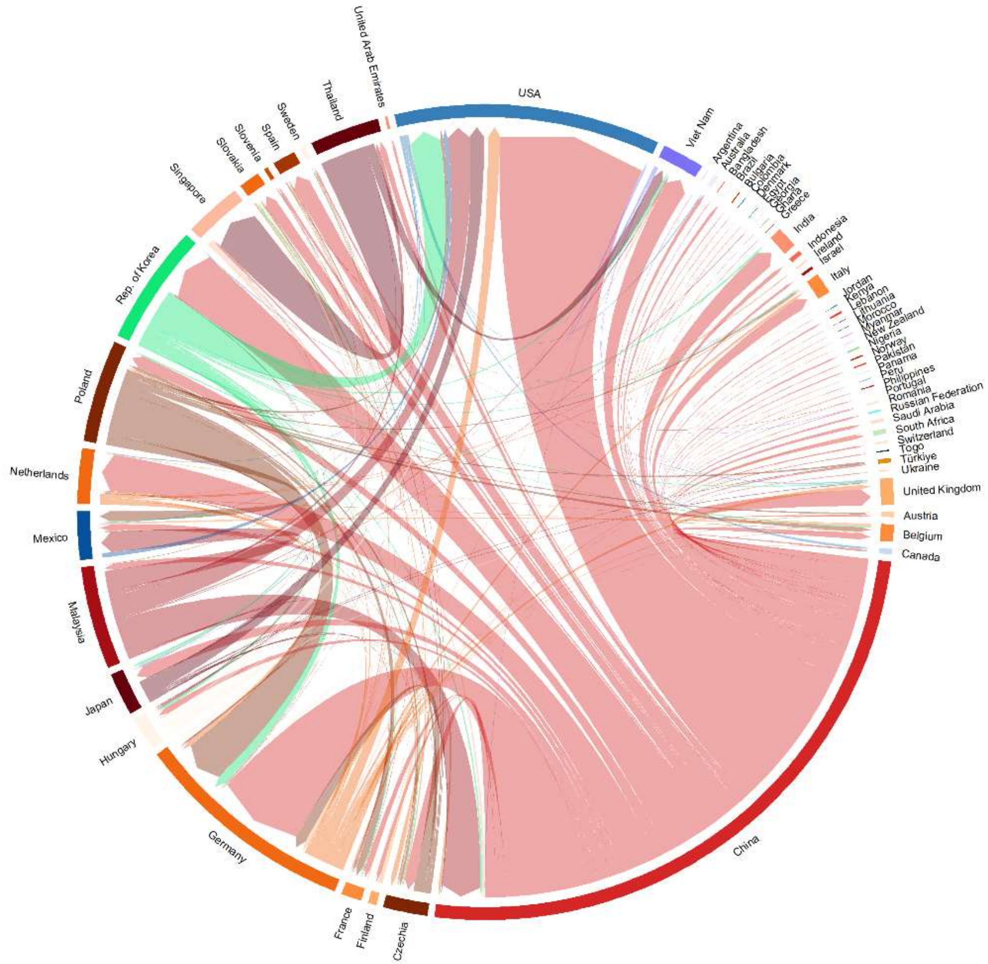


Figure 6. The top 20 countries of gross temporal flexibility in 2022.



(a) Lithium-ion battery trade flows in 2012



(b) Lithium-ion battery trade flows in 2022

Figure 7. Chord diagram of lithium-ion battery trade with volume over 1 tonne (direction means export; width means volume).

4.4. Country of origin of raw materials for lithium-ion batteries

This section maps the beginning of global value chain, the raw material supply. The methodology as presented in section 3.4 is applied to cobalt concentrates and lithium carbonate to trace their original suppliers in global trade. The derived results are compared to the relevant market process data in Ecoinvent.

Market composition of cobalt concentrates and lithium carbonate

Figure 8 presents the market composition of cobalt concentrates in 2022. Countries with effectively identical market compositions (absolute tolerance of 0.5%) are integrated in Group 1-4 in Figure 8b. The reason for this similarity is that the countries in a group share intermediate trading partners. For example, 99.9% of Italy's cobalt imports originate from France, resulting in a similar structure of original cobalt suppliers.

