The Material Constraints of the Energy and Climate Transition

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Acknowledgments

I would like to express my deepest gratitude to my supervisors, Gang and Ciprian, whose guidance, expertise, and unwavering support have been invaluable throughout the journey of this thesis. Their insightful feedback and encouragement have played a pivotal role in shaping the direction and quality of my research.

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Summary

The transition to a sustainable and carbon-neutral economy is increasingly constrained by the availability and management of critical materials. This research delves into the complexities surrounding these materials, with a focus on their role in green technologies such as electric vehicles and wind turbines. This thesis presents an exploration into the integration of Material Flow Analysis (MFA) with Input-Output (IO) methodologies, a union pivotal to the field of Industrial Ecology (IE) and particularly crucial in the study of critical materials. This integrated approach, forming the backbone of the research, enables a comprehensive examination of the flow of materials and their economic ramifications, essential for understanding and managing the complex dynamics of critical resources in a sustainable manner. Structured around three distinct case studies, the thesis delves into various dimensions of critical materials, with a specific focus on nickel due to its significance in renewable technologies.

The first case study explores the global nickel supply chain through the integration of MFA and the Multi-Regional Input-Output (MRIO) framework, employing Complex Network Analysis (CNA). This methodology provides a comprehensive view of the dynamic trade relationships and strategic roles of different countries, uncovering the complex network that supports the global trade of nickel.

The second case study broadens the analysis to include a detailed supply risk assessment of global nickel products, from mining to manufacturing, across various layers of the supply chain. By leveraging the global nickel network and incorporating a range of socio-economic and environmental indicators, this study offers a sophisticated understanding of the vulnerabilities and geopolitical interdependencies within the nickel supply chain.

In the third case study, the research merges dynamic Material Flow Analysis (dMFA) with MRIO to project future demand for critical materials such as Cobalt, Lithium, Neodymium, and Dysprosium under different low-carbon energy scenarios. The findings from this study are pivotal, highlighting significant supply risks for certain materials and the potential role of recycling in mitigating these risks.

Throughout the thesis, the complexities and challenges inherent in the integration of MFA and IO methodologies are acknowledged, with emphasis on the limitations posed by data dependency and

the intricacies of such analyses. The thesis concludes with strategic recommendations for future research directions, including the potential integration of other methodologies with the MFA-IO framework and improvements in MRIO modeling and data collection methods.

Overall, this thesis makes a significant contribution to the field of IE by employing a multidisciplinary approach to the study of critical materials. It provides essential insights for policymakers and industry leaders, offering strategic guidance for the sustainable management of these materials, which is crucial for advancing the green transition.

Dansk sammenfatning

Omstillingen til en bæredygtig og CO_2-neutral økonomi begrænses i stigende grad af tilgængeligheden og håndteringen af kritiske materialer. Denne forskning dykker ned i kompleksiteten omkring disse materialer med fokus på deres rolle i grønne teknologier som f.eks. elbiler og vindmøller. Denne afhandling præsenterer en udforskning af integrationen af materialestrømsanalyse (MFA) med input-output- (IO) metoder, en forening der er afgørende for feltet 'industriel økologi' (IE) og især afgørende i studiet af kritiske materialer. Denne integrerede tilgang udgør rygraden i forskningen og muliggør en omfattende undersøgelse af materialestrømmene og deres økonomiske konsekvenser. Dette er afgørende for at forstå og håndtere den komplekse dynamik i kritiske ressourcer på en bæredygtig måde. Afhandlingen er struktureret omkring tre forskellige casestudier og dykker ned i forskellige dimensioner af kritiske materialer med særligt fokus på nikkel, grundet dets betydning for vedvarende teknologier.

Det første casestudie undersøger den globale forsyningskæde af nikkel gennem anvendelsen af MFA- og MRIO- (Multi-Regional Input-Output) metoder og ved hjælp af kompleks netværksanalyse (CNA). Denne metode giver et omfattende indblik i de dynamiske handelsrelationer og de forskellige landes strategiske roller. Dertil afdækker metoden det komplekse netværk, der understøtter den globale handel med nikkel.

Det andet casestudie udvider analysen til at omfatte en detaljeret vurdering af forsyningsrisikoen for globale nikkelprodukter, fra minedrift til produktion, på tværs af forskellige lag i forsyningskæden. Ved at udnytte det globale nikkelnetværk og inddrage en række socioøkonomiske og miljømæssige indikatorer, giver denne undersøgelse en sofistikeret forståelse af sårbarhederne og den geopolitiske indbyrdes afhængighed i nikkelforsyningskæden.

I det tredje casestudie kombineres dynamisk materialestrømsanalyse (dMFA) med MRIO for at fremskrive den fremtidige efterspørgsel på kritiske materialer, såsom kobolt, litium, neodym og dysprosium, under forskellige kulstoffattige energiscenarier. Resultaterne fra dette studie er væsentlige, idet de fremhæver betydelige forsyningsrisici for visse materialer og den potentielle rolle, som genanvendelse kan spille for at mindske disse risici.

Gennem hele afhandlingen anerkendes de kompleksiteter og udfordringer, der er forbundet med integrationen af MFA- og IO-metoder. Dette gælder særligt de begrænsninger der er forbundet med dataafhængighed og forviklinger af sådanne analyser. Afhandlingen afsluttes med strategiske anbefalinger til fremtidige retninger indenfor forskningen, herunder den potentielle integration af andre metoder, der inkluderer MFA-IO og forbedringer i MRIO-modellering samt dataindsamlingsmetoder.

Samlet set bidrager denne afhandling væsentligt til IE-feltet idet den anvender en tværfaglig tilgang til studiet af kritiske materialer. Afhandlingen giver vigtige indsigter til politiske beslutningstagere og ledere i industrien og tilbyder strategisk vejledning til bæredygtig forvaltning af kritiske materialer, hvilket er afgørende for at fremme den grønne omstilling.

Preface

This doctoral thesis is an integral component of the ambitious project "ReCAP: Critical Resource Bottlenecks and Constraint Aware Pathways towards 100% Renewable Energy in Denmark." Initiated in June 2020, my research journey unfolded at the SDU Life Cycle Engineering, Institute of Green Technology, at the University of Southern Denmark in Odense.

Under the astute guidance of my main supervisor, Prof. Gang Liu, along with the invaluable assistance of Prof. Cimpan Ciprian, this thesis has been meticulously crafted. I am also deeply indebted to Dr. Burak Sen and Prof. Morten Birkved for their invaluable insights and co-supervision throughout this academic venture. I also want to thank Prof. Daniel Müller from NTNU that hosted me during my exchange of research environments and his help to gather the data that were fundamental to build the cases studies here performed, and Ricardo Ferreira from International Nickel Study Group (INSG) for his help to have access to dataset.

The essence of this thesis is anchored in Denmark's visionary declaration to become the world’s first nation to achieve 100% renewable energy across all sectors by 2050. This transformation, unprecedented in its scale and complexity, necessitates an extensive utilization of critical and precious materials. These materials are pivotal in emerging technologies, such as neodymium-intensive permanent magnets for offshore wind turbines and platinum-based catalysts for fuel cells. However, this reliance also sparks significant concerns about potential resource bottlenecks, considering both geotechnical and geopolitical dimensions.

As I present this work, I am filled with gratitude for the support and insights from my supervisors, peers, and the academic community at the University of Southern Denmark. Their collective wisdom has been instrumental in shaping the research contained within these pages. It is my sincere hope that this thesis contributes meaningfully to our understanding of renewable energy transitions and paves the way for more sustainable and resource-efficient future endeavors.

Research activities

1. May 2022 - **Mines Nancy conference** ”Academia Stands for Green Deal”, Nancy (FR)
   Oral presentation - Demand Forecast of Critical Materials under Low Carbon Energy Scenarios: Integration of Dynamic Material Flow Analysis (dMFA) with Multi-Regional Input-Output Analysis (MRIO)

2. July 2023 - **ISIE conference** ”Transition in a world in turmoil”, Leiden (NL)
   Oral presentation - Assessing Supply Risks and Unveiling Holistic Insights: A Comprehensive Analysis of the Global Nickel Supply Chain

Change of Research Environment

1. Sept 2023 – Oct 2023, **NTNU Trondheim**, hosted by Prof. Daniel Müller

Publications included in the thesis.

This thesis is largely based on the following articles:

I. Simone Della Bella, Marceau Cormery, Burak Sen, Romain Billy, Ciprian Cimpan, Daniel Müller, Gang Liu. Navigating the Nickel Network: Insights from a Ten-Year Global Supply Chain Study (manuscript under preparation)

II. Simone Della Bella, Marceau Cormery, Burak Sen, Romain Billy, Ciprian Cimpan, Daniel Müller, Gang Liu. Integrating MRIO Network Analysis in Assessing Nickel Supply Risks: A Multidimensional Approach (manuscript under preparation)

III. Della Bella, S.; Sen, B.; Cimpan, C.; Rocco, M. V.; Liu, G. Exploring the Impact of Recycling on Demand–Supply Balance of Critical Materials in Green Transition: A Dynamic Multi-Regional Waste Input–Output Analysis. Environ. Sci. Technol. 2023, 57. https://doi.org/10.1021/ACS.EST.2C09676.

List of contents

List of figures

List of tables

List of abbreviations

BC	Betweenness Centrality
BGS	British Geological Survey
BL	Backward Linkage
CBA	Consumption-Based Accounting
CC	Clustering Coefficient
CNA	Complex Network Analysis
Co	Cobalt
COP	Conference of the Parties
dMFA	dynamic Material Flow Analysis
dMRWIO	dynamic Multi Regional Waste Input Output
D^{in}	Degree-in
D^{out}	Degree-out
Dy	Dysprosium
EC	Eigenvector Centrality
EE-IOA	Environmentally Extended Input-Output Analysis
EoL	End-of-Life
EPI	Environmental Performance Index
EVs	Electric Vehicles

FeNi	Ferronickel
GII	Global Innovation Index
HDI	Human Development Index
HHI	Herfindahl–Hirschman Index
IAMs	Integrated Assessment Models
IDR	Import Dependecy Ratio
IE	Industrial Ecology
IEA	International Energy Agency
IOA	Input Output Analysis
IO-AMCs	Input-Output Absorbing Markov Chains
INSG	International Nickle Study Group
JRC	Joint Research Center
LCA	Life Cycle Assessment
LCSA	Life Cycle Sustainability Assessment
Li	Lithium
LiBs	Lithium-ion Betteries
MFA	Material Flow Analysis
MRIO	Multi Regional Input Output
MHP	Mixed Hydroxide Precipitate
MSP	Mixed Sulphide Precipitate
NA	Network Analysis
ND	Network Density
Nd	Neodymium
Ni	Nickel
NPI	Nickel Pig Iron
PIOTs	Physical Input-Output Tables
PMs	Permanent Magnet
REEs	Rare Earth Elements
RoW	Rest of the World
SD	System Dynamics modeling

SD^{in}	Strength Degree-in
SD^{out}	Strength Degree-out
SLCA	Social Life Cycle Assessment
SR	Supply Risk
TEA	Techno-Economic Analysis
UPIOM	Unit Physical Input-Output by Materials
USGS	United States Geological Survey
VA	Value Added
WEO	World Energy Outlook
WGI	World Governance Index
WIO	Waste Input Output
WTs	Wind Turbines

1. Introduction

1.1. The Green Transition

The urgency to shift towards a more sustainable and eco-friendly future is underscored by the mounting effects of climate change, a concern that has risen to the top of the global agenda. The planet has been witnessing increasingly severe environmental events, including catastrophic wildfires, extraordinary floods, intense droughts and powerful storms. These climatic phenomena are not confined to environmental realms alone; they profoundly influence social and economic systems, affecting daily lives, public health and the economic stability of nations worldwide[1–3].

International initiatives, such as those orchestrated under the auspices of the Conference of the Parties (COP), demonstrate a growing consciousness about these pressing issues. Yet, actualizing the ambitious goals of carbon neutrality and sustainable development remains a complex task.

At the COP28 in Dubai, 118 countries pledged to triple renewable energy capacity and double energy efficiency by 2030, marking a significant step as it was the first COP to officially recognize fossil fuels as the main cause of climate change. This progress, building on COP26’s initial mention of fossil fuels, highlighted a global shift in climate policy. However, the "global stocktake" at COP28 revealed a concerning truth: the world is significantly lagging in its efforts to combat climate change. The data indicated that the Paris Agreement’s goal of limiting global warming to 1.5 °C is at serious risk, underscoring the need for more ambitious global climate action.

A central aspect of these discussions is the role of critical materials in enabling the green transition. These materials are essential for developing technologies crucial in combating climate change. Yet, they present challenges, including limited availability and geopolitical dependencies, making them a focal point in sustainable development narratives[4,5].

Decarbonization is essential across various sectors, including energy, transport, and industries. In the energy sector, renewable sources like solar, wind and hydroelectric powers are key. For instance, solar power capacity has grown exponentially, with global installations exceeding 700 GW by 2022. Wind energy, too, has seen a surge, with over 650 GW of capacity installed worldwide[6].

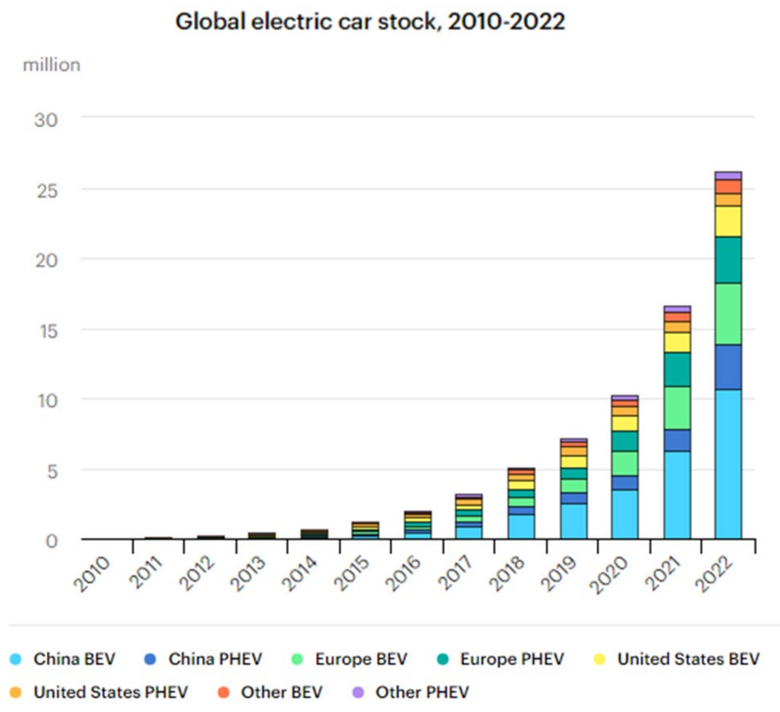

Figure 1: Global electric car stock, 2010-2022 (source: IEA)

The transport sector is witnessing a shift towards electric vehicles (EVs) and sustainable fuels. As shown in Figure 1, EV sales have skyrocketed, with over 10 million units sold globally by 2022, reducing significant carbon emissions[7]. In industries, efforts focus on energy-efficient technologies and transitioning to lower-carbon fuels. For example, in steel manufacturing, new methods like hydrogen-based production are being explored to reduce carbon footprint. The development of green technologies like battery storage, carbon capture and smart grids is pivotal for this transition. Battery technology, especially in the context of EVs and energy storage, is advancing rapidly.

In summary, the transition to a sustainable future is complex and multi-faceted, requiring concerted efforts across sectors and the development of innovative technologies. The role of critical materials and the challenges they present in this transition cannot be overstated. The ongoing global dialogue, as seen in forums like at the COP28, continues to be crucial in navigating these challenges and steering the world towards a more sustainable path.

1.2. Critical materials

The growing awareness of the essential role of critical materials in the development of green technologies marks a significant shift in how these resources are viewed. Elements like rare earths, vital in producing efficient magnets for wind turbines and electric vehicles, and others such as lithium and cobalt, crucial for battery storage systems, have moved beyond their conventional industrial uses. These materials are now seen as key drivers in building a sustainable infrastructure, going beyond their traditional applications and becoming central to the advancement of eco-friendly technologies. This transition is strategically aimed at diminishing the dependency on hydrocarbon fuels while ameliorating anthropogenic environmental impact, a narrative corroborated by a multitude of academic inquiries[4,8–10].

In an unprecedented initiative, the International Energy Agency (IEA) unveiled the *Critical Minerals Market Review 2023*[11], a compendium that underscores the intensifying focus on these pivotal materials by various stakeholders, delineating the interdependence of the green transition on the assured availability and logistical network of certain key substances. Figure 2 encapsulates the anticipated demand dynamics for these materials within the ambit of the IEA's Net Zero Scenarios, prognosticating a scenario wherein the requisition for green technologies will become a significant determinant in the consumption patterns of these already indispensable materials.

As the significance of critical materials in global sustainability and economic strategies becomes more apparent, nations around the globe are initiating measures to ensure the stability and security of their supply chains, thereby mitigating potential vulnerabilities. The European Union, recognizing the centrality of these materials, has enacted the "*Critical Raw Materials Act*", which systematically categorizes these resources based on their importance to the Union's economic fortitude and its sustainability objectives. This legislative action, as explicated by the European Commission, serves as a blueprint for securing the supply of these essential materials.

Concurrently, the United States has adopted a Federal Strategy with a dual focus: to guarantee a steadfast supply of critical minerals and to encourage the increase of domestic production capacities. This strategic direction is not just about reducing the country's dependence on international sources but also about fostering self-sufficiency, thereby enhancing national security and economic independence.

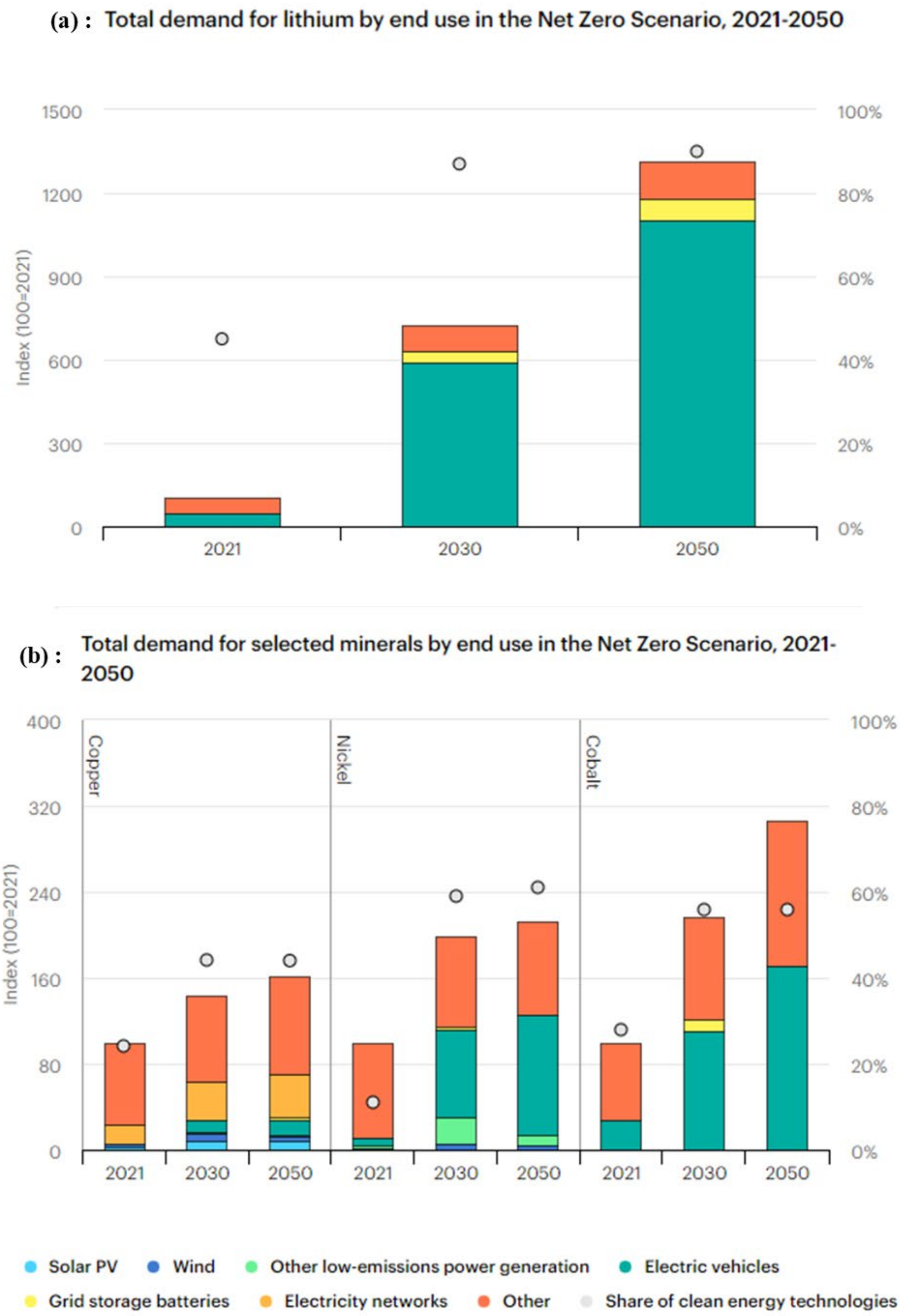

Figure 2 (a): Total demand for Li by end use in the Net Zero Scenario, 2021-2050; (b): Total demand for Copper, Nickel and Cobalt by end use in the Net Zero Scenario, 2021-2050. (source: IEA)

The importance of ongoing international discussions and research cannot be overstated. They are the bedrock upon which policies and strategies are built to confront the complex challenges associated with these critical materials. Such scholarly and diplomatic engagements are pivotal in charting a course towards a more resilient and sustainable global infrastructure.

Innovation in technology plays a parallel and equally critical role in this journey. The advent of new technologies not only demands an increased supply of these materials but also offers novel ways to manage and utilize them efficiently. Strategic management of these resources, therefore, becomes an indispensable aspect of ensuring that the progress towards green technology is both sustainable and inclusive.

These concerted efforts across multiple fronts are fundamental to realizing the lofty objectives set forth by the international community: to diminish the environmental footprint of human activity and to advance the cause of sustainable development. In essence, the journey towards a greener future is predicated on the judicious use and careful management of the planet's precious resources, a task that calls for cooperation, innovation, and unwavering commitment.

Enhancing the narrative around the securing and management of critical materials for green technologies requires a deeper exploration of the intricacies and challenges involved, along with the strategic responses necessary to address them[12].

- **Environmental Stewardship**: Mining practices for critical materials must prioritize ecological conservation. It is imperative to implement methods that minimize landscape disruption, prevent pollution of water bodies, and protect wildlife, thus aligning resource extraction with environmental responsibility[13–15].
- **Social Justice:** Ensuring social justice is essential for creating a fair and sustainable system. Frequently, the extraction of raw materials is associated with various social catastrophes—including the displacement of local communities[16], child labor[17], and local conflicts[18]—all exacerbated by a capitalist system that exploits and depletes global resources for profit.
- **Economic Stability:** The economic landscape of critical materials is marked by price fluctuations, driven by variable demands, speculative trading and policy shifts. This necessitates adaptive financial strategies and forecasting models to manage the uncertainties inherent in these markets[19].

- **Geopolitical Considerations:** The geopolitical dominance of certain countries over materials like lithium, cobalt and rare earth elements and others, calls for a strategic diversification of supply sources. Mitigating risks associated with supply monopolies involves establishing alternative supply lines and international collaborations to reduce reliance on a single or limited number of suppliers[12,20].
- **Resource Optimization:** Given the finite nature of these materials, a shift towards a circular economy is critical. This includes developing efficient recycling processes for end-of-life products, thereby extending the lifecycle of these materials, reducing waste and lessening the environmental impact of new extractions[21,22].
- **Streamlining Supply Chains**: The complexity of the supply chain, from extraction to final product, demands robust and agile management. This involves enhancing logistics, improving transparency and adopting technologies that ensure efficiency and sustainability at each stage of the supply chain[23,24].

By integrating these approaches into a cohesive management strategy, we can effectively address the multifaceted challenges in securing critical materials. This strategy must be comprehensive, encompassing sustainable extraction methods, economic resilience planning, geopolitical risk assessment, resource recycling innovation and supply chain optimization. Such an approach not only ensures the continuous support of critical materials for advancing technologies but also contributes significantly to sustainable development and environmental conservation, ultimately leading to a more sustainable and equitable future.

1.3. The role of Industrial Ecology in Addressing Critical Materials – Methodologies comparison

Industrial Ecology (IE) has evolved as a field by integrating methodologies from various disciplines, each contributing to its unique approach towards sustainable industrial development. The story of IE's evolution is marked by the adoption and refinement of these methodologies. The inception of IE can be traced back to the late 20th century, with its roots in recognizing the need for more sustainable industrial practices. As awareness about environmental impacts grew, so did the need for a systematic approach to address these issues. This led to the development and application of several key methodologies within the field of IE[25]. As IE matured, the increasing demand for and scarcity of certain raw materials brought criticality assessment to the forefront of the field's methodology spectrum. This approach specifically addresses the risks associated with the supply of critical materials—those elements essential for modern industry and technology but at risk of supply disruptions due to geopolitical, environmental, or market pressures.

Criticality assessments evaluate the vulnerability of material supplies in a detailed, systematic manner[26,27]. By analyzing factors such as geopolitical risk, market dynamics, concentration of supply, and environmental impact of extraction and processing, these assessments provide essential insights into which materials are most at risk and why. This is crucial not only for securing supply chains but also for guiding sustainable resource management and technological innovation strategies. Furthermore, criticality assessments interact dynamically with other methodologies within IE. For instance, they often utilize data and insights from Material Flow Analysis (MFA) and Life Cycle Assessment (LCA) to comprehensively evaluate the environmental impacts and supply chain vulnerabilities of critical materials. This integration ensures that the field not only identifies risks but also devises practical strategies to mitigate them, thereby supporting the broader goals of sustainable industrial development.

MFA, which emerged in the late 1980s, is a cornerstone methodology in IE[28]. It focuses on examining material flows and stocks within specific systems to track the intricacies of resource utilization and waste generation. This analysis is instrumental in identifying the sources and destinations of materials, thereby facilitating the optimization of resource use and reduction of waste. MFA offers valuable insights for environmental impact assessments and resource optimization. However, while it provides a detailed analysis of specific materials or regions, its scope is sometimes limited to these areas, potentially overlooking broader systemic issues.

LCA, originating in the 1960s, is one of the earliest and most fundamental methodologies in IE[29,30]. It offers a comprehensive view of a product's environmental impacts across its entire lifecycle, from raw material extraction to disposal. This tool assesses the ecological footprint of products and services by evaluating environmental impacts at every stage of the product's life, providing a detailed picture from cradle to grave. LCA is extensively used to guide sustainable design and policy decisions. However, while it provides a broad overview, it can be data-intensive and may lack specificity for certain impact categories or processes, which are critical for targeting interventions effectively.

Environmentally Extended Input-Output Analysis (EE-IOA) plays a critical role in IE by providing a macroeconomic perspective on the environmental impacts of economic activities[31,32]. This economic model integrates environmental data with economic input-output tables, helping to understand the complex interdependencies between different industrial sectors and their environmental impacts. EE-IOA is particularly effective for policy analysis, offering insights into how changes in one sector can ripple through the entire economy, affecting resource use and environmental emissions. While its macroeconomic focus is valuable for highlighting economic-environmental linkages and the sustainability of industrial systems, it may not delve deeply into specific industrial processes and depends on comprehensive and accurate economic data.

Alongside its core methodologies, IE employs a diverse set of tools including Network Analysis (NA), Integrated Assessment Models (IAMs), Techno-Economic Analysis (TEA), Life Cycle Sustainability Assessment (LCSA), and Social Life Cycle Assessment (SLCA), all of which significantly enhance its analytical framework.

Network Analysis[33] is crucial for mapping complex interconnections within industrial systems, enabling the exploration of resilience and efficiency opportunities by identifying critical nodes and links. It is particularly useful for scenario planning, helping predict how changes in one part of the network might affect the entire system. However, while effective at detailing connections, NA often lacks the granularity to accurately represent physical resource flows, which can be essential for operational and tactical decisions.

IAMs[34] offer a broad perspective on the interplay between environmental, economic, and technological aspects, making them invaluable for evaluating long-term environmental strategies and policy impacts. IAMs are adept at modeling future scenarios, including climate change projections and policy responses. Yet, they typically simplify complex industrial processes to a few variables, which can obscure detailed resource dynamics and physical flows.

TEA provides insights into the economic viability and technological feasibility of environmental solutions[35,36]. TEA combines technical and economic data to forecast the performance and costs associated with new technologies, thus informing both business and policy decisions regarding sustainable practices.

Furthermore, the LCSA[37,38] extends the traditional LCA framework to include not only environmental but also economic and social impacts throughout a product's life cycle. This holistic approach ensures that sustainability assessments reflect a broader spectrum of impacts and support more comprehensive decision-making.

Lastly, Social LCA[39,40] complements environmental LCA by focusing on the social aspects of product life cycles. It evaluates factors such as labor rights, community benefits, and social equity, which are critical for a complete sustainability profile but often overlooked in more conventional analyses.

These methodologies collectively enhance the robustness of IE's toolkit, providing a multifaceted view of industrial systems that supports sophisticated future scenario analysis and comprehensive sustainability evaluations.

In this thesis, the emphasis is placed on the core methodologies of IE, which are the most prevalent and instrumental in analyzing and studying critical materials and their varying degrees of criticality. These include MFA, LCA, and EE-IOA, each providing distinct perspectives and tools to address the complexities of sustainable industrial practices. Additionally, given the increasing complexity of supply chains for critical materials and their interdependencies, NA is also considered to understand and map the intricate relationships within these systems. This focused approach allows for a detailed comparison and evaluation of how each methodology contributes to our understanding and management of critical material criticalities, thereby supporting robust, sustainable policy-making and industrial strategies.

In Table 1, the four selected methodologies are systematically compared across several critical dimensions: Strengths and Applications, Challenges and Limitations, Primary Focus, Scope and Scale, Environmental Impact Focus, and Data Requirements. This comparison aims to provide a comprehensive overview of the respective advantages and challenges associated with each method. By evaluating these aspects, the table facilitates an understanding of how each methodology can be optimally applied within IE, particularly in the context of managing and analyzing critical materials.

Table 1: Method comparison.

	Strengths and Applications	Challenges and Limitations	Primary Focus	Scope and Scale	Environ. Impact Focus	Data Requirem.
MFA	Effective in resource optimization and waste reduction; valuable for resource governance.	Focuses primarily on physical flows, possibly overlooking economic and social dimensions.	Material flows within systems; resource efficiency and waste management.	Specific to materials or regions; often does not cover entire lifecycle.	Resource depletion, waste generation, recycling and recovery potentials.	Quantitative data on material stocks and flows in a specific region or sector.
LCA	Holistic environmental impact assessment; applicable to product design and policy-making.	Resource-intensive; potential for data inaccuracy; scope often limited to specific products or processes.	Ecological footprint of products/services throughout their lifecycle.	Cradle-to-grave: encompasses all stages from production to disposal.	Emissions, resource use, toxicity, energy use.	Extensive quantitative data on material and energy use, emissions, etc., for each life cycle stage.
EE-IOA	Broad economic-environmental linkage analysis; valuable in macroeconomic policy and sustainability reporting.	May lacks granularity; dependent on comprehensive and up-to-date economic data.	Economic activities' impact on the environment; sectoral interdependencies.	Regional/national economies; inter-sectoral economic activities.	Indirect environm. impacts, like emissions and resource use in supply chains.	Comprehensive economic transaction data, environmental impact data for each sector.
NA	Reveals system interconnections and key influencers; applicable in industrial symbiosis and supply chain management.	Complexity in real-world application; requires sophisticated data analysis.	Network dynamics in industrial/ecological systems; optimization of interconnected systems.	Flexible: can range from localized industrial networks to global supply chains.	Network vulnerabilities, optimization opportunities, resilience.	Detailed data on nodes (e.g., industries) and links (material flows) in the network.

MFA is particularly effective in identifying resource use inefficiencies and aiding in waste reduction strategies, thereby facilitating resource optimization. Its limitation lies in its often-narrow focus on specific materials or regions and a tendency to overlook non-material aspects. MFA's scope is typically confined to material flows and stocks within a specific region, industry, or material cycle.

LCA, on the other hand, provides a comprehensive view of environmental impacts by considering the entire product lifecycle, making it immensely useful for sustainability assessment. However, it is data-intensive and can be time-consuming, sometimes lacking specificity in certain impact categories. Its primary focus is on the environmental impact of products and services from cradle to grave, encompassing the entire spectrum from raw material extraction to disposal or recycling.

EE-IOA offers a macroeconomic perspective and is instrumental in identifying economic-environmental linkages, proving useful for policy analysis. However, this methodology may lack detail in specific industrial processes and requires comprehensive economic data. EE-IOA's focus area encompasses the interactions between different sectors of the economy and the environment, typically within a regional or national economic framework.

Finally, NA, which identifies key nodes and links in systems, is adept at revealing system vulnerabilities and optimization opportunities. It is particularly useful for understanding the interconnectedness and dynamics of industrial and ecological systems. Despite its strengths, NA faces challenges due to the complexity of modelling real-world systems, its data-intensive nature, and the requirement of advanced computational resources. The system boundaries for NA often include entire networks of industries, cities, or global supply chains. In the field of critical materials, a specific application of NA known as Complex Network Analysis (CNA) is employed. This approach focuses on complex networks, such as those found in the supply chains of critical materials.

Each methodology offers unique insights into sustainability and environmental impacts, with distinct strengths and weaknesses that determine their suitability for various focus areas and system boundaries. This comparative analysis highlights the critical importance of choosing the right methodology based on the specific objectives and limitations of each project. However, a significant challenge persists in harmonizing these diverse methods to achieve detailed and precise representations of resources and physical flows, which are crucial for effective environmental management and policy formulation.

1.4. Integrating diverse methodologies in Industrial Ecology

In the dynamic and interdisciplinary field of Industrial Ecology, the integration of various methodologies is not just beneficial but essential for a comprehensive understanding of industrial and environmental systems. Remarkably, these methodologies, now converging in the realm of Industrial Ecology, have their origins in diverse academic disciplines. For instance, EE-IOA has its roots in economics, offering a macroeconomic perspective on industrial activities. LCA, emerging from environmental science, provides a holistic view of a product's environmental impact. MFA is grounded in environmental engineering, focusing on material flows in industrial systems. NA, derived from network theory and mathematics, examines the interdependencies within systems.

The integration of these methodologies within Industrial Ecology symbolizes a harmonious blend of diverse academic insights, contributing to a more nuanced and holistic understanding of complex industrial and ecological systems[41]. In the interdisciplinary field of Industrial Ecology, the integration of diverse methodologies enriches our understanding of industrial and environmental systems. Each methodology contributes unique strengths and perspectives, and their collective application enables a more comprehensive analysis than any single approach could achieve. Among these, IOA holds a distinct position due to its versatile framework, which shares notable similarities with the other methodologies[42].

IOA, initially conceptualized in 1936 by Wassily Leontief[43], was innovative in its approach to understanding economic systems. While it is widely recognized for its analysis of monetary flows between industries, its scope extended beyond economic transactions from its inception. Leontief's pioneering work included the development of Physical Input-Output Tables (PIOTs), which incorporated not just monetary, but also material and energy flows[44]. This early integration of physical dimensions in IOA laid the groundwork for its compatibility with MFA. The convergence of MFA and IOA methodologies was notably advanced by the Waste Input-Output (WIO) model, developed by the Japanese scholars Nakamura and Kondo[45,46]. This model represented a significant milestone in the field of Industrial Ecology, as it integrated waste and emission data into the input-output framework. The WIO model exemplifies the synergistic potential of combining IOA and MFA, demonstrating how the integration of these methodologies can provide a more holistic understanding of industrial and environmental systems.

This evolution in Industrial Ecology reflects an ongoing process of innovation and interdisciplinary collaboration, highlighting the importance of adapting and integrating various approaches to address the complexities of modern industrial and ecological challenges.

The intersections of these methodologies can be visualized in a Venn Diagram (Figure 3), where the overlapping areas highlight the interdisciplinarity of IE. For example, in 1970, Leontief was the first to extend the IO model to consider links between the economy and the environment, particularly focusing on atmospheric pollution[47].

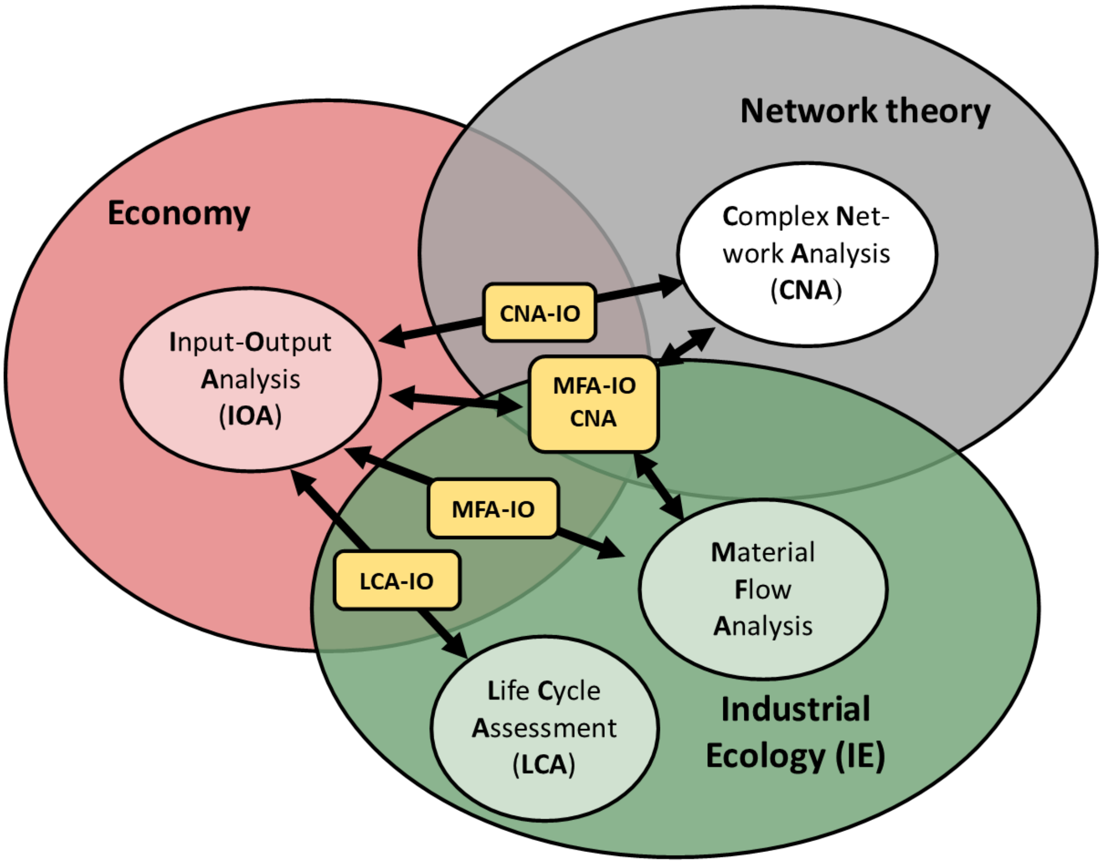

Figure 3: Venn Diagram of methodology interaction.

The LCA-IO combines environmental impact assessments with economic transactions to offer a comprehensive view of a product's life cycle and its broader economic effects. Similarly, MFA-IO links the physical flow of materials with economic transactions, offering insights into resource usage and environmental impacts associated with material consumption.

An IO table can be envisioned as a network where sectors are depicted as nodes and the directed, weighted edges represent the IO transactions among these sectors. The fusion of IO models with contemporary CNA has been instrumental in yielding deeper insights into economic structures[48]. IOA serves as a foundational framework for deciphering the interactions between different industries and the consequent environmental repercussions. This framework is typically organized as a matrix, mapping out the sectoral inputs and outputs, making it an essential instrument for evaluating both the direct and indirect implications of economic shifts on the environment. Conversely, CNA offers a suite of methods dedicated to examining interaction patterns within networks. These methods facilitate the detection of emergent patterns, assessment of node and link significance, and investigation of network behavior.

When IOA is combined with CNA, the resulting analytical tool is exceptionally adept at dissecting the intricate web of economic-environmental connections. It unveils pivotal sectors and elucidates the routes through which economic activities influence environmental outcomes.

By transforming economic exchanges into physical flows using MFA integrated with IO, it becomes possible to apply CNA in the realm of material networks. This expanded application of CNA probes into the networked character of material flows, scrutinizing the intricacies of inter-sectoral interactions as well as the systemic strengths and weaknesses within the network[49]. This threefold integration of MFA, IOA, and CNA affords a comprehensive perspective of the socio-economic and environmental facets, which is indispensable for crafting sustainable industrial strategies[50,51].

To summarize, these synergistic methodologies offer an intricate comprehension of industrial ecosystems and stand as cornerstones for sustainable progress, empowering stakeholders to make well-rounded decisions that encompass environmental, economic and societal considerations. While integrating these approaches poses certain challenges, especially in terms of methodological synchronization, their combined application remains crucial for tackling the complex demands of sustainable industrial advancement.

1.5. Objectives of this PhD work

This PhD research undertakes a comprehensive examination of integrative methodologies within IE, with a special emphasis on managing critical materials crucial for the transition to a green economy.

Central to this study is the exploration of synergies between the MFA-IO framework and additional analytical tools. This effort is designed to deepen our understanding of the supply chains associated with critical materials.

The following section presents a detailed literature review, focusing on various aspects of integrating MFA-IO with other methodologies such as CNA; assessing supply risks of critical materials; and forecasting the demand for these materials. The literature review helps to pinpoint research gaps that subsequently shape the research questions this PhD thesis aims to address.

1.5.1. State of the art and research gaps

Integration of Complex Network Analysis with Input-Output Models in the study of critical materials

The fusion of CNA with IO models for economic structural studies was pioneered by P.B. Slater in 1978[52]. This innovative approach has since inspired a growing body of research, particularly as it proves critical for examining intricate relational structures, key industries, and industrial clusters. The utility of this methodology spans the elucidation of energy and mineral industries' roles in shaping industrial patterns, aiding in forecasting industrial development, and simulating policy intervention impacts. The breadth of CNA-IO methodology applications within IE is extensive. It covers different areas of research such as: Agricultural Land Use[53]; Deforestation[54]; Water Resources[55]; Energy[56,57] and Emissions[58–62].

These explorations have been crucial in addressing material criticalities, with notable studies focusing on the flow and trade dynamics of rare earth elements[51,63,64] (REEs), copper[65], aluminum[66], global embodied metal trading[50], and mineral-related industries[67]. Despite these advances, the integration of CNA-IO methodologies is still emerging, with significant room for deeper application, particularly concerning global[68–71] and regional[72] trade dynamics and material criticalities in mineral-related industries.

The utility of CNA has been prominently highlighted in studies focusing on the trade dynamics of various critical materials at global and regional levels. Yet, the integration with IOA is notably scant, revealing significant research gaps that need addressing:

- *Data Integrity Issues*: Challenges persist with primary trade datasets like ComTrade, marked by discrepancies in reported material flows. These issues highlight the urgent need for more reliable data collection and verification methods to ensure accurate supply chain analyses.
- *Insufficient National Flow Analysis*: There is a general lack of detailed examination of national industrial flows. This gap significantly hinders a comprehensive understanding of internal market dynamics and the interdependencies of industries within national borders.
- *Limited Focus*: Research often concentrates on a narrow selection of products for each critical material, which may not adequately represent the broader industrial uses of these materials. Expanding the focus to include a wider range of derivatives and compounds is crucial for a more complete evaluation of their roles in various technologies.

Supply Risk Assessments of Critical Materials

Understanding the vulnerabilities in complex supply chains is crucial, particularly for strategic minerals essential for advancing a zero-carbon economy[73]. Traditional supply risk assessments often concentrate on the mining phase, neglecting the entirety of the material supply chain. These minerals have been designated as critical by various governments and international organizations due to their pivotal role in technologies that facilitate the zero-carbon transition.

Recent methodologies in supply chain risk assessment have broadened to include a range of factors such as environmental, geopolitical, and socio-economic aspects, which encompass consumption rates, recovery rates, market balance, and substitutability. The European Commission[74], United States, China[75], the British Geological Survey[76] (BGS) and the United States Geological Survey[77] (USGS) have made progress in defining metal supply risks using indicators like geological availability and mining governance. However, notable gaps remain that necessitate further research and targeted analysis:

- *Product-Specific Differentiation*: Current studies lack detailed differentiation among products derived from critical materials, such as various compounds and alloys used in different applications. This gap highlights the need for more nuanced, product-specific risk analyses that consider the unique uses and supply dynamics of each derivative.
- *Integration of Supply Chain Phases*: Research typically does not cover the entire supply chain comprehensively. There is a crucial need for integrating assessments that span from extraction

to end-use, including manufacturing and recycling stages, to provide a complete picture of supply risks.

Demand forecast of critical materials.

The urgency of transitioning to a net-zero carbon economy is underscored by the pivotal role of green technologies, which are substantially reliant on critical materials. This dependency has intensified investigations into the material implications of renewable transitions, utilizing a variety of analytical methods to project future demands and assess potential supply constraints such as MFA[5,78–80], System Dynamics (SD) modeling[81,82], and IOA[83,84]. MFA is frequently employed to estimate metal flows and stocks, offering insights through both top-down approaches for aggregate demand and bottom-up methods for specific technologies or sectors. SD modeling complements this by simulating complex interactions within systems, thus aiding in understanding the long-term impacts and feedback loops that affect supply chains.

IOA, which addresses economic interdependencies between sectors, enhances the understanding of resource and environmental issues by characterizing supply chains comprehensively. When combined with MFA, it enables the tracing of intricate material flows across multiple sectors.
Recent research has integrated these models to specifically address bottlenecks in the supply of critical materials for green technologies. Examples include the combined use of dynamic MFA with IO models to study copper in China and global cobalt (Co) demand, emphasizing the critical roles of recycling and mining risk management[85]. Furthermore, the coupling of MRIO with LCA methodologies has been explored to assess global metal requirements under various future scenarios[83].

Despite progressive strides in modeling critical material flows and impacts, existing literature reveals several gaps that necessitate further research:

- *Recycling Dynamics*: The complexities of the recycling sector, including the efficiency of recovery processes and the viability of recycled materials as substitutes, are often inadequately addressed.
- *Management of In-use Stocks*: There is a noticeable deficiency in strategies for managing stocks of materials that are currently in use but will eventually be available for recycling. This gap

affects accurate forecasting of future material availability and recycling potentials.

- *Need for Integrated Approaches*: There is a pressing need for more holistic models that integrate various methodologies to provide a comprehensive view of the supply, demand, and sustainability challenges of critical materials within the context of green technology adoption.

These gaps highlight the critical areas where future research could develop more refined models to support the sustainable and efficient use of critical materials in green technologies. This would not only aid in mitigating supply risks but also in promoting environmental stewardship throughout the lifecycle of these pivotal resources.