Several globally dominant cobalt producers can be identified through the first "Global" bar in Figure 8a, which represents the global production share. These producers are the Democratic Republic of Congo (DRC), Indonesia, Russia, and Australia, with the DRC accounting for the largest share. While the DRC dominates global supply, most of which goes to China and Japan, two major battery producers, as shown in Group 1. Zambia, though producing moderate volumes, supplies multiple European countries via intermediary trade routes through the United Kingdom and Belgium, as shown in Figure 8a and Groups 2 and 3 of Figure 8b. South Africa also appears as a key supplier for some markets in Group 4.

Some countries are entirely self-sufficient due to large domestic production. These countries are grouped in Group 5. Within this group, several countries, such as USA and Turkey, not only satisfy their own requirements but also export cobalt to other nations. Others, such as Finland and the Philippines, produce exclusively for domestic consumption.

Comparatively, the lithium carbonate market is more concentrated than the cobalt market, as shown in Figure 9, which illustrates present the market composition in 2022. Lithium carbonate production in 2022 is limited to Chile, Argentina and Bolivia, and all other countries source from these three with varying shares. Chile dominates most markets, while Bolivian lithium carbonate appears mainly in Russia, Kyrgyzstan and Kazakhstan. The demand in these three supplier countries is met by their own domestic production.

Market composition changes over time

To illustrate the ability of the proposed methodology to trace market composition changes over time, the cobalt market composition for China and Finland from 1995 to 2022 is present in Figure 10. In the late 1990s and early 2000s, China sourced cobalt from several countries, with shares shifting year by year. From 2004, supply became increasingly concentrated as the DRC share surged, reaching almost 100% by 2006. Thereafter, domestic supply has increased and in 2022, supply was roughly split 50-50 between China and the DRC.

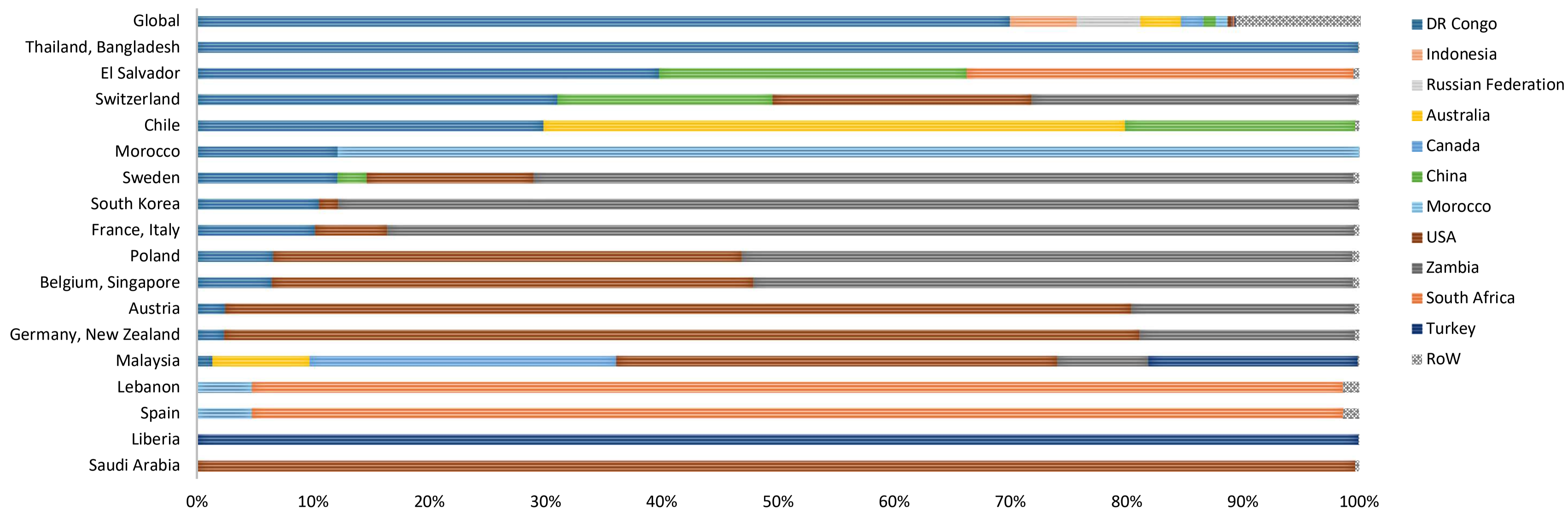
Finnish's cobalt supply also saw several distinct phases. Until the early 2000s, it relied almost entirely on external sources, primarily the DRC, later shifting toward Russia. From 2005, domestic production begun to appear and increased steadily thereafter. By 2012, domestic supply became dominant, and from 2015 Finland relied exclusively on its own production.

Comparison to Ecoinvent

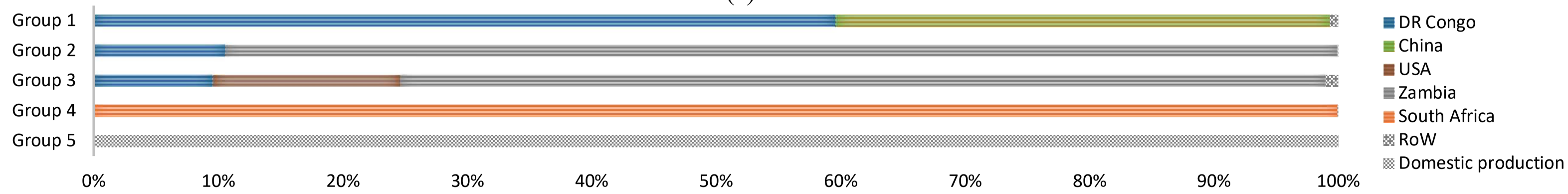
These results are compared to market processes in Ecoinvent (Wernet et al., 2016). Compared to our findings, Ecoinvent's market process data are less temporally and spatially sensitive. The market data for primary cobalt concentrates and lithium carbonate is not available, even at the global level, across all versions. In contrast, our results reveal that cobalt supply patterns can differ considerably between countries. For example, Finland relies solely on domestic cobalt production whereas Argentina depends entirely on cobalt from South Africa. This indicates that our methodology can supplement Ecoinvent in providing higher spatial and temporal resolution of market composition.

While providing less information on the origin of primary supply, Ecoinvent allows for more technological nuances, i.e., the data is sometimes differentiated by extraction technology. For instance, lithium carbonate from brines or spodumene is distinguished in Ecoinvent, but not in our result. In trade data, lithium carbonate from brines and spodumene are treated as the same product.

In addition, Ecoinvent also distinguishes between primary and secondary production whereas the method presented here only accounts for trade of primary minerals. Trade data can sometimes allow for distinguishing primary production from secondary, but not always. This depends on the availability of specific HS codes. For example, recycled aluminium is classified under HS code 760200, which covers aluminium waste and scrap. When such codes exist, secondary production can be identified; otherwise not.



(a)



(b)

Figure 8. Market composition of cobalt concentrates in 2022.[1,2]

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[1] **Group 1**: China, Japan, Mauritius, Pakistan. **Group 2**: Czechia, India, Ireland, Serbia, Slovakia, UK, Zambia. **Group 3**: Bahrain, Bulgaria, Croatia, Cyprus, Denmark, Estonia, Greece, Hungary, Kuwait, Latvia, Lithuania, Luxembourg, Netherlands, Portugal, Romania, Slovenia, United Arab Emirates. **Group 4**: Argentina, Guatemala, Lesotho. **Group 5**: Australia, Canada, DR Congo, Cuba, Finland, Indonesia, Madagascar, New Caledonia, Papua New Guinea, Philippines, Russian Federation, South Africa, Turkey, USA, Viet Nam, Zimbabwe. For countries in Group 5, 99.5% of cobalt comes from domestic production.

[2] RoW refers to all other suppliers within the same country that are not explicitly listed, rather than suppliers from countries not represented in the legend.