1.5.2. Objectives and research questions

Following the comprehensive literature review and the identification of critical research gaps, this PhD thesis is designed to explore innovative integrative methodologies that can enhance the management and assessment of critical materials within industrial ecology. This section outlines the specific objectives and formulates precise research questions that aim to address the previously highlighted gaps:

1) *How can the integration of MFA-IO with CNA improve our understanding of critical material supply chains by providing a more nuanced analysis of economic structures and interconnections?*

2) *How can an enhanced MFA-IO framework improve the granularity and accuracy of supply risk assessments for critical materials, particularly by incorporating detailed evaluations of different product derivatives?*

3) *In what ways can the integration of dynamic modeling techniques in the MFA-IO framework, enhance the accuracy of demand forecasts for critical materials, considering both the global economic landscape and the dynamic nature of secondary material flows?*

1.6. Thesis structure

The research framework is succinctly depicted in Figure 4, which illustrates the structured methodology adopted throughout this study. At its core, the approach integrates MFA with IOA, forming the MFA-IO framework. This framework is then extended into a MRIO flow network, which serves as the foundational model for the three case studies conducted.

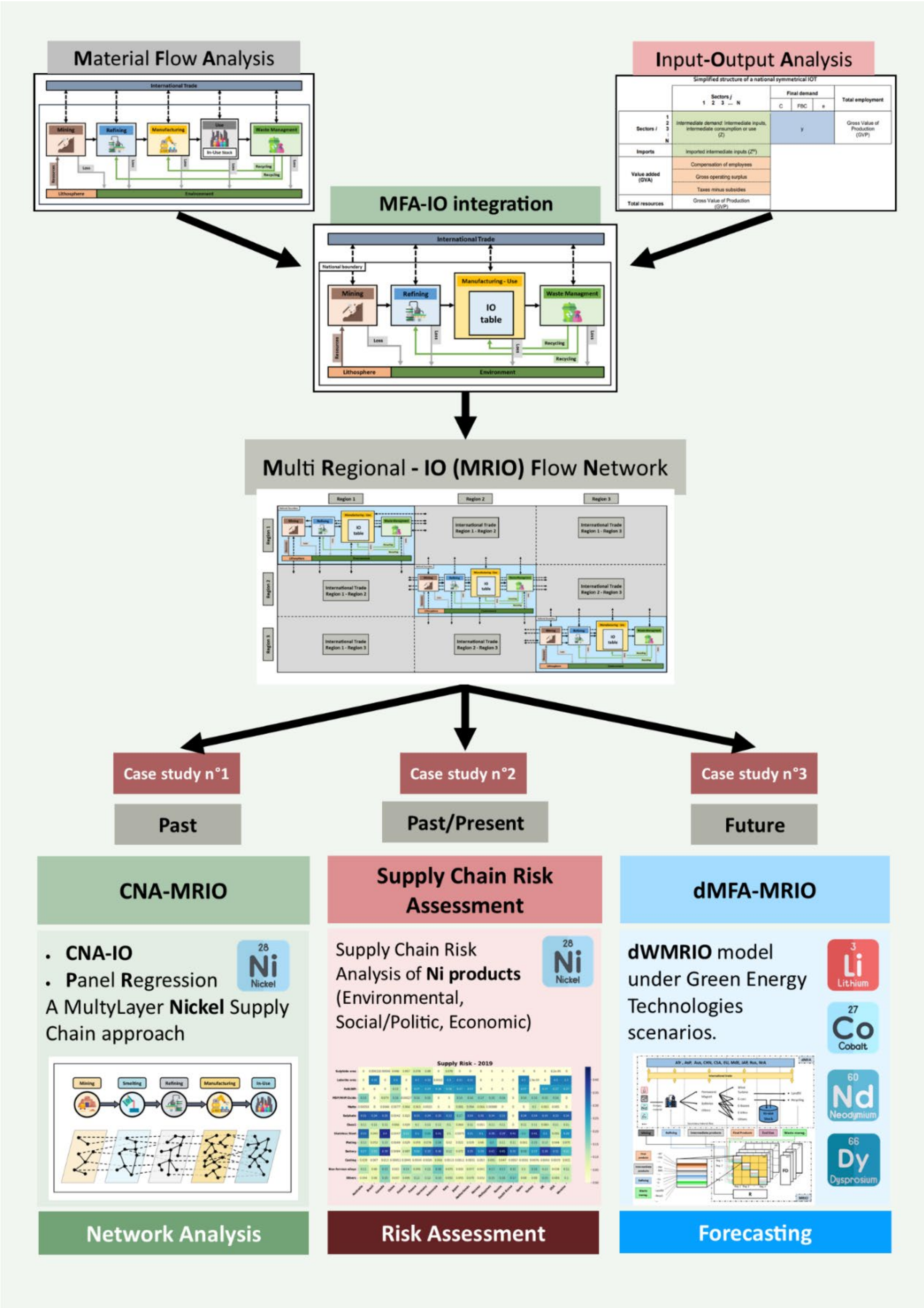

Figure 4: Ph.D. work framework.

The first case study explores the integration of CNA with the MRIO framework to analyze the multi-layered supply chain of nickel. The second case study focuses on assessing the risks associated with the nickel supply chain, utilizing the enhanced capabilities of the MRIO framework. Lastly, the third case study develops a dynamic model based on the MRIO framework to forecast the demand for four critical materials: Cobalt (Co), Lithium (Li), Neodymium (Nd), and Dysprosium (Dy). This hierarchical and integrative approach is pivotal in advancing our understanding of critical material supply chains and their dynamics.

The thesis is structured as follows:

- Chapter 2 lays out the methodologies employed throughout the thesis, setting the stage for their application in subsequent analyses. Introduces a case study on nickel, detailing the framework used to construct the associated material flow network foundational to case studies 1 and 2.
- Chapters 3, 4 and 5 are dedicated to the presentation of case studies 1, 2 and 3, respectively. Each case study delves into specific applications and implications of the research within the context of Industrial Ecology.
- Finally, Chapter 6 synthesizes the main findings from the case studies and the overall doctoral work. It discusses the implications of the research, offering recommendations and drawing conclusions that extend beyond the immediate scope of the thesis to inform future work in the field.

2. Methods

In the first part of this chapter, we delve into the integration of MFA and IOA, foundational to our understanding of sustainable industrial systems. We present the methodologies that underpin the material flow network for case studies 1 and 2. The second part transitions to the dynamic MFA-IO framework, introducing the dynamic Waste Input-Output Model (dWIO) as the base model for the analysis conducted in case study number 3.

2.1. Integration of MFA and IO

The integration of MFA and IOA represents a significant advancement in the field of IE, offering a comprehensive framework for understanding and managing the complex interplay of material flows and economic activities. Historically, MFA and IOA have developed somewhat independently, with MFA focusing on the physical flows of materials through industrial and environmental systems, and IOA analyzing economic transactions and interdependencies between different industrial sectors. Compared with MFA and other methods of IE, IOA is unique in that it uses an established mathematical tool/model that was initially developed for economic analysis. Thanks to its characteristics, in the last three decades the IOA has become the basic methodological framework encompassing LCA and MFA[32,86].

Despite their distinct origins, MFA and IOA are inherently interconnected: MFA provides detailed insights into the physical movement of materials, essential for understanding the environmental impacts of industrial processes[28]; IOA, on the other hand, offers a macroeconomic perspective, mapping out the economic interactions between different sectors in monetary terms[87].

The synergy between these two approaches lies in their ability to provide a more holistic understanding of industrial systems, combining the physical reality of material flows with the economic context in which these flows occur. Figure 5 illustrates a general framework for the integration of these 2 models.

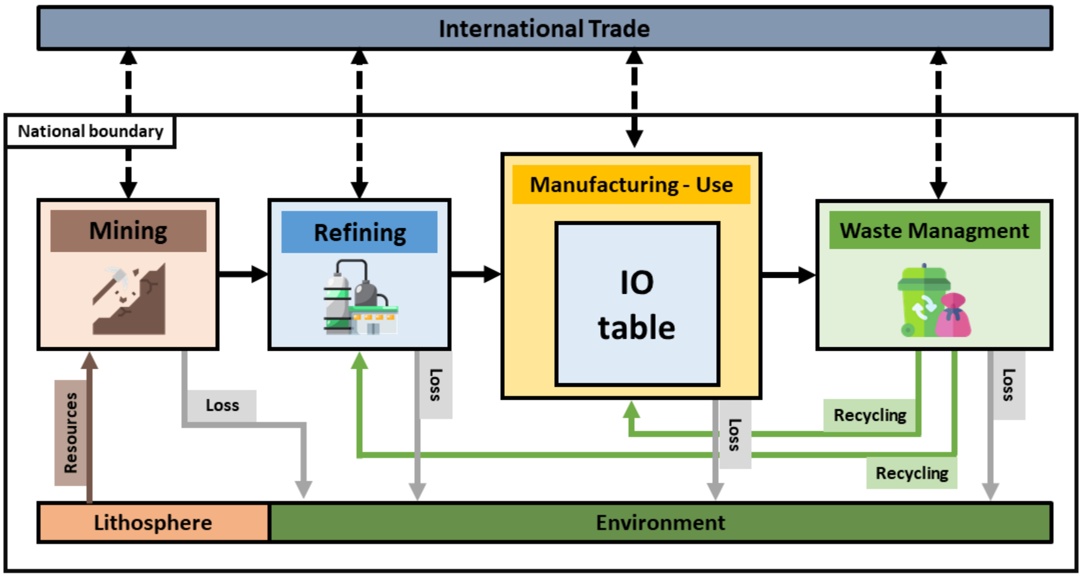

Figure 5: MFA-IO general framework integration.

One of the challenges in integrating MFA and IOA has been the difference in their primary units of analysis – physical units for MFA and monetary units for IOA. This discrepancy has historically limited the direct application of IOA to MFA. However, recent developments, such as Waste Input-Output Material Flow Analysis (WIO-MFA), have begun to bridge this gap[45,46]. WIO-MFA offers a methodology to convert monetary flows in IO tables into physical flows, categorized by specific materials. This conversion allows for a more seamless integration of the two analyses, enabling researchers and practitioners to trace both the economic value and physical substance of materials through industrial systems.

The integration of MFA and IOA is particularly valuable in addressing sustainability challenges. For instance, it enables the assessment of resource efficiency and environmental impacts across entire supply chains[88,89], from raw material extraction to end-of-life disposal[90,91]. This integrated approach can identify key leverage points for reducing environmental impacts and improving resource efficiency, which are often overlooked when considering economic and material aspects in isolation.

Moreover, this integration supports the development of circular economy strategies[41]. By understanding both the physical flow of materials and their associated economic activities, policymakers and industry leaders can design more effective policies and business models that promote the reuse, recycling and sustainable management of resources.

Within the ambit of the MFA-IO framework, various methodologies have been developed to trace physical flows within an IO table, each with its own set of principles and applications. Four principal methods stand out: WIO[45], Consumption-Based Accounting[92] (CBA), Input-Output Absorbing Markov Chains[93] (IO-AMCs) and the Partial Ghosh Input-Output Model[94]. These methodologies differ in their approach to reconciling the physical quantities of materials with their economic transactions and in their capacity to map the environmental implications of industrial and consumption activities.

CBA is a method commonly used to estimate environmental footprints[95]. This approach assigns environmental burdens from socio-economic activities to categories of final demand, revealing the "embodied" environmental burdens along global supply chains. The environmental extension used in CBA can be constructed as either a supply-extension, which pertains to the extraction of raw materials by various sectors, or as a use-extension, which is related to the downstream use of semi-manufactured goods like cement in construction[96]. CBA has been employed in various studies, including those concerning critical materials like construction minerals. It allows for the allocation of domestic production to various material end-uses[97].

Additionally, IO-AMCs have been proposed to trace resources through industrial networks and calculate end-use shares, providing a framework to understand the flow of resources like ores to final products.

Furthermore, partial Ghosh input-output approaches have been used to derive end-use shares for materials, offering a perspective on the direct allocation of a sector's output to inter-industry sectors and tracing material flows through the supply chain to their end-use. This method has been applied in the context of the Chinese and Indonesian economies for materials such as cement and wood, demonstrating its practical utility in national MFA.

The model adopted in this thesis is predicated on the WIO methodology. The fidelity of the WIO approach is rooted in its meticulous exclusion of massless transactions and waste flows from the analysis[98]. This exclusionary practice is not merely a methodological preference but a strategic delineation that enhances the accuracy of the results. By focusing exclusively on the substantive mass flows that bear economic significance, the WIO model provides a refined and precise representation of material cycles within the economic framework. Such precision is indispensable when the goal is to pinpoint critical junctures within the supply chain that offer opportunities for intervention to bolster sustainability and resource conservation.

The choice of the WIO model is thus a deliberate one, aimed at harnessing the most accurate and actionable insights into the physical-material landscape of industrial systems. In doing so, the model lends itself to a more rigorous analysis of resource flows, enabling the identification of strategic leverage points where improvements can yield substantive benefits in terms of environmental impact and resource efficiency. This aligns closely with the thesis's overarching objective to contribute meaningfully to the discourse on sustainable industrial practices and to forge pathways toward a more circular economy.

In the subsequent section, we briefly introduce the Unit Physical Input-Output by Materials (UPIOM), based on the WIO model, that it has been used to build the MRIO material flow network used for case studies n° 1 and 2.

2.1.1. UPIOM Model: Tracking Material Flows in Complex Supply Chains

The Unit Physical Input-Output by Materials (UPIOM)[99] model emerges as a sophisticated tool for quantifying material flows within complex supply chains. Central to UPIOM's functionality is its ability to identify the physical flow of individual materials required for the production of a specific product. This model extends the scope of complementarity between MFA and LCA.

In IOA, used to track production activities back to final consumer demand, we define several key elements: $x = [x_j]$, for an $n \times 1$ vector of outputs; $X = [x_{ij}]$ for an $n \times n$ matrix of interindustry flows x_{ij} represents the output of sector i used in sector j; and f for an $n \times 1$ vector of final demand. The matrix $A = [a_{ij}]$, with input coefficients $a_{ij} = x_{ij}/x_j$, is used to calculate the production needed to meet final demand through the equation:

$$x = (I - A)^{-1} f \qquad \textit{(Eq. 1)}$$

where I is the identity matrix. The interindustry flow matrix X is calculated as:

$$X = A\, diag(x) = A\, diag((I - A)^{-1} f) \qquad \text{(Eq. 2)}$$

mapping the flow of goods across industries, where, for a $k \times 1$ vector v, $diag(v)$ refers to a $k \times k$ matrix the diagonal element of which consist of a v with all the off-diagonal elements equal to zero. For a single product's contribution to the economy, we focus on:

$$T(j) = A\, diag(((I - A)^{-1})_{\cdot j}) \qquad \text{(Eq. 3)}$$

Where only the jth element of $(f)_j$ is unity and all other elements are zero. This isolates the flow matrix for delivering one unit of product j, linking inputs and outputs directly to final demand. Transitioning to MFA involves modifying A to $\tilde{A}$:

$$\tilde{A} = \Gamma \odot (\Phi \mathrm{A}) \qquad \text{(Eq. 4)}$$

Where $\Gamma = [\gamma_{ij}]$ is the yield matrix with $\gamma_{ij} \epsilon [0,1]$, $\odot$ is the Hadamard product (element wise product of two matrices), Φ is a diagonal matrix with its ith diagonal element Φ_i which is unity when i is physical, and zero otherwise. This transformation removes from A all the elements that do not become the physical components of physical outputs, which include inputs without mass (service and energy), auxiliary inputs such as inputs for cleaning, and process waste.

The second step consists of permuting the order of the producing sectors along their degrees of fabrication. The permuted matrix can be turned into a lower triangular matrix. For this purpose, n outputs are partitioned into three groups: *products* P (e.g. car), *materials* M (e.g. steel), and *resource* R (e.g. iron ore). Let there be n_R types of *resources*, n_M types of *materials*, and n_P types of *products,* with $n = \mathrm{n}_P + \mathrm{n}_M + \mathrm{n}_R$. Write $\tilde{A}_{IJ}(I, J \epsilon \{P, M, R\})$ for an $\mathrm{n}_I \times \mathrm{n}_J$ matrix that refers to the input of items in I to produce items in J. For instance, $\tilde{A}_{MP}$ is an $\mathrm{n}_M \times \mathrm{n}_P$ matrix, the (i, j)-element of which refers to the amount of material i that is used to produce a unit of product j. $\tilde{A}$ can be represented as:

$$\tilde{A} = \begin{pmatrix} \tilde{A}_{PP} & \tilde{A}_{PM} & \tilde{A}_{PR} \\ \tilde{A}_{MP} & \tilde{A}_{MM} & \tilde{A}_{MR} \\ \tilde{A}_{RP} & \tilde{A}_{RM} & \tilde{A}_{RR} \end{pmatrix} = \begin{pmatrix} \tilde{A}_{PP} & 0 & 0 \\ \tilde{A}_{MP} & 0 & 0 \\ 0 & \tilde{A}_{RM} & 0 \end{pmatrix} \qquad \text{(Eq. 5)}$$

Where each 0 in 5 refers to a zero matrix of suitable dimension and indicates the absence of corresponding flows. For instance, $\tilde{A}_{MR} = 0$ because materials have higher degrees of fabrication than resource. Analogously, the same logic applies to $\tilde{A}_{PM} = \tilde{A}_{PR} = 0$.

While it might seem clear that zero matrices occur in the mentioned scenarios, the case of $\tilde{A}_{RP} = 0$ might not be as straightforward. This hinges on an assumption that goes back to how we define *materials* in this context. Here, "*materials*" are considered to be objects whose flow we want to track. Those objects that are less processed than *materials* are called *resources*, and those that are more processed are referred to as *products*. Finally, from (Eq. 5) the material-composition matrix of products, C, is derived:

$$C = \tilde{A}_{MR}(I - \tilde{A}_{PP})^{-1} \qquad \text{(Eq. 6)}$$

The order of which is $\mathrm{n}_M \times \mathrm{n}_P$. If the elements of M are measured in physical units [kg], the (m, j)-element of this matrix gives the mass of material m that is contained in products j.

By use of the material composition matrix C, the equation of $T(j)$ can be converted to an $(\mathrm{n}_P + 1) \times \mathrm{n}_P$ matrix of physical flow of material m, $U(m, j)$ as:

$$U(m, j) = \begin{pmatrix} diag((C)_{m\cdot})\tilde{A}_{PP} \\ (\tilde{A}_{MR})_{m\cdot} \end{pmatrix} diag(\left((I - \tilde{A}_{PP})^{-1}\right)_{\cdot j}) \qquad \text{(Eq. 7)}$$

Where $(\tilde{A}_{MR})_{m\cdot}$ refers to the row of $\tilde{A}_{MR}$ that refers to the inputs of material m. While $diag((C)_{m\cdot})\tilde{A}_{PP}$ refers to the "indirect" inclusion of material m in products in the form of products (semis or parts), $(\tilde{A}_{MR})_{m\cdot}$ refers to "direct" inclusion in the form of material m.

Henceforth, $U(m, j)$ is termed the unit physical input-output by materials (UPIOM) of material m associated with product j. It refers to the flow of inputs that become the physical components of products. The (i, k)-element of $U(m, j)$, $(U(m, j))_{ik}$ gives the mass of material m (e.g., iron) that is embedded in product j (e.g. a car) as product k (e.g. ball bearings) in the form of input i (e.g. hot rolled steel).

By definition, a final product, say, product j, is used for final demand only, but not for intermediate demand, which implies that the (j, j)-element of $(I - \tilde{A}_{PP})^{-1}$ is unity, that is, $(\left(I - \tilde{A}_{PP}\right)^{-1})_{jj} = 1$. Accordingly, the jth column of $U(m, j)$ becomes:

$$U(m,j) = \begin{pmatrix} diag((C)_{m\cdot})(\tilde{A}_{PP})_{\cdot j} \\ (\tilde{A}_{MR})_{mj} \end{pmatrix} \quad \text{(Eq. 8)}$$

A unique aspect of the UPIOM model is its ability to trace and quantify the use of materials throughout the entire production process. For instance, it can illustrate how a primary material like pig iron is transformed into various parts and components in a passenger car, capturing the transformation at every stage of the supply chain. The model not only tracks the primary material flow but also the flow of secondary materials, like iron and steel scrap, revealing insights into the quality and quantity of recycled materials used in the production process.

The UPIOM model, therefore, stands out as a powerful tool in IE for mapping and understanding the complex webs of material flows within supply chains. Its precision and depth of analysis enable stakeholders to gain a comprehensive understanding of material utilization, from raw material extraction to the final product, thus facilitating more informed decisions in resource management and sustainability practices in industrial systems.

In chapter 2.3, the UPIOM model is used in a Multi-Regional Input-Output (MRIO) context, enabling the coverage of global economic interactions. This expansion provides a more extensive understanding of material and economic interdependencies on a global scale, crucial for effective resource management and sustainability practices in industrial systems.

The final part of this chapter introduces the dynamic MFA-IO model, utilized for case study number 3. This model represents the latest evolution in integrating dynamic material flow analysis with IO frameworks, underlining the continuous development and refinement of methodologies in IE.

2.2. From static MFA-IO to dynamic

This thesis transitions from exploring static MFA to its dynamic counterpart (dMFA), underscoring the significant benefits that arise from this evolution. Static MFA, while effective in capturing material flows at a specific point in time, is limited in its ability to account for changes over time. The shift to dMFA is a response to this limitation, offering a more nuanced view that includes the temporal dimension, crucial for understanding the long-term dynamics of material stocks and flows. This progression is not merely methodological; it represents a fundamental shift in how we understand and model the biophysical basis of societies, allowing for more accurate predictions and effective policy interventions in line with sustainable development goals.

However, the static nature of classical IO tables, which are pivotal in economic analysis, poses a significant limitation when integrated with MFA. Traditional IO tables offer a snapshot of economic interactions within a specified period, usually a fiscal year, but lack the capacity to represent the dynamics of material stocks and economic activities over time. This static approach, while useful in certain contexts, falls short in addressing the complexities of evolving material and economic interdependencies.

The integration of dMFA with IO analysis is a response to these limitations, combining the strengths of both methods to create a more robust and dynamic model. This integration not only enriches the economic data from IO tables with the temporal dynamics of material flows from dMFA but also enables a comprehensive understanding of the interactions between economic activities and material usage. This synthesis provides a powerful tool for examining the sustainability of resource use, economic policies, and environmental impacts over time, thus offering significant advantages over traditional, static models.

The first groundbreaking attempt to integrate these methodologies was made by Nakamura and Kondo[100], through the development of the dynamic Waste-Input-Output (dWIO) model. This model represents a pioneering effort in blending the principles of dMFA with the structural framework of IO analysis, specifically focusing on the dynamics of waste materials in economic transactions. The dWIO model has set a precedent in the field, offering a novel perspective on how waste management is intertwined with economic processes over time.

In this chapter, we will delve into the intricacies of the dWIO model by Nakamura and Kondo, exploring how this innovative approach has paved the way for advanced modeling techniques in the realm of sustainable material management and influenced subsequent research in this domain.

This chapter is organized into three subsections: 2.2.1 introduces the static WIO model; 2.2.2discusses the MaTrace-Alloy model, which is a dynamic MFA model; and finally, 2.2.3 culminates in the presentation of the dWIO, which is a synthesis of the two aforementioned models.

This discussion will not only highlight the significance of the dWIO model in the broader context of dynamic material flow and economic analysis but will also set the background for the case study n° 3 showed in this thesis.

2.2.1. The static WIO-MFA Method

The WIO developed by Nakamura and Kondo[101] is a modelling technique that extends the standard IO analysis by incorporating waste flows and waste treatment processes into the core IO table to account for the end-of-life (EoL) phase of products[102]. Such an extension allows to include the EoL phase of products involving waste management and recycling into IOA, making it applicable to all the stages in a product lifecycle which are production, use, and EoL.

Table 2: A schematic WIO account.

	Products (n_1)	Waste tratment (n_2)	Final Demand (n_y)
Products (n_1)	X_1	X_2	y_1
Waste (n_w)	W_1	W_2	w_y

Table 2 presents a schematic WIO account with: n_1 producing sectors (each producing a single product), n_2 waste treatment sectors, $n_y = 1$ final demand sector, n_w waste categories. The set of n_1 products is denoted by "1" and that of n_2 waste treatment sectors by "2". X_1 refers to the flows of goods and services among production sectors while y_1 to the final demand (FD).

The other elements of the model refer to the flows associated with waste and waste treatment, with:

- W_1: flow of waste generated and/or absorbed by production sectors, with its (i, j)-element, $ij\ \ w, W_1\ > 0$ if sector j generates waste i, $W_1\ < 0$ if sector j uses (recycles) waste i.
- W_2: amount of generated waste (treatment residue) minus the amount of recycled waste by treatment sector in a year.
- X_2: flow of goods and services that are necessary for this transformation including products obtained from treatment processes (electricity from the waste heat of waste incineration facilities), or material recycled from refinery, which occur as negative inputs.

- w_y that refers to the generation of waste from final demand, garbage, wastewater, and EoL products).

Denoting by x_1 the quantity of n_1 products produced and by w the quantity of n_w waste for treatment, we can write the following balance:

$$\begin{pmatrix} X_1 & X_2 \\ W_1 & W_2 \end{pmatrix}\begin{pmatrix} \iota_1 \\ \iota_2 \end{pmatrix} + \begin{pmatrix} y_1 \\ w_y \end{pmatrix} = \begin{pmatrix} x_1 \\ w \end{pmatrix} \tag{Eq. 9}$$

where ι_1 refers to $n_\alpha \times 1$ vector of ones used for summation, where the symbol α represents a set of sectors, products, scrap, or waste. Denoting by x_2 the activity level of treatment sectors (that refers to the quantity of waste treated in each treatment sector), the input coefficient matrices A (as the technical coefficient matrix as we have seen before) and waste generation coefficients G are given by:

$$A_1 = X_1 * \hat{x}_1^{-1}\ ;\ A_2 = X_2 * \hat{x}_2^{-1} \tag{Eq. 10}$$

$$G_1 = W_1 * \hat{x}_1^{-1}\ ;\ G_2 = W_2 * \hat{x}_2^{-1} \tag{Eq. 11}$$

Where $\hat{v} = diag(v)$ refers to a diagonal matrix, the element of which is the i-th element of a vector v. By using A and G obtained, we can write:

$$\begin{pmatrix} A_1 & A_2 \\ G_1 & G_2 \end{pmatrix}\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} + \begin{pmatrix} y_1 \\ w_y \end{pmatrix} = \begin{pmatrix} x_1 \\ w \end{pmatrix} \tag{Eq. 12}$$

By definition, the sum of waste for treatment is equal to the sum of waste treated:

$$\iota_2^T x_2 = \iota_w^T w \tag{Eq. 13}$$

Where T is the transpose operator. This is the Duchin–Leontief environmental IO model of waste and waste management[103]. The system obtained in Eq. 12 is not solvable unless each waste is exclusively submitted to a single treatment process; that is, $w = x_2$. This requirement does not accurately represent the complexities of real-world waste management. For example, solid waste can be disposed of in landfills, but various treatment options can be applied to the same kind of waste; organic waste, for instance, can be either landfilled, incinerated, or composted.

This problem can be solve introducing the allocation matrix S, as proposed by Nakamura[102] and Kondo[101]. This matrix allocates waste to treatment processes of order $n_2 = n_w$ it is possible to obtain:

$$x_2 = Sw \qquad \textit{(Eq. 14)}$$

By applying the matrix S to the system of equation Eq. 12 it is possible to write the solution of the system as:

$$\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} 1 - A_1 & -A_2 \\ -SG_1 & I - SG_2 \end{pmatrix}^{-1} \begin{pmatrix} y_1 \\ Sw_y \end{pmatrix} \qquad \textit{(Eq. 15)}$$

The WIO is a static model because it does not involve any index referring to different times: it is not a system of difference/differential equations.

2.2.2. MaTrace-Alloy model

Based on their previous work, Nakamura et al.[104] in 2014 developed the MaTrace-Alloy model, a dMFA model capable of tracing the fate of materials (metals) over time across products involving the mixing of materials over repeated recycling[105]. The model is based on the following assumption:

1. **Products, alloy, and metal**: A product consists of alloys. Alloys consist of metals.
2. **EoL products and scrap**: EoL products are disassembled into several types of scrap, each of which consists of alloys.
3. **Refinery**: A refinery sector produces a secondary alloy from scrap, and it is the only sector (process) in which the metal composition of scrap (a combination of alloys) can be altered.

The $\mathrm{n_1}$ producing sectors are categorized as follows: $\mathrm{n_q}$ durable final products, $\mathrm{n_p}$ parts and component, $\mathrm{n_a}$ alloys, $\mathrm{n_m}$ metals, $\mathrm{n_o}$ other goods and service.

The producing sectors is the sum of all the other sectors mentioned above. The $\mathrm{n_2}$ waste sector, that is equal to $\mathrm{n_2 = n_r + n_d + n_l}$ where $\mathrm{n_r}$ refers to refineries; $\mathrm{n_d}$ to disassemblers and $\mathrm{n_l}$ other waste treatments and landfill and $\mathrm{n_w}$ waste categories, are equal to $\mathrm{n_w = n_e + n_s + n_z}$ where $\mathrm{n_e}$ refers to the EoL products $\mathrm{n_s}$ to scrap types and $\mathrm{n_z}$ to treatment residues and other waste type.

The MaTrace-alloy model represents the development of the durable final product $\mathrm{y_q(t)}$ over time and is based on the following system of differential equations:

$$y_q(t) = (\Delta \odot D(t) \operatorname{diag}\left(\left(R^T \odot \Omega\Gamma V(t)\right)\iota_m\right))\iota_m \quad \textit{(Eq. 16)}$$

$$V(t) = \sum_{r=0}^{t} \hat{u}(t,r) C^T(t-r) \quad \textit{(Eq. 17)}$$

$$u(t,r) = B(t-r)\delta(t-r)\phi(t-r) \quad \textit{(Eq. 18)}$$

Where:

- $\odot$: Hadamard product[106]
- $C(n_m \times n_a)$: metal composition of alloys [kg-metal/kg-alloy]
- $B(n_a \times n_q)$: alloy composition of final products [kg/$]
- $\Gamma(n_s \times n_a)$: scrap transformation of alloys recovered from EoL products [dimensionless quantity]
- $\Omega(n_r \times n_s)$: allocation scrap to refinery processes [dimensionless quantity]
- $R(n_m \times n_r)$: yield of metals at the refining of scrap into secondary alloys [dimensionless quantity]
- $D(n_q \times n_r)$: allocation of secondary alloys to products [dimensionless quantity]
- $\Lambda(n_q \times n_r)$: manufacturing yields products [dimensionless quantity]
- $\delta(n_q \times 1)$: recovery yields of EoL products products [dimensionless quantity]
- : fraction of products that is discarded after r years of use products [dimensionless quantity]

The logic behind the Eq. 16 is as follow: the term u gives the amount of alloys recovered in year t from EoL products that were produced in $(t \times r)$ and discarded in t. Multiplying by the material composition of alloys, C, and summing over all r such that $r < t$, the transpose of the term $V(n_a \times n_m)$ gives the metal composition of EoL alloys recovered in the year. The EoL alloys are then allocated to scrap categories via Γ, and scrap is further allocated to refinery processes via Ω. Once the metals in scrap are submitted to refinery processes, they are rearranged via R into new alloys, which are subsequently allocated to new products via D. For further detail please refer to[107].

MaTrace-alloy is a supply-driven model and does not consider issues of supply-demand balances. To our knowledge, this feature is not limited to MaTrace-alloy, but is common to most dMFA studies[108,109]. These issues arise because, in practical scenarios, the ability to dilute and manage contamination through impurities can be constrained by the existing demand[110], and the market for secondary alloys may be limited due to concerns over their quality[111]. Additionally, a significant drawback of the MaTrace-Alloy model, a problem that appears to be widespread in dMFA studies, is its failure to explicitly account for the quantitative relationship between the flows it monitors and those it does not, such as energy and chemicals in this context, which are crucial for evaluating the environmental impacts of the relevant flows. These challenges can be addressed by integrating MaTrace-Alloy with the WIO model.

2.2.3. Dynamic Waste Input-Output model

By integrating the MaTrace-Alloy model in the WIO, Nakamura and Kondo developed the dynamic WIO model (dWIO)[112]. The dWIO is the base used to build the model developed for this study because it takes into account the recycling process of products, that depends on their past production, incorporated in an IO analysis.

Table 3: WIO account of the flows in the dWIO model.

	q	p	a	m	o	r	d	l	y
q	0	0	0	0	0	0	0	0	y_q
p	X_{pq}	X_{pp}	0	0	0	0	0	0	0
a	X_{aq}	X_{ap}	0	0	0	X_{ar}^{Θ}	0	0	0
m	0	0	X_{ma}	0	0	0	0	0	0
o	X_{oq}	X_{op}	X_{oa}	X_{om}	X_{oo}	X_{or}	X_{od}	X_{ol}	y_o
e	0	0	0	0	0	0	0	0	w_{ey}
s	0	0	0	0	0	0	W_{sd}	0	0
z	W_{zq}	W_{zp}	W_{za}	W_{zm}	W_{zo}	W_{zr}	W_{zd}	W_{zl}	0

Where the classification is the following: **q** as final product; **p** as parts and components; **a** as alloys; **m** as metals; **o** as others. Treatment sectors consist in: **e** as EoL products; **s** as scraps; **z** as residues; **r** as refineries; **d** as disassemblers; **l** as landfill.

In the dWIO the amount of secondary alloys is represented by X_{ar}^{θ} , with a negative sign indicate its substitution for competing primary alloys. For the sake of simplicity, it is assumed that process waste is internally recycled (no occurrence as a waste item), that EoL final durable products are the only waste items generated from the final demand, that there is a one-to-one correspondence between final durable products and EoL products ($\mathrm{n_q} = \mathrm{n_e}$) and that there is a single disassembling sector ($\mathrm{n_d} = 1$), and a landfill sector ($\mathrm{n_l} = 1$). The balance equation for the Table 3 can be written as follow:

$$\begin{pmatrix} A_1 & A_2 \\ G_1 & G_2 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} + \begin{pmatrix} y_1 \\ w_y \end{pmatrix} = \begin{pmatrix} x_1 \\ w \end{pmatrix} \quad \text{(Eq. 19)}$$

With:

$$x_1 = \begin{pmatrix} x_q \\ x_p \\ x_a \\ x_m \\ x_o \end{pmatrix};\ x_2 = \begin{pmatrix} x_r \\ x_d \\ x_l \end{pmatrix};\ w = \begin{pmatrix} w_e \\ w_s \\ w_z \end{pmatrix};\ y_1 = \begin{pmatrix} y_q \\ y_p \\ y_a \\ y_m \\ y_o \end{pmatrix} = \begin{pmatrix} y_q \\ 0 \\ 0 \\ 0 \\ y_o \end{pmatrix};\ w_y = \begin{pmatrix} w_{ey} \\ w_{sy} \\ w_{zy} \end{pmatrix} = \begin{pmatrix} w_{ey} \\ 0 \\ 0 \end{pmatrix}; \quad \text{(Eq. 20)}$$

$$A_1 = \begin{pmatrix} A_{qq} & A_{qp} & A_{qa} & A_{qm} & A_{qo} \\ A_{pq} & A_{pp} & A_{pa} & A_{pm} & A_{po} \\ A_{aq} & A_{ap} & A_{aa} & A_{am} & A_{ao} \\ A_{mq} & A_{mp} & A_{ma} & A_{mm} & A_{mo} \\ A_{oq} & A_{op} & A_{oa} & A_{om} & A_{oo} \end{pmatrix} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 \\ A_{pq} & A_{pp} & 0 & 0 & 0 \\ A_{aq} & A_{ap} & 0 & 0 & 0 \\ 0 & 0 & A_{ma} & 0 & 0 \\ A_{oq} & A_{op} & A_{oa} & A_{om} & A_{oo} \end{pmatrix} \quad \text{(Eq. 21)}$$

$$G_1 = \begin{pmatrix} A_{qr} & A_{qd} & A_{ql} \\ A_{pr} & A_{pd} & A_{pl} \\ A_{ar} & A_{ad} & A_{al} \\ A_{mr} & A_{md} & A_{ml} \\ A_{or} & A_{od} & A_{ol} \end{pmatrix} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ A_{ar}^{\theta} & 0 & 0 \\ 0 & 0 & 0 \\ A_{or} & A_{od} & A_{ol} \end{pmatrix}; \quad \text{(Eq. 22)}$$

$$G_2 = \begin{pmatrix} G_{eq} & G_{ep} & G_{ea} & G_{em} & G_{eo} \\ G_{sq} & G_{sp} & G_{sa} & G_{sm} & G_{so} \\ G_{zq} & G_{zp} & G_{za} & G_{zm} & G_{zo} \end{pmatrix} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ G_{zq} & G_{zp} & G_{za} & G_{zm} & G_{zo} \end{pmatrix} \quad \text{(Eq. 23)}$$

Here it is possible to note that the production of final products is always equal to the final demand for it ($x_q = y_q$) and that the EoL products are solely generated by the final demand sector ($w_e = w_{ey}$). The allocation matrix S is needed in order to transform the system in a solvable form.

The EoL products are allocated to disassembling via (S_de = δT) to which recovery yields of EoL products are applied, and then via (S_rs = Ω) the scrap is allocated to refineries. It is assumed that “residue” is entirely allocated to “landfill,” and none of it is recycled. The resulting allocation matrix is shown in the following equation:

$$S = \begin{pmatrix} S_{re} & S_{rs} & S_{rz} \\ S_{de} & S_{ds} & S_{dz} \\ S_{le} & S_{ls} & S_{lz} \end{pmatrix} = \begin{pmatrix} 0 & \Omega & 0 \\ \delta^T & 0 & 0 \\ (\iota_q - \delta)^T & 0 & \iota_q^T \end{pmatrix} \quad \textit{(Eq. 24)}$$

Thus, by applying the matrix S to the system the following equations are obtained:

$$\begin{pmatrix} x_r \\ x_d \\ x_l \end{pmatrix} = \begin{pmatrix} 0 & \Omega & 0 \\ \delta^T & 0 & 0 \\ (\iota_q - \delta)^T & 0 & \iota_q{}^T \end{pmatrix} \begin{pmatrix} w_e \\ w_s \\ w_z \end{pmatrix} = \begin{pmatrix} \Omega w_e \\ \delta^T w_s \\ (\iota_q - \delta)^T w_e + \iota_q^T w_z \end{pmatrix} \quad \textit{(Eq. 25)}$$

The last step for the integration of the MaTrace-Alloy with the WIO is done by establishing links between their elements. The amount of EoL products in year t is given by:

$$w_{ey}(t) = \sum_{r=0}^{t} \phi(t-r) y_q(r) \quad \textit{(Eq. 26)}$$

Where $\phi(r)(n_q \times 1)$ [dimensionless quantity] is the fraction of products that is discarded after r years of use products. The disassembling process transforms n_a alloys constituting EoL products into n_s types of scrap, resulting in an $n_s \times 1$ matrix of the flow of scraps:

$$W_{sd}(t) = \Gamma \sum_{r=0}^{t} B(r)\delta(t)\phi(t-r)y_q(r) \quad \textit{(Eq. 27)}$$

Where:

$$B(r) = A_{aq}(r) + A_{ap}(r)(I - A_{pp}(r))^{-1} A_{pq}(r) \quad \textit{(Eq. 28)}$$

The quantity of recovered EoL products intended to for disassembling x_d is:

$$x_d(t) = \delta(t) w_{ey}(t) \quad \text{(Eq. 29)}$$

The matrix G_{sd} is given by:

$$G_{sd}(t) = W_{sd}(t) x_d^{-1}(t) \quad \text{(Eq. 30)}$$

Being that the activity level of the refinery sector is:

$$x_r = \Omega G_{sd} \delta(t) w_{ey}(t) \quad \text{(Eq. 31)}$$

This implies that x_r depends on the past values of y_q not only through w_{ey} but also through G_{sd}. The quantity of scrap treated by refinery processes is given by:

$$x_r = \Omega\Gamma V(t)\iota_m \quad \text{(Eq. 32)}$$

Where $V(t)$ indicates the metal composition of EoL products in alloy, and is given by:

$$V(t) = \sum_{r=0}^{t} \mathrm{diag}(B(r)\delta(t)\phi(t-r)y_q(r))C^T(r) \quad \text{(Eq. 33)}$$

By multiplying the quantity of metal that enters the refineries by the yield of the process we obtain the metal that has been recycled:

$$x'_r = (R^T \odot \Omega\Gamma V(t))\iota_m \quad \text{(Eq. 34)}$$

Therefore, the terms $X_{ar}^{\ominus}$ and $A_{ar}^{\ominus}$ can be obtained as:

$$X_{ar}^{\ominus}(t) = \begin{pmatrix} -x'_r \\ 0 \end{pmatrix} = \begin{pmatrix} -\mathrm{diag}((R^T \odot \Omega\Gamma V(t))\iota_m \\ 0 \end{pmatrix} \quad \text{(Eq. 35)}$$

$$A_{ar}^{\ominus}(t) = X_{ar}^{\ominus}(t)x'_r(t) = \begin{pmatrix} x'_r(t)x_r^{-1}(t) \\ 0 \end{pmatrix} \quad \text{(Eq. 36)}$$

where the $(n_a \times n_r) \times n_r$ matrix of zeros added at the bottom corresponds to the alloys that are not produced by the refineries. The dWIO model overcomes the limitation of the MaTrace-Alloy because the supply-demand balance of secondary materials is properly considered, and the flow of goods and services other than the material of primary interest is captured. There is nevertheless a drawback in this model: the additional requirement of data necessary for its implementation, such as a time series of the final demand for durable products together with their material composition and the lifetime distribution. For further detail about the dWIO please refer to[112].

2.3. MRIO – Nickel Flow Network

2.3.1. Background to Nickel as case study choice

While the focus of this analysis is on nickel due to its critical role in modern industrial applications, it is important to recognize the significance of other materials that also play vital roles in the global economy. Materials such as copper, known for its excellent electrical conductivity, and aluminum, valued for its light weight and recyclability, are integral to numerous sectors including construction, transportation, and electronics. Cobalt and lithium are essential in the manufacture of rechargeable batteries, while platinum is crucial in catalytic converters and other high-tech applications. These materials are pivotal in the advancement of technology and sustainable development but are also subject to complex geopolitical and environmental challenges.

Despite the broad utility and significance of these materials, nickel has been specifically chosen as the focal point for these two case studies for several compelling reasons:

- **Comprehensive Data Availability**: The global importance and extensive use of nickel ensure that its data are better documented compared with other "minor" materials. This availability of data spans numerous sectors and geographic regions, providing a robust and detailed dataset. Such extensive information enhances the reliability and depth of CNA and MFA-IO, making nickel an excellent subject for these analytical methods.
- **Industrial and Environmental Impact**: Nickel's extensive use in critical sectors such as stainless-steel[113] production and its emerging role in battery technology for electric vehicles make it a pivotal element in discussions around sustainability and technological innovation[114]. Moreover, the environmental impacts arising from nickel mining, especially in biodiverse regions like Indonesia and the Philippines, present crucial points for analysis in understanding the ecological costs of nickel extraction and processing[115].
- **Complex Supply Chain Dynamics**: The nickel supply chain exemplifies complexity, stretching from extraction to final products. Nickel ores undergo a series of steps including mining, smelting, and refining, which can vary significantly based on the type of ore (sulfide or laterite). Particularly, the refining process to produce nickel sulfate, a key ingredient in LiB[114], relies on specific supply chain pathways. These pathways involve precise and high-purity

material handling to ensure the performance standards required for battery manufacture[116]. This complexity makes nickel a prime candidate for detailed study using CNA and MFA.

- **Geopolitical and Economic Dynamics**: Nickel's supply chain is significantly influenced by geopolitical events, such as Indonesia's export bans, and the market dynamics controlled by major nickel-producing countries[117]. These factors, along with nickel being classified as a "critical" element by regions such as the EU[74], USA[118] and China[119], make it a particularly interesting case for exploring the interplay between natural resource management, international trade, and economic policy.

By examining nickel through the lenses of CNA and MFA-IO, we can gain insights not only into the material's lifecycle from extraction to EoL but also into how these flows affect broader environmental and economic policies. This case study not only illuminates the specific challenges and opportunities associated with nickel but also serves as a model for analyzing other materials that are critical to both industry and sustainability. This approach demonstrates the utility of integrating CNA and MFA-IO in material science, providing a comprehensive framework that can be applied to various materials to address global challenges of resource management and sustainable development.

2.3.2. System Framework

The system framework (Figure 6), designed for analyzing nickel supply chain, adopts a hybrid approach that integrates classical MFA with MRIO tables, used to develop the so called MRIO nickel flow network, that provide a detailed and comprehensive overview of nickel flows. The MFA component of the framework meticulously tracks the physical movement of nickel from mining through to refining and its EoL. Conversely, the IO method is employed to trace the material's journey within the manufacturing and end-use sectors. This integrated model aims to bridge two main gaps inherent in each methodology: from the MFA perspective, MRIO tables are utilized to estimate the flow of nickel products through the global economy; From the IO perspective, the MFA method is instrumental in disaggregating the flows of nickel and its sub-products from extraction up to their entry into the manufacturing sector. This is crucial since most common MRIO tables either lump the nickel sector with other metals or aggregate it at a level that obscures the distinction between different nickel sub-products. Table 4 provides a detailed explanation of all processes/flows depicted in Figure 6, that was taken from the work of Cormery[120] in his thesis,.

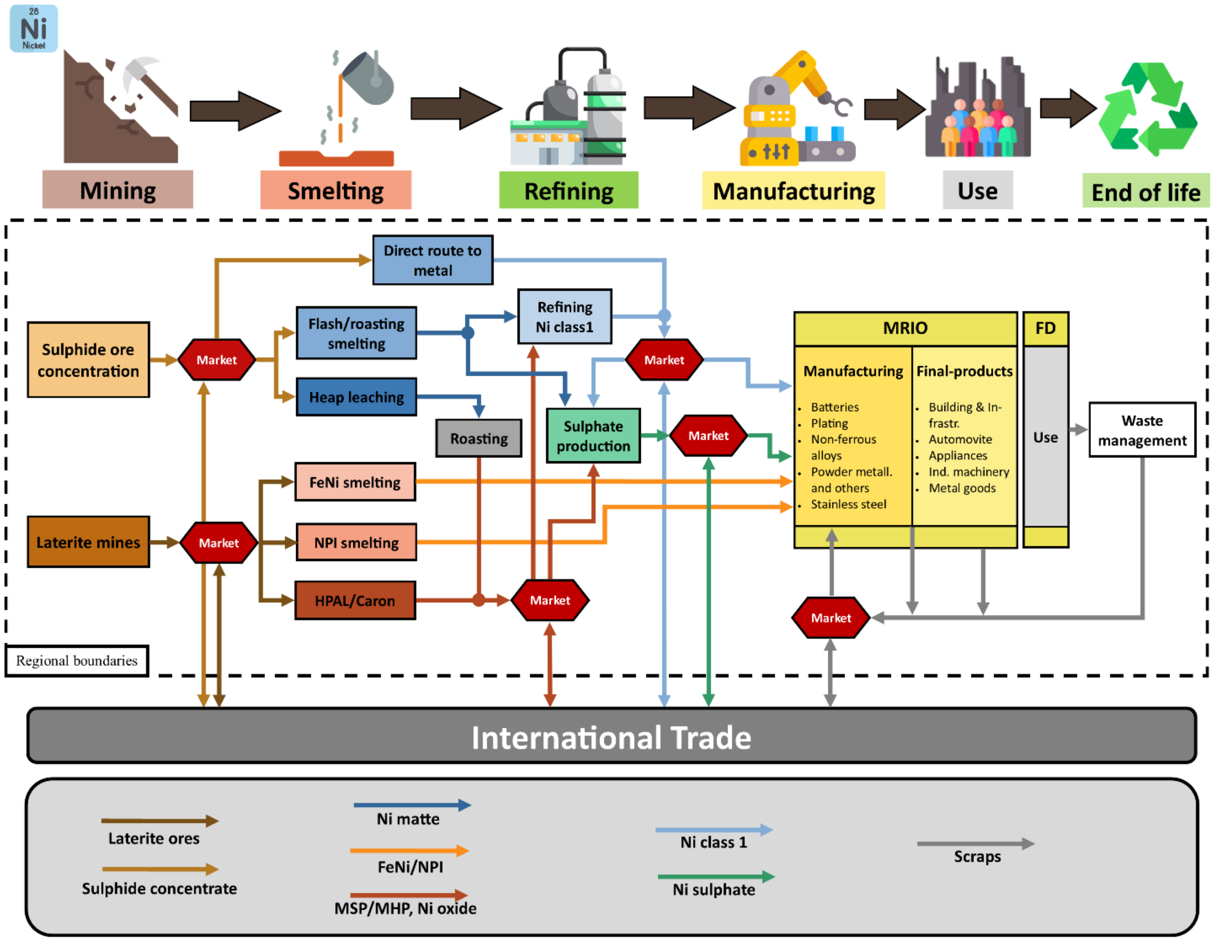

Figure 6: Framework of the MRIO nickel flow network.

Table 4: Flow description and assumptions

Supply chain	Process	Description
Mining	Sulphide ore concentration	Sulphide ores are concentrated to increase their metal content through physical processes like grinding and crushing, followed by separation from unwanted materials using magnetic or hydrophobic techniques[121–123].
	Laterite mines	Nickel is extracted from sulphide and laterite ore deposits, a challenging task to describe using MFA terminology due to the dynamic nature of geological reserves and resources. These quantities vary based on economic viability, market prices, and technological advances. Ore extraction processes are beyond MFA's scope, leading to the oversight of nickel in tailings, which could be substantial[121].
Smelting – sulphide ores	Direct route to metal	Vale's Long Harbour facility in Canada was the sole location employing direct hydrometallurgical refining to process sulphide concentrate into class I metal, as reported by INSG[124].
	Flash/roasting smelting	Pyrometallurgical treatments, smelting in an electric arc furnace and flash smelting, both result in the production of nickel matte. The key difference lies in the traditional

		method's higher nickel and byproduct recovery rates, albeit with greater electricity consumption, compared to flash smelting. Following, a conversion step reduces the iron content in the matte. Nickel is also obtained as a by-product from Ni-Cu-PGM (Platinum Group Metals) concentrates, which undergo smelting to matte, magnetic separation from PGMs, and leaching to yield crude nickel sulphate. In this study, these processes are tracked from matte production to nickel sulphate creation[121,124].
	Heap leaching	A mixed sulphide precipitate (MSP) is generated from sulphide concentrate through a series of processes including crushing, screening, mixing with sulphuric acid, and leaching. Currently, this method is exclusively employed at Terrafame's Talvivaara mine in Finland[124–126].
Smelting – laterite ores	FeNi/NPI smelting	Pyrometallurgical treatment of laterite ores involves smelting them in a rotary kiln electric furnace to produce ferronickel. An uncommon approach is used at the Sorowako smelter in Indonesia, where sulphur is added to create a matte, mimicking the sulphide process. Since 2005, the production of nickel pig iron (NPI), a low-grade ferronickel, has surged in popularity in China due to high class I metal prices and the availability of numerous small, old iron blast furnaces. The Indonesian ore export ban discussions beginning in 2014 further motivated Chinese companies to invest in NPI smelters within Indonesia[127].
	HPAL/Caron	High-Pressure Acid Leaching (HPAL) is a method for processing laterite ores using sulphuric acid under high pressures and temperatures of 245-270°C. This process separates liquids from solids and can directly yield class I metal with a refinery or produce intermediates like mixed sulphide precipitate (MSP), mixed hydroxide precipitate (MHP), and nickel hydroxide cake (NHC). These intermediates, due to their similar nickel content and the absence of distinct data, are treated uniformly as feedstock for refining into class I metal or nickel sulphate[121]. The Caron process, a hybrid technique, involves roasting laterite ore before ammonia leaching, resulting in nickel oxide. This process its use was limited to Cuba[124,128,129].
	Roasting	Matte is oxidatively roasted to create nickel oxide granules with an elevated nickel content, a process utilized solely at Vale's Matsusaka plant in Japan. However, for the purposes of this study, this method is also considered to represent the production of nickel oxide at Vale's Sudbury flash smelter in Canada[121,124].
Refining	Refining Ni class 1	Refining processes remove impurities like iron, copper, lead, or phosphorus from intermediates (MSP/MHP, matte, or nickel oxide), with some by-products (e.g., cobalt, platinum) being sold on other markets. While "refining" broadly refers to any process that increases metal content, in this context, it specifically pertains to downstream nickel recovery methods. These techniques produce class I metal, resulting in nickel in forms like cathodes, pellets, briquettes, and electrolytic nickel, with a purity exceeding 99.8% Ni[130].
	Sulphate production	Nickel sulphate ($NiSO_4$) can be manufactured from various sources, including mixed sulphide precipitate (MSP)/mixed hydroxide precipitate (MHP), matte, crude nickel sulphate from the PGM industry (treated as part of the matte process in this analysis), battery scrap, and the dissolution of class I metal. For the purposes of this study, other nickel compounds with significantly lower production volumes, such as nickel chloride and nickel hydroxide, are also included under the broader term "nickel sulphate"[116].
Manufacturing	Batteries	This process involves the creation of nickel-containing batteries, such as NMC (nickel manganese cobalt), NCA (nickel cobalt aluminum), NiMH (nickel-metal hydride), and NiCd (nickel-cadmium), covering the production of cathodes, cell formation, and their assembly into modules and packs, with nickel sulphate serving as the primary input[116].
	Plating	Class I metal and nickel sulphate are employed in electroplating to deposit a thin nickel layer on metal objects, enhancing their resistance to corrosion and wear or improving their appearance[131].
	Non-ferrous alloys	Class I metal and stainless steel scrap can be used to make nickel-base alloys and copper-based alloys[132].

	Alloy steels and casting	Class I metal, FeNi, Ni oxide and stainless steel scrap can be used to make ferrous alloys that benefit from the properties of Ni in terms of strength and corrosion resistance for instance. Stainless steel is excluded from this process.
	Powder metall. and others	Nickel is used for many other applications that capture a minor share of the annual production including powder metallurgy, catalysts or dyes[116].
	Stainless steel	Nickel's primary use is in the production of stainless steel, utilizing feedstocks such as class I metal, ferronickel (FeNi), nickel pig iron (NPI), nickel oxide, and stainless steel scrap. This process entails the creation of nickel-enriched stainless steels[133].
	Final products	Nickel-containing primary products are utilized in manufacturing end-use items, during which some material is lost. This loss, known as "new scrap," enters the nickel recycling market for reuse. These manufactured products are then bought and become part of societal stock.
End-of-life	Waste management	End-use products, once discarded, are collected, dismantled, and sorted through chemical and mechanical processes into waste products. Most of the nickel scrap is recycled functionally, with some battery scrap repurposed for sulphate production. Most post-consumer scrap, particularly from stainless steel, is reintegrated into the steel production cycle as a secondary material. However, some stainless steel scrap may be misdirected into non-recyclable streams, a process known as "downcycling," where nickel's value is diminished or seen as an impurity in unintended applications. Unrecoverable nickel scrap, due to economic or technical barriers (like certain metal goods or electronic waste), ultimately ends up in landfills[134].

2.3.3. Data sources

To build the MRIO nickel flow network for the years 2009-2019, a variety of data sources were consulted to estimate various parameters including domestic flows, trade flows and efficiency coefficients. Figure 7 illustrates the framework with the related main data sources used to estimates the nickel flows. The following subsections introduce the main data sources divide it 3 main sections: Domestic flows; Trade flows; MRIO tables.

Domestic flows

The research covered the period from 2009 to 2019, based on the data provided by the International Nickel Study Group (INSG). The production statistics were available by country for:

- Total mining volume [kton] (sulphide concentrate and laterite ore)[135].
- Production of “intermediates” [kton] covering matte, MSP/MHP, Ni oxide, and FeNi and NPI[136].
- Production of “finished nickel” [kton], which captures class I metal, sulphate (only the share made from intermediates to avoid double counting), FeNi, NPI, and Ni oxide to be used in the fabrication of first-use products[135].

Nickel sulphate production estimates, accounting for class I metal dissolution and battery scrap, were derived from market research[137]. Primary nickel consumption for first-use product fabrication was estimated for specific applications and countries, based on a Roskill report for the European Commission[116]. This report also broke down finished nickel consumption by feedstock type. At the country level, due to data unavailability, global estimates served as initial proxies, later refined by considering local production and import types.

Secondary nickel source consumption in first-use product fabrication was assumed negligible for certain manufacturing processes, such as plating and powder metallurgy, based on prior studies. Battery scrap recycling was exclusively linked to nickel sulphate production, eliminating additional scrap input in battery production.

Scrap inclusion rates for "Non-ferrous alloys" and "Alloy steels and castings" manufacturing processes were estimated at 14% and 17%, respectively, uniform across countries.[138]. The 2015 global average recycled content of stainless steel was estimated at 44%, with specific figures for China, the USA, EU countries with stainless steel production, and major Asian producers. Other countries used the global average[139].

For estimating nickel consumption in end-use product manufacturing, direct use of available estimates was avoided due to their limited coverage of primary data, uncorrected trade impacts, and opaque methodology[116]. Instead, country-specific transfer coefficients were derived, with global estimates applied to countries not covered in the report. Nickel content in waste from end-use sectors was calculated using outflow/inflow ratios or based on product lifetimes and sectoral growth rates, sourced from literature.

The amount of Ni in waste products out of the end-use sectors was calculated based on ratios of outflows/inflows or based on the lifetime of end-use products and the growth rate of the respective sector during the same period. Ratios and lifetime estimates were collected from the literature[138]. According to the Nickel Institute[134], waste management distributes post-consumer scrap between functional recycling (68%), non-functional recycling or downcycling (15%), and landfilling (17%). Without country-specific data, these ratios were assumed to be the same across individual countries. Deriving many country-level domestic flows required understanding process efficiencies, sourced from various literature[121,126,130,140–143].

Trade flows

Trade data for this study was obtained from the UN ComTrade database. To enhance the quality of this data, we utilized an algorithm developed by Cormery in his thesis[120], which performed critical functions such as outlier removal, data gap filling, and harmonization of trade data discrepancies reported by various countries. Specifically, this algorithm was applied to trade data for nickel in different forms, including ores and concentrates, matte, MHP/MSP, nickel oxide, class I metal, FeNi/NPI, and nickel sulphate. Efforts were made to accurately determine the nickel content, tailoring the data to the exporting country's specifics as much as possible:

- For laterite ores, country-specific average concentrations were established based on detailed geological studies of known deposits[122].
- The INSG directory and yearbook, which are key references for the global primary nickel supply chain[124,135], were consulted. When a facility's nickel content within a country (for example, mine, smelter, refinery) was documented, this information was taken as representative of the country's overall nickel content.
- Where country-specific data was unavailable, default values were employed, based on credible literature sources[121,123,130] , to provide a consistent basis for analysis.

This study did not derive the flows of nickel embedded in finished products from UN ComTrade, as these flows are captured within the MRIO tables. The MRIO tables account for trade flows between sectors producing products (such as batteries) that contain nickel or use these products (such as the automotive sector). These tables serve as a proxy for the international trade of the global economy, also depicting the flows of finished products during the use phase. This can include industries purchasing products as capital stock (like industrial machinery used to produce goods) or finished products bought by households (represented in the MRIO table as Final Demand).

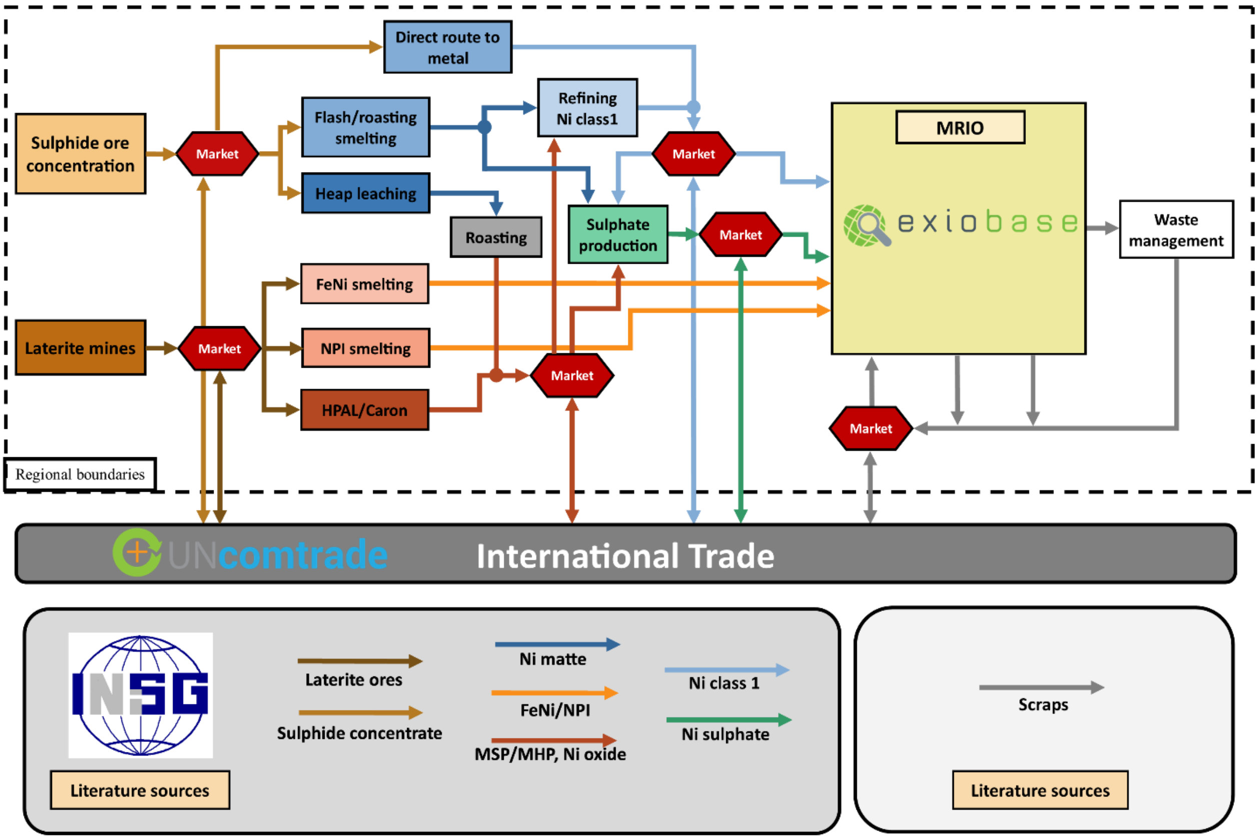

Figure 7: System framework with data sources.

MRIO table

In this research, the EXIOBASE-3[144] database, version 3.8.2, was utilized. This database offers detailed regional data, encompassing 44 countries and 5 "Rest of the World" (RoW) regions, across 163 industries and 200 products. However, given the significant role of certain countries in the nickel supply chain that were grouped under the RoW categories (such as the Philippines), we opted for a variant of EXIOBASE-3. This variant[145] extends the geographical scope from 44 countries + 5 RoW regions to 214 countries, maintaining the comprehensive and standardized sectoral detail provided in the original database.

3. MRIO-based Complex Network Analysis (Case study n° 1)

3.1. CNA-MRIO general literature review

The integration of CNA with IOA is a significant advancement in the exploration of economic and environmental systems. This fusion enables a deeper understanding of the intricate relationships between global trade, resource flows, and environmental impacts, addressing the limitations of traditional input-output network research[49].

Previously, research using single-regional IO models focused on national and provincial tables, but lacked the granularity needed for regional differentiation within countries[64,146]. The MRIO model, while more extensively used in cross-border trade studies, often neglected the heterogeneity of provinces in terms of economic endowment, geographical location, development stage, and industrial structure. This integrated approach seeks to expand the IO network research by decomposing and extending these tables to the subregional level, acknowledging the unique characteristics of each region.

In terms of research objects, there's a shift from exploring network attributes and industry associations in the whole industry or single sectors like manufacturing and finance, to a broader perspective. This includes examining the implications of global value chains for energy and materials sectors, and incorporating concepts like the footprint family, offering vast potential for research expansion.

Methodologically, the integration moves beyond merely identifying key industries and industrial communities. It incorporates complex network theory's broad and profound techniques, such as degree ranking, path search, robustness analysis, machine learning, and transmission dynamics. This enhances the ability to analyze dense weighted and directed networks, improving algorithms to mine economic implications more effectively.

Furthermore, as seen in the literature, the approach addresses gaps in research on energy and mineral industries, especially critical and bulk minerals like iron, copper, and aluminum. It emphasizes the need to focus on the role and evolution of energy and mineral industries in the IO table, including mining, smelting, and product industries.

Overall, the integration of CNA with IOA marks a critical expansion in research methods, objects, and application scope. It provides tools for comprehensively analyzing material and financial flows within and across regions, aiding in understanding global supply chains and their complex relationship. This approach is invaluable for advancing circular economy concepts, identifying key points for reducing waste and emissions, and promoting sustainable practices. It represents a significant stride in harmonizing network properties with economic and environmental data, facilitating a more nuanced understanding of complex economic and environmental systems.

3.2. The Complex Network of Nickel supply chain

Nickel is essential in many industries, primarily for stainless steel production but increasingly for LiBs in EVs. Its demand is expected to rise sharply, emphasizing its importance in a carbon-neutral future[147]. Nickel's supply chain is complex, especially for nickel sulfate, a key component in EVs batteries[116]. Recent disruptions, such as export bans and market shutdowns, underscore the chain's vulnerability[117,148].

Previous research has focused on nickel's life cycle and trade flows, often overlooking the distinctions between different purity grades. Modern studies are beginning to address these nuances, particularly for high-purity nickel sulfate. As the global nickel supply chain grows more intricate, network analysis has become crucial for understanding trade dynamics and market stability.

Literature review

Recent studies in the global nickel supply chain, enriched by CNA, have significantly contributed to our understanding of the industry. X. Zhou et al. (2023)[149] provide a comprehensive examination of the global nickel trade, elucidating the impact of geopolitical events like the Russia-Ukraine conflict on trade behaviors. In another study, Zhou et al. (2022)[150] focus on the volatility of trade prices within the nickel industry, employing risk entropy and Granger causality networks to highlight the effects of price fluctuations, particularly influenced by Indonesia.

Zheng et al. (2022)[151] explore how different countries' roles in the nickel trade affect market prices, combining network analysis with panel regression models to reveal trade position evolutions and their impact on pricing dynamics. Wang et al. (2022)[70,71] conduct two studies addressing the challenges of global trade and supply in the nickel industry. One proposes a trade redistribution strategy to meet global demand, and the other constructs a multi-layer trade network, underscoring China's vulnerability in the sector. Furthermore, Dong et al. (2021)[69] focus on optimizing the international nickel ore trade network, using a decade of trade data to propose sustainable strategies for balancing supply and demand.

These studies paint a detailed picture of the global nickel supply chain, demonstrating the benefits of network analysis for exploring trade dynamics, risks, and strategies for sustainable management. However, they frequently rely on monetary data rather than actual material flows, which can obscure the physical aspects of the supply chain. This reliance is compounded by significant data integrity issues with primary datasets like ComTrade, where discrepancies underscore the need for improved data collection and verification. Additionally, the absence of comprehensive national flow analyses impedes a deep understanding of internal market dynamics and industry interdependencies. The research also tends to focus on a limited range of products, neglecting the wider industrial uses of materials. A broader focus that includes various derivatives and compounds is crucial for a more complete understanding of their roles in technology.

In this work the MRIO nickel network has been analyzed with complex network theory to assess the nickel network's characteristics and status. Additionally, a panel regression model was used to identify key factors influencing nickel consumption.

The aim of this analysis is to provide strategic insights into the nickel multilayer network. By doing so, it assists policymakers, industry professionals, and academic researchers in making informed decisions. This comprehensive approach not only offers a deeper understanding of the nickel supply chain but also sheds light on potential areas for optimization and sustainability in the management of nickel resources. Figure 8 shows a general representation of a multilayer network of a material.

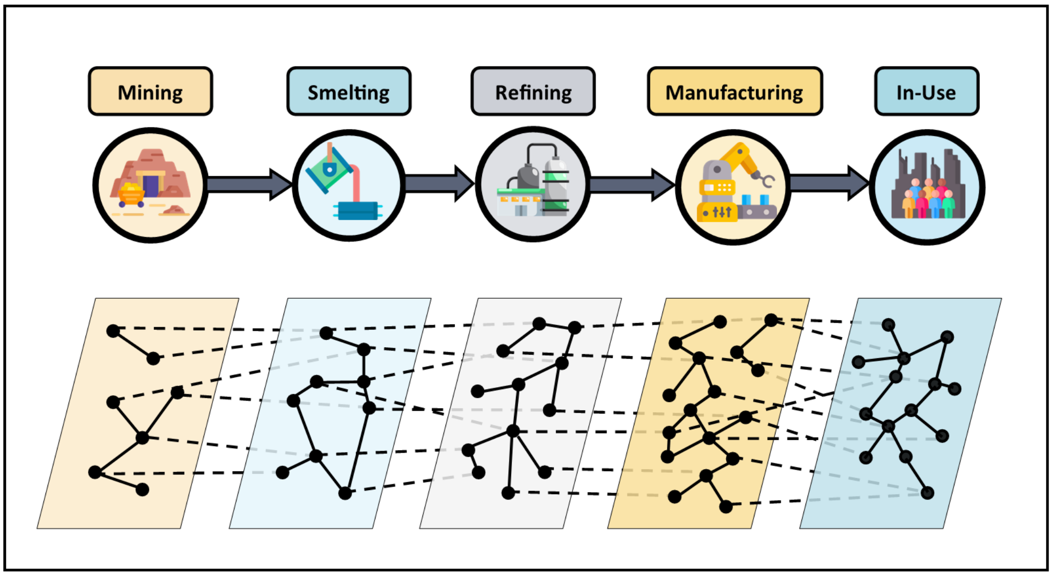

Figure 8: Representation of multilayer network.

3.3. Methodology

The MRIO tables can be conceptualized as a complex network comprising nodes (representing sectors) and directed, weighted links (serving as edges) [66,152]. Utilizing this framework, we construct a directed, weighted network from the previously introduced MRIO nickel network. This approach allows for a nuanced exploration of the economic interactions and flows within the network, highlighting the intricate dynamics and dependencies among sectors related to nickel usage and trade.

In the subsequent section, we introduce the indicators utilized for conducting complex network analysis and panel regression analysis.

3.3.1. Complex Network Indicators

- **Network Density**

Network density (ND) is a key metric for evaluating the interconnectedness of a network, defined by the ratio of actual to possible connections (edges) between nodes, ranging from 0 to 1. A higher network density implies a robust, well-integrated system, enhancing communication and material flow, thus reducing disruption risks. Conversely, lower density may indicate vulnerabilities due to less connectivity. The formula:

$$ND = \frac{2N_e}{N_n(N_n - 1)} \quad \text{(Eq. 37)}$$

calculates network density, where N_e is the number of edges, and N_n is the number of nodes. This measure is crucial for assessing the nickel supply chain's efficiency and stability.

- **Clustering Coefficient**

The clustering coefficient (CC) measures the tendency of network nodes to form tight groups, reflecting local connectivity. For the nickel supply chain, a high CC indicates strong connections among a node's neighbors, suggesting robust trade or collaborative networks within certain regions or groups. A higher network CC points to more localized networking, affecting the supply chain's resilience and efficiency. It can increase robustness to disruptions but may also pose risks if clusters become isolated. The calculation is performed with the following formula[153–155]:

$$CC_{(i)} = \frac{2T_{(i)}}{k_{(i)}(k_{(i)} - 1)} \quad \text{(Eq. 38)}$$

where $T_{(i)}$ is the number of triangles connected to node i, and $k_{(i)}$ is the degree of node i. Understanding CC reveals the network's structural impact on material and information flow within the nickel supply chain.

- **In & Out Degree**

The degree-in (D^{in}) and degree-out (D^{out}) centralities are key metrics for understanding network connectivity. D^{in} identifies "collector" nodes that receive materials from multiple sources, highlighting their role in material processing within the supply chain. D^{out} on the other hand, points out "distributor" nodes responsible for spreading materials to downstream sectors, crucial for resource distribution. The calculations for these metrics are:

$$D^{in}_{(i,c)} = \sum_j A_{ji}\,; \quad D^{out}_{(i,c)} = \sum_j A_{ij} \quad \text{(Eq. 39)}$$

Where $D^{in}_{(i,c)}$ and $D^{out}_{(i,c)}$ are the degree-in&out of sector i in country c respectively, and A_{ji} (A_{ij}) is the adjacent matrix of the MRIO nickel network. If there is an edge from node $i(j)$ to node $j(i)$, then $A_{ji}(A_{ij}) = 1$, otherwise it will be 0. These measures offer a straightforward count-based view of the network, emphasizing the roles of nodes in integrating incoming flows or facilitating outward distribution in the nickel supply chain.

- **In & Out Strength degree**

The strength degree-in ($SD_{(i,c)}^{in}$) highlights “collector” nodes in terms of material quantity, indicating their pivotal role in driving the metal supply chain. These nodes are characterized by their significant volume of incoming metal flows. On the other hand, strength out-degree centrality (SD_{i}^{out}) identifies “distributor” nodes that play a key role in dispersing materials to downstream sectors, crucial for their reliance on metal sales. These nodes are marked by their substantial role in the outward flow of materials. The equations for these measures are[156]:

$$SD_{(i,c)}^{in} = \sum_{j} e_{ji}\ ; \quad SD_{(i,c)}^{out} = \sum_{j} e_{ij} \qquad \text{(Eq. 40)}$$

Where $SD_{(i,c)}^{in}$ and $SD_{(i,c)}^{out}$ are the stength in&out degree of sector i in country c respectively, and e_{ji} or e_{ij} is the total amount of embodied nickel flowing between node i and node j. These metrics provide insights into the nodes’ roles in the network, emphasizing their importance in terms of the volume and value of the nickel flows.

- **Betweenness centrality**

This indicator is employed to identify key nodes that act as crucial intermediaries in the network. This metric measures the number of shortest paths from all nodes to all others that pass through a specific node, highlighting its role in connecting different parts of the network. The equation for betweenness centrality is as follows:

$$BC_{(k,c)} = \sum_{i} \sum_{j} \frac{\sigma_{i(k)j}}{\sigma_{ij}}, i \neq k \neq j \qquad \text{(Eq. 41)}$$

Where $BC_{(k,c)}$ is the betweenness centrality of node k in country c, σ_{ij} is the number of shortest paths between node i and j, and $\sigma_{i(k)j}$ is the number of these shortest paths passing through node k. A high betweenness centrality score signifies that a node functions as a critical conduit or 'bottleneck' in the network, indicating that its removal would likely disrupt the flow of materials or information more significantly than the removal of other nodes. Essentially, betweenness centrality underscores the importance of certain nodes in controlling or influencing the flow of resources and information, reflecting their capacity to regulate and manage the network dynamics.

- **Eigenvector centrality**

Eigenvector centrality is a pivotal metric for identifying influential nodes within the network. This measure is based on the principle that a node's importance is not only determined by the number of its connections but also by the importance of its connected nodes. Essentially, it reflects the idea that connections to highly influential nodes contribute more to a node's centrality. A node with high eigenvector centrality in the nickel network indicates its significant role in the network, often connected to other central nodes, and thus holds substantial influence over the network's dynamics. The equation for eigenvector centrality is given by:

$$EC_{(i,c)} = \frac{1}{\lambda}\sum_{j=1}^{n} a_{ij} \cdot EC(j) \qquad \text{(Eq. 42)}$$

In this equation, $EC_{(i,c)}$ is the eigenvector centrality of node i in country c, a_{ij} is an element of the adjacency matrix representing the connection between nodes i and j, $EC_{(j,c)}$ is the eigenvector centrality of node j, and λ is a constant, that is the is the largest eigenvalue of network. This centrality measure helps to identify key players that might have a disproportionate influence on the network, not just due to their direct connections but also because of their strategic position within the network's structure.

3.3.2. Panel Regression Analysis

In our analysis of the MRIO nickel network from 2009 to 2019, the role of various sectors in the network is observed to vary across both individual sectors and different time periods. This variation highlights the dynamic nature of the network, where sectors play distinct roles at different times. To accurately capture this relationship between the network roles of sectors and their nickel consumption, we employ a panel regression model, as depicted in formula:

$$Y_{it} = \alpha + \beta_{1,it}X_{it} + \beta_{2,it}control_{it} + \epsilon_{it} \qquad \text{(Eq. 43)}$$

Here Y_{it} represents the dependent variable, indicating the consumption of embodied nickel in various sectors over time. The independent variable X_{it} includes key network metrics such as $SD_{(i,c)}^{in}$, $SD_{(i,c)}^{out}$, $BC_{(k,c)}$, and $EC_{(i,c)}$ within the MRIO nickel network. $SD_{(i,c)}^{in}$ and $SD_{(i,c)}^{out}$ reflect the sectors' diversity in trading partners, highlighting key supply and consumption sectors. $BC_{(k,c)}$ identifies intermediary sectors, and $EC_{(i,c)}$ points to sectors with influential trading partners. The control variable $control_{it}$ encompasses sector GDP, industrial structure, and population, where:

- **Sector VA**: This influences each sector's production level and is a significant driver of nickel resource consumption. The value added (VA) of each sector is used as a proxy for the sector's GDP.
- **Industrial Structure**: Represented by the backward linkage, this indicates the impact of a sector's output change on the overall economy. It is calculated using formula (13):

$$BL_j = \sum_{i=1}^{n} l_{ij} \Big/ \sum_{ij} l_{ij} \qquad \text{(Eq. 44)}$$

  Here, $\sum_{i=1}^{n} l_{ij}$ is the sum of vectors in column k in the Leontief inverse, and $\sum_{ij} l_{ij}$ is the sum of all elements in the Leontief inverse. A larger BL_j for a sector suggests a greater economic stimulus from an added unit of output in that sector, thereby driving higher nickel consumption.
- **Population**: This indicates the market scale of a country. A larger population denotes higher consumption demand, influencing the demand for nickel resources.

This model allows us to examine the multifaceted interactions and dependencies within the MRIO nickel network, providing insights into how sectoral roles and economic factors influence nickel consumption patterns over the studied period.

3.4. Key Results

In this section, the results are presented in two parts: the complex network analysis, which provides an overview of the main findings including network density, clustering coefficient, In & Out strength, and In & Out degree; and the results from the panel regression analysis.

3.4.1. Complex Network Analysis result

Network Density

The results presented in Figure 9 (a) illustrates the progression of network density within the global nickel supply chain from 2009 to 2019, across different supply chain layers: mining, smelting, refining, semi-products, and manufacturing. In contrast, Figure 9 (b) provides comparative network density results from multiple studies to contextualize these findings. Notably, it references ND findings for cobalt from Li Y. et al. (2022)[157], categorized into three segments (upstream, midstream, and downstream), and REEs from studies by Zou Z. et al. (2022)[158] and Hou W. (2018)[159], focusing on three layers and a single layer, respectively.

In the nickel supply chain, ND values rise progressively through each layer, reflecting increasingly dense interconnections as raw materials move closer to final product stages. Specifically, the mining and smelting phases show the lowest ND, around 0.01, indicating sparse networks where international collaborations are limited and suggesting substantial potential for strengthening economic ties. The refining stage exhibits a slight increase in ND to approximately 0.025, still signaling a relatively loose network.

Significantly higher ND values in the semi-products (0.2) and manufacturing (0.3) stages imply much stronger inter-country relationships. These stages benefit from denser networks, enhancing the reliability and robustness of the supply chain, crucial for end-stage production processes.

The stability of ND trends across the period studied, with only minor variations, suggests consistent supply chain dynamics. Similar trends are observed in the cobalt supply chain, where initial ND values align with those in nickel mining and escalate as materials move downstream. This pattern underscores shared characteristics between nickel and cobalt supply chains, likely because cobalt is frequently mined as a nickel byproduct and both metals are essential for similar end uses, such as batteries and metal alloys.

Meanwhile, the REE supply chain exhibits a similar upward trend in ND but achieves a lower maximum value of 0.11. This reflects a less dense network, concentrated among fewer countries, with China dominating the REE market from extraction to manufacturing. This concentration poses risks related to supply chain resilience and geopolitical dependencies.

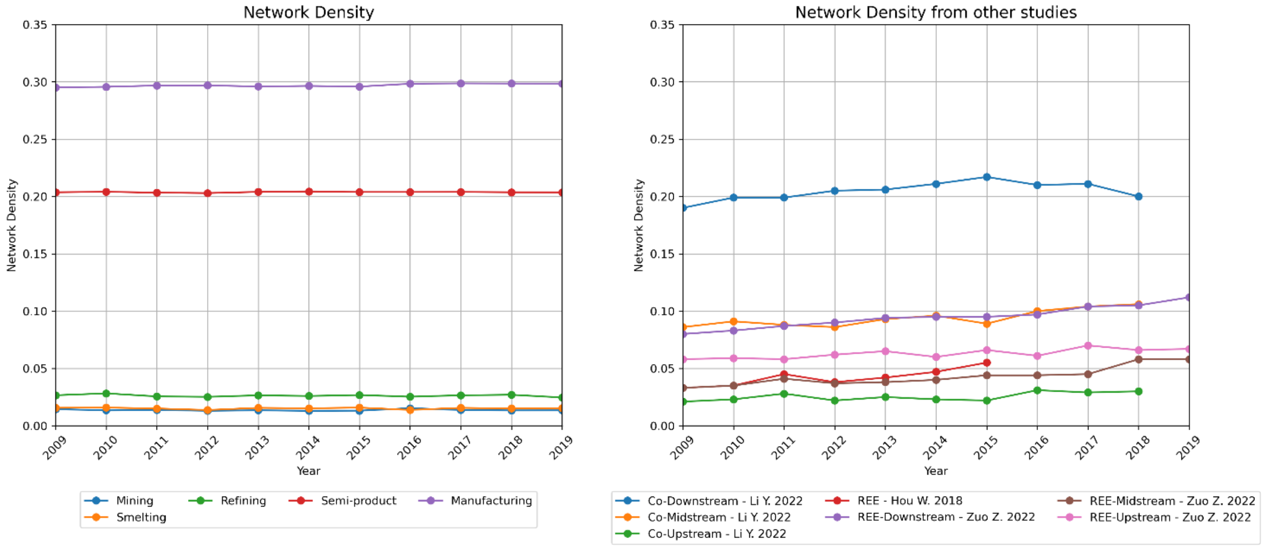

Figure 9: Network Density Trends for Nickel and Comparative Materials: (a) Nickel Network Density; (b) Network Density of Co and REEs derived from other studies.

Overall, these trends highlight the varying degrees of network density and interconnectivity within and between different material supply chains, influencing their stability, efficiency, and susceptibility to external shocks. This analysis underscores the importance of strategic international cooperation to mitigate vulnerabilities and ensure supply chain reliability.

Clustering coefficient

Figure 10 illustrates the clustering coefficient (CC) trends within the global nickel network, highlighting the interconnectedness of the top 20 countries involved in nickel trade from 2009 to 2019. The CC is a measure of the cohesiveness of trade, where a higher coefficient suggests that a country and its trade partners form a close-knit group, with a high likelihood of mutual trade connections among them.

China emerges as the preeminent node with the highest CC, approximately 0.65, showing a slight but steady rise over the decade. This trend underscores the robustness of China's trade network, which is possibly fortified by durable trade agreements fostering consistent and dependable links within the global nickel arena.

The United States exhibits a gradual increase in CC, culminating in 0.61, making it the second most interconnected country by 2019. This gradual ascent reflects the United States' expanding influence as a key participant in the nickel market, engaged significantly in both importing and exporting activities. Japan's CC also displays a consistent upward trajectory, beginning at 0.45 in 2009 and ascending to just below the United States' coefficient by 2019, placing it solidly in third. Following a similar upward trend, Brazil has bolstered its position within the nickel supply chain. With rich nickel mines and augmented production capabilities, Brazil has climbed to the fourth rank, highlighting its growing prominence.

Conversely, other nations like Spain and Italy show decreasing CC trends. This pattern may indicate a strategic pivot toward decentralizing trade networks or diversifying trade partnerships, aiming to lessen reliance on a singular trade network and to buffer against the vagaries of economic and geopolitical changes. The graph, in totality, captures the fluid and complex nature of the global trade network, revealing how shifts in economic policy, geopolitical dynamics, technological progress, and the evolving landscape of global production and demand influence the web of trade connections.

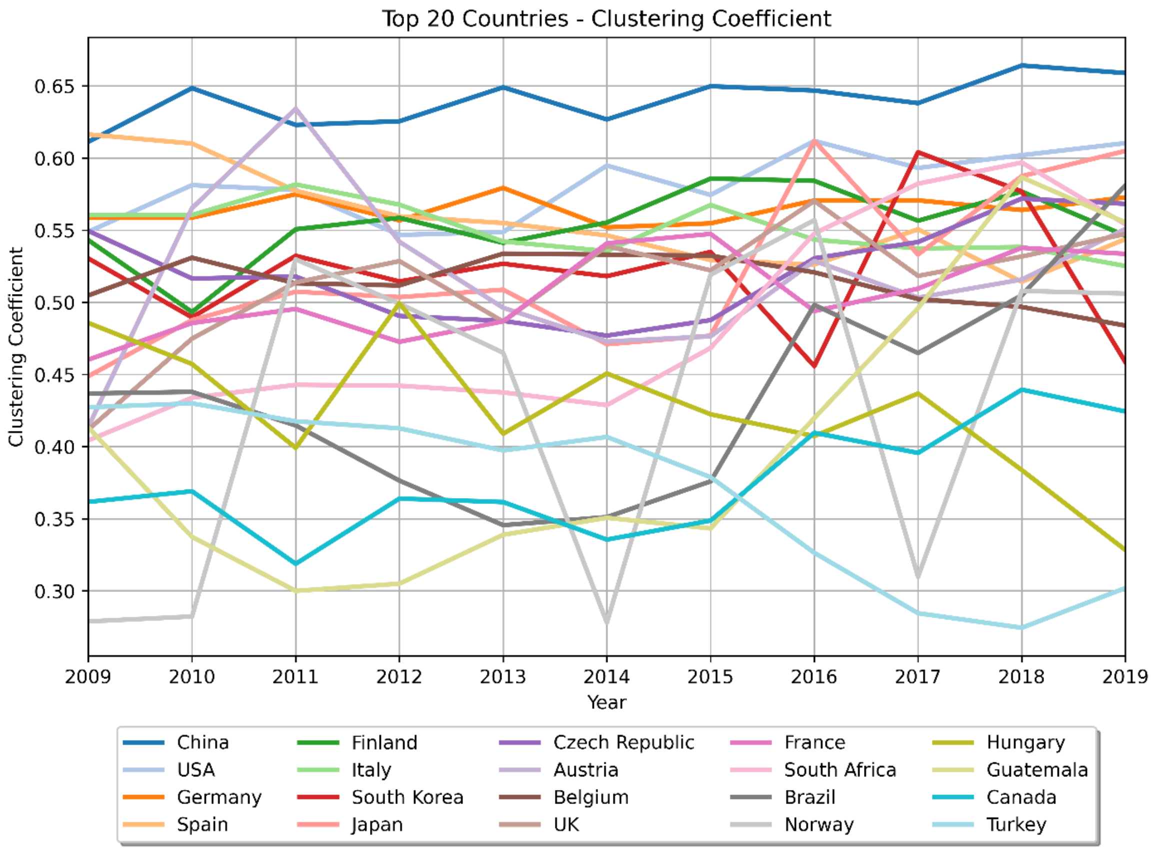

Figure 10: Clustering coefficient of the top 20 countries in the nickel supply chain.

In&Out Strength Degree

Figure 11 illustrates the In&Out strength of the global nickel supply chain from 2009 to 2019, revealing the trade volumes and dynamic shifts among the top 10 countries engaged in nickel production and consumption at various supply chain levels, from mining to end-use. In the mining layer, the SD^{in} consistently registers as zero, indicating no inputs into the mining process. Conversely, in the end-use layer, the SD^{out} is zero, reflecting that the end-use sector does not contribute outputs back into the supply chain.

The output from the mining sector shows temporal variations, highlighting changes in regional production capacities and influences. Indonesia and the Philippines are significant contributors to the Out Strength in mining. Indonesia experienced a decline in 2014 due to an export ban on nickel ores but recovered steadily post-ban, reestablishing its position as a major nickel ore exporter. Meanwhile, the Philippines saw a continuous increase over the decade, with a notable dip in 2016 following the environmental clampdown by then Environment and Natural Resources Secretary Gina Lopez[160], which led to the closure or suspension of numerous mines.

At the refining layer, there is a marked rise in both inputs and outputs, underlining the complexity and interconnectedness of this stage. China emerges as the primary importer of nickel ores, compensating for its scant domestic reserves and meeting its substantial internal demand. Despite a consistent decrease in inputs since 2015, Russia remains a key player, whereas Japan has seen a progressive increase in inputs during this period. Notably, China also excels as an exporter of refined nickel, leveraging its extensive refining capabilities and competitive edge. Similarly, Japan's increasing imports of refining materials highlight its expanding influence in this sector.

The semi-product layer serves a pivotal role by linking upstream suppliers with downstream manufacturers, and here China's involvement is particularly significant. It acts both as a major recipient and a producer of semi-products, with its output tripling over the analyzed period. Other countries display much lower levels of In&Out strength, maintaining stable trends throughout the decade.

Figure 11: Top 10 In-Strength (left) and Out-Strength (right) countries.

In the manufacturing domain, China dominates by processing and utilizing the majority of the world's nickel, underscoring its central role in the nickel supply chain. This trend continues into the end-use layer, where China's substantial input levels further establish its status as a leading consumer of nickel products and a manufacturing powerhouse, pivotal to global trade dynamics.

In&Out degree

In Figure 12 the In&Out degrees for the top 10 countries involved in the nickel supply chain are presented. While the strengths, previously showed, provide insights into the roles of these nodes in terms of nickel flow volume and value, highlighting their importance in the network, the degrees offer a straightforward, count-based view of network connections.

This comparison illuminates key differences: China plays a predominant role in the strength metrics due to the substantial quantity of nickel it processes, yet this dominance is not mirrored in the In&Out degrees.

In the mining sector, the distribution among the top 10 countries is relatively balanced, with connections ranging from 2 to a maximum of 11. This suggests that while Indonesia and the Philippines may exhibit the highest out-strengths, indicating large volumes of nickel exports, they maintain fewer trading connections compared to their output volume.

Moving to the refining layer, China exhibits the highest In-degree, reinforcing its status as a major importer of nickel ores. Interestingly, China does not feature among the top in Out-degree, highlighting a discrepancy between its import capacity and export activities. The number of connections notably expands from the refining to other layers, increasing from a maximum of 40 to 200. This expansion underscores the limited number of global refining facilities, which a larger number of players depend on, thus adding layers of complexity to the supply chain.

Similar trends and results are observed in the semi-products and manufacturing layers. Unlike the strength metrics, China does not stand out significantly in terms of degrees, presenting a more diversified scenario. The increase in the number of connections from In to Out degrees across these layers reflects the escalating complexity of the network. This aligns with previously reported network density results, confirming the growing intricacy and connectivity within the global nickel supply chain.

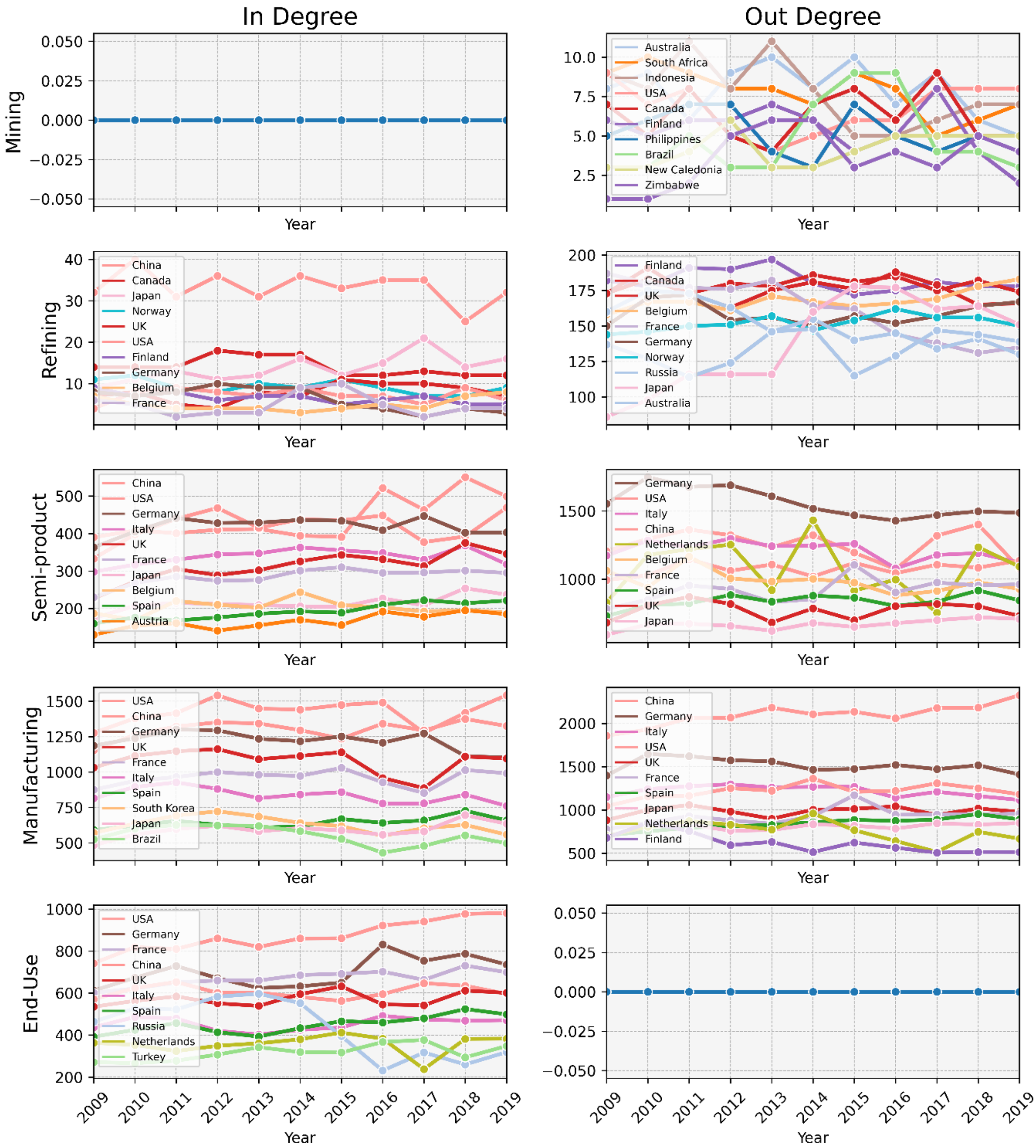

Figure 12: Top 10 In-degree (left) and Out-degree (right) countries.