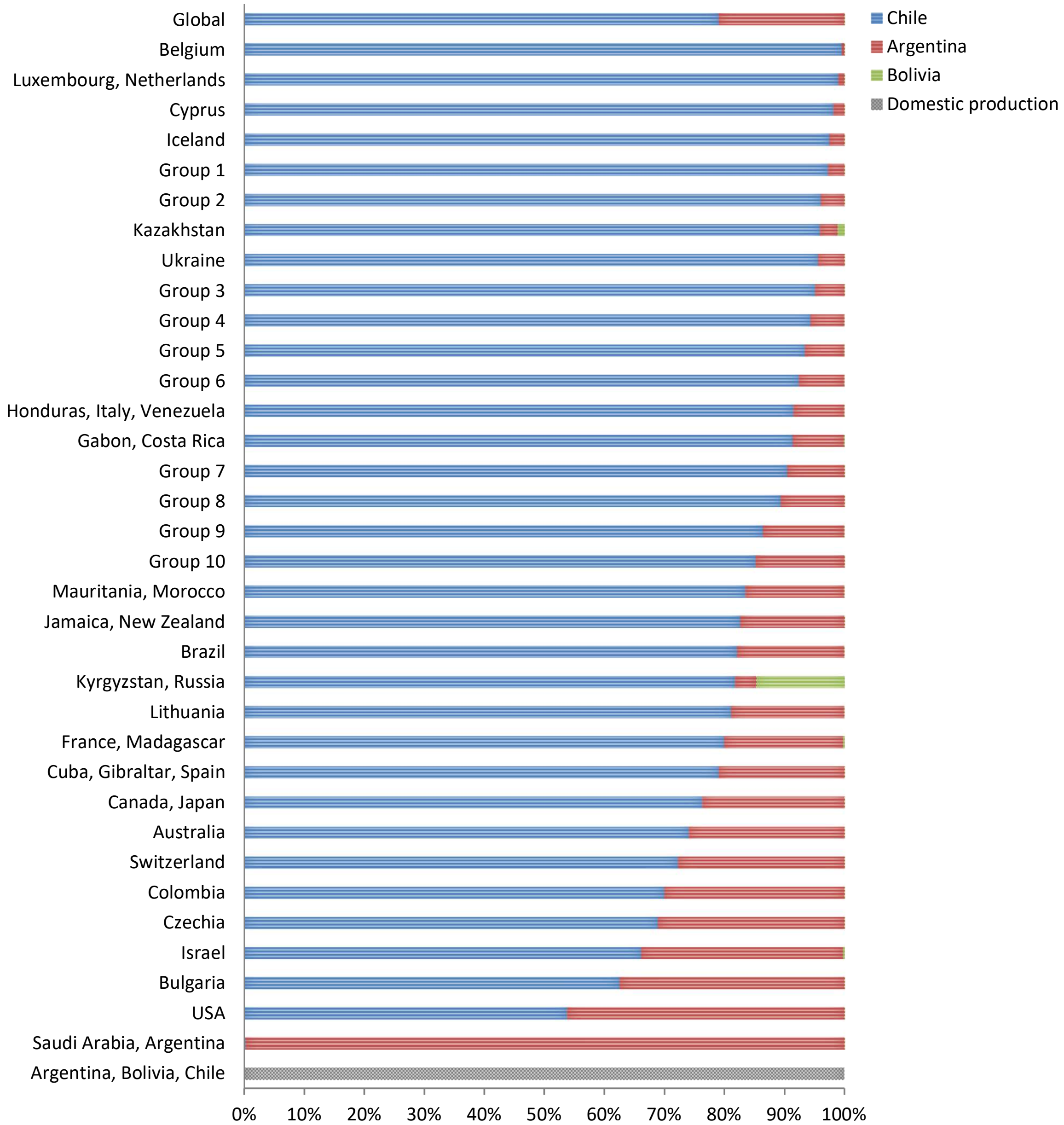
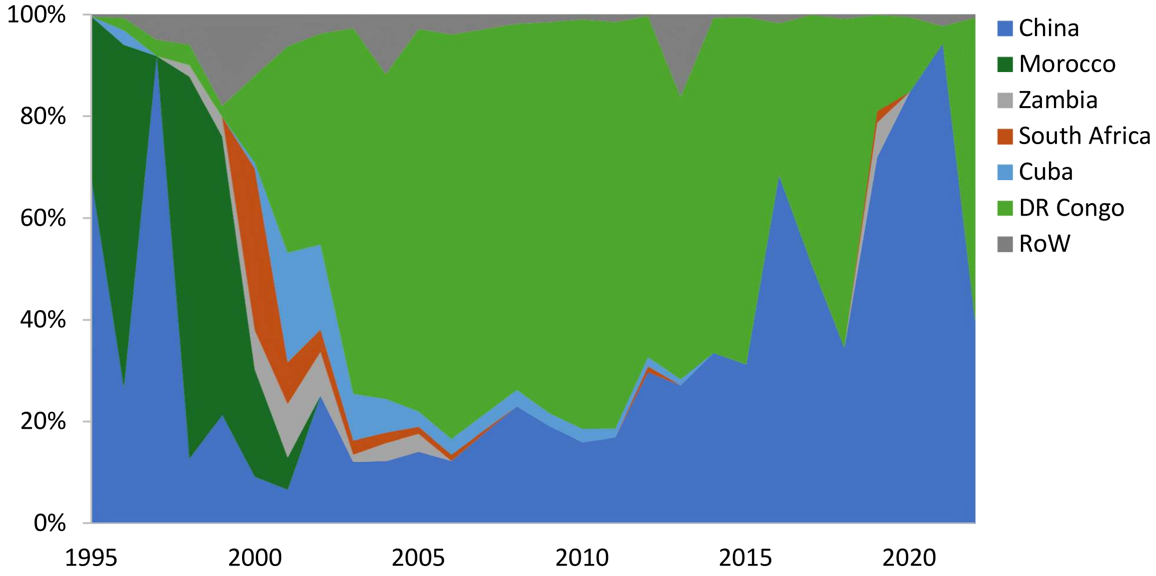