Overall, this narrative portrays a dynamic and multifaceted global nickel supply chain. Each country's role is nuanced and evolves over time, influenced by economic policies, global demand, and their strategic position in the network. This complexity underscores the importance of ongoing monitoring and analysis to understand and anticipate future shifts in this vital industry.

3.4.2. Panel Regression Analysis result

Table 6 in the study provides a descriptive statistical analysis of key variables related to nickel consumption, including Value Added (VA), Backward Linkage (BL), network degrees and strengths, and centrality measures. The wide variation in these variables necessitated a logarithmic transformation for normalization and comparability.

The study constructs eight panel regression models to analyze the impact of these variables on embodied nickel consumption. The first model establishes a baseline with control variables, and subsequent models incrementally add variables like In-Degree (D^{in}), Out-Degree (D^{out}), In-Strength (SD^{in}), Out-Strength (SD^{out}), Betweenness Centrality (BC), and Eigenvector Centrality (EC) to assess their unique influences. The final model aggregates all variables for a comprehensive analysis.

Table 5: Descriptive statistics of variables for Ni embedded consumption.

	count	mean	std	min	max
Dependend variable					
Ni consumption	16832	3868.802	32419.66	0	1606354
Control Variables					
Value_Added	16832	39842.8	355667	0	15702604
Backward Linkage	16832	2.512277	2.197469	1	59.86078
Population	16832	1.51E+08	3.75E+08	245950	2.23E+09
Independent Variables					
Degree In	16832	215.2165	153.0699	0	687
Degree Out	16832	211.7586	333.9351	0	1390
Strength In	16832	3868.746	32419.67	0	1606354
Strength Out	16832	2116.049	26954.17	0	1563325
Betweenness Centrality	16832	0.000279	0.000911	0	0.014886
Eigenvector Centrality	16832	0.021302	0.014134	0	0.057872

The Hausman test determines the suitability of fixed or random effects models for each regression, leading to the use of Random-Effects for most models, with Fixed-Effect models applied for In-strength and Eigenvector models. The key findings of the panel regression here performed are the following:

- *Value Added:* exhibits a consistently positive influence on nickel consumption, indicating that higher economic output within nodes positively affects their consumption of nickel. This effect is more pronounced with outbound connections (D^{out}), suggesting that nodes with higher value-added significantly leverage their outward linkages to consume and possibly distribute more nickel. However, the impact slightly diminishes when considering the presence of numerous inbound connections (D^{in}), potentially due to the dilutive effects of dependency on multiple supply sources.
- *Backward Linkages:* The influence of BL on nickel consumption is multifaceted and highly context dependent. It is statistically significant in scenarios involving D^{in} connections, emphasizing that nodes with extensive BL are adept at managing incoming relationships, which correlates with increased nickel consumption. However, this influence is less evident with D^{out} connections, implying that BL do not necessarily enhance a node's ability to manage or expand its outbound trade effectively.
- *Population*: while a fundamental demographic indicator, exerts a less pronounced impact on nickel consumption than network-specific or economic measures. This subtlety might reflect the indirect relationship between population size and industrial nickel usage, which is more directly driven by industrial activities and network structures rather than sheer population metrics.
- *In Degree (D^{in}) and Out Degree (D^{out})*: A higher D^{in} strongly correlates with increased nickel consumption, highlighting the importance of a well-connected input network. In contrast, D^{out}, representing the number of distribution links, does not strongly predict nickel usage, suggesting that having numerous output links does not necessarily increase consumption.
- *In Strength (SD^{in}) and Out Strength (SD^{out}):* high SD^{in} signifies substantial nickel input volumes, and high SD^{out} indicates significant output volumes, both correlating with increased economic activity and nickel consumption at those nodes.

- *Betweenness Centrality (BC):* emerges as a significant strategic influencer, with sectors scoring high on this metric playing pivotal roles in regulating nickel flow and consumption patterns within the network.
- *Eigenvector Centrality (EC):* though indicative of a node's influence within the network, reveals a nuanced impact on nickel consumption. This complexity suggests that while EC is crucial for understanding potential control or influence points within the network, its direct correlation with consumption is less straightforward.

Table 6: Panel Regression result of embodied Nickel consumption.

	Controls Only			**In Degree**			**Out Degree**			**In Strength**		
	Std.	T-stat	P-value	Std.	T-stat	P-value	Std.	T-stat	P-value	Std.	T-stat	P-value
VA	0.0030	1.8307	0.0672	-0.2699	-8.4833	0.0000	0.4637	23.339	0.0000	0.0043	1.7895	0.0735
BL	168.51	1.4100	0.1586	0.0035	0.5824	0.5603	0.0333	1.7384	0.0822	0.0006	0.6746	0.4999
Pop	4.585e-05	1.1073	0.2682	1.5358	1.9779	0.0480	-0.9177	-1.0530	0.2924	-0.0186	-1.8685	0.0617
D^{in}				0.0188	40.321	0.0000						
D^{out}							21.720	27.474	0.0201			
SD^{in}										0.9972	1357.6	0.0000
SD^{out}												
BC												
EC												
Hausman test		0.069146			3.1921			1.5357			17.032	

	Out Strength			**Betweenness Centrality**			**Eigenvector Centrality**			**All Independent Variables**		
	Std.	T-stat	P-value	Std.	T-stat	P-value	Std.	T-stat	P-value	Std.	T-stat	P-value
VA	0.5224	22.939	0.0000	0.3825	20.298	0.0000	-0.2356	-7.3814	0.0000	0.0072	2.1490	0.0316
BL	0.0319	1.7392	0.0820	0.0603	2.2516	0.0244	0.0095	1.2183	0.2231	0.0006	0.6464	0.5181
Pop	-1.4245	-1.6687	0.0952	0.3817	0.3724	0.7096	4.0239	4.8914	0.0000	-0.0182	-2.0837	0.0372
D^{in}										-7.61e-05	-0.8694	0.3846
D^{out}										3.669e-06	0.3572	0.7210
SD^{in}										0.9909	255.98	0.0000
SD^{out}	0.5813	34.158	0.0000							0.0058	1.6777	0.0934
BC				1050.7	6.2995	0.0000				-2.4032	-1.6651	0.0959
EC							186.24	29.224	0.0000	1.0563	0.9029	0.3666
Hausman test		2.974445			0.071281			23.2288			1.56449	

The analysis illustrates the intricate interactions between economic output, backward linkages, demographic factors, and network dynamics in shaping nickel consumption patterns. Nodes with high economic output and strategic network positions are critical in influencing both the volume and pathways of nickel consumption. The role of backward linkages, in particular, highlights how effectively nodes manage and utilize their incoming supply connections to support their consumption and potentially their outward trade activities.

This analysis elucidates a complex interplay of factors shaping nickel consumption patterns, indicating that effective resource management strategies must extend beyond traditional economic and demographic considerations to include a nuanced understanding of network dynamics and material flows. The integration of VA, BL, and various centrality measures in our models not only highlights the multifaceted influences on consumption but also suggests pathways for optimizing supply chain resilience and efficiency.

For instance, the pronounced impact of BL on consumption underlines the potential benefits of strengthening these connections to buffer against supply disruptions. Similarly, the strategic roles identified through Betweenness and Eigenvector Centrality metrics can inform targeted policy interventions aimed at mitigating risks associated with key nodes within the supply network. Therefore, this analysis should serve as a foundational tool for policymakers and industry leaders, guiding the development of comprehensive strategies that ensure sustainable and secure nickel supply chains in the face of evolving economic, environmental, and geopolitical landscapes.

4. Supply Risk assessment materials/products (Case study n° 2)

4.1. Using MRIO frameworks in Supply Risk Assessment

The MRIO framework presents a pivotal advancement in the field of supply risk assessment for critical materials. Its inherent capacity to elucidate the complexities of global supply networks is invaluable, particularly when combined with MFA. This synthesis creates a multi-faceted lens through which the flow of critical materials, such as nickel, can be examined not merely in terms of quantity but also in regard to the intricate web of economic relationships and dependencies that define the global market. Incorporating MRIO into supply risk assessments enables the dissection of international trade layers, revealing the nuances of inter-regional exchanges and the propagation of risk through the supply chain. This granular visibility is instrumental in identifying potential bottlenecks and vulnerabilities that could disrupt material flows, and thus, it provides a robust basis for strategic planning and policy-making.

Moreover, the augmentation of the MRIO model with datasets like the Human Development Index (HDI) and the Worldwide Governance Index (WGI) introduces a multi-dimensional perspective to the study. These indices, reflecting the socio-political and governance landscapes of nations, add depth to the traditional economic and technical parameters, allowing for a more holistic risk assessment. For instance, HDI can illuminate aspects of labor quality and social stability which may impact supply chains, while WGI offers insights into the regulatory and political environments that can affect material sourcing and trade.

By integrating these diverse datasets, the study transcends conventional risk evaluations, facilitating a nuanced understanding of how socio-economic and governance factors intertwine with the physical flow of materials. This comprehensive approach not only enriches the analytical depth of the research but also ensures that the resulting risk profiles are reflective of the multifarious nature of global supply chains. In essence, the MRIO framework, enhanced by MFA and external datasets, equips researchers and decision-makers with a sophisticated toolkit to navigate and strategize within the increasingly complex domain of critical material supply risk.

4.2. Background Case Study n° 2

The research presented in this case study ventures beyond conventional supply risk assessments by pioneering a nuanced approach that hinges on the MRIO nickel flow network. This novel framework facilitates an enhanced disaggregation of nickel products within the MRIO model, thereby offering a refined lens to view the supply chain intricacies.

This study illustrates how the augmentation of the MRIO network with a granular breakdown of nickel products from the MFA approach, can substantially improve supply risk assessments. By incorporating additional indicators from external datasets such as the WGI and the Environmental Performance Index (EPI), along with insights derived from CNA, the research culminates in a comprehensive supply risk indicator that transcends traditional assessment parameters.

The integration of these diverse indicators and methodologies unveils a more holistic view of the supply risks associated with nickel. The MRIO network's augmented capability to differentiate between nickel products—particularly those pertinent to the electric vehicle sector—allows for a more detailed risk analysis. This enhanced level of detail is critical, given the varied and specific applications of nickel products, which demand tailored risk mitigation strategies.

In this section of my thesis, the journey from the creation of the disaggregated MRIO flow network to the development of a comprehensive supply risk indicator is chronicled. The process underscores the innovative merging of multiple data sources and analytical techniques to reveal the multifaceted nature of supply risks for nickel. This research not only fills a critical gap in the existing literature but also sets the stage for the application of this advanced approach to other critical materials, giving a better understanding of the risk along all the supply chain of a critical material.

Through detailed analysis, the study demonstrates how this integrative method can inform more effective policy formulation and strategic decision-making. By capturing the complexity of nickel supply chains, the research aligns with the thesis's overarching aim: to deliver a robust, evidence-based foundation for the sustainable management of critical materials in an era characterized by rapid technological advancement and escalating resource demands.

4.3. Material & Method

4.3.1. System definition

In this research, the system under study is meticulously defined through a framework that integrates supply risk indicators across the nickel supply chain, illustrated in Figure 13. This framework delineates the assessment of political and social risk, environmental and technological risk, and economic and network risk, each quantified by specific indicators such as the HDI, WGI, EPI and the Herfindahl-Hirschman Index (HHI), among others. At the heart of the framework is the recognition of "General Risk" as a confluence of these multidimensional indicators, flowing through the stages of the nickel supply chain – mining, smelting, refining, manufacturing, usage, and waste management. The granularity of this approach is evident in the detailed classification of nickel products at different processing stages, such as matte, sulphide ore and laterite ore in the early stages, to more refined products like Ni class I and Ni sulphate. This classification is vital for understanding the unique risks each product carries through its life cycle, from extraction to its EoL.

The research pivots on the MRIO flow network's capability to disaggregate nickel products, allowing for a supply risk assessment that is both precise and aligned with the complexities of global supply chains. The framework provides a structured methodology to evaluate risks, considering the interdependencies within the supply chain and the multiplicity of external influences. This systemic approach empowers the research to go beyond simple supply and demand analysis, offering a sophisticated understanding of the inherent risks in the nickel supply chain which are pivotal for formulating resilient, future-proof strategies in resource management.

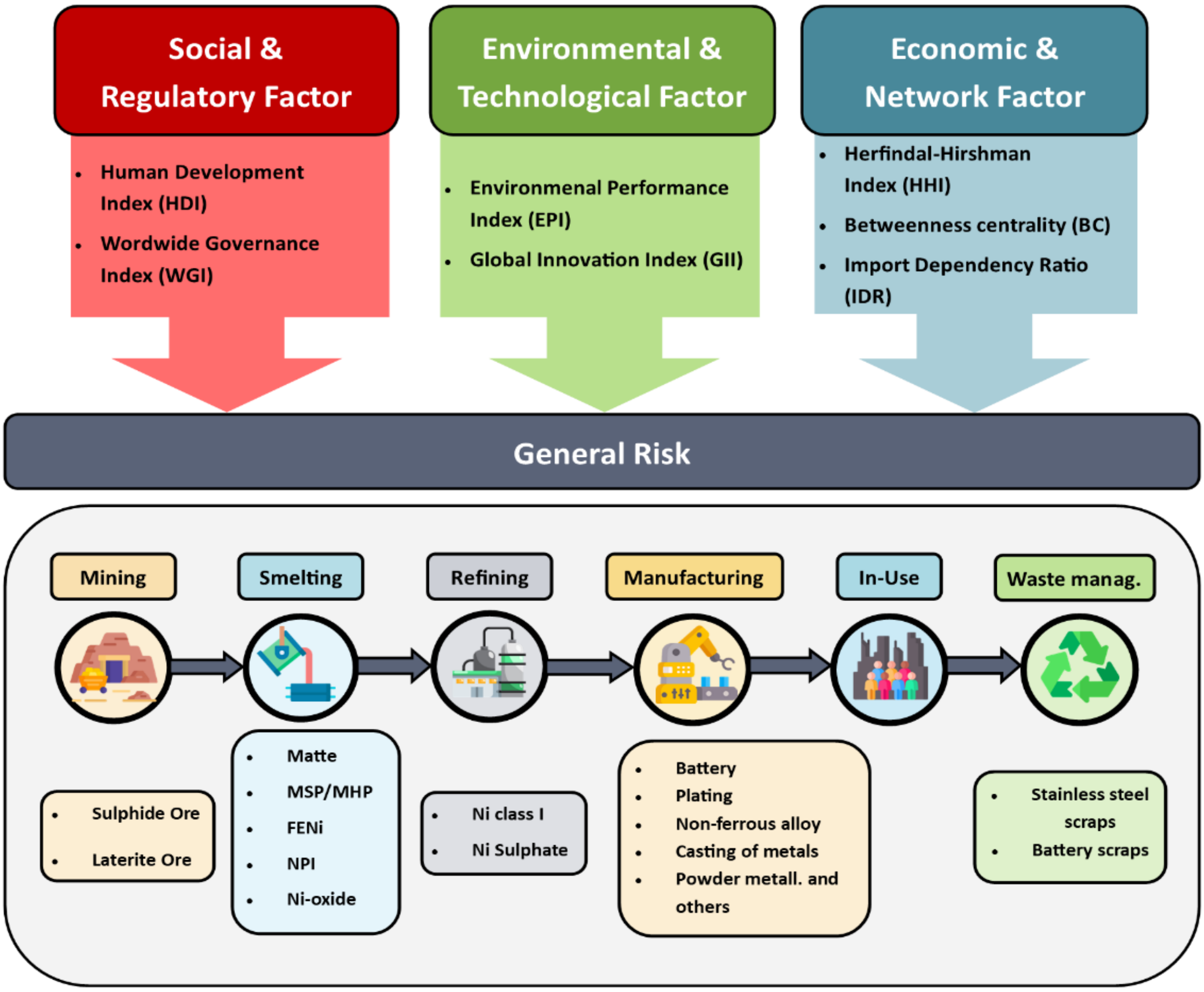

Figure 13: Study Framework - Supply Risk Indicator - Nickel supply chain (products)

4.3.2. Supply Risk

The supply risk equation $SR(p, c)$ introduced in this research is a sophisticated model that assesses the risk associated with the supply of nickel products across various countries. Designed to reflect a multitude of risk factors, the equation incorporates a suite of strategically selected components to capture the full breadth of supply risk across economic, political, social, environmental and technological dimensions.

- **Economic and Network Factors**

From an **economic** perspective, market concentration and competitiveness are gauged using the **HHI**, which reflects potential risks tied to market dominance for a particular nickel product “p”. The

HHI is normalized dividing by 10000 to have a value comprise between 0 and 1:

$$HHI_{\text{p,norm.}} = \frac{\sum_i S_i^2}{10000} \qquad \text{(Eq. 45)}$$

where Si is the market share of country i.

The **Import Dependency Ratio** (**IDR**) provides insights into a country's "c" reliance on imports of nickel product "p", highlighting vulnerabilities and dependencies within the supply chain. The Import Dependency Ratio (IDR) reflects a country's reliance on imports, with higher values denoting greater risk due to foreign market dependency:

$$\text{IDR}_{c,p} = \frac{\text{Net imports}}{\text{Apparent consumption}} = \frac{\text{Net Imports} - \text{Exports}}{\text{Domestic Production} + \text{Imports} - \text{Exports}} \qquad \text{(Eq. 46)}$$

Network factors are assessed using **BC**, a metric that quantifies the influence of a country "c" as a pivotal node within the global nickel network. This measure identifies strategic positions within the network, signifying a country's control over the flow and distribution of nickel products, and is calculated as follows:

$$BC_i = \sum_{j<k} \frac{g_{jk}(i)}{g_{jk}} \qquad \text{(Eq. 47)}$$

The variable g_{jk} represents the number of shortest paths between country j and country k, and $g_{jk}(i)$ represents the number of shortest paths between country j and country k through country i. Variable BC_i is the betweenness centrality of country i. BC ranges from 0 to 1, with higher values indicate higher centrality and therefore lower network risk.

- **Social and Regulatory Factors**

The **WGI**[161] and the **HDI**[162] are incorporated to account for political and social variables. The WGI evaluates governance quality, encompassing aspects such as regulatory quality and political stability, which can influence nickel supply.

For the WGI, that typically ranges from approximately -2.5 (weak governance) to 2.5 (strong governance) is normalized and inverted with a commonly used approach that linearly transforms WGI scores to a standardized scale based on hypothetical bounds, as shown:

$$\mathrm{WGI}_{\mathrm{norm.}} = 20 \cdot (2.5 - \mathrm{WGI}) \quad \textit{(Eq. 48)}$$

The HDI, which ranges from 0 to 1, on the other hand, provides a socio-economic progress overview, factoring in education, health and standard of living. Higher HDI scores reflect better health, education, and income levels, suggesting a more robust environment for sustainable supply chain operations. For this analysis, the HDI is inverted, so that higher values indicate greater social risk.

- **Environmental and Technological Factors**

Environmental and technological dimensions are evaluated using the and the **Global Innovation Index**[163] (**GII**). The EPI assesses a country's commitment to environmental sustainability, which is crucial in the context of nickel production. It is traditionally scored on a scale from 0 to 100, with higher scores reflecting better environmental performance. For this analysis, the index is rescaled to range from 0 to 1 and inverted, so that higher values indicate greater environmental risk.

Similarly, the GII measures a nation's capacity for innovation, which plays a significant role in advancing technological methods in nickel processing. Like the EPI, the GII is scored from 0 to 100, where higher scores denote a stronger innovation environment. For the purposes of this study, the GII is also rescaled from 0 to 1 and inverted to reflect increased technological risk with higher values.

This comprehensive approach integrates these diverse indicators into the $SR(p,c)$ equation, rendering a multi-dimensional supply risk assessment for nickel products. The methodology is vital for stakeholders in the nickel industry to make informed strategic decisions and manage risks in a complex global market. The equation is formalized as follows:

$$SR_{p,c} = HHI_{\mathrm{p,norm.}} * \left(\sum_{i}^{n} IDR_{p,c,i} * (1 - WGI_i * HDI_i * EPI_i * GII_i)\right) * (1 - BC_c) \quad \textit{(Eq. 49)}$$

Applying this sophisticated methodology to the nickel supply chain, the research explores the intricacies of supply risks from the initial mining stage to the end-product manufacturing phase. The integration of diverse data sets and analytical perspectives leads to a nuanced understanding of supply risks that is unprecedented in previous studies.

The findings of this research have profound implications for policymakers, investors and industry leaders. By providing a detailed risk profile of the global nickel supply, informed decisions can be made that consider the full spectrum of economic, social, political, environmental and technological factors. The $SR_{p,c}$ equation serves as a cornerstone of this investigation, exemplifying the thesis's commitment to advancing the field of supply risk assessment for critical materials.

4.4. Key Results

4.4.1. Global production

Figure 14 provides an in-depth analysis of the worldwide nickel supply chain, detailing country-by-country production trends from 2009 to 2019 for a variety of nickel products, including laterite and sulphide ores, FeNi, NPI, nickel matte, MSP/(MHP, nickel class 1, and nickel sulphate. This illustration effectively maps out the geographic spread and the temporal development of nickel production, underscoring the influence of geographical and technological factors on the industry.

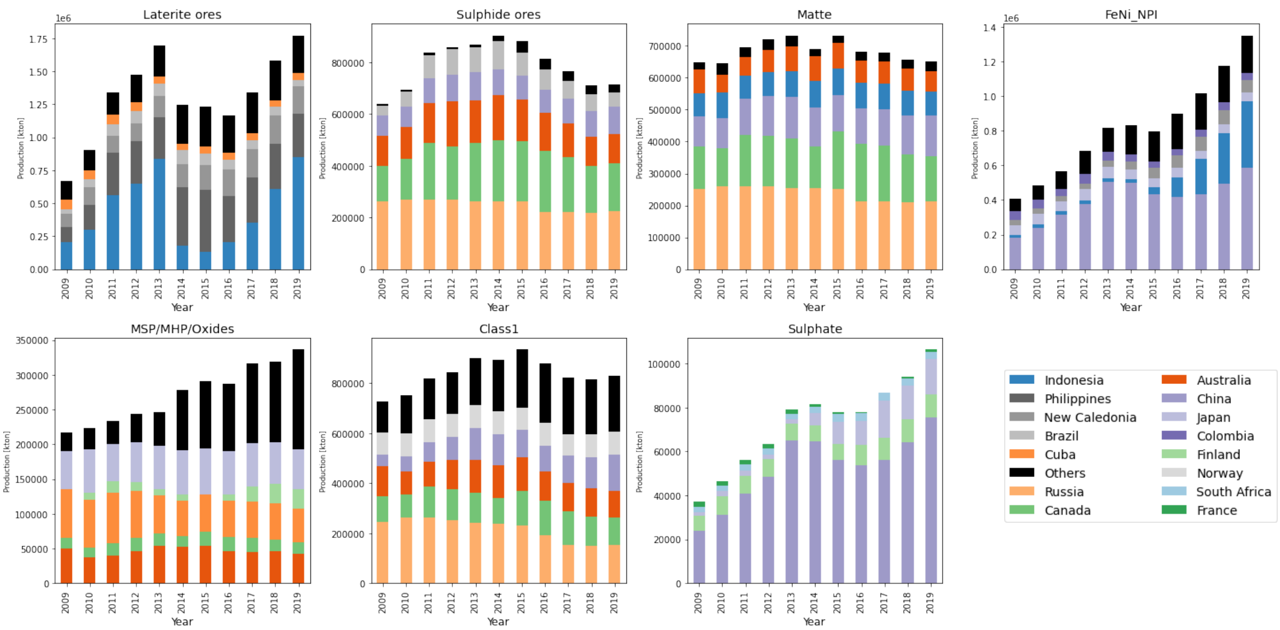

Figure 14: Comparative Annual Production of Nickel Ores and Intermediates from 2009 to 2019.

There's a clear trend of increasing production volumes over this ten-year span, with notable growth in certain countries and product categories. Indonesia, for instance, has seen a significant uptick in laterite ore production, largely due to its export ban that shifted the focus to in-country processing, leading to an increase in NPI and FeNi production. The Philippines stands out as the second-largest producer, maintaining a strong presence in the laterite nickel sector. Production of sulphide ore has been steady, with Russia, Canada and Australia leading as the top producers, respectively. This steadiness is also seen in nickel matte production, which mainly comes from sulphide mines.

Interestingly, Indonesia has made strides in matte production as well, utilizing its laterite ore in a move towards more value-added processing. FeNi global production has seen a threefold increase over the decade, with China as the primary producer, mainly using laterite ores imported from other countries. Post the export ban on raw ores, Indonesia's domestic FeNi production has seen a significant rise, showcasing a strategic shift in its nickel industry. Production of nickel class 1 has been relatively steady, with Russia, Canada, and Australia leading the production. China, however, has significantly expanded its production capacity, adding variety to its nickel product mix. Nickel sulphate production has almost tripled in the last decade, with China leading the pack, responsible for about 70% of the worldwide production. This boost is largely driven by the electric vehicle battery sector demand, particularly within China. Finland's production levels have remained stable, while Japan has experienced an increase, highlighting the evolving dynamics of the global nickel sulphate market.

Figure 15 showcases the annual production data from 2009 to 2019 for finished nickel products. It highlights that the majority of production for both stainless steel and batteries, crucial commodities in various industries and the burgeoning electric vehicle market, respectively, predominantly originates from China. During this period, China experienced a consistent growth in production, ultimately securing a global share of approximately 80%.

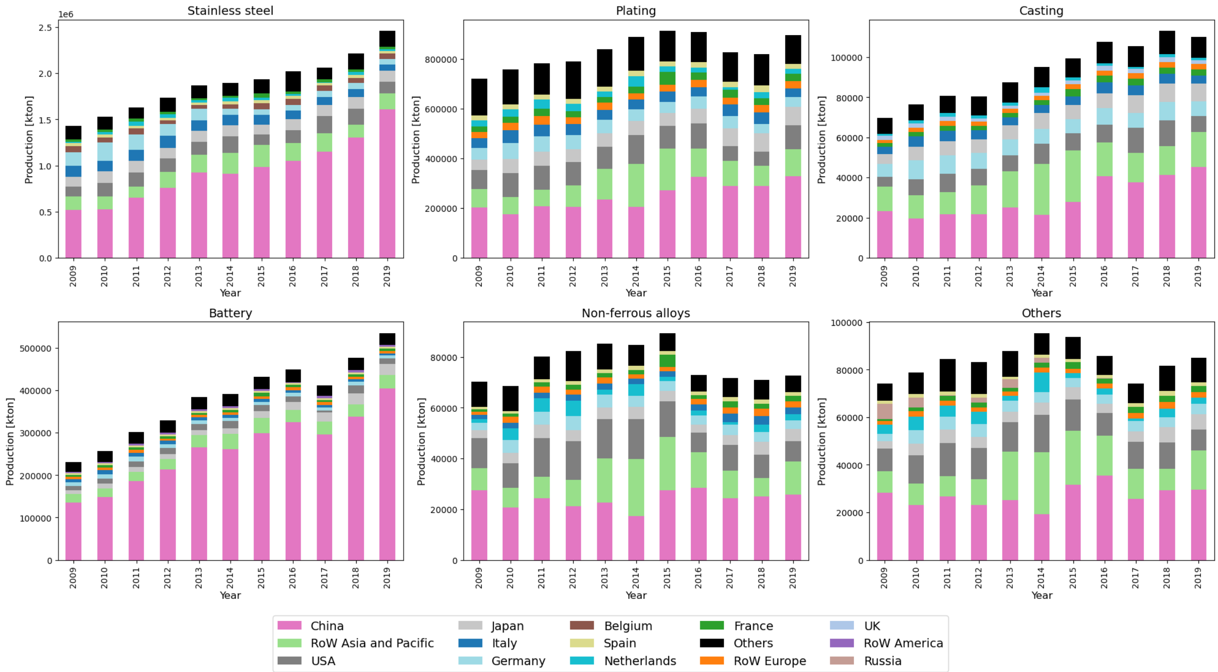

Figure 15: Annual Production of Nickel finished products from 2009 to 2019.

This establishes China as the leading producer of these two key commodities. Notably, the global production of batteries more than doubled over the decade, while stainless steel production surged from 1.4 million tonnes to nearly 2.5 million tonnes. The supply chain for other nickel products is characterized by a greater diversity of contributors, though China remains a significant player in these sectors as well. The production of these products remained relatively stable overall, with casting products witnessing a modest increase over the analyzed period. The "Rest of the World Asia and Pacific" region ranks as the second-largest producer for these latter four products, followed by the USA and Japan. Within Europe, Italy, Germany, and Belgium are the main producers, but contribute a smaller fraction to the global production, positioning Europe as a minor participant in the supply chain for these nickel products.

Bridging the detailed analysis of nickel production trends and the exploration of market concentration through the Herfindahl-Hirschman Index, we delve into how these production shifts translate into market dynamics and potential supply chain vulnerabilities.

The HHI for nickel products, as illustrated in Figure 16 for the years 2009 to 2019, offers a quantitative perspective on the supply chain's structure. Higher HHI values indicate greater market concentration, which in turn suggests increased supply chain risk due to a heavy dependence on limited sources. Notably, the HHI for steel and battery sectors has experienced a significant rise, mirroring China's expanding share in production. This climb in HHI signals a market becoming more centralized in China, highlighting potential vulnerabilities due to this consolidation.

For the sulphate sector, which possesses the third highest HHI, the figures affirm the previous data that spotlighted the high degree of market concentration in China. This centralized control over the sulphate supply can lead to increased exposure to market shifts and supply disruptions. Regarding FeNi, the decline in HHI since 2014 can be attributed to Indonesia's escalated production following the nation's implementation of an export ban on nickel ores. This policy spurred a substantial increase in domestic production of nickel products, refining from these ores, which in turn contributed to a decrease in the HHI for FeNi. This diversification effectuates a more distributed market, diluting the previous concentration risks.

As for NPI, similar dynamics are at play. Indonesia's bolstered internal production has not only amplified supply but also introduced new competitive dynamics into the market, further contributing to the dilution of market concentration and the reduction in HHI.

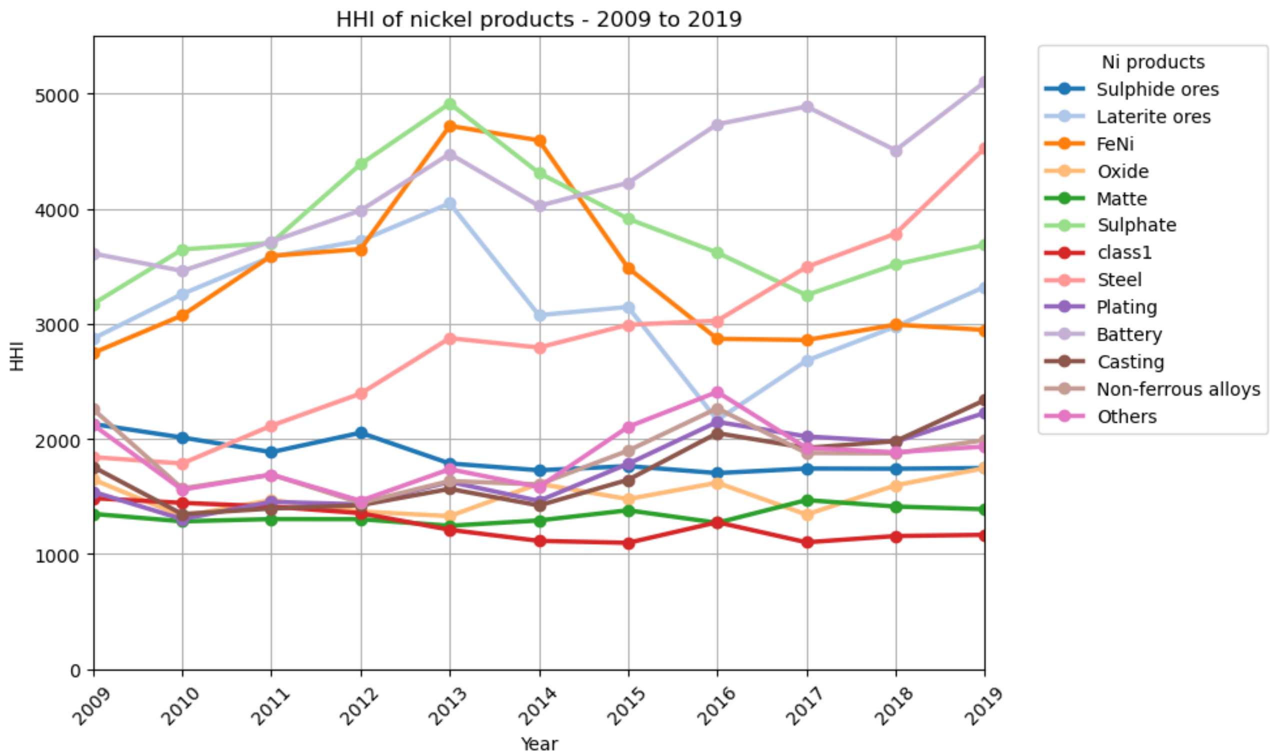

Figure 16: HHI development of nickel products.

Other nickel products such as class 1 nickel, plating, and non-ferrous alloys have shown more stability in their HHI values throughout the decade. This steadiness indicates a relatively constant market structure, with no single country or producer becoming significantly more dominant. The consistent HHI readings suggest that the supply chains for these products are less vulnerable to the risks associated with high market concentration and maintain a steady presence in a diversely competitive field.

4.4.2. Supply Risk

This section presents the findings related to the supply risk in the nickel market. Utilizing a heatmap, we illustrate the supply risk associated with various nickel products across the top 20 players in the nickel supply chain for the year 2019. In the subsequent part, we delve into the historical supply risk for a specific country, alongside its share of imports, spanning from 2009 to 2019.

Heat map Supply Risk

Figure 17 presents a heat map that quantitatively showcases the supply risk associated with a range of nickel products across various nations in 2019. By employing a color gradient that transitions from light yellow to dark blue, the map effortlessly distinguishes between areas of low and high supply risk. This visualization method adeptly simplifies the complex dynamics of supply risks, unveiling significant vulnerabilities among the principal countries engaged in the nickel supply chain for the evaluated nickel products. This approach not only enhances understanding but also underscores the critical areas requiring attention within the global nickel market.

Sulphide ores exhibit low supply risks globally due to their processing typically occurring within the mining country, thus minimizing the impact of international supply chain disruptions. Accordingly, nickel matte shows almost negligible risk across all countries, highlighting the self-contained nature of sulphide ore processing.

In contrast, laterite ores present a higher supply risk, largely because they are sourced from regions like Indonesia and the Philippines, which face socio-political and environmental challenges, and are key exporters. China, as a major importer from these countries, stands out for its high supply risk for laterite ores, revealing its susceptibility to supply chain interruptions.

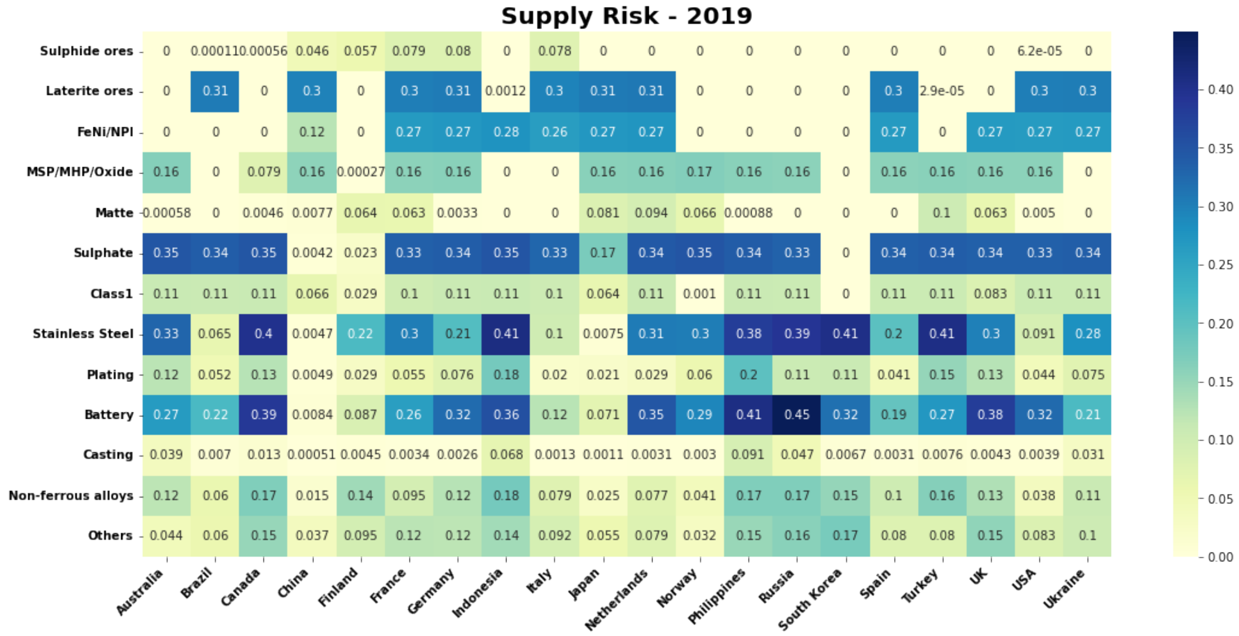

Figure 17: Heat map depicting the supply risk for different nickel products in various countries for the year 2019.

FeNi and NPI, essential for stainless steel production, carry a medium supply risk. This is due to the concentration of their production in countries with known supply risk factors, such as China and Indonesia, reflecting the potential volatility in the supply chain rooted in the socio-political and environmental conditions of these regions.

Nickel Sulphate, crucial for EVs batteries, shows varied risk levels. It's higher in most countries except for those like China, Finland, South Korea, and Japan, where the risk is lower due to advanced production infrastructure and integration within the EVs battery supply chain. China's robust Ni Sulphate production, essential for battery manufacturing, exemplifies its reduced supply risk. Conversely, countries lacking in domestic production or processing capabilities face increased supply risks, highlighting their dependency on a few production hubs and the importance of developing diversified and secure sources for this key material.

This risk analysis extends to the battery sector, with China being the dominant producer, countries reliant on Chinese imports for LiBs are exposed to increased supply chain vulnerabilities. This situation emphasizes the strategic need for alternative, resilient sources for critical battery components to mitigate risks in the burgeoning battery market.

Historical supply risk

The following figure depicts the historical trend of supply risk and import shares for the nickel products for a single country. On the left vertical axis, the import shares are shown as stacked bars, indicating the percentage contribution of each country to the total imports of a specific product per year. On the right vertical axis, the supply risk is represented as a line plot (black), demonstrating the annual risk level associated with each product. This format allows for a comparative analysis between the diversification of import sources and the supply risk over time, providing a visual summary of market dynamics for each nickel product.

Over the last ten years, the supply risk landscape for various nickel products in China has seen notable fluctuations, mirroring the country's strategic adjustments in the industrial sector and the shifting dynamics of the international market, as depicted in Figure 18.

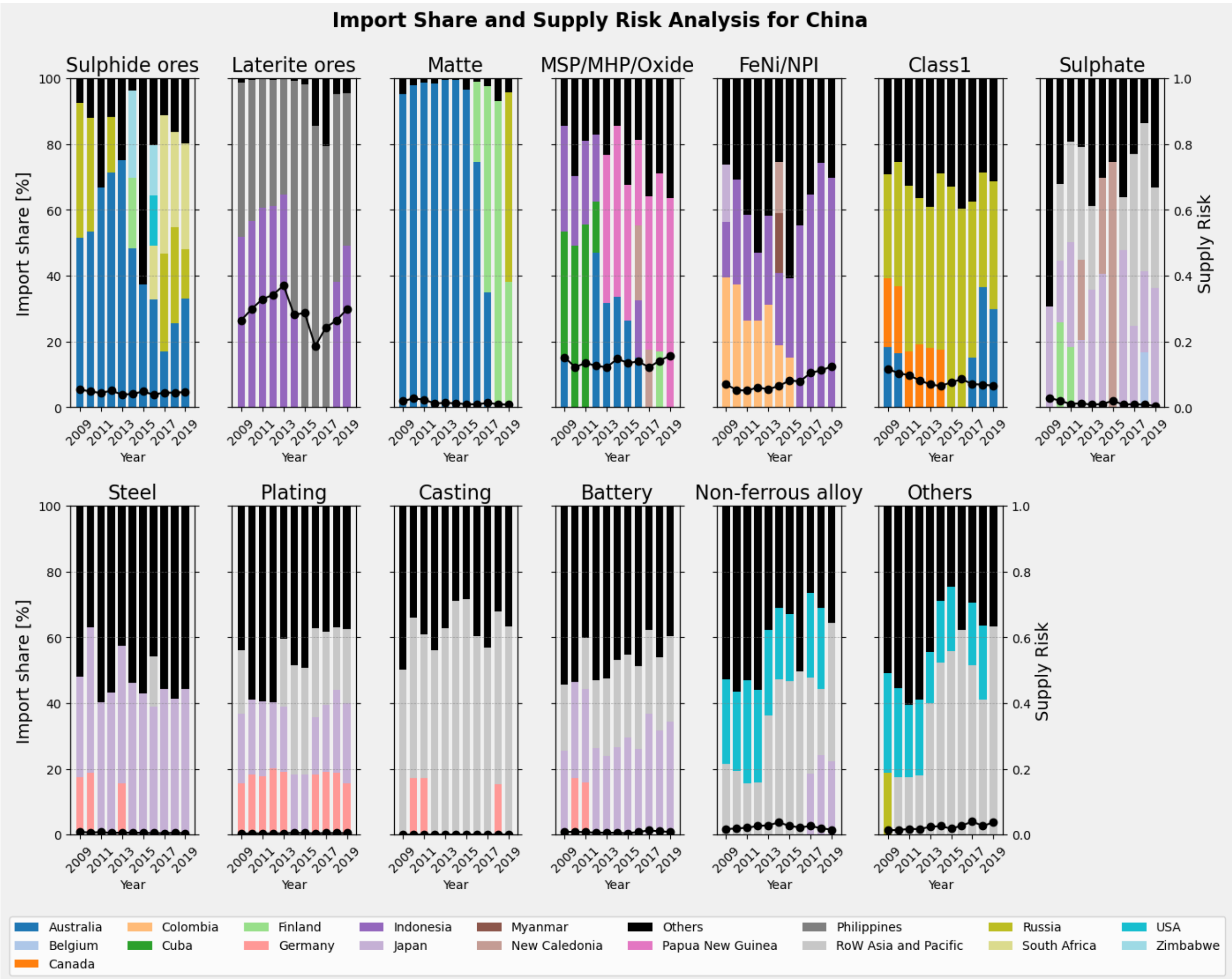

Figure 18: Import Shre and Supply Risk Analysis for China.

The risk linked to laterite ores notably surged due to an increased reliance on imports from Indonesia. Following Indonesia's 2014 export ban, this risk diminished as Indonesia's significant contribution to global laterite ore production lowered the HHI, thereby reducing the supply risk.

However, after 2016, this risk experienced an upswing once again as China's dependency on Indonesian imports intensified. Regarding sulphide ores and nickel matte, China has consistently enjoyed a low supply risk, thanks to steady production from nations such as Australia and Canada and solid trade relations.

The period observed also witnessed a slight decrease in supply risk for nickel class 1, likely due to changes in import sources away from countries like Russia considered higher risk, coupled with an increase in domestic output.

In the realms of FeNi and NPI, a minor rise in supply risk was noted, attributed to China's increasing imports from Indonesia and highlighting Indonesia's impact on China's supply chain dynamics. The supply risk for MSP/MHP/Oxide remained fairly constant, averaging around 0.16, with a growing import portion from Papua New Guinea pointing to potential vulnerabilities in China's nickel supply chain. The analysis indicates a consistently low supply risk for various nickel products throughout the decade, suggesting a robust and stable supply chain with minimal risk of disruptions. This stability is largely attributed to the substantial manufacturing capacities that China has developed over recent decades, establishing itself as a global leader in manufacturing.

This revised examination of China's supply risk for nickel products showcases the nation's dynamic response to evolving market conditions and supply challenges, emphasizing the necessity of flexible strategies in the management of global commodity supply chains. It further highlights the diverse nature of supply risks across different nickel products and the paramount importance of developing diversified and secure supply chains to counter these risks.

5. dMRWIO model: Demand Forecasting for 4 critical materials (Case study n° 3)

5.1. Background case study (3)

In this case study the focus is on the increasing urgency of transitioning to a net-zero carbon economy, highlighting the role of green technologies like EVs and wind turbines (WTs) in reducing CO_2 emissions. These technologies, however, rely heavily on critical materials such as cobalt, lithium and rare earth elements like neodymium and dysprosium, essential for lithium-ion batteries and permanent magnets in EVs and WTs. The surge in demand for these materials has prompted a rise in studies exploring future demand and potential supply bottlenecks[164]. Methodologies like MFA[5,78,79], SD modeling[81,82], LCA[80], and IOA[83,84] are commonly used. However, these methods have limitations, such as the inability to provide detailed information on interindustry flows or to address interconnected material flows in various sectors[99,165].

To overcome these limitations, in this work an integrating dMFA with MRIO modeling is proposed. This novel approach, based on the dWIO[100] model, captures the dynamics of waste generation and recycling within an IO model structure, addressing key aspects of recycling like the supply-demand balance of secondary materials and quality issues due to material mixing.

The extended dynamic Multi-Regional Waste Input-Output framework (dMRWIO) assesses the demand for various critical materials under low-carbon energy scenarios and evaluates the potential of the recycling sector to reduce reliance on primary critical materials. The framework is applied to analyze future demand-supply balance of critical materials like Co, Li, Nd and Dy in green technologies under different scenarios from the World Energy Outlook 2020 (WEO2020), offering insights into how recycling can impact the demand for virgin materials.

This comprehensive approach aims to bridge knowledge gaps and provide a more detailed understanding of the material flows and recycling dynamics in the context of a green transition.

5.2. Data & Methodology

The system of our integration modelling framework is defined as shown in Figure 19. The dMFA and MRIO modelling principles have been integrated through the following three aspects: (i) international trade of refined metals, intermediate products and final products between relevant industries within and across multiple regions, (ii) relevant waste management industries and the forecasted amount of waste, and (iii) transactions of resources between economies and the environment, providing information regarding raw material extraction in each studied region. The integration of the two modelling approaches is illustrated through colored arrows that represent all these elements and is elaborated in the following sections.

As shown in chapter 2.2, the dMRWIO builds upon the dWIO model, integrating MFA and MRIO modeling techniques. It is designed to address the international trade of raw materials, intermediates and final products containing critical metals, and the dynamic impacts of waste management on the primary demand for these metals. The dMRWIO model allows for tracking inputs, outputs and impacts of producing a typical product output across its global value chain, quantifying contributions from different economic sectors and countries.

For this study, Exiobase v.3[166,167] is used, a database with monetary MRIO tables for 49 national economies and various industries, to model the global economy. This database was modified to include four industries specifically for refining cobalt, lithium, neodymium, and dysprosium.

Global sector specific use of these materials was estimated for the year 2011 using data from the European Joint Research Center[168] (JRC) and USGS to match the global demand and use patterns. The study also considered the regional use and distribution of these materials, focusing on their applications in green technologies like wind turbines and electric vehicles. The model accounts for the sector-specific uses of these materials, disaggregating and hybridizing the MRIO table to include these critical materials, despite their relatively small share in the overall non-ferrous metals sector.

Furthermore, the end-of-life and waste treatment processes was model for all four materials and products, including collection, disassembly and recycling. It outlines the efficiency rates for disassemblers and refineries and how recycled materials re-enter the manufacturing cycle.

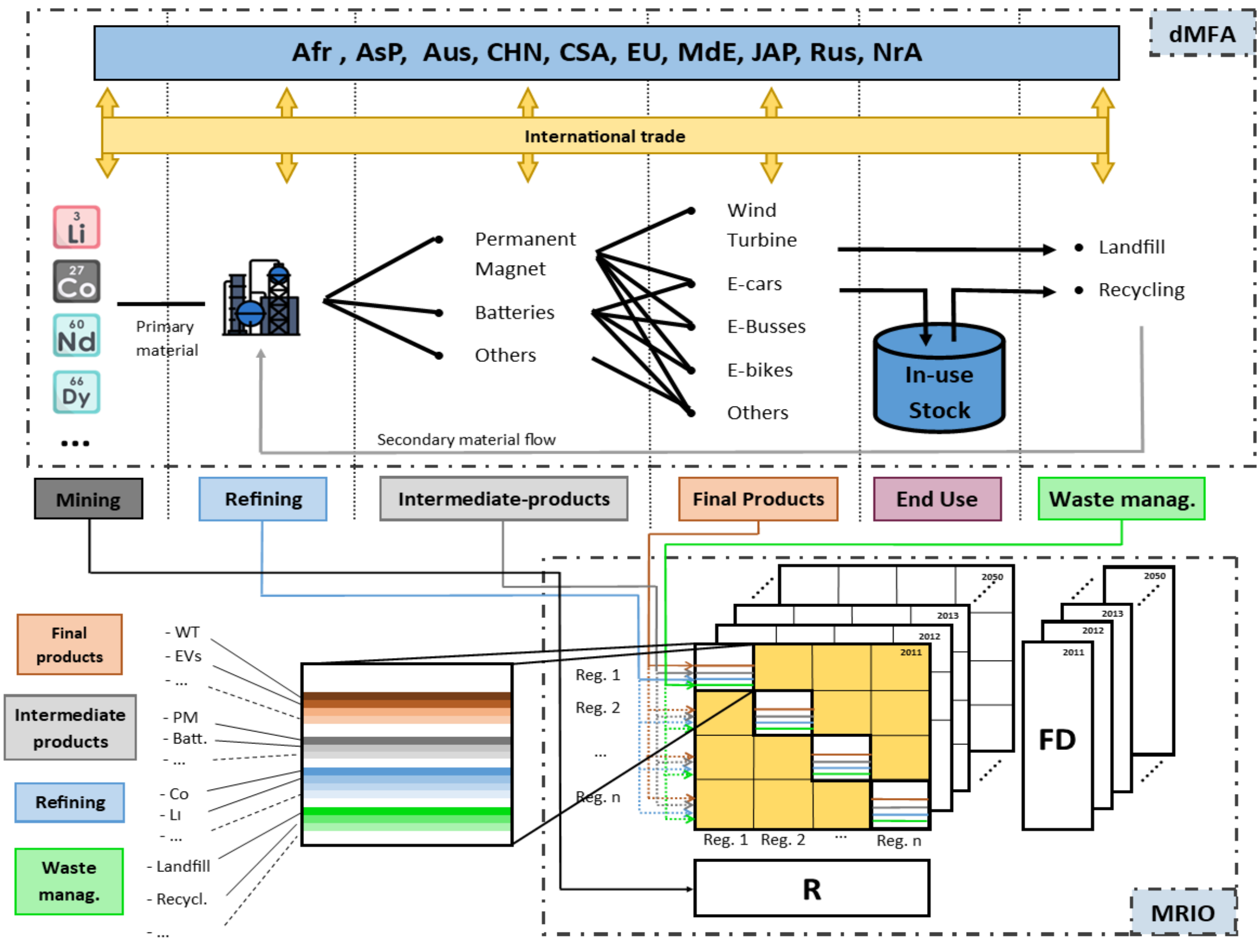

Figure 19: System definition for the dynamic multi-regional waste input-output (dMRWIO) modelling framework. Afr: Africa; AsP: Asia Pacific regions; Aus: Australia; CHN: China; CSA: Central & South America; EU: Europe; MdE: Middle East; JAP: Japan; Rus: Russia; NrA: North America. WT: wind turbines; EVs: electric vehicles; PMs: permanent magnets; FD: Final Demand

Scenarios such as Baseline, Stated Policies and Sustainable Development, based on the WEO2020, are defined to project the final demand and supply potentials. The model estimates the annual demand for the studied materials driven by green technology adoption and final demand for other sectors, projecting cumulative demand up to 2050 and comparing it with available reserves and resources. This comprehensive approach aims to assess the balance between demand and supply for critical metals under different global energy scenarios, highlighting the potential of recycling in reducing the need for primary materials.

5.3. Key Results

- **Cumulative Demand vs. Reserves and Resources**: The study highlights a significant concern for cobalt, with its cumulative demand potentially surpassing known reserves under specific scenarios (Stated Policies Scenario and Sustainable Development Scenario) (Figure 16 (right)). This could lead to supply bottlenecks, affecting cobalt's market price and its use in LiBs, which are critical for the evolution of electromobility. Lithium, while less critical than cobalt, could see its demand consuming nearly 60% of reserves by 2050. Regarding rare earth elements, Nd faces a relatively lower supply risk, with demand expected to reach a maximum of 27% of reserves by 2050. In contrast, Dy presents a higher supply risk, with its demand potentially consuming around 80% of the total known reserves by 2050.

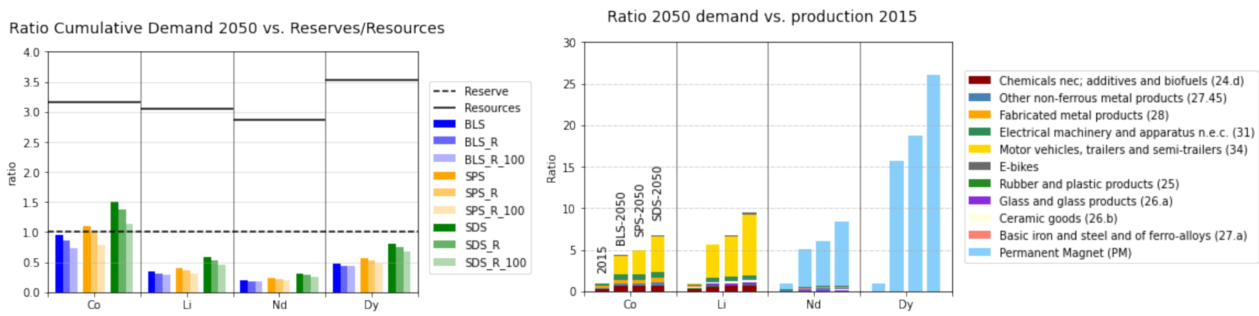

Figure 20: Ratio demand 2050 vs. Production 2015 (left) and Cumulative demand by products (right)

- **Impact of Recycling**: The study underscores the significant role of recycling in reducing the reliance on virgin cobalt and lithium. By increasing recycling efforts, it is possible to substantially lower the consumption of these primary materials. For Nd and Dy, however, the benefits of recycling are less pronounced due to lower efficiencies in waste management and challenges in recycling PMs.
- **Demand in 2050 vs. Production in 2015**: There is an anticipated substantial increase in demand for Li, Co, Nd and Dy by 2050 (Figure 20(left)). Dy, in particular, could experience a growth factor of up to 25 under the Sustainable Development Scenario, compared to 2015 levels. While Dy reserves are projected to meet global demand until 2050, the rapid increase in demand could lead to future supply shortages. The growing demand for Co and Li is primarily driven by the widespread adoption of LiBs in EVs, which are expected to account for 70-75% of total vehicle

demand by 2050. Similarly, the demand for Nd and Dy is mainly fueled by their use in PMs across various applications like WTs, EVs and e-bikes.

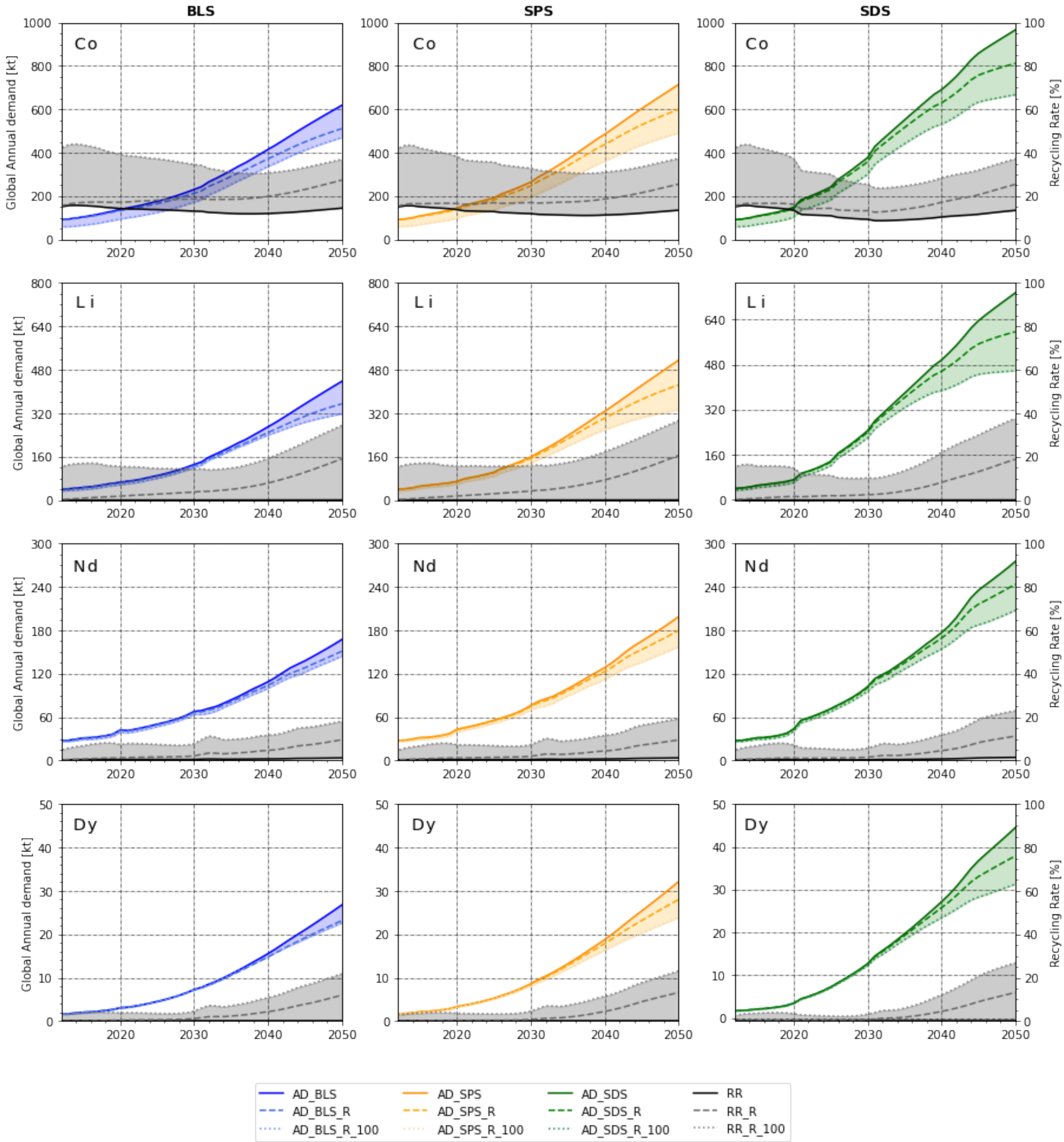

Figure 21: Global annual demand and recycling content rate. The line style identifies the different recycling scenarios: solid = Baseline scenarios; dashed =R; dotted = R_100. The grey lines, reported on the right y axis, refer to the RR content

- **Domestic Material Consumption by Region**: The analysis indicates that China is the leading consumer of these critical materials, driven by ambitious national policies and its large population. However, its dominance is expected to decrease over time, with developing regions like the Asia Pacific, Africa and Central and South America increasing their consumption shares. The EU27 follows China as the second-largest consumer, and North America, initially the third-largest consumer, is likely to be overtaken by the Asia Pacific region, reflecting the growth of green technology investments in countries like India.
- **Annual Demand and Recycling Content Rate**: For cobalt, the recycling content rate is already high, with a potential to increase to 40% by 2050 (Figure 21). This rise is attributed to the growing stock of EVs and WTs, which will become available for recycling at their end of life. In contrast, the impact of increased recycling on the annual demand for Li, Nd and Dy is minimal until 2035, due to the long lifetimes of products like EVs and WTs and the continual increase in demand for these technologies. However, post-2035, recycling rates for these materials are expected to rise significantly, potentially reaching 40% for Li and 25% for Nd and Dy by 2050.

6. Discussion, perspectives, and conclusion

6.1. Case studies: Main Findings, Contributions to IE research, and Limitations

Case study n° 1 – Complex Network Analysis

This research delved into the global nickel supply chain dynamics from 2009 to 2019, employing a multifaceted approach that includes a MRIO model, CNA and panel regression analysis.

Main research contributions

The MFA-IO integration with CNA significantly enhances the examination of the global nickel supply chain, addressing two primary limitations identified in existing literature.

Firstly, the MFA-IO framework develops a more comprehensive supply chain model. Unlike earlier studies which primarily constructed trade networks from ComTrade data, this approach not only utilizes trade data but also incorporates physical flow information. This methodology affords a more accurate representation of reality by mitigating common issues found in trade data such as discrepancies in material flow balances, inconsistencies between reported import and export flows, and the presence of outlier data. Consequently, the use of physical flows over monetary values in constructing the network ensures a robust depiction of actual material transfers, unlike the abstracted financial estimations used previously.

Secondly, employing CNA within the MFA-IO framework allows for a nuanced analysis of the entire nickel supply chain—from extraction to end-use. This comprehensive coverage is unprecedented in the literature and facilitates a detailed exploration of the intricate dynamics within the network. By mapping the entire supply chain, this integrated approach reveals critical interactions and dependencies among various nodes (countries and sectors), thus illuminating key relationships that are pivotal for understanding the structural complexities of the nickel market.

Overall, this innovative integration not only transcends the traditional methodologies used in supply chain analysis but also provides a foundational platform for strategic decision-making in nickel resource management and sustainability practices.

Main Limitations

- **Reliability on Data Sources**: The study's conclusions are significantly dependent on the accuracy, comprehensiveness, and recency of the data used. This reliance can lead to potential inaccuracies, particularly in cases where data sources are limited, outdated, or uneven across different countries and sectors.
- **Analytical Intricacy**: The integration of multiple indicators (economic, network metrics, etc.) into a unified framework introduces a high level of complexity. This can make the interpretation of results challenging, requiring careful consideration to avoid misinterpretation.
- **Masking of Individual Factor Impacts**: The combined analysis might mask the specific impacts of individual variables. As a result, significant nuances might be overlooked, especially where one factor's influence significantly outweighs others.
- **Influence of Underlying Assumptions**: The study's methodology and outcomes are closely tied to the initial assumptions made in the analytical process. These include assumptions about data correlations, causality, and the relevance of certain metrics.

Case study n° 2 – Supply Risk Assessment

The outcomes of this research present an intricate view of the global nickel supply chain's dynamics, deftly illustrating how production trends, geopolitical factors and market demands intertwine. Employing a data-centric methodology, this study sheds light on the supply risk factors for various nickel products across diverse geographical regions. This segment aims to critically evaluate the merits and constraints of the adopted research methodologies.

Main research contributions

The implementation of a MRIO flow network significantly enhances the granularity of the nickel supply chain analysis by differentiating among various nickel sub-products. This distinction is crucial for precise supply risk assessments, addressing a notable gap in existing research which predominantly concentrates on the mining sector, and to a lesser extent, the refining sector without differentiating between nickel derivatives. Recent developments underscore the significance of specific nickel sub-products, such as nickel sulphate in battery manufacturing, highlighting their critical roles across various industrial sectors.

The study also pioneers a holistic Risk Assessment approach by integrating a diverse array of indicators that encompass economic, political, social, environmental, and technological factors. This comprehensive framework facilitates a detailed risk evaluation for each nickel product and involved country, thereby providing a multidimensional perspective on potential vulnerabilities within the nickel supply chain. This methodological advancement offers a more robust foundation for strategic decision-making and policy development aimed at mitigating risks associated with nickel supply globally.

Main limitations

- **Data Dependence**: The reliability of MRIO and other utilized indicators is contingent upon the quality and currency of the underlying data. This reliance could skew findings, particularly in regions with limited or outdated data.
- **Yearly Snapshot Limitations**: While the annual snapshots offer a time-bound perspective, they may not fully capture the nuances of dynamic market shifts or sudden geopolitical changes occurring within the year.
- **Interpretative Complexity**: The amalgamation of various indicators into a unified risk profile, while thorough, introduces complexities in result interpretation and may mask the impact of individual factors.
- **Generalization Challenges**: Despite its broad coverage, the study's conclusions might not extend to all contexts or predict future market evolutions, especially in fast-changing sectors.
- **Assumption Sensitivity**: The study's outcomes are intrinsically linked to the initial assumptions of the risk assessment process. Altering these assumptions, such as the weighting or interpretation of indicators, could significantly modify the risk evaluations.

In essence, while the study provides a nuanced and multifaceted analysis of the nickel supply chain, these benefits are balanced by considerations of data dependency, the static nature of the analysis, interpretive challenges, the risk of overgeneralization, and sensitivity to underlying assumptions.

Case study n° 3 – dMRWIO model: demand forecasting for 4 critical materials

This research underscores the utility of the dMRWIO in evaluating the prospective demand and recycling potentials of four critical metals (cobalt, dysprosium, lithium, and neodymium) across various low-carbon energy scenarios.

Main research contributions

- **Integrated Material Flow Analysis**: The dMRWIO model melds the insights of IO modeling with dMFA, facilitating a simultaneous analysis of multiple material flows. This fusion offers a more complex and interconnected perspective of global material demands and supplies, taking in consideration also the dynamic nature of the system.
- **Advanced Waste Management Insights**: Excelling in waste management sector modeling, the dMRWIO model adeptly handles the supply-demand equilibrium of secondary materials and addresses quality concerns arising from unintended material mixing. This aspect is pivotal for enhancing the understanding and efficiency of recycling processes for critical metals.
- **Global Scope with Regional Specificity**: Offering a global overview while also delving into detailed regional and sectoral analysis, the dMRWIO model is crucial for pinpointing potential supply chain disruptions and devising region-specific strategies.
- **Strategic Guidance for Industry and Government**: By forecasting future demands and identifying potential supply constraints, the model offers invaluable insights for both industry and governmental decision-making, assisting in the formulation of policies and investments to mitigate supply chain risks related to resource scarcity or geopolitical factors.
- **Recycling Potential Assessment**: The model effectively assesses the impact of recycling in reducing the reliance on primary materials, which is vital for planning future recycling capacities and understanding recycling's role in sustainable supply chains.
- **Model Flexibility and Adaptability**: The dMRWIO model's capacity to integrate various scenarios and assumptions renders it a versatile tool, essential for examining different potential futures, particularly under conditions of uncertainty and technological evolution.

Main Limitations

- **Constant Material Intensity and Penetration Rates**: The study assumes fixed material intensities and penetration rates of green technologies, which may change due to technological advancements, affecting material demand.
- **Data Gaps in Waste Management**: More accurate data on waste management operations and inclusion of different EoL strategies beyond recycling are needed for a better understanding of secondary material flows.
- **Assumption of Constant Technical Coefficients**: The model assumes static technical coefficients, potentially overlooking future improvements in production efficiency and possibly leading to an overestimation of material demand.
- **Global Reserve Comparisons and Market Dynamics**: The study's approach of comparing cumulative demand with global reserves does not fully consider market dynamics, such as the development of new mining operations in response to resource scarcity.
- **Recycling and Technological Capacity Limitations**: Current recycling technologies, particularly for LiBs, lack the capacity to handle the anticipated increase in EoL product volume, necessitating investment and time for technological advancement.

In essence, the dMRWIO methodology stands out as a comprehensive and multifaceted tool. It adeptly integrates diverse aspects of material flow and waste management, proving invaluable in strategizing for a sustainable and resilient supply chain for critical metals, especially in the context of the global shift towards green technologies.

6.2. Final discussion

The integration of MFA and IO models presents a nuanced approach for understanding material flows and economic transactions in environmental studies. This integration offers a comprehensive view of how materials are used and transported across different economic sectors and geographical regions, aiding in the assessment of environmental impacts and resource efficiency. Here's a discussion based on the three research questions elaborated in this thesis:

1. *How can the integration of MFA-IO with CNA improve our understanding of critical material supply chains by providing a more nuanced analysis of economic structures and interconnections?*

The integration of MFA-IO with CNA substantially enhances our understanding of critical material supply chains by providing a more nuanced analysis of economic structures and interconnections. This fusion addresses several key research gaps: it improves data integrity by consolidating material flow and economic transaction data, which helps rectify discrepancies often found in traditional datasets like ComTrade. This integration allows for a more reliable foundation for supply chain analysis, mitigating the risks associated with data inaccuracies.

Additionally, the combined approach facilitates a comprehensive examination of national industrial flows. Where individual analyses may overlook internal market dynamics and interdependencies, the MFA-IO and CNA integration captures both the macro and microeconomic interactions. This detailed view is critical for understanding how materials move within and between industries, revealing not only direct but also indirect relationships that shape the economic landscape.

Furthermore, this methodology broadens the scope of research to encompass a wider range of materials and their derivatives. Classical studies often limit their focus to a select few materials, which skews understanding and policy-making. By incorporating a broader array of substances, the integrated approach offers a more complete evaluation of their roles across various technologies, enhancing the strategic management of resources.

Most significantly, the network built from the MFA-IO integration gives a better representation of the reality of material flows and the connections between industries or sectors. This model overcomes the limitations of classical complex network analysis, which can oversimplify complex relationships and fail to capture the real-world intricacies of industrial ecosystems. Through this integration, the network not only maps direct interactions but also uncovers indirect dependencies and feedback loops, providing a comprehensive map of economic activities and strategic points within the supply chain.

In conclusion, the integration of MFA-IO with CNA improves the analysis of critical material supply chains by overcoming significant research challenges and offering a sophisticated tool for mapping and managing economic and material interdependencies in industrial ecosystems. This holistic approach is essential for policymakers, industry leaders, and researchers aiming to optimize resource management, enhance sustainability, and strengthen economic resilience against supply disruptions.

2. *How can an enhanced MFA-IO framework improve the granularity and accuracy of supply risk assessments for critical materials, particularly by incorporating detailed evaluations of different product derivatives?*

An enhanced MFA-IO framework can significantly improve the granularity and accuracy of supply risk assessments for critical materials by incorporating detailed evaluations of various product derivatives. This integration addresses pivotal gaps in current methodologies, which often overlook the complexity and specificity needed to manage modern supply chains effectively.

Current supply chain risk assessment methodologies, while incorporating a broad range of environmental, geopolitical, and socio-economic factors, still fall short in several areas. These methodologies frequently lack the specificity required for different product derivatives of critical materials, such as various compounds and alloys, which may have distinct uses and supply dynamics. For instance, the risk profiles and supply chain vulnerabilities of nickel sulfates used in battery manufacturing significantly differ from those of bulk nickel used in stainless steel production.

By enhancing the MFA-IO framework to include a detailed evaluation of these derivatives, risk assessments can become more nuanced. This enhancement allows for the differentiation among products derived from the same material, recognizing that each product may face unique risks and opportunities. Such detailed scrutiny is crucial in developing more effective risk mitigation strategies and in fostering a supply chain that can respond more dynamically to disruptions.

Moreover, traditional approaches often segment the supply chain into isolated phases without sufficient consideration of the interdependencies between them. An integrated MFA-IO approach facilitates a comprehensive view that spans the entire lifecycle of materials—from extraction through to end-use and recycling. This holistic perspective is essential not only for identifying where vulnerabilities exist but also for understanding how disturbances in one phase of the supply chain can ripple through to others. For example, a disruption in the availability of raw materials not only affects the initial extraction phase but also has downstream impacts on manufacturing and end-product availability.

The integration of supply chain phases under a refined MFA-IO framework therefore provides a clearer picture of supply risks that is both granular and expansive. It ensures that risk assessments reflect the true complexity of modern supply chains and are capable of identifying critical leverage points where interventions could be most effective. This approach does not merely adapt to current complexities but anticipates future supply chain challenges, thereby enhancing strategic planning and risk management for critical materials within a global context.

In conclusion, enhancing the MFA-IO framework to incorporate detailed evaluations of product derivatives and to integrate assessments across all supply chain phases dramatically improves the accuracy and utility of supply risk assessments. This advancement is crucial for managing the supply of critical materials more effectively, ensuring resilience against disruptions, and supporting sustainable development initiatives globally.

3. *In what ways can the integration of dynamic modeling techniques, enhance the accuracy of demand forecasts for critical materials, considering both the global economic landscape and the dynamic nature of secondary material flows?*

The integration of dynamic modeling techniques within the MFA-IO framework can significantly enhance the accuracy of demand forecasts for critical materials by addressing the complexities of the global economic landscape and the dynamic nature of secondary material flows. This approach effectively fills several crucial gaps identified in the current literature, particularly around recycling dynamics, management of in-use stocks, and the need for comprehensive, integrated modeling approaches.

Current forecasting models often fail to account for the complexities of the recycling sector, particularly the efficiency of recovery processes and the viability of using recycled materials as substitutes. Traditional static models typically overlook these aspects, which can lead to significant discrepancies in supply predictions and hinder effective resource management. This improvement not only enhances the precision of material flow analyses but also supports the development of more robust, circular economy strategies where recycled materials are reintegrated into supply chains.

Another significant gap is the management of in-use stocks—materials that are currently in use within the economy but will eventually return to the market as recycled content. This factor is often neglected in conventional demand forecasting models, leading to potential overestimations or underestimations of future material availability. Dynamic MFA-IO modeling can track these materials throughout their lifecycle stages, from production and usage to disposal and recycling, thereby providing a more accurate forecast of when and how much material will likely become available for reuse. This lifecycle approach not only predicts future material flows more accurately but also helps in planning for EoL recycling and reuse processes.

The existing literature also emphasizes the necessity for models that holistically integrate various methodologies to capture the full spectrum of supply, demand, and sustainability challenges faced by critical materials. The dMFA-IO models can synthesize data from diverse sources and processes, incorporating economic, environmental, and material flow data into a unified framework. This integration allows for the simulation of various scenarios under different global economic conditions, policy environments, and technological advancements. Such comprehensive models are crucial for understanding the intricate interdependencies within material supply chains and for developing strategies that ensure the sustainable and efficient use of critical resources in green technologies.

By addressing these gaps, the integration of dynamic modeling techniques into the MFA-IO framework not only enhances the accuracy of demand forecasts but also contributes significantly to resource efficiency and environmental stewardship. It provides stakeholders with the tools to make informed decisions that align with sustainable development goals and to adapt to changes in the global market and regulatory environments. This approach thus supports the mitigation of supply risks and promotes a more sustainable, resilient approach to managing critical material flows essential for the future of green technologies.

In conclusion, the integration of MFA and IO models represents a significant advancement in the field of environmental systems analysis. This combined approach facilitates a more nuanced and comprehensive understanding of material flows, effectively bridging the gap between the physical movement of materials and their economic implications. However, it is imperative to acknowledge and address inherent challenges such as data integrity and methodological incongruences. Progressive enhancements in data acquisition methodologies and the refinement of integration techniques are crucial for augmenting the efficacy of this approach in the realms of environmental research and policy development.

This thesis has elucidated the potential of the MFA-IO framework as an instrumental basis for conducting in-depth analyses of critical materials. Its inherent flexibility in accommodating diverse datasets and methodologies enables a multifaceted examination of the subject matter from various disciplinary perspectives. Emphasizing a multidisciplinary approach is essential for grappling with the increasing complexity of environmental challenges in the contemporary context.

The use of the MFA-IO framework in this study offers a deeper and more complete exploration of the complexities associated with critical materials, overcoming the constraints of traditional studies that typically focus on isolated factors. This methodological integration signifies not just a merging of different analytical approaches but a substantial shift towards a holistic understanding of material utilization and the supply chain characteristics. The comprehensive insights gained from such interdisciplinary research are crucial for developing more effective and sustainable strategies for resource management and environmental protection. Ultimately, the MFA-IO framework underscores the necessity of interdisciplinary efforts to address the complex challenges that critical materials face today.

6.3. Research perspectives

In this thesis, we have extensively explored the integration of IO analysis with MFA models. However, an important aspect that remains unaddressed is the incorporation of Environmental Assessment. The integration of LCA with the MFA-IO framework, which has been applied in various studies including those focused on critical materials, was initially planned to be a part of this thesis. The intention was to employ LCA methodology alongside the MFA-IO framework to analyze Greenhouse Gas emissions and other environmental impacts associated with nickel products in the global supply chain. Unfortunately, due to constraints in resources and time, this component had to be excluded from the study.

Incorporating LCA into the MFA-IO framework can offer deeper insights into the environmental impacts associated with the life cycles of critical materials. This integration would allow for a more comprehensive assessment, encompassing not only the flow and economic dimensions of materials but also their environmental footprints. Key environmental aspects, such as greenhouse gas emissions, energy consumption, and ecological impacts, would be more thoroughly evaluated. Such an integrated approach is essential for the development of more sustainable material and energy policies, offering a holistic perspective on the environmental implications of material flows and economic activities.

In this thesis, a notable limitation highlighted is the reliance on global MRIO dataset, such as Exiobase[144] database, utilized in this thesis. Exiobase for example, has been updated until 2011, and then projected until 2022 thanks to the use of a variety of auxiliary data sources, predominantly trade and macro-economic information. While this approach provides a comprehensive overview, it's important to acknowledge that the projections are based on estimates, which might affect the precision of the data.

However, it’s important to note that there are alternative global MRIO databases available, each with its unique features and specifications. For instance, the World Input-Output Database[169] covers 43 countries and includes a model for the rest of the world, spanning from 2000 to 2014, and categorizes data into 56 sectors. The Eora database[170], on the other hand, standardizes all countries into a 26-sector classification, converting the supply-use tables from the comprehensive Eora MRIO into symmetric product-by-product IO tables using the Industry Technology Assumption. Additionally, the Global Trade Analysis Project[171] version 11, with reference years including 2004, 2007, 2011, 2014, and 2017, distinguishes 65 sectors across 141 countries and 19 aggregated regions.

While these databases offer more recent updates compared to Exiobase, they differ significantly in sectoral resolution. Exiobase, for instance, details 163 sectors in 44 countries, providing a more granular view compared to the lesser sectoral breakdown offered by World Input-Output Database (WIOD), Eora, and the Global Trade Analysis Project (GTAP). This difference in sectoral resolution is a critical aspect to consider when choosing an MRIO database for specific research or analysis purposes, especially in contexts where sector-specific details are crucial.

For instance, similar national-level studies, such as Chen's research on the U.S. aluminum network[172], demonstrate the value of high-resolution sectoral data. In Chen's study, the U.S. input-output table, which categorizes around 230 sectors as manufacturing with a total of 393 sectors, provided a clearer picture of material flows within the national economy. Such detailed breakdowns are beneficial for comprehending the dynamics of material use and distribution.

Future research should focus on enhancing the industrial structure and projection of MRIO tables to overcome this limitation. This improvement could involve incorporating more dynamic and sector-specific economic data, better reflecting the evolving economic landscape and technological advancements. Such developments would address the issue of constant technical coefficients in MRIO analysis, allowing for a more accurate and responsive representation of economic and environmental interactions.

In the expanding field of CNA within IE, particularly for critical materials, future research should focus on several key areas. Firstly, enhancing MRIO models to include subregional level analysis is essential for capturing the intricate economic dynamics within countries. This involves addressing the diverse economic endowments, developmental stages, and industrial structures at a more granular level. Secondly, diversifying research objects within IO networks can provide new insights, especially in exploring the roles and implications of different sectors in global value chains and environmental impacts. Thirdly, the application of advanced analytical techniques from complex network theory, such as machine learning and transmission dynamics, can significantly improve our understanding of socio-economic network dynamics. Lastly, increasing focus on critical energy and bulk minerals, such as iron, copper, and aluminum, is crucial due to their significant roles in global industries and supply chains. These approaches will collectively deepen our understanding of industrial ecosystems and aid in developing more effective management strategies for critical materials.

Furthermore, the integration of ComTrade (or similar datasets) with material intensity analysis needs refinement. The ComTrade data, used for translating monetary values into material flows, requires a robust cleaning algorithm to address data errors and inconsistencies. Also, efforts should be directed towards improving data collection methodologies and standardizing data reporting to reduce discrepancies, such as divergent product coding by different countries.

Additionally, there is a need to develop more comprehensive and region-specific datasets to enhance the transformation of monetary values into physical values, as the current data are primarily derived from the Japanese WIO tables. Improving these datasets will allow for more accurate and regionally nuanced material intensity factors, which are crucial for understanding changes in material use due to efficiency improvements, substitution, and other factors.

6.4. Conclusion

This thesis concludes with a grounded perspective on the study of critical material flows and their economic impacts, acknowledging both the achievements and the challenges in the field of environmental systems analysis. While the integration of MFA with MRIO models has undeniably shed light on important aspects of material use and its ramifications, it also brings to the forefront the complexity and inherent challenges of such interdisciplinary research. The limitations in data quality, integration of diverse methodologies, and the dynamic nature of models underline the necessity for continuous and cautious advancement in this field.

The importance of a multidisciplinary approach in studying critical materials cannot be overstated. It is through the confluence of various disciplines - economics, environmental science, policy studies, and more - that a more holistic and effective understanding of material flows can be achieved. This thesis underscores the need for such an approach, as it is only through the integration of diverse perspectives and expertise that we can hope to navigate the intricacies of critical material management effectively.

In essence, this thesis serves as a realistic checkpoint in the ongoing journey of environmental systems analysis. It highlights the significance of multidisciplinary approach in enhancing our understanding of critical materials, stresses the importance of addressing current methodological and data-related challenges, and encourages continued collaboration across various fields.

This thesis, therefore, serves as a realistic assessment of where we currently stand in understanding and managing critical materials, acknowledging both the progress achieved and the considerable work that remains. It is a reminder of the ongoing need for meticulous research, critical analysis, and collaborative efforts to advance this crucial field.

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Paper nº 1

Navigating the Nickel Network: Insights from a Ten-Year Global Supply Chain Study

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Abstract

This study presents a comprehensive analysis of the global nickel supply chain from 2009 to 2019, offering new insights into the complex dynamics of nickel flow in response to growing demand for sustainable energy technologies. Utilizing a Multi-Regional Input-Output-Nickel Network (MRIO-Nickel Network), we assess the interconnectedness and vulnerability of the global nickel market, focusing on the expanded role of nickel in battery technology and the automotive electrification movement.

Our findings reveal the intricate web of supply risks, influenced by geopolitical events, environmental policies, and technological advancements. We demonstrate the shifting roles of countries and sectors within the network, notably China's growing dominance and the strategic importance of the manufacturing layer. The integration of network analysis with panel regression and structural path analysis allows for a nuanced understanding of how economic factors and network structures impact nickel consumption patterns.

The study provides significant insights for policymakers and industry stakeholders, emphasizing the need for robust supply chain management strategies to mitigate risks and ensure a reliable supply of nickel. This research contributes to the broader discourse on securing critical mineral supply chains for a zero-carbon economy and underscores the importance of diversifying economic activities and embracing sustainable practices to meet future nickel demand.

Keywords: Nickel Supply Chain, Sustainable Energy, Battery Technology, MRIO-Nickel Network, Complex Network Analysis, Panel Regression Analysis, Structural Path Analysis.

1. Introduction

Nickel, a versatile and widely utilized industrial metal, is prized for its unique combination of hardness, ductility, high-temperature stability, and exceptional corrosion resistance. Its applications span across various sectors, with about two-thirds of its consumption dedicated to the production of stainless steel. The industrial and aesthetic applications of nickel are far-reaching, extending to the chemical, petrochemical, food industries, as well as in construction, transportation, and consumer products[1].

In recent years, nickel's role has expanded significantly in the realm of battery technology, particularly in lithium-ion batteries, making it a pivotal component in the automotive electrification movement[2]. By 2040, it's anticipated that the demand for nickel in this sector will increase exponentially, up to 26 times compared to 2020 levels[3]. This surge in demand places nickel at the forefront of efforts to achieve a zero-carbon economy, leading various governments, including the Europe[4] and United States[5].

The production of nickel sulfate, a high-purity chemical form essential for electric vehicle (EV) batteries, underscores the complexity of its supply chain. This form of nickel is derived from various sources, including battery scrap, class 1 metal, and leaching intermediates[6]. However, environmental considerations have shifted the focus away from laterite ore-derived products like FeNi and NPI, favoring those from sulfide ores[7]. The nickel supply chain has proven to be fragile, as evidenced by events like Indonesia's export restrictions[8] and the London Metal Exchange shutdown in 2022 during Russia's invasion of Ukraine[9]. These incidents highlight the need for a comprehensive understanding of the global nickel supply chain, particularly concerning nickel sulfate.

Historically, nickel has been a subject of extensive research due to its critical role in stainless steel production. The first global-scale life cycle analysis of nickel, conducted by Reck et al. in 2008[10], examined the anthropogenic nickel cycle across various countries and regions. This research paved the way for further studies, such as those by Elshkaki et al.[11] and Japanese scholars[12,13], who expanded upon this work by exploring nickel's global trade flow and its environmental impact.

Regional studies, like those by Ciacci et al.[14], have provided a more localized perspective, analyzing the anthropogenic cycle of nickel in Europe. However, these studies often overlooked the differentiation between high-purity class 1 and lower-purity class 2 nickel products. Addressing this gap, recent research by Schmidt et al.[15] and the Joint Research Center's Roskill[6] report has begun to explore the supply and demand dynamics of high-purity nickel sulfate.

The increasing complexity of the global nickel supply chain has necessitated new research approaches. Network analysis has emerged as a powerful tool in this regard, offering insights into the dynamics, functionality, and topology of complex systems. It has been instrumental in studying international trade and optimizing commodity trading networks.

The narrative of nickel supply chain research, enriched by complex network analysis, unfolds through several key studies, each shedding light on different aspects of the industry. X. Zhou et al.[16] offer a comprehensive exploration of global nickel trade, integrating econometrics and complex network methods. Their work highlights the multifaceted nature of trade behaviors, interwoven with the complexities of geopolitical events like the Russia-Ukraine conflict.

In a parallel study, Zhou et al.[17] delve into the intricacies of trade price volatility within the nickel industry. Employing systematic risk entropy and Granger causality networks, they uncover the far-reaching impacts of price fluctuations, emphasizing how regional differences, particularly Indonesia's stainless steel export prices, influence global markets. Zheng et al.[18] contribute to this narrative by examining how the roles of countries in the nickel trade shape market prices. Their approach, blending complex network analysis and panel regression models, unravels the evolution of trade positions and their influence on pricing dynamics.

Wang et al.[19,20] in two distinct studies, navigate the challenges of global trade and supply. One study proposes a trade redistribution strategy based on the maximum entropy principle, addressing the growing global demand for nickel. The other study constructs a multi-layer trade network, revealing the competitive landscape and highlighting China's vulnerability in the nickel industry. Finally, Dong et al.[21] focus on optimizing the international nickel ore trade network. Their innovative approach, utilizing a decade of trade data, suggests ways to balance supply and demand perspectives, aiming for sustainable resource management.

These studies collectively create a detailed narrative of the global nickel supply chain, showcasing the effectiveness of network analysis in understanding trade dynamics, risks, and strategies for sustainable management within the nickel industry. However, there are notable shortcomings, including data integrity issues with primary trade datasets like ComTrade, where discrepancies in reported material flows underscore the pressing need for improved data collection and verification methods. Additionally, there is a significant lack of thorough national flow analyses, which impedes a deep understanding of internal market dynamics and the interdependencies within industries at a national level. Furthermore, the research often limits its focus to a select few products for each critical material, failing to capture the broader industrial applications. Broadening the scope to encompass a wider array of derivatives and compounds is essential for a more comprehensive evaluation of their roles across various technologies.

This study aims to address existing research gaps by analyzing the flow of various nickel products within the global supply chain from 2009 to 2019. To achieve this, we implement a Multiregional Input-Output-Nickel Network (MRIO-Nickel Network) approach. This method combines Multiregional Input-Output (MRIO) analysis with complex network theory to understand the characteristic and status of the nickel network through various indicators. Additionally, we employ a panel regression model to identify the most influential factors affecting nickel consumption.

2. Material and Methods

In this study, we adopt a Multi-Regional Input-Output (MRIO) approach to analyze global nickel flows from 2009 to 2019. The methodology involves constructing an MRIO flow network using data on nickel production, trade, and consumption. We then perform a complex network analysis to calculate various indicators, revealing the structure and influence of different nodes in the network. This is followed by a panel regression analysis to examine factors influencing nickel flows. Finally, we conduct a structural path analysis to identify and interpret critical paths within the network, providing insights into the dynamics of the global nickel market.

2.1. Complex Network Analysis

In this study, we employed several complex network indicators to analyze the global MRIO nickel network. These indicators are crucial for understanding the structural and functional properties of the network. Below, we detail each indicator.

Degree In & Out.

In the analysis of the global nickel network, non-weighted in-degree and out-degree centralities are key metrics for understanding network connectivity. Non-weighted in-degree centrality identifies "collector" nodes that receive materials from multiple sources, highlighting their role in material processing within the supply chain. Non-weighted out-degree centrality, on the other hand, points out "distributor" nodes responsible for spreading materials to downstream sectors, crucial for resource distribution. The calculations for these metrics are:

$$D_{(i,c)}^{in} = \sum_{j} A_{ji}\,; \quad D_{(i,c)}^{out} = \sum_{j} A_{ij}$$

Where $D_{(i,c)}^{in}$ and D_{i}^{out} are the in&out-degree of sector *i* in country *c* respectively, and A_{ji} (A_{ij}) is the adjacent matrix of the MRIO nickel network. If there is an edge from node *i*(*j*) to node *j*(*i*), then $A_{ji}(A_{ij}) = 1$, otherwise it will be 0. These measures offer a straightforward count-based view of the network, emphasizing the roles of nodes in integrating incoming flows or facilitating outward distribution in the nickel supply chain.

Strength Degree In & Out.

In our study of the global nickel network, we focus on weighted in-degree and out-degree centrality to understand the flow dynamics. Strength in-degree centrality ($SD_{(i,c)}^{in}$) highlights "collector" nodes that bring together various materials for value addition, indicating their pivotal role in driving the metal supply chain. These nodes are characterized by their significant volume or value of incoming metal flows. On the other hand, Strength out-degree centrality (SD_{i}^{out}) identifies "distributor" nodes that play a key role in dispersing materials to downstream sectors, crucial for their reliance on metal sales. These nodes are marked by their substantial role in the outward flow of materials. The equations for these measures are:

$$SD_{(i,c)}^{in} = \sum_{j} e_{ji} \, ; \quad SD_{(i,c)}^{out} = \sum_{j} e_{ij}$$

Where $SD_{(i,c)}^{in}$ and SD_{i}^{out} are the weighted in&out degree of sector *i* in country *c* respectively, and e_{ji} or e_{ij} is the directed edge between node *i* and node *j*. These metrics provide insights into the nodes' roles in the network, emphasizing their importance in terms of the volume and value of the nickel flows.

Betweenness centrality

This indicator is employed to identify key nodes that act as crucial intermediaries in the network. This metric measures the number of shortest paths from all nodes to all others that pass through a specific node, highlighting its role in connecting different parts of the network. A high betweenness centrality score signifies that a node functions as a critical conduit or 'bottleneck' in the network, indicating that its removal would likely disrupt the flow of materials or information more significantly than the removal of other nodes. Essentially, betweenness centrality underscores the importance of certain nodes in controlling or influencing the flow of resources and information, reflecting their capacity to regulate and manage the network dynamics. This analysis is fundamental in understanding the structural vulnerabilities and the pivotal roles of specific nodes within the global nickel supply chain, contributing to the strategic planning for enhanced resilience and efficiency of the network. The equation for betweenness centrality is as follows:

$$BC_{(k,c)} = \sum_{i} \sum_{j} \frac{\sigma_{i(k)j}}{\sigma_{ij}}, i \neq k \neq j$$

Where $BC_{(k,c)}$ is the betweenness centrality of node k in country *c*, σ_{ij} is the number of shortest paths between node *i* and *j*, and $\sigma_{i(k)j}$ is the number of these shortest paths passing through node *k*.

Eigenvector centrality

Eigenvector centrality is a pivotal metric for identifying influential nodes within the network. This measure is based on the principle that a node's importance is not only determined by the number of its connections but also by the importance of its connected nodes. Essentially, it reflects the idea that connections to highly influential nodes contribute more to a node's centrality. A node with high eigenvector centrality in the nickel network indicates its significant role in the network, often connected to other central nodes, and thus holds substantial influence over the network's dynamics. This centrality is especially relevant in understanding the power dynamics and the flow of influence through the network, identifying nodes that are not just well-connected but also crucial in terms of their strategic connections. The equation for eigenvector centrality is given by:

$$EC_{(i,c)} = \frac{1}{\lambda}\sum_{j=1}^{N} a_{ij}EC(j)$$

In this equation, $EC_{(i,c)}$ is the eigenvector centrality of node *i* in country *c, a_{ij}* is an element of the adjacency matrix representing the connection between nodes *i* and *j*, $EC_{(j,c)}$ is the eigenvector centrality of node *j*, and λ is a constant. This centrality measure is critical for our understanding of the nickel supply chain, as it helps to identify key players that might have a disproportionate influence on the network, not just due to their direct connections but also because of their strategic position within the network's structure.

Network density

Network density is a crucial metric that provides insight into the overall interconnectedness and compactness of the network. Network density is defined as the ratio of the actual number of edges in the network to the maximum possible number of edges. This measure helps in understanding how densely connected the nodes in the network are. In the context of the nickel supply chain, a higher network density indicates a more interconnected network, suggesting a robust and comprehensive system of nickel flows among different nodes. A densely connected network often implies efficient communication and material transfer paths, reducing the likelihood of supply chain disruptions. Conversely, a lower density might suggest a more fragmented network with potential vulnerabilities in the connectivity and flow of materials. The equation for network density is given by:

$$ND = \frac{2L}{N(N-1)}$$

Where ND is the network density, L represents the total number of edges in the network, and N is the total number of nodes. This equation calculates the proportion of potential connections in the network that are actual connections, providing a quantitative measure of how well-connected the network is.

Understanding the network density is essential for assessing the robustness and efficiency of the global nickel supply chain, as it reveals the overall structure and integration of the network, which are key factors in ensuring a stable and reliable flow of materials.