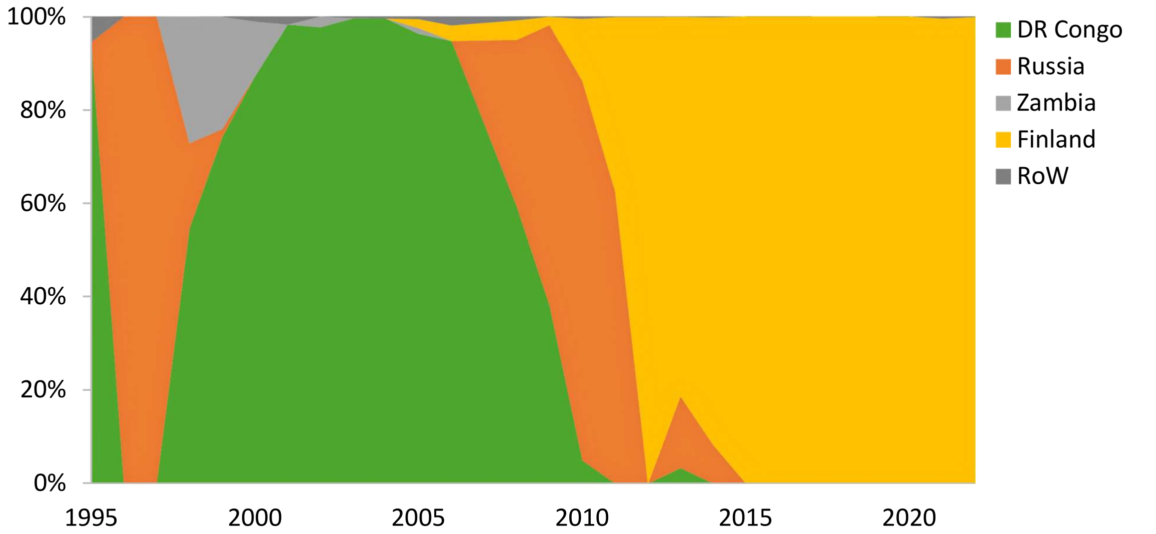