Clustering Coefficient

The clustering coefficient (CC) is an important metric that measures the degree to which nodes in the network tend to cluster together. This indicator is particularly useful in understanding the local connectivity and the tendency of nodes to form tightly knit groups or clusters.

In the context of the nickel supply chain, a high clustering coefficient for a node indicates that its immediate neighbors are also likely to be interconnected. This can be indicative of strong collaborative or trade relationships within a subset of the network, such as regional clusters or groups of entities that frequently interact or trade with each other. A higher overall clustering coefficient in the network suggests a greater propensity for localized networking, which can have implications for the resilience and efficiency of the supply chain. It can enhance robustness against disruptions in one part of the network, but also potentially create vulnerabilities if these closely knit clusters become isolated.

$$CC(i) = \frac{2T(i)}{k(i)(k(i)-1)}$$

Where $CC(i)$, is the clustering coefficient of node i , $T(i)$ is the number of triangles through node i (i.e., the count of closed triplets), and $k(i)$ is the degree of node i (i.e., the number of edges connected to i).

This calculation provides insights into how nodes within the nickel network are embedded in their immediate neighborhoods, highlighting potential areas of tight collaboration or interdependence. Understanding the clustering coefficient helps in identifying how the network's structure might influence material flow and information dissemination within the nickel supply chain.

2.2. Panel Regression Analysis

In our analysis of the MRIO nickel network from 2009 to 2019, the role of various sectors in the network is observed to vary across both individual sectors and different time periods. This variation highlights the dynamic nature of the network, where sectors play distinct roles at different times. To accurately capture this relationship between the network roles of sectors and their nickel consumption, we employ a panel regression model, as depicted in formula:

$$Y_{it} = \alpha + \beta_{1,it}X_{it} + \beta_{2,it}control_{it} + \epsilon_{it}$$

Here Y_{it} represents the dependent variable, indicating the consumption of embodied nickel in various sectors over time. The independent variable X_{it} includes key network metrics such as Weigthed-Degree-in $WD_{(i,c)}^{in}$, Weigthed-Degree-in $WD_{(i,c)}^{out}$, Betweenness Centrality $BC_{(k,c)}$, and Eigenvector Centrality $EC_{(i,c)}$ within the MRIO nickel network. Weigthed-Degree-in&out reflect the sectors' diversity in trading partners, highlighting key supply and consumption sectors. Betweenness Centrality identifies intermediary sectors, and Eigenvector Centrality points to sectors with influential trading partners.

The control variable $control_{it}$ encompasses sector GDP, industrial structure, and population, where:

- **Sector GDP**: This influences each sector's production level and is a significant driver of nickel resource consumption. The value added of each sector is used as a proxy for the sector's GDP.
- **Industrial Structure**: Represented by the backward linkage, this indicates the impact of a sector's output change on the overall economy. It is calculated using formula (13):
$$BL_j = \sum\nolimits_{i=1}^{n} l_{ij} \Big/ \sum\nolimits_{ij} l_{ij}$$
Here, $\sum_{i=1}^{n} l_{ij}$ is the sum of vectors in column k in the Leontief inverse, and $\sum_{ij} l_{ij}$ is the sum of all elements in the Leontief inverse. A larger BL_j for a sector suggests a greater economic stimulus from an added unit of output in that sector, thereby driving higher nickel consumption.
- **Population**: This indicates the market scale of a country. A larger population denotes higher consumption demand, influencing the demand for nickel resources.

This model allows us to examine the multifaceted interactions and dependencies within the MRIO nickel network, providing insights into how sectoral roles and economic factors influence nickel consumption patterns over the studied period.

3. Results

3.1. Complex Network Analysis

3.1.1. Overall network structural characteristics

Figure 1 (a) displays the evolution of network density (ND) within the global nickel supply chain from 2009 to 2019, spanning various layers of the supply chain: mining, smelting, refining, semi-products, and manufacturing. Conversely, Figure 1 (b) offers comparative ND results from multiple studies, providing context to these findings. Notably, it includes ND data for cobalt from Li Y. et al. (2022)[22], segmented into upstream, midstream, and downstream, and for Rare Earth Elements (REEs) from studies by Zuo Z. et al. (2022)[23] and Hou W. (2018)[24], which focus on three layers and a single layer, respectively.

In the nickel supply chain, ND values incrementally increase across each layer, indicating a trend toward denser interconnections as materials advance toward the final product stage. The mining and smelting stages have the lowest ND, at approximately 0.01, reflecting limited international collaborations and a sparse network, pointing to significant opportunities for enhancing economic connections. The refining stage shows a modest rise in ND to about 0.025, indicating a still relatively loose network.

Notably, the semi-products and manufacturing stages exhibit significantly higher ND values, at 0.2 and 0.3 respectively, suggesting robust inter-country connections. These stages feature denser networks, which are crucial for improving the reliability and robustness of the supply chain, particularly in the final production phases.

The stability of ND trends over the analyzed period, with only minor fluctuations, indicates consistent dynamics within the supply chain. Similar patterns are observed in the cobalt supply chain, where initial ND values are comparable to those in nickel mining and rise as the material progresses downstream. This similarity highlights the shared dynamics between the nickel and cobalt supply chains, likely due to cobalt often being mined as a byproduct of nickel and both metals being vital for similar applications, such as batteries and metal alloys.

In contrast, the REE supply chain also shows an upward ND trend but reaches a peak value of only 0.11. This lower maximum ND reflects a less dense network, largely concentrated among fewer countries, with China playing a dominant role from extraction to manufacturing. This concentration introduces risks associated with supply chain resilience and geopolitical dependencies.

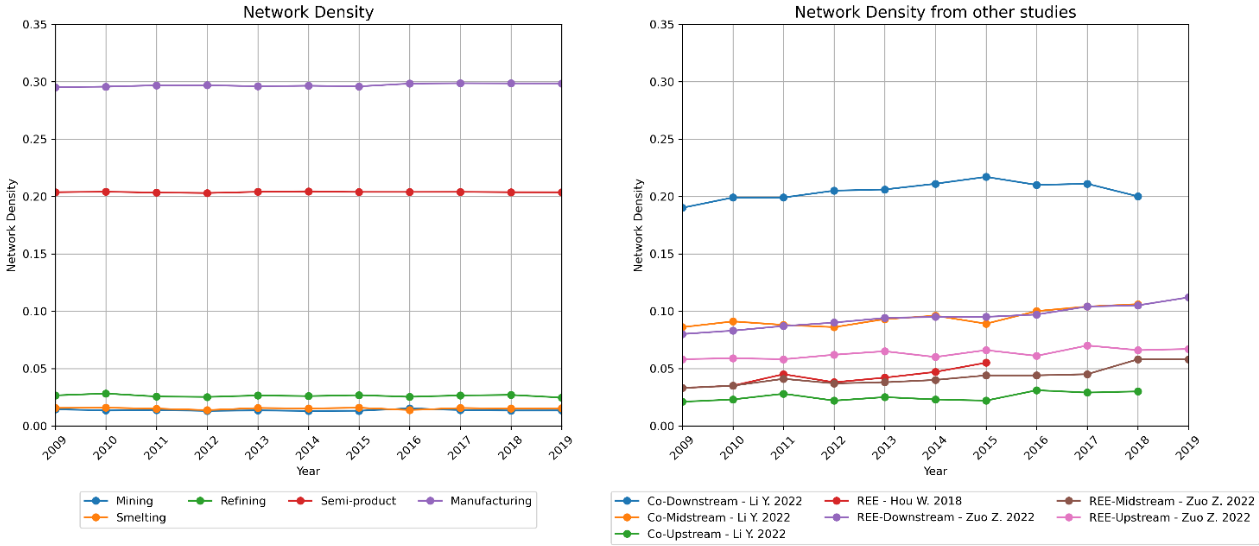

Figure 1: Network Density Trends for Nickel and Comparative Materials: (a) Nickel Network Density; (b) Network Density of Co and REEs derived from other studies.

Overall, these trends highlight the varying degrees of network density and interconnectivity within and between different material supply chains, influencing their stability, efficiency, and susceptibility to external shocks. This analysis underscores the importance of strategic international cooperation to mitigate vulnerabilities and ensure supply chain reliability.

Figure 2 displays the trends in the clustering coefficient (CC) within the global nickel network, showcasing the interconnectedness of the top 20 countries involved in nickel trade from 2009 to 2019. The CC measures trade cohesiveness, where a higher coefficient indicates that a country and its trading partners form a tightly-knit group with frequent mutual trade connections.

China stands out as the dominant node with the highest CC, approximately 0.65, exhibiting a slight yet steady increase throughout the decade. This trend highlights the strength of China's trade network, likely reinforced by stable trade agreements that ensure reliable and consistent links within the global nickel market.

The United States shows a steady rise in its CC, reaching 0.61 by 2019, positioning it as the second most interconnected country. This gradual increase reflects the growing role of the United States in the nickel market, marked by significant import and export activities. Japan, too, shows a consistent increase in its CC, starting at 0.45 in 2009 and nearly matching the United States by 2019, securing a strong third place. Brazil follows a similar trajectory, enhancing its global standing in the nickel supply chain with rich nickel deposits and increased production capabilities, pushing its rank to fourth.

In contrast, countries like Spain and Italy exhibit declining CC trends. This may suggest a strategic shift towards decentralizing their trade networks or diversifying their trade partnerships, aiming to reduce dependence on any single trade network and mitigate the impacts of economic and geopolitical shifts. Overall, the graph effectively captures the dynamic and complex nature of the global trade network, illustrating how changes in economic policy, geopolitical dynamics, technological advancements, and shifts in global production and demand influence the intricate web of trade relationships.

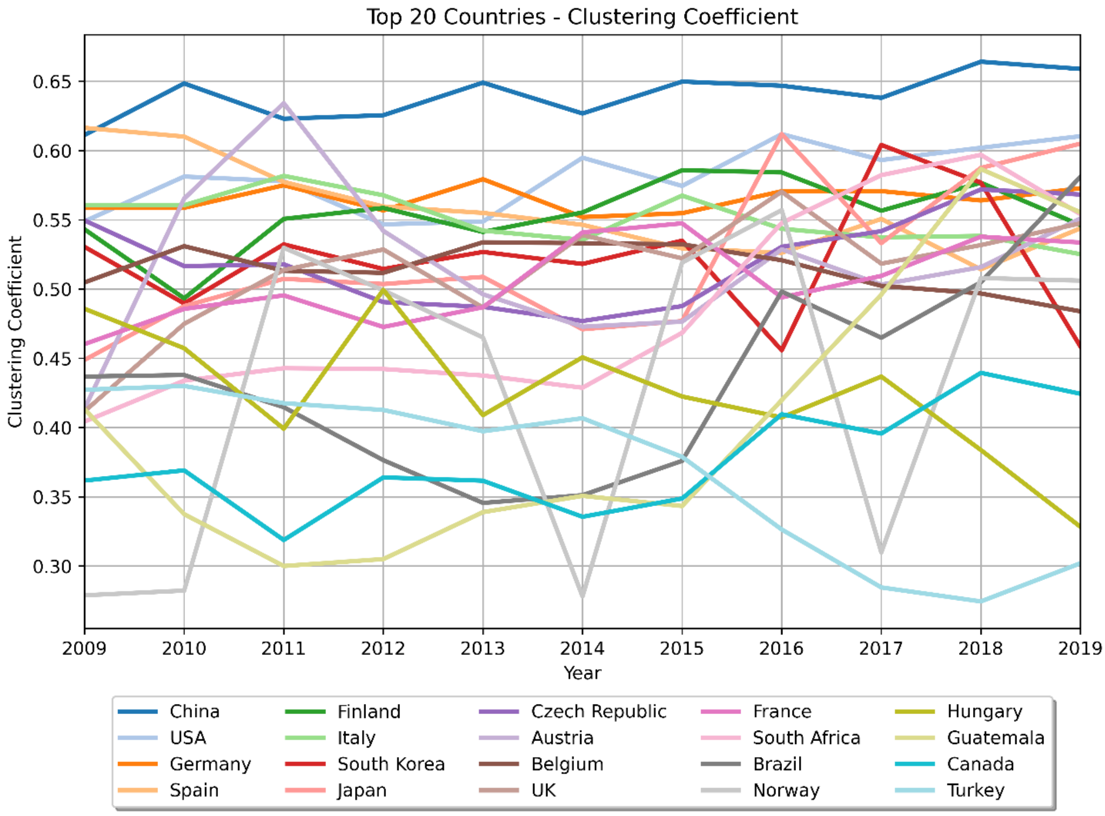

Figure 2: Top 20 Countries - Clustering Coefficient

Each of these countries' clustering coefficients represents the interconnections of their respective trade networks, and changes therein may be attributed to economic policies, geopolitical shifts, or changes in production and consumption cycles. The graph also shows other countries with notable trends, such as a decline in the clustering coefficient for some, which might indicate a decentralization or diversification of trade relationships. Overall, the data illustrates the fluid nature of global trade networks, where shifts in economic power and trade policies can have a pronounced impact on the clustering of trade relationships.

3.1.2. Network layers structural characteristics

Figure 3 illustrates the In&Out strength of the global nickel supply chain from 2009 to 2019, charting the trade volumes and dynamic shifts among the top 10 countries involved in nickel production and consumption across various supply chain levels, from mining to end-use. In the mining layer, the “In Strength” consistently registers as zero, indicating that there are no inputs into the mining process. Conversely, the “Out Strength” at the end-use layer is zero, showing that the end-use sector does not reintroduce outputs into the supply chain.

The output from the mining sector demonstrates temporal fluctuations, which highlight changes in regional production capacities and external influences. Indonesia and the Philippines are key contributors to the Out Strength in mining. Indonesia saw a dip in 2014 due to an export ban on nickel ores but rebounded post-ban, reaffirming its status as a significant exporter of nickel ore. Conversely, the Philippines experienced a steady rise throughout the decade, with a notable dip in 2016 following environmental regulations by then Environment and Natural Resources Secretary Gina Lopez160, leading to the closure or suspension of numerous mines.

At the refining layer, there is a notable increase in both inputs and outputs, emphasizing the complexity and interconnectedness of this stage. China emerges as the top importer of nickel ores, making up for its limited domestic reserves to satisfy substantial internal demand. Despite a consistent reduction in inputs since 2015, Russia remains a key player, while Japan has witnessed a consistent increase in inputs during this period. Notably, China also stands out as a major exporter of refined nickel, utilizing its extensive refining capabilities and competitive edge. Similarly, Japan's increasing imports of refining materials underscore its growing influence in this sector.

The semi-product layer plays a crucial role by connecting upstream suppliers with downstream manufacturers, with China's involvement particularly significant. It acts as both a major recipient and producer of semi-products, with its output tripling over the analyzed period. Other countries maintain much lower levels of In&Out strength, displaying stable trends throughout the decade.

In the manufacturing domain, China dominates by processing and utilizing the majority of the world's nickel, reinforcing its central role in the nickel supply chain. This trend extends into the end-use layer, where China's substantial input levels further solidify its status as a leading consumer of nickel products and a manufacturing powerhouse, central to global trade dynamics.

Figure 3: Top 10 In (left) and Out (right) Strength countries.

In Figure 12, the In&Out degrees for the top 10 countries in the nickel supply chain are shown. While the strengths provide insights into the roles of these nodes in terms of nickel flow volume and value, the degrees offer a count-based view of network connections.

This comparison reveals key differences: China plays a predominant role in the strength metrics due to the substantial quantity of nickel it processes, yet this dominance is not reflected in the In&Out degrees.

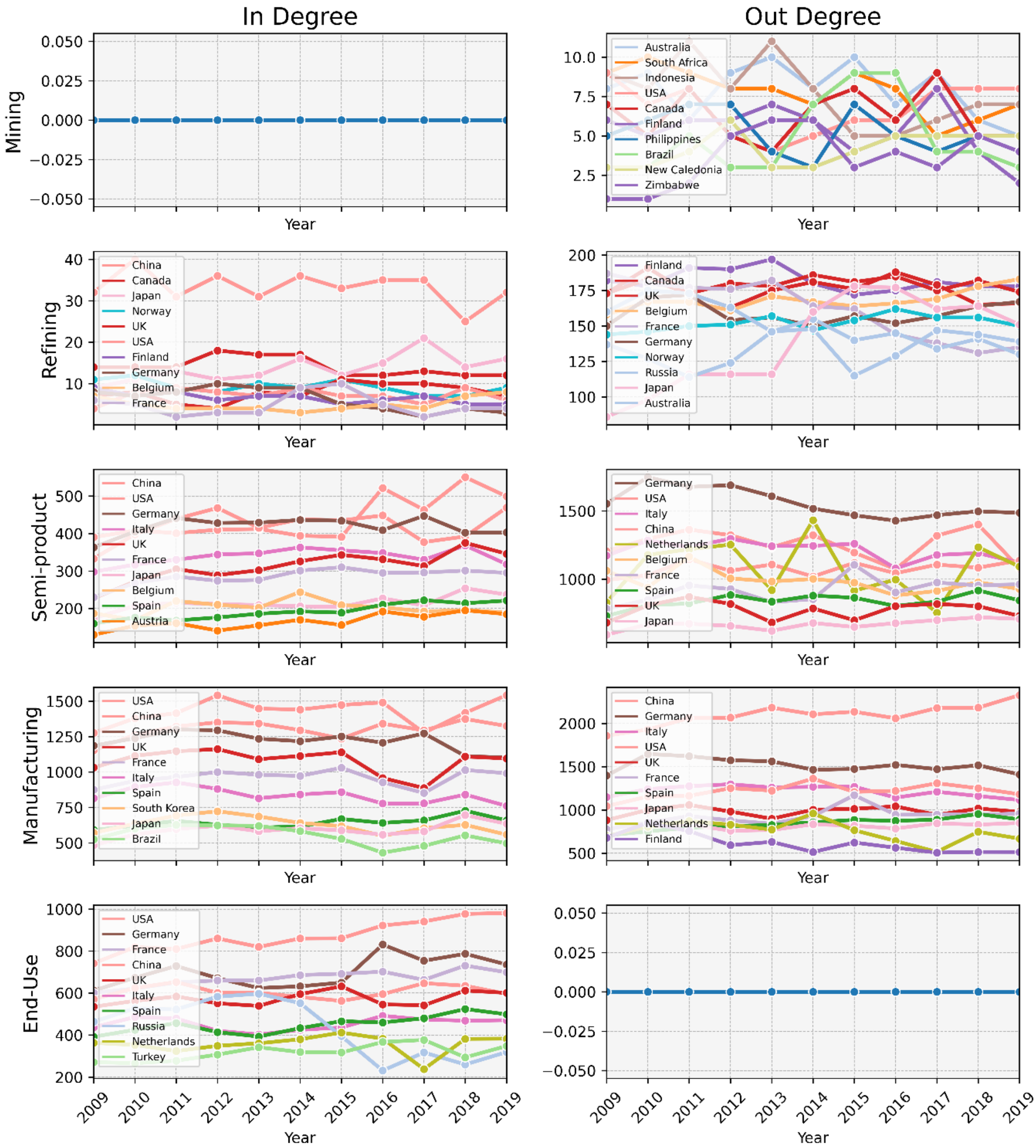

Figure 4: Top 10 countries - In & Out Degree

In the mining sector, the distribution among the top 10 countries is relatively balanced, with connections ranging from 2 to a maximum of 11. This suggests that while Indonesia and the Philippines may have the highest out-strengths, indicating large volumes of nickel exports, they maintain fewer trading connections compared to their output volume.

Moving to the refining layer, China shows the highest In-degree, reinforcing its role as a major importer of nickel ores. Interestingly, China does not rank among the top in Out-degree, highlighting a mismatch between its import capacity and export activities. The number of connections notably increases from the refining to other layers, growing from a maximum of 40 to 200. This expansion emphasizes the limited number of global refining facilities, which many players rely on, adding layers of complexity to the supply chain.

Similar trends and results are observed in the semi-products and manufacturing layers. Unlike the strength metrics, China does not stand out significantly in terms of degrees, presenting a more diversified scenario. The increase in the number of connections from In to Out degrees across these layers reflects the escalating complexity of the network. This aligns with previously reported network density results, confirming the growing intricacy and connectivity within the global nickel supply chain.

Overall, this narrative portrays a dynamic and multifaceted global nickel supply chain. Each country's role is nuanced and evolves over time, influenced by economic policies, global demand, and their strategic position in the network. This complexity underscores the importance of ongoing monitoring and analysis to understand and anticipate future shifts in this vital industry.

Figure 5 presents a comprehensive analysis of betweenness and eigenvector centrality measures across different stages of the nickel value chain. In the Mining layer, South Africa and the USA exhibit the highest betweenness centrality, indicating their roles as significant transitional nodes through which a large number of shortest paths pass. This suggests they are key intermediaries in the mining sector's global network. However, there is notable volatility in the centrality scores, with South Africa showing sharp increases and decreases, reflecting changes in its intermediary role over the examined period.

The Refining layer shows China with the highest betweenness centrality, reflecting its critical position as a transit point in the refining network, likely due to its substantial import and processing of nickel ores. European countries, including Norway and France, also have notable centrality values, indicating their significant roles in nickel refining networks.

In the Semi-product layer, China maintains the highest betweenness centrality, consistent with its dominant role in importing semi-processed materials for further value addition. Germany and Italy also exhibit high centrality, aligning with their strong manufacturing industries that process semi-products.

The Manufacturing layer sees a dispersion in betweenness centrality, with China, Germany, and the USA consistently occupying central positions. This dispersion suggests a more distributed network structure in manufacturing, where multiple regions act as important intermediaries.

In the End Use layer, Spain and Germany show peaks in centrality, indicating shifts in the nickel consumption network, possibly due to changes in end-use manufacturing or consumer demand patterns.

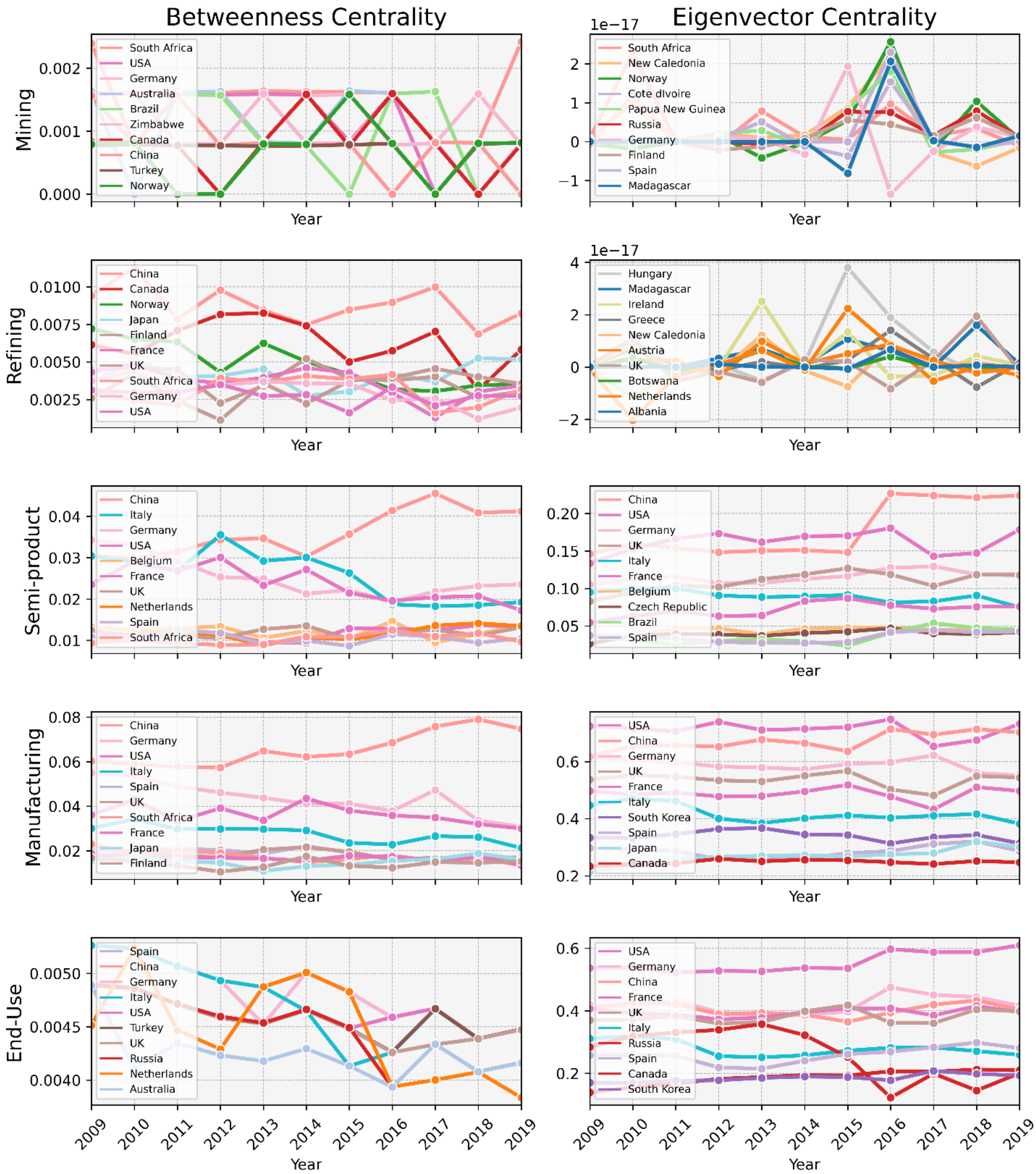

Figure 5: Top 10 countries - Betweenness Centrality & Eigenvector Centrality

3.2. Panel Regression Analysis

Table 1 provides a descriptive statistical analysis of variables integral to nickel consumption. The table highlights a wide variation in the values of variables such as Value Added (VA), Backward Linkage (BL), In Degree, Out Degree, In Strength, Out Strength, Betweenness Centrality, and Eigenvector Centrality. These variables range broadly in their count, mean, standard deviation, minimum, and maximum values, indicating the necessity for a methodological approach to normalize these differences. To address the disparate scales and mitigate the dimensional influence among these variables, a logarithmic transformation was applied. This mathematical treatment helps to attenuate the skewness of the data, thereby enhancing the comparability and interpretability of the variables[25].

In the pursuit of a robust analytical framework, eight distinct panel regression models were constructed. The first model focused on estimating the control variables to set a baseline for comparison. Subsequent models, from the second to the seventh, progressively incorporated additional variables—Degree-in, Degree-out, Strength-in, Strength-out, Betweenness Centrality, and Eigenvector Centrality—each aiming to estimate the unique influence of these network characteristics on the consumption of embodied nickel.

The eighth and final model was an aggregate estimation, where all variables were included to provide a comprehensive view of their collective impact. This holistic approach allows for a nuanced understanding of the interplay and relative significance of each factor within the MRIO framework[26].

To ensure the methodological rigor and the selection of the most appropriate regression model for our analysis, the Hausman test was employed across all models. This statistical test is crucial for determining whether a fixed effects or random effects model is more suitable based on the consistency of the estimators. From the test's results we applied the random effect model for most of the model here presented, except for the In-strength and Eigenvector models where a linear model was applied.

In the comprehensive examination of nickel consumption patterns through the lens of a Multi-Regional Input-Output (MRIO) framework, spanning a critical decade from 2009 to 2019, this doctoral study delineates the complex interplay between economic output, network structures, and resource utilization. The data unveils a multifaceted narrative where various sectors demonstrate fluctuating degrees of influence and prominence in the flow of nickel over time.

Table 1: Descriptive statistics of variables for Ni embedded consumption.

	count	mean	std	min	max
Dependend variable					
Ni consumption	16832	3868.802	32419.66	0	1606354
Control Variables					
Value_Added	16832	39842.8	355667	0	15702604
Backward Linkage	16832	2.512277	2.197469	1	59.86078
Population	16832	1.51E+08	3.75E+08	245950	2.23E+09
Independent Variables					
In Degree	16832	215.2165	153.0699	0	687
Out Degree	16832	211.7586	333.9351	0	1390
In Strength	16832	3868.746	32419.67	0	1606354
Out Strength	16832	2116.049	26954.17	0	1563325
Betweenness Centrality	16832	0.000279	0.000911	0	0.014886
Eigenvector Centrality	16832	0.021302	0.014134	0	0.057872

Value Added (VA), representing the economic output of sectors, emerges with a nuanced yet discernible impact on nickel consumption. As illustrated by the data, VA's coefficient stands at a modest 0.0030 (Standard deviation), complemented by a T-statistic of 1.8307, signaling a positive, albeit restrained, influence on nickel consumption—a subtle narrative that is substantiated by a P-value of 0.0672. As the analysis progresses to incorporate network metrics, VA's storyline exhibits resilience. The influence of VA slightly recedes, as indicated by a decrease in the coefficient to 0.0007 (Standard deviation) with an associated T-statistic of 1.4146 in the presence of In Degree connections, suggesting a more subdued role amidst an intricate web of trade interactions. Conversely, the Out Degree analysis accentuates VA's role, with the coefficient increasing to 0.0049 (Standard deviation) and a T-statistic of 1.8244, underscoring the sectors' increased engagement and consumption of nickel in relation to their outbound trade connections.

The Backward Linkage (BL) factor presents as a complex yet significant actor within this framework. Its coefficient of 168.51 (Standard deviation) alongside a T-statistic of 1.4100, presents a narrative of potential influence on nickel consumption, albeit one that the data cannot confirm with complete statistical certainty, reflected in a P-value of 0.1586. This complex role of BL is further complicated when dissected through the In Degree and Out Degree perspectives. The influence of BL appears context-dependent, fluctuating from being significant within the In Degree connections to becoming negligible or even inversely related in the context of outbound trade connections, as the T-statistic shifts to -1.0739.

Table 2: Panel Regression Results

	Controls Only			In Degree			Out Degree			In Strength		
	Std.	T-stat	P-value	Std.	T-stat	P-value	Std.	T-stat	P-value	Std.	T-stat	P-value
VA	0.0030	1.8307	0.0672	-0.2699	-8.4833	0.0000	0.4637	23.339	0.0000	0.0043	1.7895	0.0735
BL	168.51	1.4100	0.1586	0.0035	0.5824	0.5603	0.0333	1.7384	0.0822	0.0006	0.6746	0.4999
Pop	4.585e-05	1.1073	0.2682	1.5358	1.9779	0.0480	-0.9177	-1.0530	0.2924	-0.0186	-1.8685	0.0617
ID				0.0188	40.321	0.0000						
OD							21.720	27.474	0.0201			
IS												
OS												
BC										0.9972	1357.6	0.0000
EC												
Hausman test	0.069146			3.1921			1.5357			17.032		

	Out Strength			Betweenness Centrality			Eigenvector Centrality			All Independent Variables		
	Std.	T-stat	P-value	Std.	T-stat	P-value	Std.	T-stat	P-value	Std.	T-stat	P-value
VA	0.5224	22.939	0.0000	0.3825	20.298	0.0000	-0.2356	-7.3814	0.0000	0.0072	2.1490	0.0316
BL	0.0319	1.7392	0.0820	0.0603	2.2516	0.0244	0.0095	1.2183	0.2231	0.0006	0.6464	0.5181
Pop	-1.4245	-1.6687	0.0952	0.3817	0.3724	0.7096	4.0239	4.8914	0.0000	-0.0182	-2.0837	0.0372
ID										-7.61e-05	-0.8694	0.3846
OD										3.669e-06	0.3572	0.7210
IS										0.9909	255.98	0.0000
OS	0.5813	34.158	0.0000							0.0058	1.6777	0.0934
BC				1050.7	6.2995	0.0000				-2.4032	-1.6651	0.0959
EC							186.24	29.224	0.0000	1.0563	0.9029	0.3666
Hausman test	2.974445			0.071281			23.2288			1.56449		

The Population variable, while a critical element of the socioeconomic landscape, assumes a less pronounced role in our analysis. Despite its foundational importance, Population's coefficient of 4.585e-05 (Standard deviation) and a T-statistic of 1.1073 fail to significantly influence the consumption narrative of nickel, as indicated by a P-value of 0.2682. This trend holds true irrespective of whether sectors are characterized as hubs of incoming or outgoing trade flows. Network dynamics are further explored through In Degree and Out Degree metrics. The In Degree connections reveal a significant standard coefficient of 38.392 and a T-statistic of 1.9360, highlighting sectors as influential nodes where increased linkages correlate with higher nickel consumption, as evidenced by a P-value of 0.0529. In stark contrast, Out Degree connections, while present within the dataset, show a reduced narrative impact, indicating that a sector's number of outbound connections does not necessarily predict its nickel consumption levels.

Betweenness Centrality (BC) is identified as a crucial strategic influencer within the network. With a substantive standard coefficient of 15.595 and a T-statistic of 2.1883, sectors with high BC are positioned as key intermediaries within the network, substantially shaping nickel consumption patterns through their pivotal intermediary roles as indicated by a P-value of 0.0287.

Eigenvector Centrality (EC) assumes a more enigmatic influence. Despite the high centrality of EC within the network, its impact on nickel consumption is not straightforward, as suggested by the complex interdependencies within the network. This nuanced role adds an additional layer of complexity to the overall narrative.

The analysis delineates the complex interconnections among economic output, backward linkages, demographic elements, and network dynamics in determining nickel consumption patterns. Nodes with substantial economic output and strategic positions within the network play a pivotal role in dictating both the volume and routes of nickel consumption. Specifically, the function of backward linkages sheds light on how nodes efficiently manage and leverage their incoming supply connections to bolster their consumption and potentially enhance their export activities.

This analysis reveals a multifaceted interplay of factors that shape nickel consumption patterns, suggesting that effective resource management strategies should transcend traditional economic and demographic considerations to embrace a detailed understanding of network dynamics and material flows. Incorporating Value Added, Backward Linkages, and various centrality metrics into our models not only underscores the diverse influences on consumption but also indicates opportunities for enhancing supply chain resilience and efficiency.

For example, the significant influence of backward linkages on consumption underscores the potential advantages of reinforcing these connections to safeguard against supply interruptions. Similarly, strategic insights derived from Betweenness and Eigenvector Centrality metrics can guide targeted policy measures aimed at reducing risks associated with crucial nodes within the supply network. Thus, this analysis should act as an essential resource for policymakers and industry leaders, steering the formulation of holistic strategies that ensure sustainable and secure nickel supply chains amid changing economic, environmental, and geopolitical conditions.

4. Discussion

Interpretation of findings

Our research into the global nickel supply chain has uncovered a complex and dynamic landscape. The complex network analysis revealed the crucial roles that different countries and sectors play in this global market. A notable aspect of these findings is the manufacturing layer's significant connectivity, highlighting its central role in the nickel supply chain. This points to the manufacturing sector as a key hub where various supply lines intersect and disperse. Similar result on in-out degree were also reported by Wang et al[19].

The study also brought into sharp focus the evolving role of China in the nickel market. The consistent growth in China’s in-strength across all stages of the supply chain suggests an increasing integration into global nickel resources and possibly a strategic shift towards strengthening domestic capabilities in the nickel value chain[18]. This trend offers insights into China's broader industrial strategies and its changing role in the global economic landscape.

The panel regression analysis shed light on the nuanced impact of various economic variables on nickel consumption. Value Added (VA) and Backward Linkage (BL) emerged as significant factors, although their influence varied across different network connections. This highlights the intricate interplay between economic output, trade dynamics, and resource utilization within the global nickel market. Intriguingly, the study found that population size, despite being a fundamental socioeconomic factor, did not have a significant influence on nickel consumption patterns.

The strategic importance of network metrics such as Betweenness Centrality (BC) and Eigenvector Centrality (EC) was also evident in our findings. These metrics help in understanding the flow and influence within the nickel supply chain, with high BC sectors emerging as key intermediaries that significantly shape nickel consumption patterns.

Implications

The insights from this study have significant implications for policymakers and industry stakeholders. Understanding the dynamic roles of different countries and sectors can aid in strategic planning, especially in mitigating risks associated with supply chain disruptions. For countries like China, which are increasingly central to the global nickel supply chain, there's a need for policies that balance domestic demands with global trade dynamics.

The increasing demand for nickel, especially for EV batteries, raises important questions about sustainability and environmental impact. Our study underscores the need for continued research and development in sustainable mining practices and recycling technologies to meet the growing demand in an environmentally responsible manner.

The variability in network density and centrality across countries and sectors suggests the need for economic diversification to enhance resilience. Countries heavily reliant on nickel exports or imports may consider diversifying their economic activities to reduce vulnerability to market fluctuations and geopolitical events.

Future Research Directions

Future research could integrate environmental metrics into the analysis to assess the ecological impact of nickel mining and processing. This would provide a more holistic view of the nickel supply chain, encompassing both economic and environmental sustainability.

Further investigation into the role of recycling and circular economy principles in the nickel supply chain could yield valuable insights. This would help in understanding the potential of these practices in reducing environmental impact and meeting the increasing demand for nickel.

Exploring the impact of technological innovations in mining, refining, and battery manufacturing on the global nickel market could provide foresight into future trends and shifts in the supply chain dynamics.

Incorporating geopolitical and economic modelling could enhance the understanding of how international relations and economic policies influence the global nickel market. This could be crucial in anticipating and preparing for potential disruptions in the supply chain.

Our comprehensive analysis of the global nickel supply chain from 2009 to 2019, employing a multifaceted approach that combines complex network analysis and panel regression analysis, offers vital insights into the dynamics of the nickel market. These insights are pivotal for informed decision-making in policy, strategic planning, and sustainable resource management in the global nickel market. As the world moves towards a more electrified future, the importance of understanding and efficiently managing resources like nickel becomes increasingly paramount.

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6. Note

The authors declare no conflict of interest.

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Paper nº 2

Integrating MRIO Network Analysis in Assessing Nickel Supply Risks: A Multidimensional Approach

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Abstract

The global transition to sustainable energy technologies has significantly amplified the strategic importance of nickel, particularly due to its critical application in lithium-ion batteries for electric vehicles (EVs). This paper presents an innovative, comprehensive assessment of supply risks across the entire nickel supply chain, from extraction to end-use, with a focus on the period from 2009 to 2019. We adopt a multidimensional approach, integrating a Multi-Regional Input-Output (MRIO) network analysis with an array of supply risk indicators, including economic, political, social, environmental, and technological factors.

Our study reveals the varied risk landscapes for different nickel products and stages of the supply chain, highlighting the influence of geopolitical, environmental, and market dynamics. We delve into the nuances of the nickel supply chain, underscoring the significant impact of national policies such as the Indonesian export ban and the Philippines' mining regulations. The research also discusses the implications of the United States' Inflation Reduction Act and the need for comprehensive legislation that encompasses the full scope of supply chain challenges for critical minerals like nickel.

Through granular examination of nickel sub-products, our analysis offers a detailed risk profile that surpasses previous models focused primarily on mining data. We find that while countries like China have successfully mitigated supply risks for nickel sulphate, others remain vulnerable due to import reliance. This underscores the need for targeted risk mitigation strategies and diversified supply sources.

The paper contributes to the strategic conversation on securing mineral supply chains in the era of clean energy, suggesting the importance of recycling initiatives, international cooperation, and forward-looking policies. Our findings serve as a valuable guide for stakeholders in navigating the complexities of supply risks associated with nickel, a mineral integral to the realization of a zero-carbon economy. This research marks a significant step towards a more resilient and sustainable approach to managing the supply chains of critical minerals.

Keywords: Nickel, Supply Chain, Risk Assessment, Sustainable Energy, Electric Vehicles, Multi-Regional Input-Output Network, Lifecycle Analysis, Critical Minerals.

1. Introduction

Nickel has ascended to a crucial role in the advancement towards sustainable energy solutions, with its use extending across a diverse range of applications. This versatile metal is essential for producing stainless steel and corrosion-resistant alloys, and it plays a significant role in the defense and civil industries. In the era of new energy, nickel's importance has been magnified due to its indispensable role in the fabrication of lithium-ion batteries (LiBs), attributed to the extensive use of nickel cathode material[1]. The shift towards low-carbon energy sources predicts a continued increase in nickel demand, potentially leading to a shortage of nickel resources—a concern that has loomed since the 1980s. The market faces a distinct challenge with Ni Class 1, which meets higher quality and delivery standards, being in shorter supply compared to the more abundantly produced Nickel Class 2, which is of lower quality. This disparity has caused the London Metal Exchange (LME) to experience low nickel deliverability, frequently resulting in market volatility and short-squeeze situations[2].

The ongoing nickel supply dilemma has been significantly influenced by Indonesia's export ban on unprocessed nickel ore in 2014, which has had a profound effect on global supply chains[3]. Subsequent to Indonesia's ban, the Philippines shut down 23 mines and enforced strict regulations on open-pit mining, further diminishing nickel ore exports and introducing significant seasonality to supply dynamics. Indonesia's intermittent adjustments to its nickel ore export policy and nickel content standards over the years have perpetuated concerns over supply. The situation was exacerbated by the Russian invasion of Ukraine, disrupting the trade of Russian nickel products. This conflict led to unprecedented volatility in the nickel market, culminating in the temporary closure of the London Metal Exchange due to a surge in nickel prices to $100,000 per ton—a fivefold increase[4]. This context underscores the soaring demand for nickel, particularly from the electric vehicle sector, and highlights the imperative for thorough supply chain risk assessments to mitigate the impact of geopolitical instabilities, environmental regulations, and market fluctuations. These considerations are critical for ensuring the security of nickel supplies and for addressing potential disruptions that could affect global nickel availability.

The nickel supply chain, vital for various industries including the rapidly growing electric vehicle (EV) market, is fraught with environmental and social challenges that underscore the need for sustainable and responsible mining practices. The geographical distribution of nickel reserves often overlaps with geopolitically sensitive and ecologically significant areas, posing risks of disruption from political instability, regulatory changes, or environmental degradation.

Environmental concerns primarily revolve around the impact of nickel mining and processing on local ecosystems and global climate change. For instance, sulfide and laterite ore mining have distinct environmental footprints. Sulfide orebodies, while having a limited surface impact, require smelting that emits sulfur dioxide-rich gases, whereas laterite mining, often conducted in areas rich in biodiversity like tropical rainforests, involves surface mining that causes extensive habitat destruction. The refinement processes for both ore types can lead to the emission of harmful substances such as arsenic, fluorine, and chlorine, further exacerbating environmental harm.

Social challenges in the nickel industry are equally pressing[5]. The International Council on Mining and Metals (ICMM) has set Mining Principles aimed at maximizing benefits to local communities and minimizing negative impacts. However, implementation varies, and there are instances of significant social injustices. For example, in Indonesia, the world's largest nickel producer, there have been reports of land grabbing, coercion, and intimidation by companies, often with the involvement of local authorities[6]. This has threatened the livelihoods and cultural heritage of Indigenous Peoples and local communities, who have seen their environments degraded by pollution and deforestation associated with nickel mining and processing activities.

Despite these adversities, there are pathways to improvement. Transitioning to renewable energy sources for mining operations, adopting responsible waste management practices like dry stacking of tailings, and ensuring transparent and respectful engagement with local communities are steps toward mitigating environmental and social risks. Moreover, companies in the nickel supply chain, including EV manufacturers sourcing nickel for batteries, have a critical role in demanding and ensuring responsible mining practices that respect human rights and environmental standards. Addressing the environmental and social risks associated with nickel mining is not only a matter of ethical responsibility but also crucial for the sustainability of the industries that depend on this critical material. It requires a collective effort from governments, corporations, and civil society to enforce and adhere to higher standards of environmental management and social responsibility.

Understanding the vulnerabilities within complex supply chains is essential, especially for strategic minerals like nickel, pivotal in driving a zero-carbon economy. Traditional supply risk assessments often focus mainly on the mining phase, neglecting the broader spectrum of the material supply chain[7]. Recognizing nickel's strategic significance, various governments have classified it as a mineral of critical importance. For instance, the European Commission defined nickel as a critical material[8], as also China listed nickel among its 24 strategic minerals[9], the British Geological Survey (BGS) identified it as a risky mineral in 2017[10], and the Japanese government included it in its top 10 priority minerals in 2020. Similarly, the United States Geological Survey (USGS) added nickel to its list of critical minerals in 2022[11].

Moreover, the U.S. Inflation Reduction Act (IRA) of August 2022, promoting electric vehicle (EV) adoption through tax credits, misses critical points on mineral supply chains, such as mining's environmental impacts and recycling needs. This highlights the necessity for a comprehensive strategy in managing critical minerals like nickel, addressing both economic and environmental concerns.[12]

Emerging methodologies in supply chain risk assessment address environmental, geopolitical, and socio-economic factors, considering factors like consumption time based on production and reserves, recovery rate, market balance, and substitutability[13]. These studies, carried out by countries including the United States, China, Australia, and Japan, have helped define metal supply risk using indicators such as geological availability, mining governance, policy stability, global market concentration, and environmental sustainability. However, a notable gap remains in the literature: the differentiation between various nickel products (ex. nickel sulphate used in lithium-ion batteries (LiBs)), is often not adequately addressed in these assessments. This oversight highlights the need for more nuanced and product-specific risk analysis in the nickel supply chain.

Recent research efforts have increasingly focused on evaluating the supply risks associated with nickel (Ni), such as Zhang[14] and colleagues that undertook a comprehensive supply risk assessment for metals used in these technologies, considering factors like geological availability, mining governance and policy stability, global market concentration, and environmental sustainability. Another example is the study of Helbig et al.[15] that developed a semi-quantitative scheme to assess the relative supply risks of materials used in six different types of LiBs. Their methodology encompassed eleven indicators across four supply risk categories, offering a detailed perspective on the supply chain vulnerabilities of these batteries. Although both studies are significant, their methodology primarily focuses on global production mining data, which restricts their analysis to the initial phase of the supply chain. In a comprehensive study, Sun et al.[16] broadened the perspective on supply risk assessment for LiBs, examining the entire supply chain encompassing mining, refining, and manufacturing phases. This research highlighted four essential materials: nickel, cobalt, lithium, and manganese, emphasizing their respective roles in the supply chain. Significantly, the study revealed that the supply risk for nickel escalates through each stage of the supply chain. However, it did not differentiate between various nickel sub-products, an aspect crucial for a more detailed risk analysis.

These studies collectively underscore the complexity of supply risk assessment in the clean energy sector, especially for vital components like nickel. As also highlighted by McNulty & Jowitt[17], despite the efforts by policymakers, researchers, and industry to mitigate these risks, decisions surrounding funding, investment, and policy are hindered by deficiencies in the knowledge base. They reveal the need for a more integrated approach that encompasses the entire supply chain, from mining to end-product manufacturing, to accurately capture the multifaceted nature of supply risks.

This paper introduces an innovative framework that extends beyond merely identifying the stage of the supply chain where various nickel products are manufactured. It offers a nuanced and accurate depiction of supply risks, tailored to the complex dynamics of the nickel supply chain. Our research embarks on a comprehensive exploration of supply risk assessment for nickel, spanning from ore extraction to the production of refined and finished products, with a particular focus on the specific demand for nickel products, such as nickel sulphate, crucial for the rapidly expanding EVs sector. To achieve this, we employ a combination of Material Flow Analysis (MFA) and Multi-Regional Input-Output (MRIO) models. These tools are instrumental in tracing the different flows of nickel sub-products through the various steps of the supply chain. This methodological approach allows for a granular analysis of the pathways through which nickel and its derivatives move from extraction to final use, providing a clearer picture of potential bottlenecks and vulnerabilities.