Figure 9. Market composition of lithium carbonates in 2022.[1]

[1] **Group 1**: Hungary, Moldova, Azerbaijan, Thailand, Kenya. **Group 2**: Belarus, Poland, Croatia, Ireland. **Group 3**: Rwanda, United Kingdom, Finland, Kuwait. **Group 4**: Turkey, Paraguay, Montenegro, Serbia, Tanzania, Slovenia. **Group 5**: Denmark, Estonia, Romania, Greece, Germany. **Group 6**: Albania, Mexico, South Korea, Slovakia, Malta, Viet Nam, Iran, Turkmenistan, United Arab Emirates, Malaysia, Philippines. **Group 7**: China, Peru, Tajikistan, Egypt, North Macedonia, Pakistan, Panama, Austria, Qatar, Portugal. **Group 8**: Latvia, Sri Lanka, Bangladesh, Dominican Republic, Ecuador, India, Mauritius, Nepal, Nigeria, Sierra Leone, Uganda, Uruguay, Oman. **Group 9**: Democratic Republic of the Congo, Angola, Botswana, Eswatini, Lesotho, South Africa, Bosnia Herzegovina, Guatemala, Indonesia. **Group 10**: Tunisia, Sweden, Maldives, Singapore, Norway.



(a) China



(b) Finland

Figure 10. Cobalt market composition changes for China and Finland from 1995 to 2022.

5. Discussion

This section discusses the answers to the research questions and outlines directions for future research.

5.1. Research questions revisited

RQ1: How can the spatial and temporal diffusion of ESS, as flexibility enhancing technologies, be quantitatively indicated?

To answer this question, an indicator is developed to quantify temporal flexibility in electricity systems and thereby assessing the diffusion of ESS across countries. The developed indicator is the gross temporal flexibility (GTF). The temporal flexibility indicator, which normalises energy storage capacity against electricity demand, allows for an interpretation of the development of ESS deployment in relation to the different needs of electricity systems. This indicator has been applied to a sample of countries in Paper I, but not all counties, due the data limitation.

Though tested on a small set of countries, the results in section 4.1 reveal the ability of the indicator to capture the diffusion of ESS across space and time. The results also reveal that the diffusion of ESS is uneven, not only in the scale of ESS deployed but also in the direction development. Some countries, such as the USA, rely predominantly on FTM batteries, while others, such as GLA, show a stronger uptake of BTM systems, reflecting different technology preferences.

Additionally, according to our investigation, available public data does not support a quantitatively tracing ESS diffusion at the global level. This challenge is further investigated in RQ2.

RQ2: How can customs data be used to map the global diffusion of lithium-ion battery ESS and trace the supply of their main component, lithium-ion batteries?

This research question is initially developed to supplement the data problem found in answering RQ1 where publicly available data is insufficient for monitoring of global diffusion of ESS. To address this problem, a methodology is developed that uses customs data to map the global diffusion (diffusion in all countries) of a given focal product. Then the methodology is specifically applied to LIB-based ESS.

The approach captures underlying interdependencies by combining cross-border trade flows with production information, enabling systematic analysis of the spatial and temporal evolution the global diffusion of a given focal product. However, the high dependence on customs data also determines that the effectiveness of the approach depends on the availability and granularity of the disclosed customs data, particularly the specificity of HS classifications.

The mapped global diffusion of ESS reveals a global expansion of ESS. The analysis of temporal flexibility provided by diffusion of ESS in all countries further uncovers the relative depth of ESS diffusion across countries. At the global scale, a general trend of increasing ESS capacity is observed, but this is accompanied by a wide spread of flexibility values, indicating that similar levels of capacity growth correspond to markedly different levels of system temporal flexibility.

Additionally, the global supply of the main component LIB over time is also mapped using customs data. The results show that the supply of LIB remains highly concentrated, although diversification trends are emerging in response to rising demand and geopolitical pressures. These findings demonstrate that the proposed methodology can monitor the geographical diffusion of technologies, global patterns of concentration and specialisation, and their transformations over time.

RQ 3: How can the country of origin of raw materials be identified using customs data to improve market processes in LCA databases?

To address this research question, a methodology is developed that combines customs data with production information to trace raw materials back to their initial producers. IE tables are constructed to disentangle the interdependencies between countries of the global trade networks. For the methodology that traces the country of origin, considering the availability of comprehensive production databases and the resolution of HS codes, it is particularly suitable for minerals.

The analysis of cobalt concentrates and lithium carbonate shows that the geographical origins of materials can differ substantially across countries and over time, which, if accounted for, would influence the calculated environmental impact. Compared to market processes in current LCA databases, the proposed method offers higher temporal and spatial resolution, which could enable more accurate environmental assessments.

Overall, answers to these three research questions demonstrate the feasibility and value of leveraging customs data to map different parts of global value chains and thereby tracing their transformation over time and space. Although the two developed methodologies are applied specifically to LIB-based ESS, they are designed to be generalisable and therefore can be adapted to other technologies. The applicability depends on the availability of HS codes and national-level production data.

5.2. Future research

This thesis provides an overview of global value chains for selected energy storage technologies, mapping their current distribution and tracing the origins of several key raw materials. Further research could apply the proposed methods to other empirical cases. There is also a possibility of integrating the proposed way of deriving market processes in LCA databases and software.

Additionally, future studies could explore how value chains may evolve in the future and what implications such changes may have. One direction is to investigate the potential risks that may materialise as ESS value chains scale up or concentrate. Expansion scenarios of energy storage can be expected as global demand for renewable energy grows, while diversification trends have already emerged in response to geopolitical pressures. Future research could model supply requirements under different demand scenarios to detect emerging vulnerabilities and risks.

Such analysis may identify the weakest links in national supply chains, considering not only critical material scarcity but also bottlenecks at higher technological levels, such as mineral refining capacity, specialised components, and manufacturing capabilities. Ownership structures of upstream assets may also be incorporated, as ownership often differs from the country of production (Sun et al., 2024). This would provide a more comprehensive understanding of geopolitical and organisational risks beyond physical material flows.

Another research direction is to embed global value chain transformation of ESS within a broader socio-technical context. Energy storage value chains do not evolve in isolation; they both influence and are shaped by the pace and direction of energy system transitions. Future work could therefore integrate value chain analysis with insights from sustainability transition studies. This would help to understand how shifts in value chains reinforce or constrain the co-evolution of other aspects of socio-technical systems, such as infrastructure, knowledge networks, and skilled labour, and thereby contribute to global innovation systems (Binz & Truffer, 2017).

6. Conclusions

This thesis examines global value chains of energy storage technologies by focusing on different parts of the chain. By addressing the developed three research questions, the thesis contributes to the understanding of the diffusion of end-use technologies, the distribution of component supply, and the origin of raw material supply.

The quantitative analysis on the diffusion of ESS, first in a sample of countries and later in all countries, reveals an overall but uneven upward trend across countries. Differences are observed in both deployment scale and technology preferences, with some countries favouring FTM batteries and others leaning towards BTM solutions. The application of the temporal flexibility indicator reveals that ESS capacity growth does not directly translate into flexibility; smaller electricity systems can achieve higher flexibility with modest storage, whereas larger systems require greater capacity to reach comparable levels.

The analysis of LIB supply indicates that concentration remains pronounced. However, the diversification of trading partners is emerging, especially for European countries, indicating rising concerns about security of supply and geopolitical issues.

The results of tracing country of origin of cobalt and lithium, two minerals of importance for lithium-ion batteries, reveal that raw material sourcing can vary spatially and temporally. Compared to existing market processes in the Ecoinvent database, the developed methodology can provide higher temporal and spatial resolution, thereby supporting more accurate and spatially explicit environmental assessments.

Together, the findings demonstrate the feasibility and value of leveraging customs data to map different parts of global value chains, from deployment to component supply and upstream raw material supply, and its ability to capture the spatial and temporal dynamics in value chain transformation. Although the methodologies are applied primarily to LIB-based ESS and related minerals, they are designed to be generalisable to other technologies, subject to the availability of production data and HS classification granularity.

Future research could apply these methodologies to other energy technologies, or explore how ESS value chains evolve under varying deployment scenarios, identifying potential supply vulnerabilities as systems grow. Additionally, integrating ESS value chain analysis within a broader socio-technical context would provide insights into how changes in ESS value chain structures both influence and are influenced by the pace and direction of the energy transition.

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