Our study addresses a significant research gap by providing a differentiated risk assessment across nickel sub-products, enabling the formulation of more effective risk mitigation strategies amidst rising global demand. Specifically, we focus on the timeframe from 2009 to 2019, analyzing the supply risk of 7 nickel sub-products and 6 finished products containing nickel, for the top 20 countries involved in the nickel supply chain. This temporal and geographical specificity, combined with our sophisticated analytical approach, allows us to capture the evolution of supply risks in the context of geopolitical shifts, regulatory changes, and market dynamics that have impacted the global nickel supply. By doing so, we offer insights into the vulnerabilities and resilience within the nickel supply chain, facilitating a deeper understanding of how to navigate the complexities of global nickel availability and security. This comprehensive assessment is vital for stakeholders across the nickel supply chain, from miners to manufacturers, in devising strategies that ensure the sustainable and uninterrupted supply of this critical material.

2. Material and methods

2.1. System definition

Our study advances the exploration of the global nickel supply chain by leveraging an integrated framework that meticulously combines various indicators of supply risk. This framework scrutinizes the entire lifecycle of nickel—from extraction through to end-of-life disposal. At the core of our analysis is the implementation of the Material Flow Analysis-Multi-Regional Input-Output (MFA-MRIO) model. This model facilitates the construction of a comprehensive nickel flow network spanning the years 2009 to 2019, thereby uncovering distinct sub-products of nickel at each stage of the supply chain, as illustrated in Figure 1. These stages include:

- *Mining*, which yields sulphide and laterite ores;
- *Smelting*, resulting in products such as Matte, Mixed Sulphide Precipitate (MSP)/Mixed Hydroxide Precipitate (MHP), Ferronickel (FeNi), Nickel Pig Iron (NPI), and nickel oxides;
- *Refining*, producing Class 1 nickel and nickel sulphate;
- *Manufacturing*, with applications in batteries, plating, non-ferrous alloys, metal casting, powder metallurgy, among others;
- *Waste management*, involving stainless steel scraps and battery scraps.

In this study, we have chosen to aggregate ferronickel (FeNi) and nickel pig iron (NPI) owing to their analogous characteristics and their primary application in the production of stainless steel. Similarly, mixed sulfide precipitate (MSP), mixed hydroxide precipitate (MHP), and nickel oxide have been grouped together. This decision is justified by their relatively minor role in the nickel supply chain and their comparable utilization.

We categorize risk indicators into three primary dimensions: **Social & Regulatory**, captured by the Human Development Index (HDI) and Worldwide Governance Index (WGI); **Environmental & Technological**, assessed using the Environmental Performance Index (EPI) and Global Innovation Index (GII); and **Economic & Network** Factors, evaluated through the Herfindahl-Hirschman Index (HHI), Betweenness Centrality (BC), and Import Dependency Ratio (IDR). Each of these dimensions highlights different potential impacts on the nickel supply chain, contributing to a multi-dimensional risk profile. The concept of 'General Risk' is introduced as a cumulative metric, reflecting the interplay of social, environmental, technological, and economic factors, thereby offering a comprehensive view of potential vulnerabilities within the supply chain.

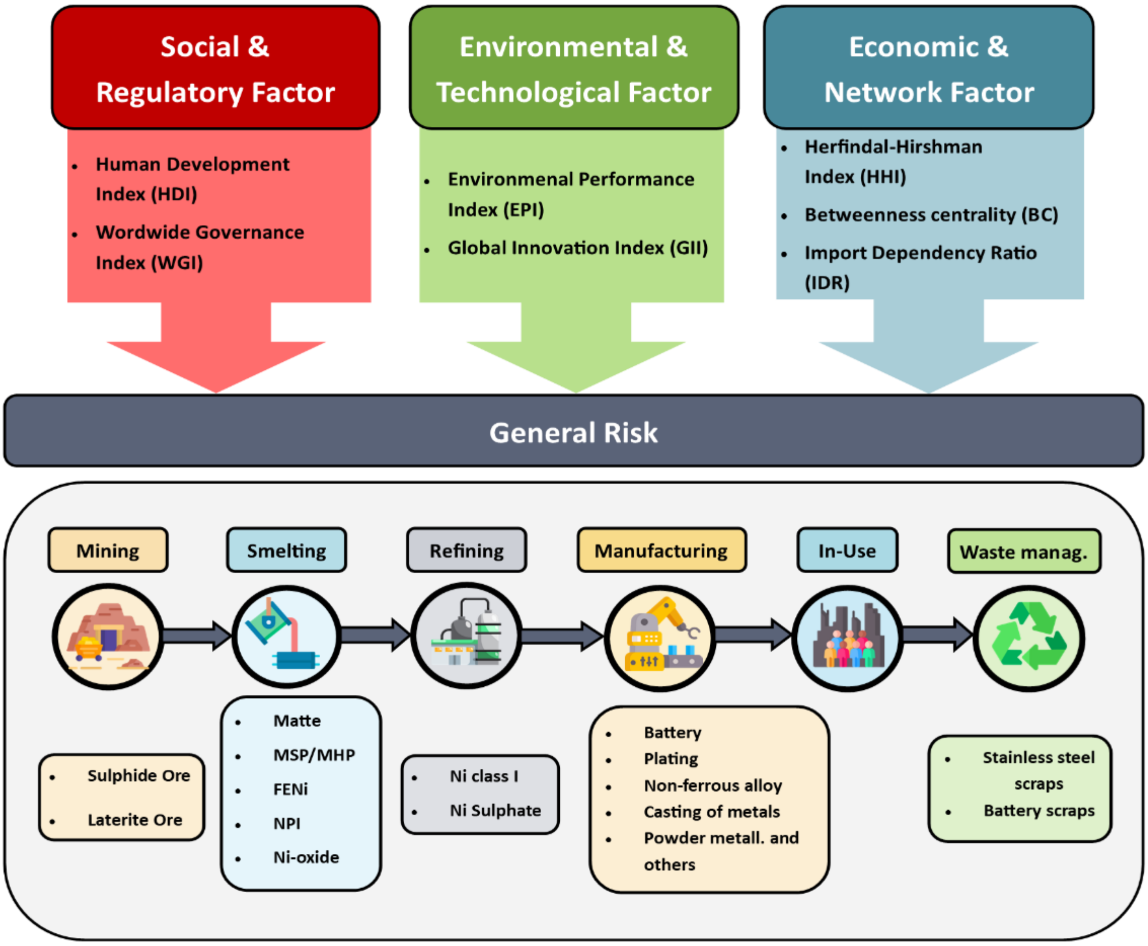

Figure 1: Study Framework - Supply Risk Indicator - Nickel supply chain (products)

By examining the nickel supply chain via the MFA-MRIO flow network, our framework not only facilitates a detailed categorization of nickel products but also enhances our understanding of the risks associated with each segment. This approach is crucial for identifying the unique challenges and risks faced by different nickel products throughout their lifecycle. The detailed nature of this analysis, combined with the specific identification of nickel sub-products and their supply chain stages, furnishes a refined methodology for precise risk assessment. This methodology accounts for the complex interdependencies within the supply chain and the global factors influencing it.

Such a nuanced understanding is critical for devising strategies that enhance resilience and adaptability in the ever-evolving global market. For comprehensive details on the nickel supply chain and its products, please refer to the SI.

2.2. Supply Risk

In the $SR_{(p,c)}$ equation used to evaluate the supply risk of nickel products in various countries, each component is strategically selected to cover diverse aspects of supply risk. It is calculated for nickel product 'p', in country 'c'. This multi-dimensional approach in the $SR_{(p,c)}$ equation enables a comprehensive assessment of supply risks for nickel products, combining economic, political, social, environmental, technological, and network structural factors. Such an analysis is vital for stakeholders in the nickel industry, aiding in strategic decision-making and risk management in a complex and interconnected global marketplace.

$$SR_{p,c} = HHI_{\mathrm{p,norm.}} * \left(\sum_{i}^{n} IDR_{p,c,i} * (1 - WGI_i * HDI_i * EPI_i * GII_i)\right) * (1 - BC_c) \qquad \textit{(Eq. 1)}$$

This equation was inspired by different studies, such as the work of Li J. et al.[18] where they assessed the supply risk of antimony. In this work we expanded their equation, to grasp the risk measured by GII and added the import dependency ratio[19,20], to “weight” the risk considering the importing country import share. In the following part all the indicators used to calculate $SR_{p,c}$ are introduced.

Indicators

Social & Political factors

- **Human Development Index:** The *HDI* offers a multi-dimensional perspective on human well-being, incorporating health (life expectancy), education (years of schooling), and standard of living (GNI per capita). It serves as a benchmark for comparing the developmental progress of nations, highlighting the capacity of countries to support stable and resilient supply chains. Higher *HDI* scores reflect better health, education, and income levels, suggesting a more robust environment for sustainable supply chain operations.

- **Worldwide Governance Indicators:** The WGI provide a comprehensive overview of governance quality, covering voice and accountability, political stability, government effectiveness, regulatory quality, rule of law, and control of corruption. These indicators shed light on the political and social environment's impact on supply chains, with higher scores indicating stronger governance structures that can enhance supply chain reliability. This normalization process scales WGI scores, originally ranging from -2.5 to 2.5, to a more usable range for analysis. The transformation inversely correlates higher governance quality with lower supply risk, acknowledging that stronger governance frameworks support more stable supply chains.

$$\mathrm{WGI}_{\mathrm{norm.}} = 20 \cdot (2.5 - \mathrm{WGI}) \qquad \textit{(Eq. 2)}$$

Economic & Network factors

- **Herfindahl–Hirschman Index:** the *HHI* is calculated in the following way:

$$HHI_{\mathrm{p,norm.}} = \frac{\sum_i S_i^2}{10000} \qquad \textit{(Eq. 3)}$$

Where S_i represents the market share of country i. The *HHI* is normalized by dividing it by 10,000, to scale the value between 0 and 1, making it interpretable within the model. A higher normalized *HHI* value indicates a higher concentration in the market, suggesting potential risks due to reduced competition and increased vulnerability to monopolistic practices.

- **Import Dependency Ratio**: Reflecting a country's reliance on imports for nickel, the IDR highlights vulnerabilities to external market fluctuations. Higher IDR values signal greater risk, emphasizing the need for strategies to enhance self-sufficiency or diversify import sources to mitigate supply chain disruptions.

$$\mathrm{IDR}_{c,p} = \frac{\text{Net imports}}{\text{Apparent consumption}} = \frac{\text{Net Imports} - \text{Exports}}{\text{Domestic Production} + \text{Imports} - \text{Exports}} \qquad \textit{(Eq. 4)}$$

- **Betweenness centrality**: By measuring a node's centrality within the global nickel network, BC reveals the influence of countries in controlling material flows. Lower BC values indicate a peripheral position in the network, correlating with higher supply risks due to potential isolation or limited influence on global supply dynamics[21–23]. The variable g_{jk} represents the number of shortest paths between country j and country k, and $g_{jk}(i)$ represents the number of shortest paths between country j and country k through country i. Variable BC_i is the betweenness centrality of country i. The calculation method is as follows:

$$BC_i = \sum_{j<k} \frac{g_{jk}(i)}{g_{jk}} \qquad \text{(Eq. 5)}$$

Environmental and Technology factors

- **Environmental Performance Index**: the EPI assesses a country's environmental health and sustainability efforts across various domains, including air and water quality, biodiversity, and climate change mitigation. Higher EPI scores suggest a stronger commitment to environmental stewardship, which is crucial for the sustainable extraction and processing of nickel.
- **Global Innovation Index:** the GII evaluates a country's innovation ecosystem, covering R&D investments, patent applications, and technology transfer, among others. A higher GII score indicates a more innovative and adaptive country, capable of developing and applying technological solutions to enhance nickel supply chain efficiency and sustainability.

2.3. Data Source

The data requirements for this study are extensive and diverse, catering to the multifaceted nature of the supply chain analysis. For the MRIO tables, we sourced our data from Exiobase[24], a detailed and comprehensive database that provides the economic, environmental, and social impacts in a multi-regional framework. Exiobase's MRIO tables are instrumental in modeling the complex interactions within the global nickel supply chain and assessing the interconnected economic activities.

MFA data, crucial for determining the physical flows of nickel and its products, are compiled from various authoritative sources. We employed the methodology used by Cormery M.[25], which integrates data from the International Nickel Study Group[26] (INSG) and the United States Geological Survey[11] (USGS) and the British Geological Survey (BGS), among others. This approach allows us to delineate the main flows of nickel products with precision, giving us a clear picture of the production, consumption, and recycling patterns of nickel globally.

For data on international trade, we turned to the United Nations Commodity Trade Statistics Database (Comtrade). By applying conversion factors calculated by Nakajima et al.[27], we were able to translate trade data into physical flows, providing a tangible sense of the quantities of nickel moving through the international markets. To ensure the accuracy and reliability of our data, we refined it using an algorithm inspired by the work of Cormery. This algorithm is specifically designed to polish the dataset and remove outliers, thereby minimizing the potential for data inaccuracies and ensuring a robust analysis. Through this meticulous data curation process, we have established a strong foundation for our comprehensive supply chain analysis, ensuring that our findings are based on the most reliable and relevant data available.

Upon gathering all the requisite data, we constructed the MRIO nickel network by adapting and extending the methodology presented in the work of Chen et al. [28] to a multi-regional context. This adaptation allowed us to capture the complexities inherent in the global nickel supply chain, reflecting the intricate interdependencies across various regions and stages of production and consumption. For a more complete explanation on data sources and methodology to develop the MRIO nickel network, please refer to the SI.

3. Results

3.1. Global production

Figure 2 offers a detailed examination of the global nickel supply chain, illustrating production trends by country from 2009 to 2019 across various nickel products, including laterite and sulphide ores, FeNi/NPI, nickel matte, MSP/MHP, nickel class 1, and nickel sulphate. This figure effectively delineates the geographical distribution and temporal evolution of nickel production, highlighting the impact of geographical and technological factors on the market.

A noticeable upward trend in production volumes over the examined decade is evident, with significant expansions in specific countries and product categories. For laterite ores, Indonesia has shown a remarkable trend, particularly influenced by its export ban, which redirected the focus towards domestic processing, thereby boosting the production of NPI and FeNi. The Philippines emerges as the second-largest producer, maintaining a significant presence in the laterite nickel sector.

Sulphide ore production has been relatively stable, with Russia and Canada being the primary and secondary producers, respectively. This stability extends to nickel matte production, which predominantly originates from sulphide mines. Notably, Indonesia has also contributed to matte production, leveraging its laterite ore resources in a shift towards value-added processing. The global production of FeNi/NPI has tripled over the past decade, with China being the foremost producer, largely sourcing laterite ores from abroad. Following the export ban on raw ores, Indonesia has significantly increased its domestic production of FeNi/NPI, demonstrating a strategic pivot in its nickel industry. Nickel class 1 production has remained relatively stable, with Russia, Canada, and Australia as the leading producers. However, China has marked a notable increase in its production capacity, diversifying its nickel product portfolio. Nickel sulphate production has witnessed a substantial growth, nearly tripling over the last decade, with China dominating this segment, accounting for an estimated 70% of global production. This surge is primarily driven by the demand from the electric vehicle battery market, especially in the Chinese national market. Finland has maintained a consistent production level, while Japan has seen a rise in production over the same period, further underscoring the dynamic nature of the global nickel sulphate market.

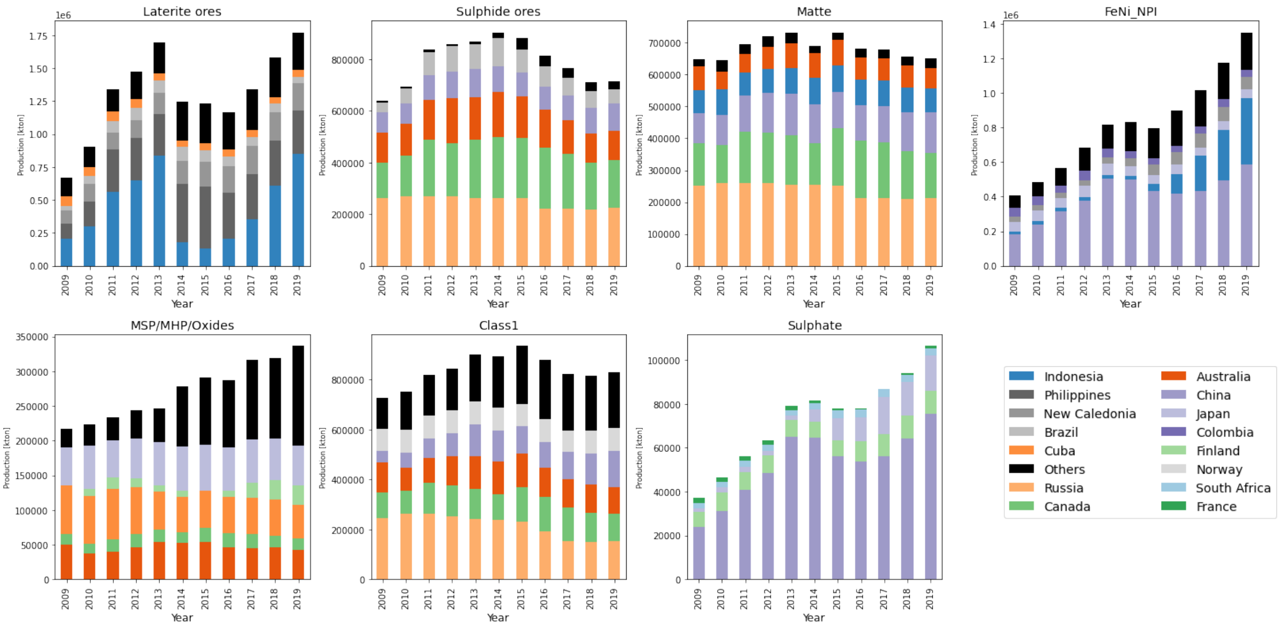

Figure 2: Comparative Annual Production of Nickel Ores and Intermediates from 2009 to 2019.

This analysis underscores the significant shifts in the nickel industry, with a pronounced move towards Asian markets, especially in the production of NPI and FeNi. These changes reflect broader economic policies, resource accessibility, and investment trends within the region. Production anomalies, such as dips due to labor strikes, natural disasters, or economic sanctions, highlight the complexity of the nickel supply chain and the need for further investigation.

Figure 3 presents the annual production data for finished nickel products from 2009 to 2019. It reveals that the bulk of production for key commodities such as stainless steel and batteries—which are vital for various industries and the rapidly growing electric vehicle market—primarily takes place in China. Over this period, China's production consistently expanded, ultimately capturing around 80% of the global market share.

Figure 15 illustrates the yearly output of nickel finished products over the same timeframe. This data confirms China's status as the predominant producer of these crucial commodities. Remarkably, global battery production more than doubled in this decade, and stainless steel output increased from 1.4 million tonnes to nearly 2.5 million tonnes. The production of other nickel products saw a more varied array of contributors, although China continued to play a substantial role. These products maintained a relatively stable production level, with casting products experiencing a slight growth.

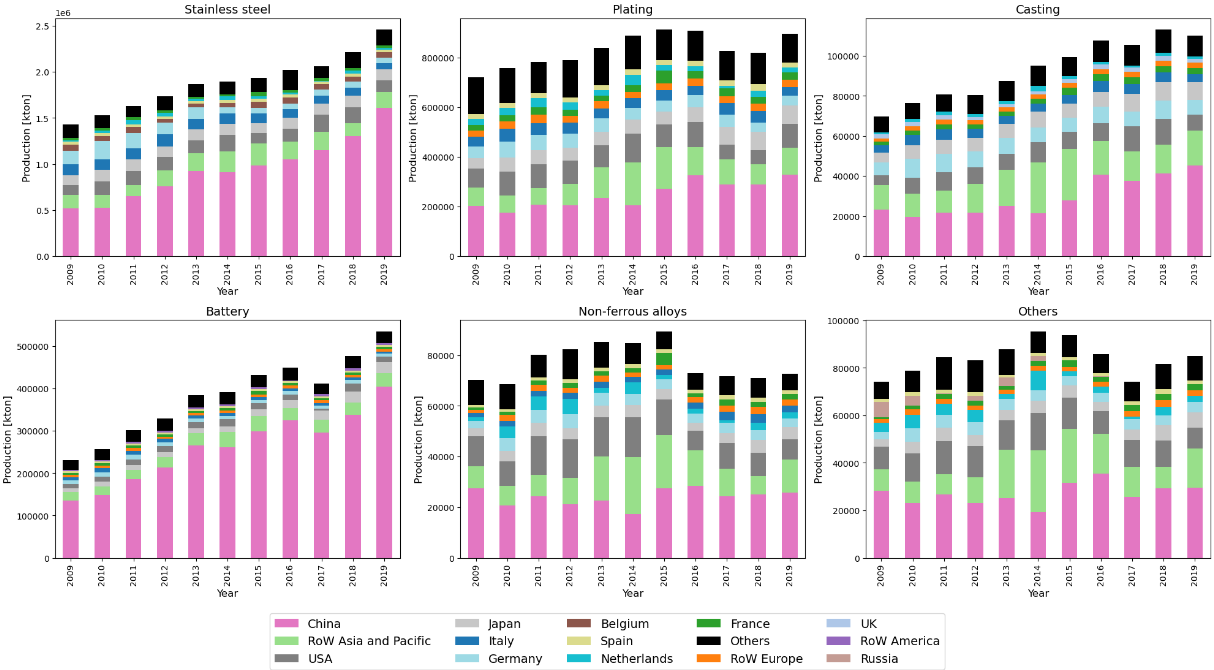

Figure 3: Annual Production of Nickel finished products from 2009 to 2019.

The "Rest of Asia and Pacific" region emerged as the second-largest producer for these products, followed by the USA and Japan. Within Europe, Italy, Germany, and Belgium are the principal producers, though their combined contributions are minor, positioning Europe as a lesser force in the global supply chain for these nickel products.

This analysis segues into a detailed review of market concentration and potential supply chain vulnerabilities through the HHI, depicted in Figure 4 for 2009 to 2019. Higher HHI values indicate increased market concentration, which correlates with heightened supply chain risk due to reliance on fewer sources. The HHI readings for the steel and battery sectors have notably increased, reflecting China's growing production dominance. This rise in HHI points to a market increasingly centralized around China, underscoring potential vulnerabilities from this concentration.

For the sulphate sector, which has the third highest HHI, the data corroborates earlier findings of significant market concentration in China. This centralization poses risks of market fluctuations and supply disruptions. Conversely, for Ferronickel (FeNi), the HHI has declined since 2014, thanks to Indonesia's boost in production following its export ban on nickel ores. This policy has led to a significant rise in domestic nickel product refinement, thus lowering the HHI for FeNi and spreading market distribution, thereby mitigating earlier concentration risks.

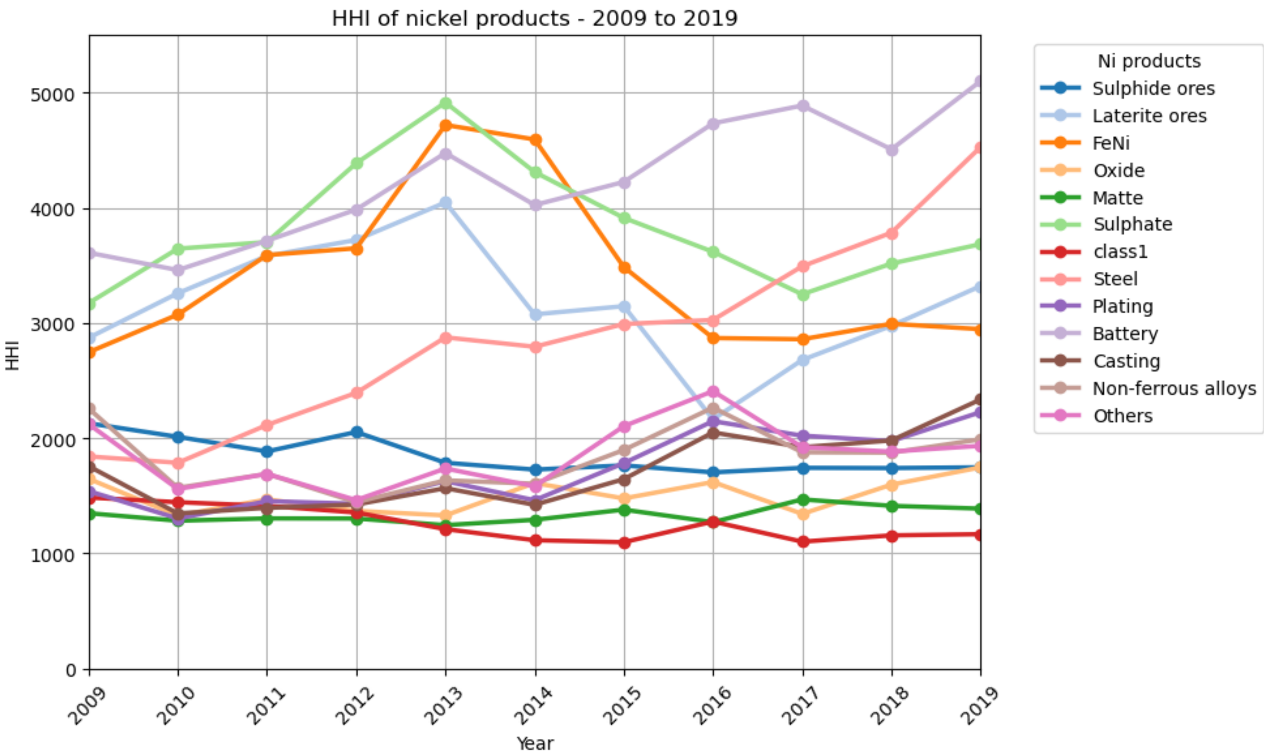

Figure 4: HHI development of nickel products.

Similar trends are observed with Nickel Pig Iron (NPI), where Indonesia's increased internal production has not only enhanced supply but also introduced new competitive forces into the market, further decreasing the HHI. Class 1 nickel, plating, and non-ferrous alloys have demonstrated stable HHI values over the decade, indicating a consistent market structure without significant shifts in dominance by any single country or producer. This stability suggests that the supply chains for these products are less susceptible to the risks associated with high market concentration and are well-positioned in a competitively diverse market.

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3.2. Supply Risk

Figure 5 offers a quantitative assessment of the supply risk associated with various nickel products, with a specific focus on the year 2019. The figure employs a heat map to visualize the supply risk metrics, utilizing a color gradient from light yellow for low risk to dark blue for high risk. This visual encoding facilitates a swift and intuitive grasp of the risk distribution across different regions and products.

Sulphide ores are denoted by a low supply risk across the board. This is predominantly because the processing of sulphide ores typically occurs in the same country where the mining takes place, limiting the exposure to international supply chain disruptions. Consequently, the supply risk for nickel matte is also minimal, verging on zero for all countries, reflecting the closed-loop nature of sulphide ore processing.

Laterite ores, in contrast, are marked by a higher supply risk. This is primarily due to the concentration of laterite ore sources in countries like Indonesia and the Philippines, which are considered high-risk due to socio-political and environmental factors, and the fact that these countries are significant exporters of laterite ores. China emerges as the country with the highest supply risk for laterite ores, attributed to its substantial imports from the Philippines and Indonesia, underscoring its vulnerability to disruptions in supply from these regions.

The medium supply risk level associated with FeNi and NPI, both crucial for stainless steel production, reflects the geographic concentration of their production in countries like China and Indonesia, which are noted for their supply risk factors. The medium risk here is indicative of the dependency on these countries and the potential for supply chain volatility due to their social, political, and environmental landscapes.

Ni Sulphate stands out in the heat map with higher levels of supply risk in most countries, except for regions such as China, Finland, South Korea, and Japan, where supply risk appears considerably lower. This disparity is likely a reflection of their comprehensive production infrastructure and the strategic integration of operations within the EV battery supply chain. China's extensive Ni Sulphate production capabilities are a testament to its strong position in the battery manufacturing industry, which reduces its exposure to supply risks. In stark contrast, other countries without substantial domestic production or advanced processing capabilities face heightened supply risks, reflecting their dependence on imports and the concentration of Ni Sulphate production in a few regions. This dependency underscores the potential vulnerabilities in the supply chain and the strategic importance of establishing diversified and secure sources of this key material. Similar profile risk is found also in the battery sector, due to the import of LiB, especially from China that is the biggest producer. This risk profile is paralleled in the battery sector, especially concerning the import of LiB. China's status as the largest producer compounds the risk for other countries, which are reliant on imports from China for these key components in the battery technology space. The reliance on a singular, dominant producer for LiB intensifies the risk of supply chain disruptions, further underscoring the strategic necessity for countries to develop or secure alternative and resilient sources for these critical components in the growing battery market.

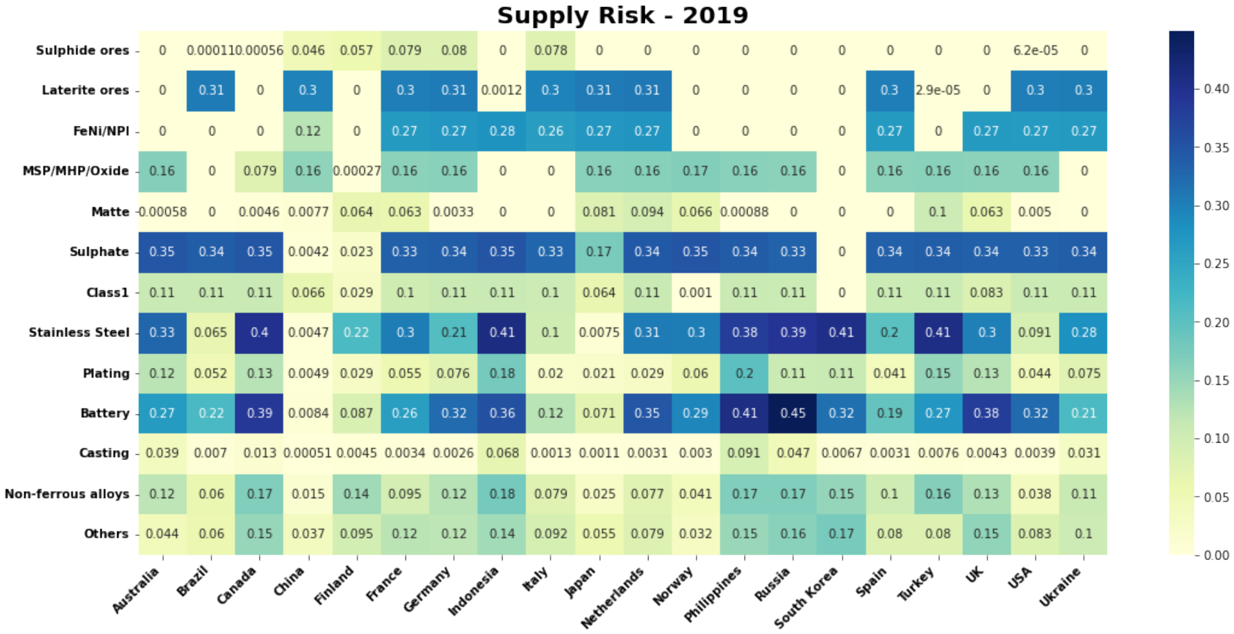

Figure 5: Heat map depicting the supply risk of nickel products in top 20 nickel producer/consumer countries for the year 2019.

The heat map provided here is not merely a representation of supply risk levels but also a reflection of the distinctive characteristics and roles that different countries play within the global nickel supply chain. It elucidates the varying degrees of risk between countries based on their position and capabilities within the industry. For instance, China displays a higher risk concerning laterite ores, as it must import these to satisfy its substantial internal demand as well as to support its exports. However, China's risk profile is significantly mitigated at other stages of the supply chain, where the country's robust production role renders the risk almost negligible. This is indicative of China's substantial vertical integration within the nickel sector, particularly in processing and production for end-use markets. On the other end of the spectrum, certain countries such as Russia, Indonesia, Canada, and Australia exhibit minimal risk at the mining and refining stages due to their rich domestic mines. Nevertheless, these countries face elevated risk at the manufacturing level of the supply chain due to a lack of production capacity in downstream operations. This stark contrast underscores the different roles and inherent characteristics within the global nickel supply chain.

Such insights into the varied risk profiles and the reasons behind them are crucial for industry stakeholders. They serve to highlight the strategic need for a balanced and integrated approach to supply chain management. By understanding these different roles and characteristics, industry participants can better identify potential risks and opportunities, ensuring that their investment planning and policy formulation are well-informed and targeted towards fostering a stable and sustainable nickel supply chain.

3.3. Historical Supply Risk for representative countries

The following charts depicts the historical trend of supply risk and import shares for various nickel products. On the left vertical axis, the import shares are shown as stacked bars, indicating the percentage contribution of each country to the total imports of a specific product per year. On the right vertical axis, the supply risk is represented as a line plot, demonstrating the annual risk level associated with each product. This format allows for a comparative analysis between the diversification of import sources and the supply risk over time, providing a visual summary of market dynamics for each nickel product.

China

Over the past decade, China's supply risk profile for various nickel products has fluctuated, reflecting the nation's strategic industrial shifts and the ebbs and flows of the global market as shown in Figure 4. The risk associated with laterite ores experienced a significant increase, largely attributed to the growing import share from Indonesia, but after the export ban of Indonesia in 2014, the supply risk saw a decline, due to the large share on the global level of laterite ores production from Indonesia that lowered the HHI, and consequently the supply risk. However, post-2016, the risk escalated once more as China's import dependency on Indonesia grew again, likely due to changes in trade policies or market demands. In the realm of Sulphide ores and the related product of nickel matte, China has maintained a low supply risk throughout the decade. This stability owes much to the continuous and reliable production from countries like Australia and Canada, bolstered by strong trade partnerships. The supply risk for nickel class 1 has seen a marginal decline over the period in question. This trend can be ascribed to a shift in import patterns, moving away from countries perceived as higher risk, such as Russia, and a simultaneous uptick in domestic production.

In the FeNi and NPI sectors, there was a slight uptrend in supply risk during the same period. This subtle increase in risk is linked to a growing reliance on imports from Indonesia, emphasizing the influence of Indonesia's export market on China's supply chain. The supply risk for MSP/MHP/Oxide has remained relatively steady, averaging around 0.16. This consistency, however, has been challenged by an increasing import share from Papua New Guinea, indicating a potential area of vulnerability for China's nickel supply chain. As for other nickel products, the figure shows a continuous and unwavering supply risk value, consistently close to zero throughout the decade. This indicates a robust supply situation for these products, with minimal exposure to supply chain disruptions. This updated analysis demonstrates China's agile response to changing market conditions and supply risks, highlighting the importance of adaptive strategies in global commodity supply chains. It also underscores the variable nature of supply risks across different nickel products and the critical role of diversified, secure supply chains in mitigating these risks.

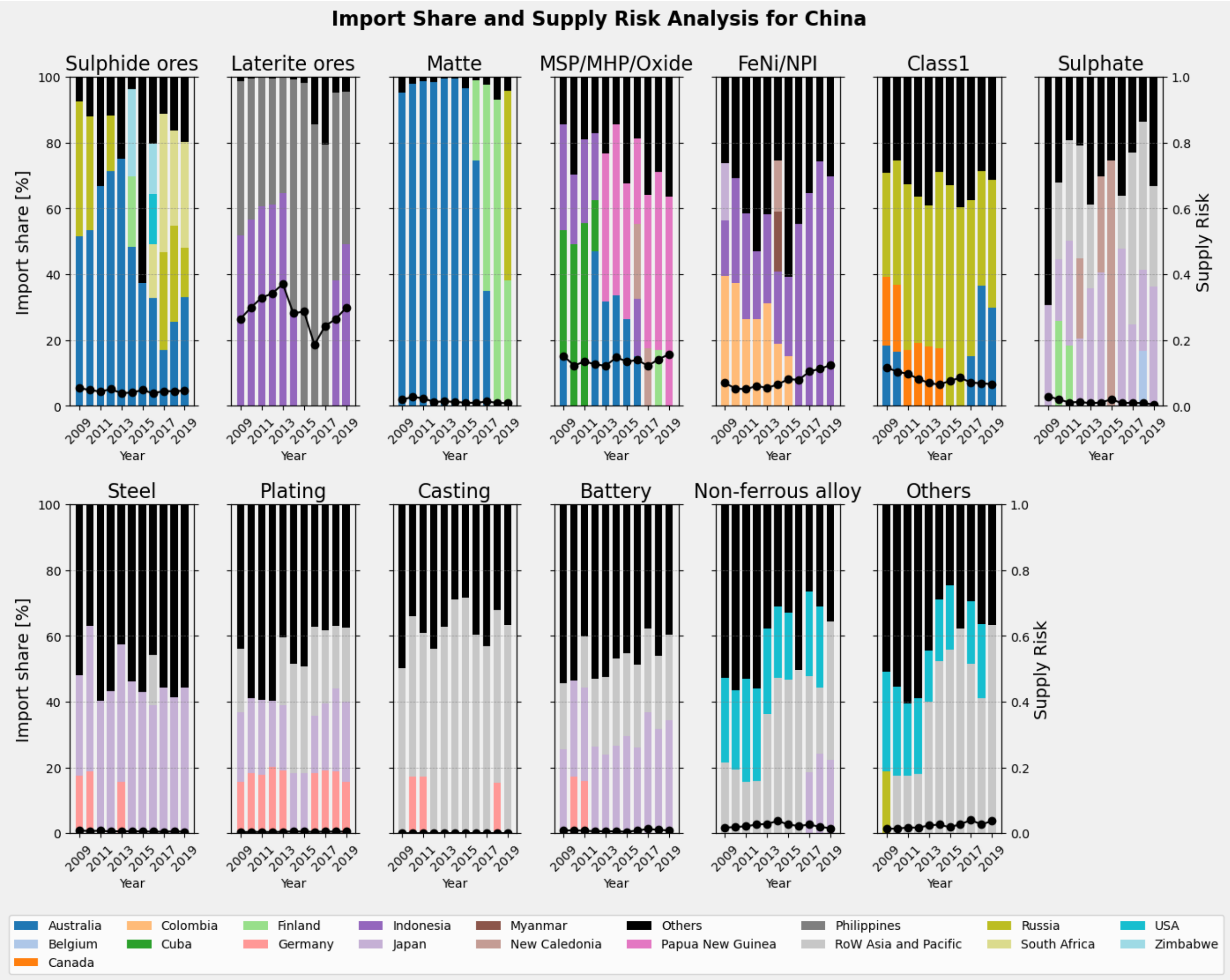

Figure 6: Import Share and Supply Risk Analysis for China.

Germany

In Figure 5 illustrates the supply risk for Germany, serving as an example for European economies. In the mining sector, laterite ores present the highest risk due to concentrated global production, which elevates the HHI as previously discussed. For intermediate products, FeNi/NPI and nickel sulphate exhibit the most significant supply risks. These risks increased steadily until 2013/2014, followed by a decline that brought them back to the levels observed in 2009. This reduction in risk is attributed to the diversification of production capacities worldwide, which decreased the HHI and provided more alternative sources for these products. Nickel class 1 and MSP/MHP/Oxide maintained relatively low and stable risks throughout the period studied. In the manufacturing sector, both steel and batteries have experienced a consistent rise in supply risk since 2009, mirroring the trend in the HHI due to the increased concentration of global production in China.

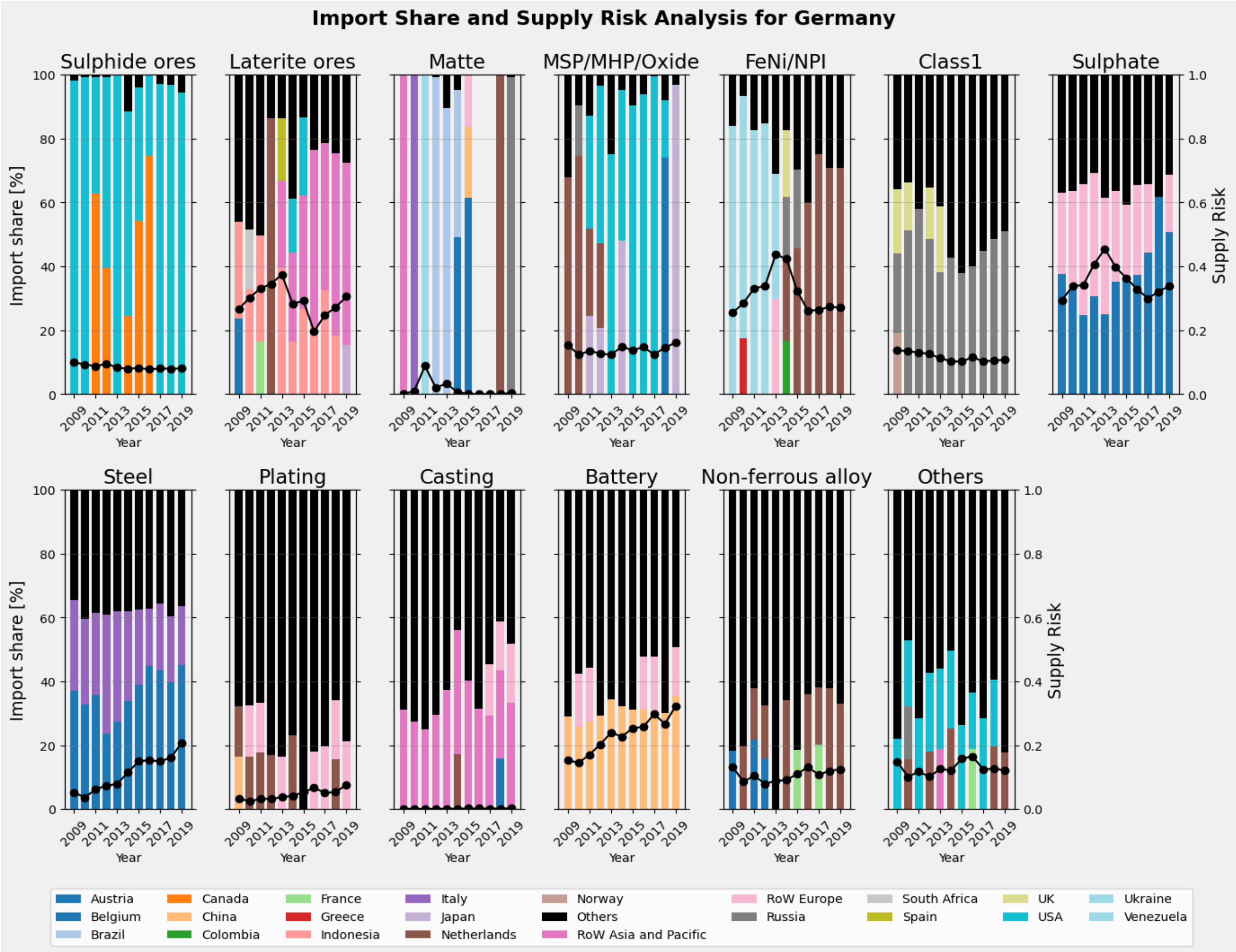

Figure 7: Import Share and Supply Risk Analysis for Germany.

USA

The USA has encountered significant supply risks for laterite ores, a key raw material in nickel production, with some years recording no imports at all. This illustrates the vulnerability of the U.S. supply chain to disruptions in global ore supplies. Similarly, as seen in the case of Germany, the USA faces high supply risks for intermediate nickel products such as FeNi/NPI and nickel sulphate. These risks stem largely from the nation's reliance on imports, making it susceptible to fluctuations in the global market.

In the manufacturing sector, the production of batteries—which are critical for the burgeoning electric vehicle industry—has seen a notable increase. China stands out as a primary source of imports for these battery materials, highlighting the USA's dependence on Chinese supplies. Conversely, other manufacturing sectors related to nickel in the USA exhibit relatively low supply risks. This stability is due to the country's strong internal manufacturing capabilities and its strategic diversification of import sources. By sourcing materials from a variety of countries, the USA mitigates the risk of supply disruptions that could arise from geopolitical tensions or economic instabilities in supplier countries.

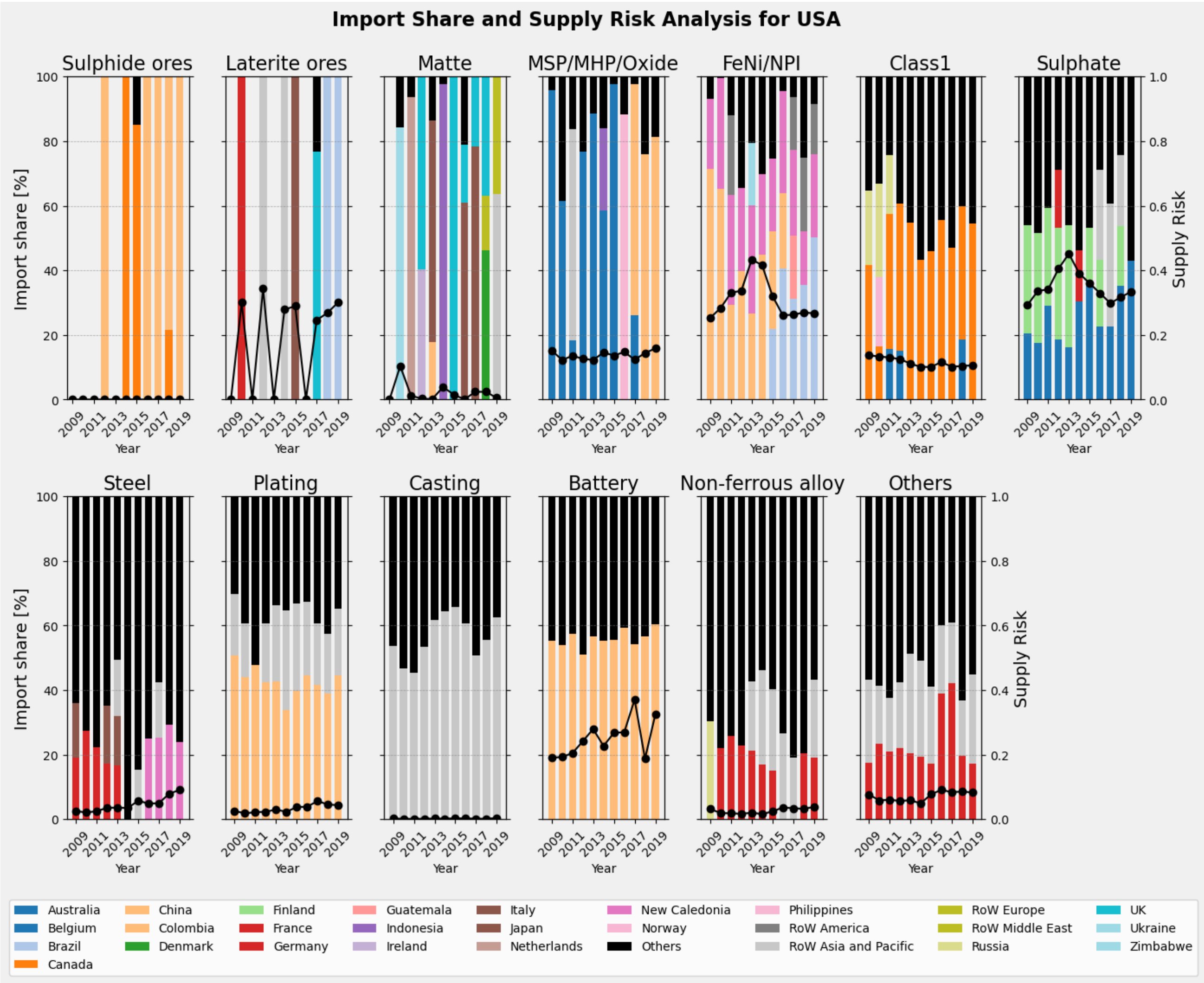

Figure 8: Import Share and Supply Risk Analysis for USA.

Overall, these dynamics underscore the complexity of the nickel supply chain in the USA and the importance of strategic planning to enhance supply security and economic resilience in critical material sectors.

4. Discussion

The comprehensive analysis of the global nickel supply chain from 2009 to 2019 highlights the complexity of managing supply risks in an era of increasing demand for sustainable energy technologies. Our research has illuminated the intricate web of factors that contribute to supply risk at every stage of the nickel lifecycle. From geopolitical instabilities to environmental policies and technological advancements, the factors influencing the nickel supply chain are numerous and varied. The Indonesian export ban and the Philippines' regulatory changes on mining practices have demonstrated the profound impact national policies can have on the global supply landscape. These events underscore the need for dynamic risk assessment models that can account for sudden shifts in policy and market access.

The integration of MRIO network analysis with supply risk indicators has allowed for a nuanced understanding of how geopolitical and economic factors intersect with environmental and social governance issues. It becomes clear that a country's position in the global supply chain network, can be as significant a risk factor as the geopolitical stability of the region.

Moreover, the burgeoning demand for nickel in the EV battery market has placed a spotlight on nickel sulphate. Our findings suggest that while countries like China have managed to reduce supply risks through domestic production, others remain vulnerable due to reliance on imports. The rise of the electric vehicle industry has not only increased demand for nickel but also introduced new complexities into the supply chain, highlighting the need for sector-specific risk assessments.

The Inflation Reduction Act in the United States, while a step forward in promoting electric vehicle adoption, has revealed gaps in addressing the full spectrum of supply chain risks. It accentuates the need for legislation that not only encourages immediate environmental benefits but also considers long-term strategic implications for critical minerals like nickel.

Our study's approach to supply risk, which includes a granular examination of nickel sub-products, offers a more comprehensive risk assessment than traditional models focused primarily on mining data[17]. By tracing the flow of nickel products from extraction to end-use, we have identified specific stages of the supply chain where risks are most pronounced and provided insights that could inform strategic decision-making and policy.

Our study expands on existing literature by providing an unprecedentedly detailed examination of the nickel supply chain. While previous research[16,19] has assessed nickel supply risk across different phases—mining, refining, and manufacturing—our analysis offers a holistic view that encompasses the entire journey of nickel. It meticulously differentiates between the distinct nickel products at each stage, from ore to end-use. To our knowledge, this approach is pioneering, marking the first instance where such a comprehensive and product-specific supply chain risk assessment for nickel has been conducted. This depth of analysis enables a more precise identification of risk factors unique to each form of nickel product, thereby enhancing the understanding of potential vulnerabilities and informing more targeted mitigation strategies.

The paper’s findings contribute significantly to the ongoing dialogue around securing mineral supply chains for a sustainable future. They advocate for a more integrated approach that considers the entire lifecycle of nickel products, emphasizing the importance of diversifying supply sources, investing in recycling technologies, and fostering international cooperation to mitigate supply risks.

As the world continues to transition towards clean energy, the insights from this study are particularly relevant for policymakers, industry leaders, and researchers. They offer a roadmap for navigating the complex supply risks associated with nickel, a mineral that will undoubtedly play a pivotal role in achieving a zero-carbon economy. The research thus serves as a clarion call for a collaborative, well-informed approach to managing the supply chains of critical minerals, ensuring that the drive for sustainability is not undermined by unforeseen vulnerabilities.

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6. Note

The authors declare no conflict of interest.

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Supporting Information for:

Integrating MRIO Network Analysis in Assessing Nickel Supply Risks: A Multidimensional Approach

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1. System definition

The system framework depicted in Figure 1, designed for analyzing the nickel supply chain, utilizes a hybrid methodology that combines traditional Material Flow Analysis (MFA) with Multi-Regional Input-Output (MRIO) tables to create what is referred to as the MRIO nickel flow network. This network offers a thorough and detailed view of nickel movements. The MFA aspect of the framework carefully monitors the physical progression of nickel from mining to refining and ultimately to its end of life (EoL). On the other hand, the Input-Output (IO) method traces the path of nickel within the manufacturing and end-use sectors. This integrated approach is designed to address key limitations found in each method: from the MFA standpoint, MRIO tables help estimate the movement of nickel products through the global economy; from the IO standpoint, the MFA technique is crucial for breaking down the flow of nickel and its derivatives from extraction to their incorporation into the manufacturing sector. This level of detail is essential, as most standard MRIO tables either combine the nickel sector with other metals or group it in a manner that blurs the distinctions between different nickel derivatives. Table 1 offers a comprehensive description of all the processes and flows illustrated in Figure 1.

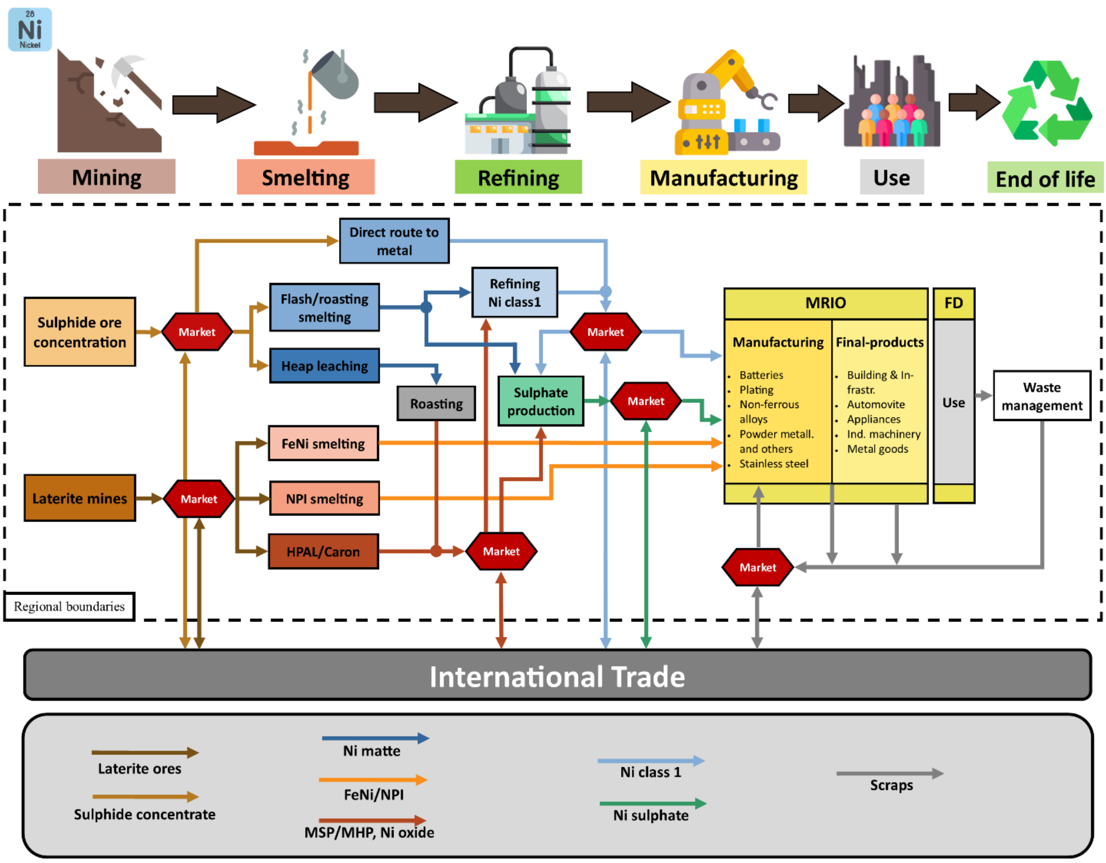

Figure S 1: Framework of the MRIO nickel flow network.

Table S 1: Flow description and assumptions

Supply chain	Process	Description
Mining	Sulphide ore concentration	Sulphide ores are concentrated to increase their metal content through physical processes like grinding and crushing, followed by separation from unwanted materials using magnetic or hydrophobic techniques[1–3].
	Laterite mines	Nickel is extracted from sulphide and laterite ore deposits, a challenging task to describe using MFA terminology due to the dynamic nature of geological reserves and resources. These quantities vary based on economic viability, market prices, and technological advances. Ore extraction processes are beyond MFA's scope, leading to the oversight of nickel in tailings, which could be substantial[1].
Smelting – sulphide ores	Direct route to metal	Vale's Long Harbour facility in Canada was the sole location employing direct hydrometallurgical refining to process sulphide concentrate into class I metal, as reported by INSG[4].
	Flash/roasting smelting	Pyrometallurgical treatments, smelting in an electric arc furnace and flash smelting, both result in the production of nickel matte. The key difference lies in the traditional method's higher nickel and byproduct recovery rates, albeit with greater electricity consumption, compared to flash smelting. Following, a conversion step reduces the iron content in the matte. Nickel is also obtained as a by-product from Ni-Cu-PGM (Platinum Group Metals) concentrates, which undergo smelting to matte, magnetic separation from PGMs, and leaching to yield crude nickel sulphate. In this study, these processes are tracked from matte production to nickel sulphate creation[1,4].
	Heap leaching	A mixed sulphide precipitate (MSP) is generated from sulphide concentrate through a series of processes including crushing, screening, mixing with sulphuric acid, and leaching. Currently, this method is exclusively employed at Terrafame's Talvivaara mine in Finland[4–6].
Smelting – laterite ores	FeNi/NPI smelting	Pyrometallurgical treatment of laterite ores involves smelting them in a rotary kiln electric furnace to produce ferronickel. An uncommon approach is used at the Sorowako smelter in Indonesia, where sulphur is added to create a matte, mimicking the sulphide process. Since 2005, the production of nickel pig iron (NPI), a low-grade ferronickel, has surged in popularity in China due to high class I metal prices and the availability of numerous small, old iron blast furnaces. The Indonesian ore export ban discussions beginning in 2014 further motivated Chinese companies to invest in NPI smelters within Indonesia[7].
	HPAL/Caron	High-Pressure Acid Leaching (HPAL) is a method for processing laterite ores using sulphuric acid under high pressures and temperatures of 245-270°C. This process separates liquids from solids and can directly yield class I metal with a refinery or produce intermediates like mixed sulphide precipitate (MSP), mixed hydroxide precipitate (MHP), and nickel hydroxide cake (NHC). These intermediates, due to their similar nickel content and the absence of distinct data, are treated uniformly as feedstock for refining into class I metal or nickel sulphate[1]. The Caron process, a hybrid technique, involves roasting laterite ore before ammonia leaching, resulting in nickel oxide. This process its use was limited to Cuba[4,8,9].
	Roasting	Matte is oxidatively roasted to create nickel oxide granules with an elevated nickel content, a process utilized solely at Vale's Matsusaka plant in Japan. However, for the purposes of this study, this method is also considered to represent the production of nickel oxide at Vale's Sudbury flash smelter in Canada[1,4].

Refining	Refining Ni class 1	Refining processes remove impurities like iron, copper, lead, or phosphorus from intermediates (MSP/MHP, matte, or nickel oxide), with some by-products (e.g., cobalt, platinum) being sold on other markets. While "refining" broadly refers to any process that increases metal content, in this context, it specifically pertains to downstream nickel recovery methods. These techniques produce class I metal, resulting in nickel in forms like cathodes, pellets, briquettes, and electrolytic nickel, with a purity exceeding 99.8% Ni[10].
	Sulphate production	Nickel sulphate ($NiSO_4$) can be manufactured from various sources, including mixed sulphide precipitate (MSP)/mixed hydroxide precipitate (MHP), matte, crude nickel sulphate from the PGM industry (treated as part of the matte process in this analysis), battery scrap, and the dissolution of class I metal. For the purposes of this study, other nickel compounds with significantly lower production volumes, such as nickel chloride and nickel hydroxide, are also included under the broader term "nickel sulphate"[11].
Manufacturing	Batteries	This process involves the creation of nickel-containing batteries, such as NMC (nickel manganese cobalt), NCA (nickel cobalt aluminum), NiMH (nickel-metal hydride), and NiCd (nickel-cadmium), covering the production of cathodes, cell formation, and their assembly into modules and packs, with nickel sulphate serving as the primary input[11].
	Plating	Class I metal and nickel sulphate are employed in electroplating to deposit a thin nickel layer on metal objects, enhancing their resistance to corrosion and wear or improving their appearance[12].
	Non-ferrous alloys	Class I metal and stainless steel scrap can be used to make nickel-base alloys and copper-based alloys[13].
	Alloy steels and casting	Class I metal, FeNi, Ni oxide and stainless steel scrap can be used to make ferrous alloys that benefit from the properties of Ni in terms of strength and corrosion resistance for instance. Stainless steel is excluded from this process.
	Powder metall. and others	Nickel is used for many other applications that capture a minor share of the annual production including powder metallurgy, catalysts or dyes[11].
	Stainless steel	Nickel's primary use is in the production of stainless steel, utilizing feedstocks such as class I metal, ferronickel (FeNi), nickel pig iron (NPI), nickel oxide, and stainless steel scrap. This process entails the creation of nickel-enriched stainless steels[14].
	Final products	Nickel-containing primary products are utilized in manufacturing end-use items, during which some material is lost. This loss, known as "new scrap," enters the nickel recycling market for reuse. These manufactured products are then bought and become part of societal stock.
End-of-life	Waste management	End-use products, once discarded, are collected, dismantled, and sorted through chemical and mechanical processes into waste products. Most of the nickel scrap is recycled functionally, with some battery scrap repurposed for sulphate production. Most post-consumer scrap, particularly from stainless steel, is reintegrated into the steel production cycle as a secondary material. However, some stainless steel scrap may be misdirected into non-recyclable streams, a process known as "downcycling," where nickel's value is diminished or seen as an impurity in unintended applications. Unrecoverable nickel scrap, due to economic or technical barriers (like certain metal goods or electronic waste), ultimately ends up in landfills[15].

1.1. Data sources

To build the MRIO nickel flow network for the years 2009-2019, a variety of data sources were consulted to estimate various parameters including domestic flows, trade flows and efficiency coefficients. Figure 2 illustrates the framework with the related main data sources used to estimates the nickel flows. The following subsections introduce the main data sources divide it 3 main sections: Domestic flows; Trade flows; MRIO tables.

Domestic flows

The research covered the period from 2009 to 2019, based on the data provided by the International Nickel Study Group (INSG). The production statistics were available by country for:

• Total mining volume [kton] (sulphide concentrate and laterite ore)[16].

• Production of "intermediates" [kton] covering matte, MSP/MHP, Ni oxide, and FeNi and NPI[17].

• Production of "finished nickel" [kton], which captures class I metal, sulphate (only the share made from intermediates to avoid double counting), FeNi, NPI, and Ni oxide to be used in the fabrication of first-use products[16].

Nickel sulphate production estimates, accounting for class I metal dissolution and battery scrap, were derived from market research[18]. Primary nickel consumption for first-use product fabrication was estimated for specific applications and countries, based on a Roskill report for the European Commission[11]. This report also broke down finished nickel consumption by feedstock type. At the country level, due to data unavailability, global estimates served as initial proxies, later refined by considering local production and import types.

Secondary nickel source consumption in first-use product fabrication was assumed negligible for certain manufacturing processes, such as plating and powder metallurgy, based on prior studies. Battery scrap recycling was exclusively linked to nickel sulphate production, eliminating additional scrap input in battery production.

Scrap inclusion rates for "Non-ferrous alloys" and "Alloy steels and castings" manufacturing processes were estimated at 14% and 17%, respectively, uniform across countries.[19]. The 2015 global average recycled content of stainless steel was estimated at 44%, with specific figures for China, the USA, EU countries with stainless steel production, and major Asian producers. Other countries used the global average[20].

For estimating nickel consumption in end-use product manufacturing, direct use of available estimates was avoided due to their limited coverage of primary data, uncorrected trade impacts, and opaque methodology[11]. Instead, country-specific transfer coefficients were derived, with global estimates applied to countries not covered in the report. Nickel content in waste from end-use sectors was calculated using outflow/inflow ratios or based on product lifetimes and sectoral growth rates, sourced from literature.

The amount of Ni in waste products out of the end-use sectors was calculated based on ratios of outflows/inflows or based on the lifetime of end-use products and the growth rate of the respective sector during the same period. Ratios and lifetime estimates were collected from the literature[19]. According to the Nickel Institute[15], waste management distributes post-consumer scrap between functional recycling (68%), non-functional recycling or downcycling (15%), and landfilling (17%). Without country-specific data, these ratios were assumed to be the same across individual countries. Deriving many country-level domestic flows required understanding process efficiencies, sourced from various literature[1,6,10,21–24].

Trade flows

Trade data for this study was obtained from the UN ComTrade database. To enhance the quality of this data, we utilized an algorithm developed by Cormery in his thesis[25], which performed critical functions such as outlier removal, data gap filling, and harmonization of trade data discrepancies reported by various countries. Specifically, this algorithm was applied to trade data for nickel in different forms, including ores and concentrates, matte, MHP/MSP, nickel oxide, class I metal, FeNi/NPI, and nickel sulphate. Efforts were made to accurately determine the nickel content, tailoring the data to the exporting country's specifics as much as possible:

- For laterite ores, country-specific average concentrations were established based on detailed geological studies of known deposits[2].
- The INSG directory and yearbook, which are key references for the global primary nickel supply chain[4,16], were consulted. When a facility's nickel content within a country (for example, mine, smelter, refinery) was documented, this information was taken as representative of the country's overall nickel content.
- Where country-specific data was unavailable, default values were employed, based on credible literature sources[1,3,10] , to provide a consistent basis for analysis.

This study did not derive the flows of nickel embedded in finished products from UN ComTrade, as these flows are captured within the MRIO tables. The MRIO tables account for trade flows between sectors producing products (such as batteries) that contain nickel or use these products (such as the automotive sector). These tables serve as a proxy for the international trade of the global economy, also depicting the flows of finished products during the use phase. This can include industries purchasing products as capital stock (like industrial machinery used to produce goods) or finished products bought by households (represented in the MRIO table as Final Demand).

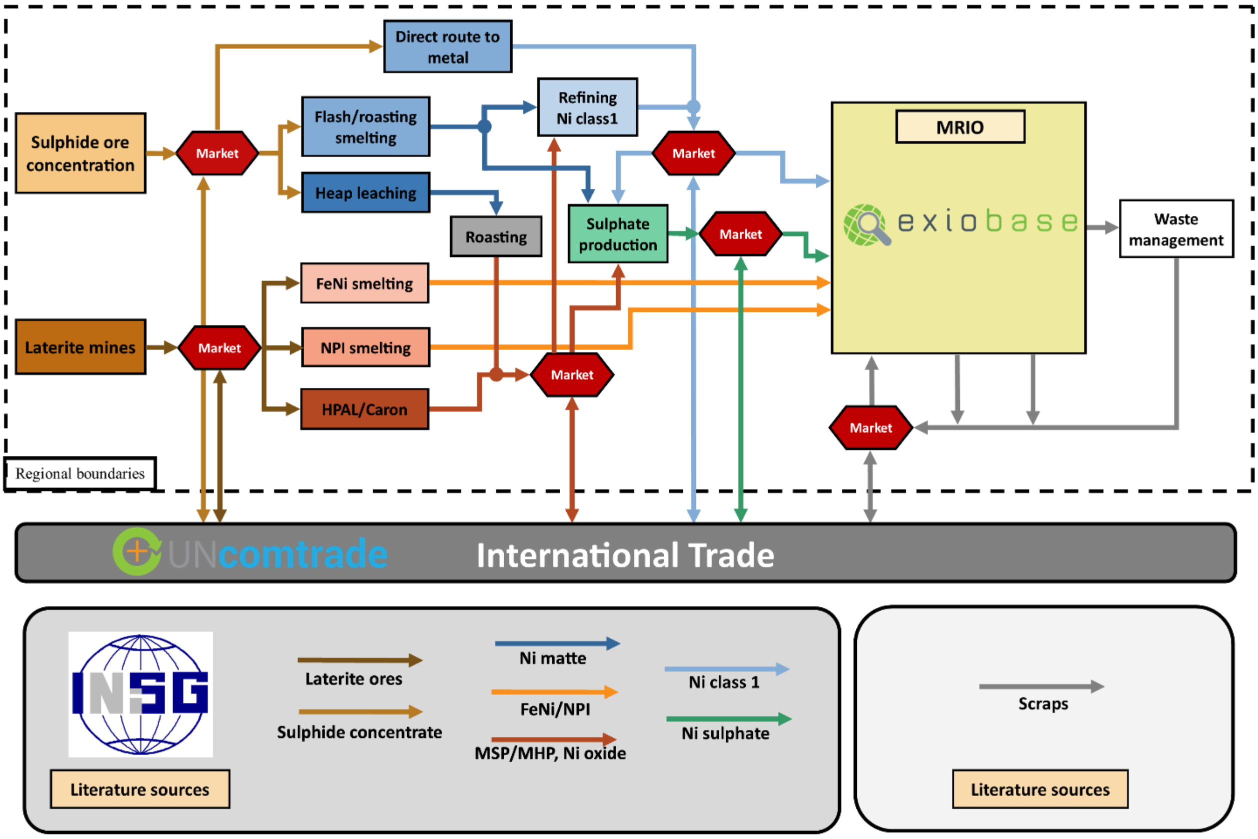

Figure S 2: System framework with data sources.

MRIO table

In this research, the EXIOBASE-3[26] database, version 3.8.2, was utilized. This database offers detailed regional data, encompassing 44 countries and 5 "Rest of the World" (RoW) regions, across 163 industries and 200 products. However, given the significant role of certain countries in the nickel supply chain that were grouped under the RoW categories (such as the Philippines), we opted for a variant of EXIOBASE-3. This variant[27] extends the geographical scope from 44 countries + 5 RoW regions to 214 countries, maintaining the comprehensive and standardized sectoral detail provided in the original database.

2. Additional result

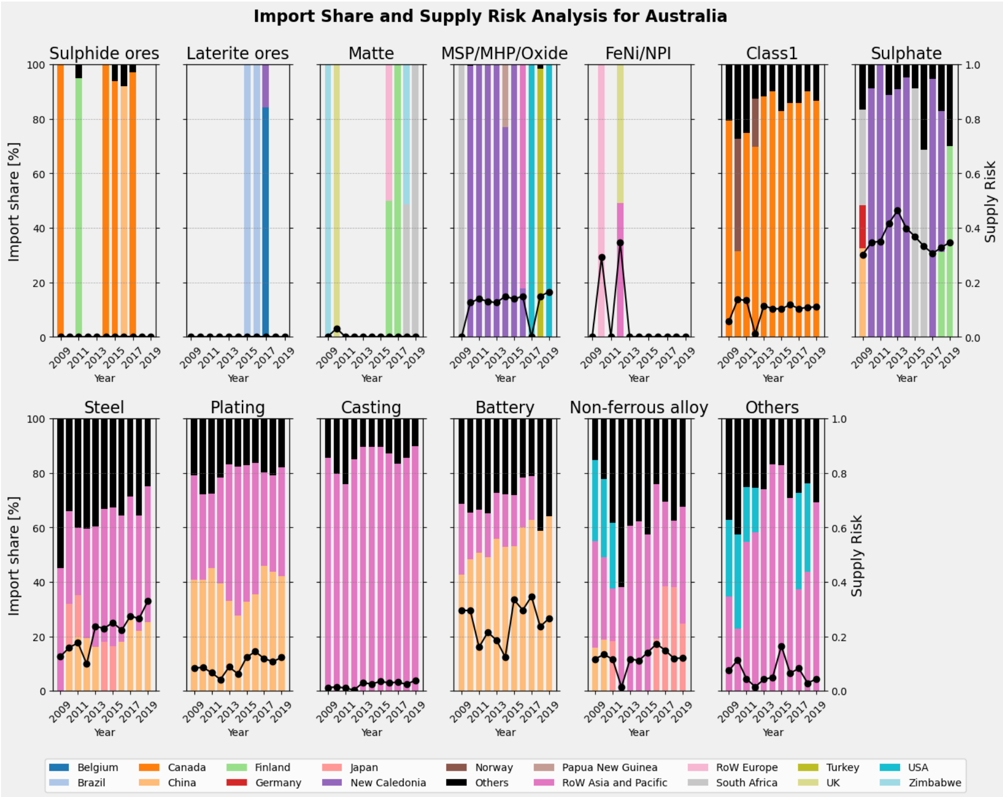

Figure S 3: Import Share and Supply Risk for Australia

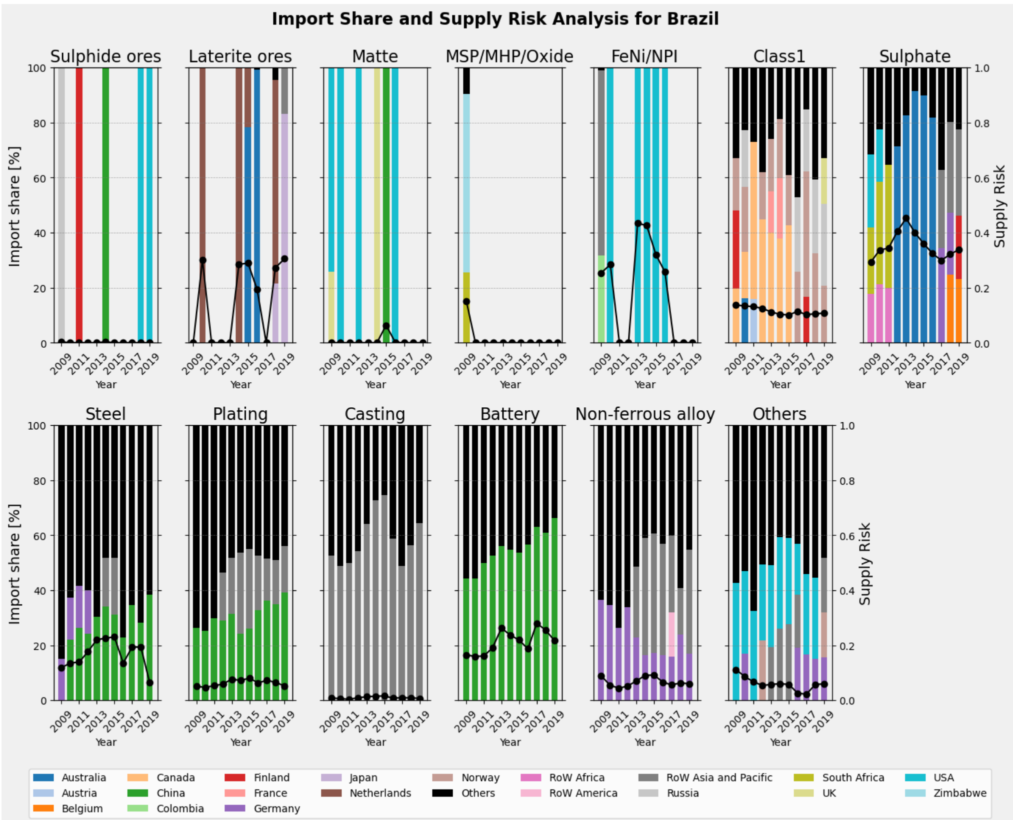

Figure S 4: Import Share and Supply Risk for Brazil

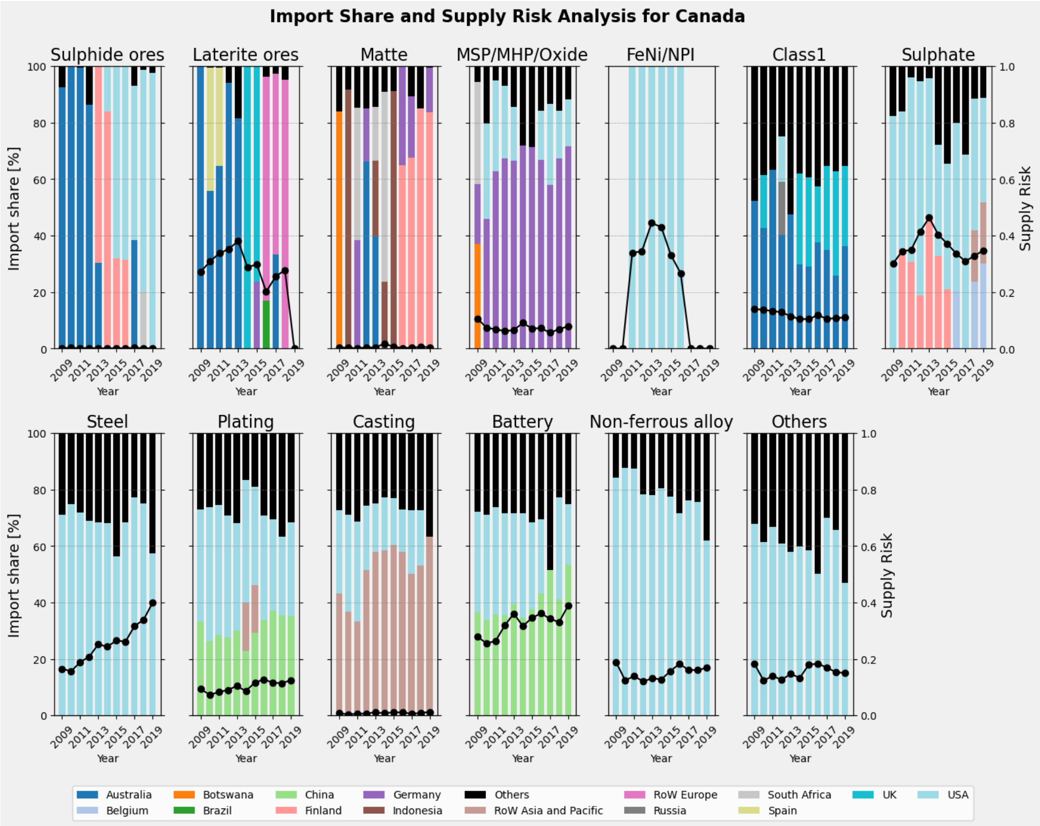

Figure S 5:Import Share and Supply Risk for Canada

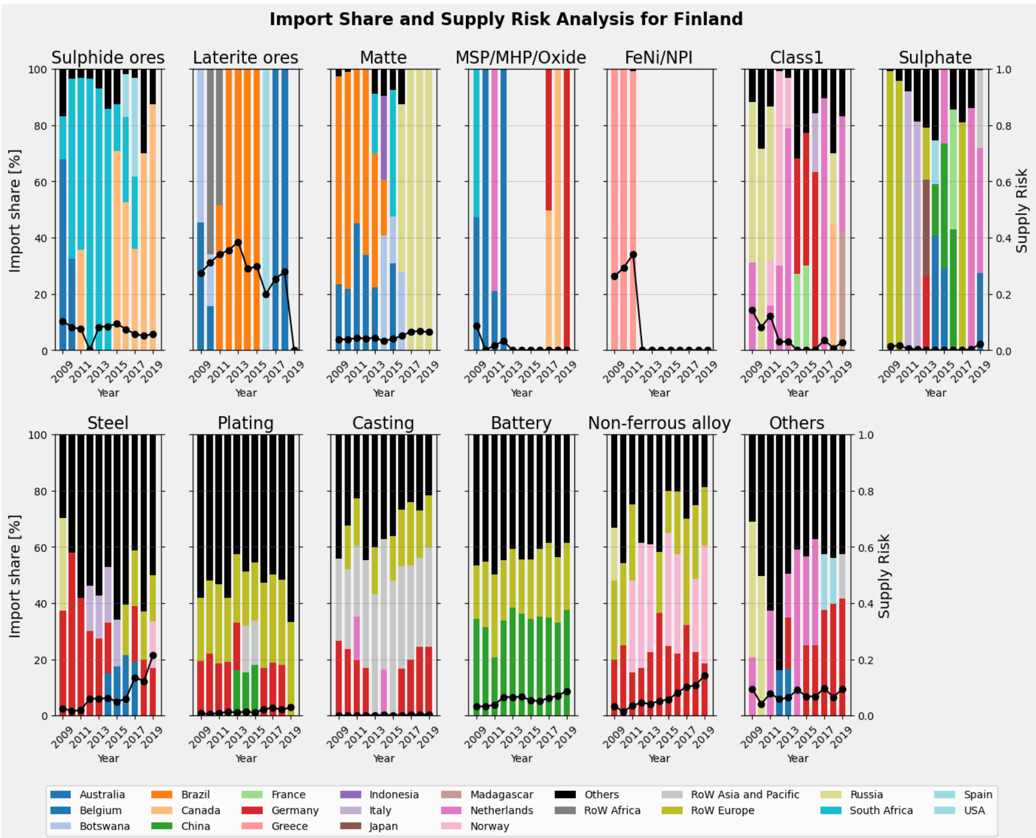

Figure S 6:Import Share and Supply Risk for Finland

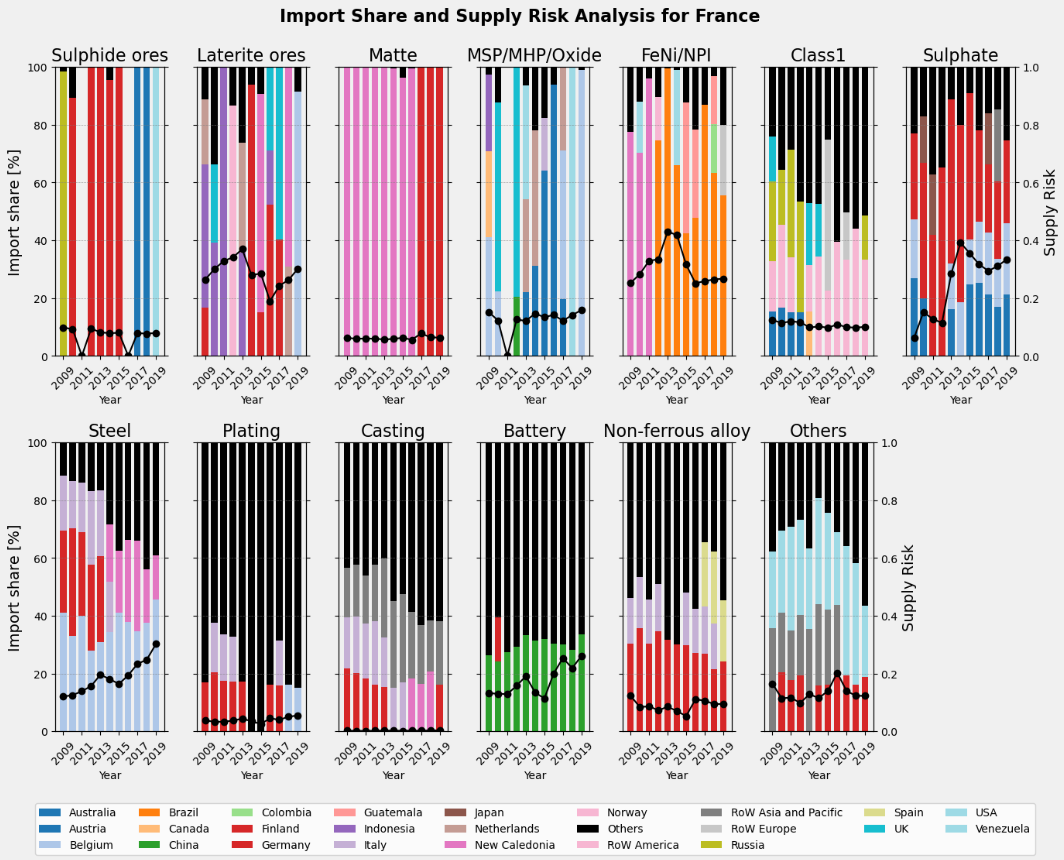

Figure S 7: Import Share and Supply Risk for France

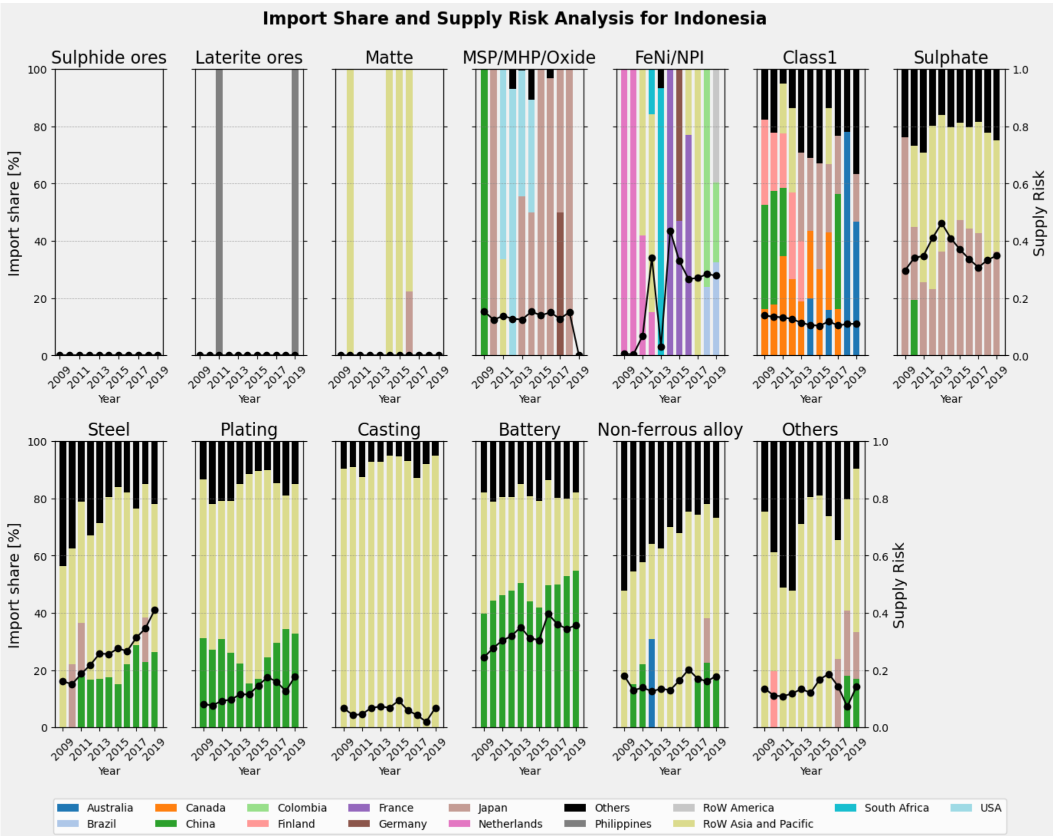

Figure S 8: Import Share and Supply Risk for Indonesia

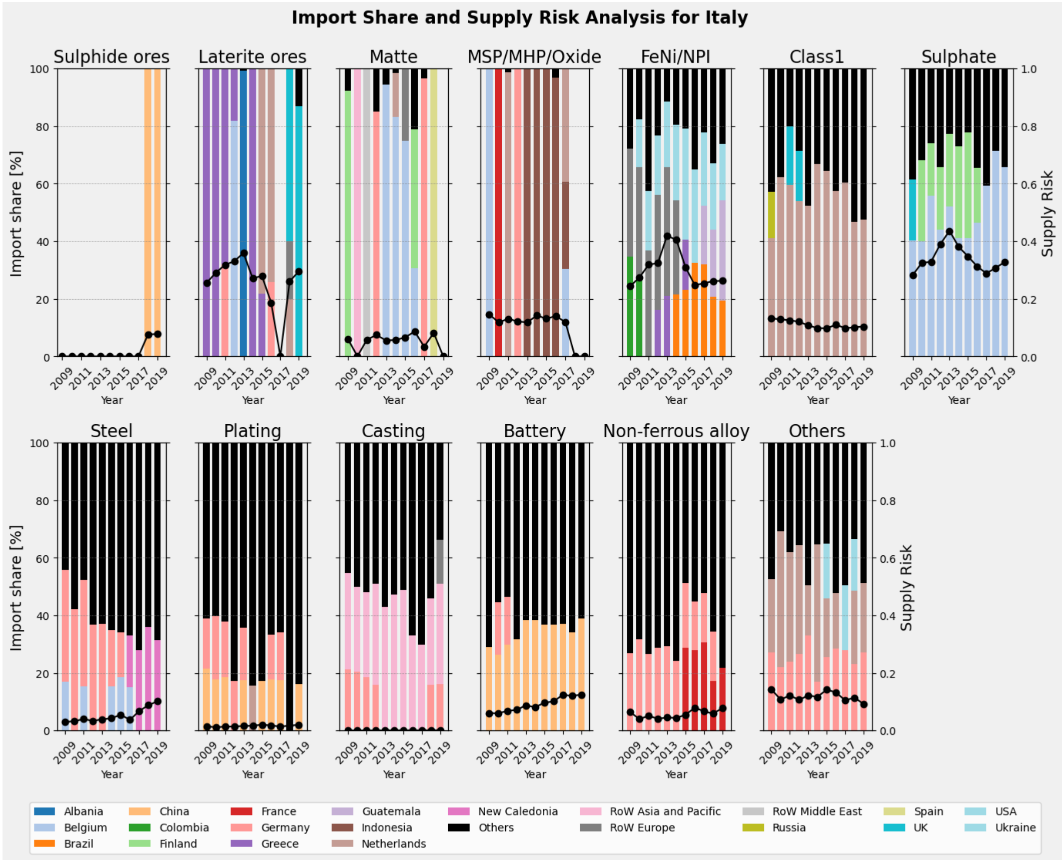

Figure S 9: Import Share and Supply Risk for Italy

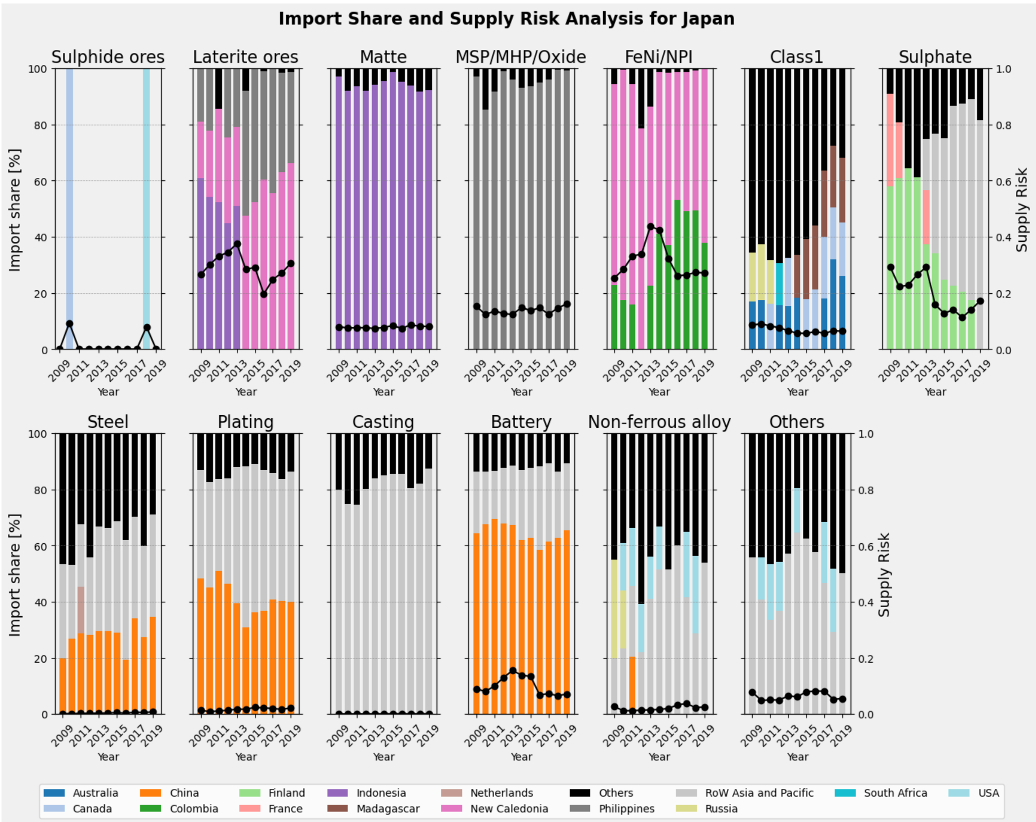

Figure S 10:Import Share and Supply Risk for Japan

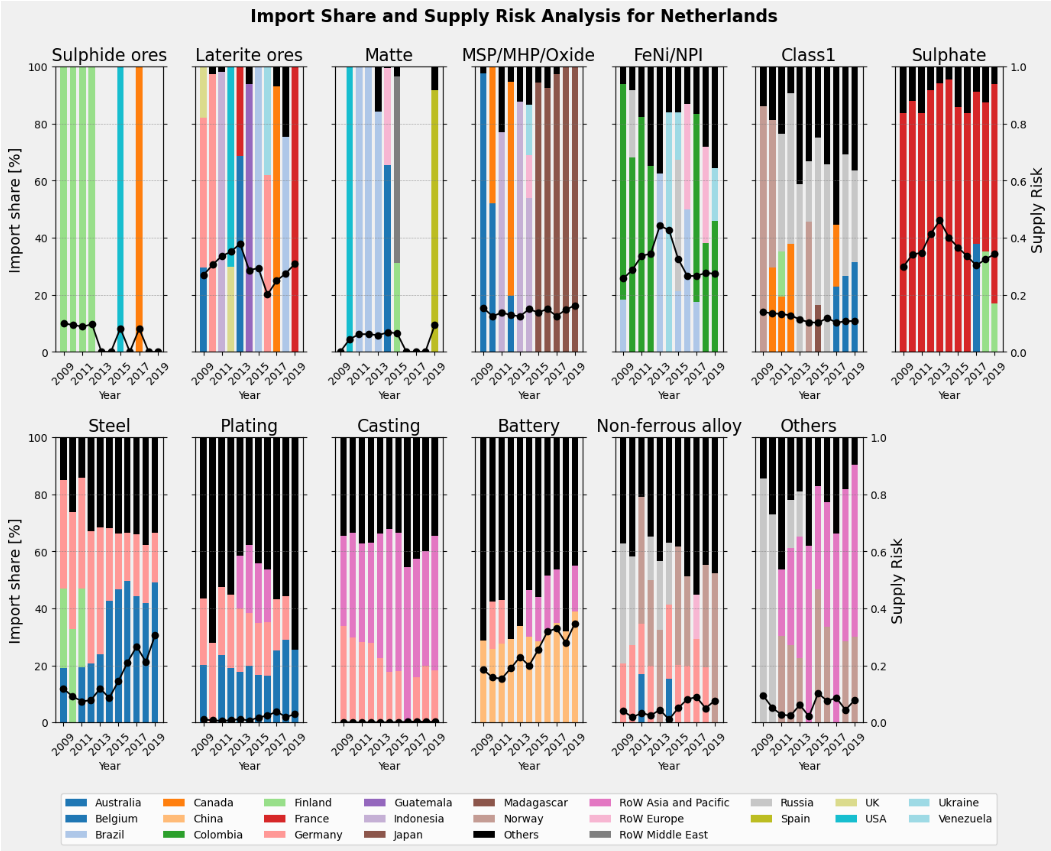

Figure S 11:Import Share and Supply Risk for Netherlands

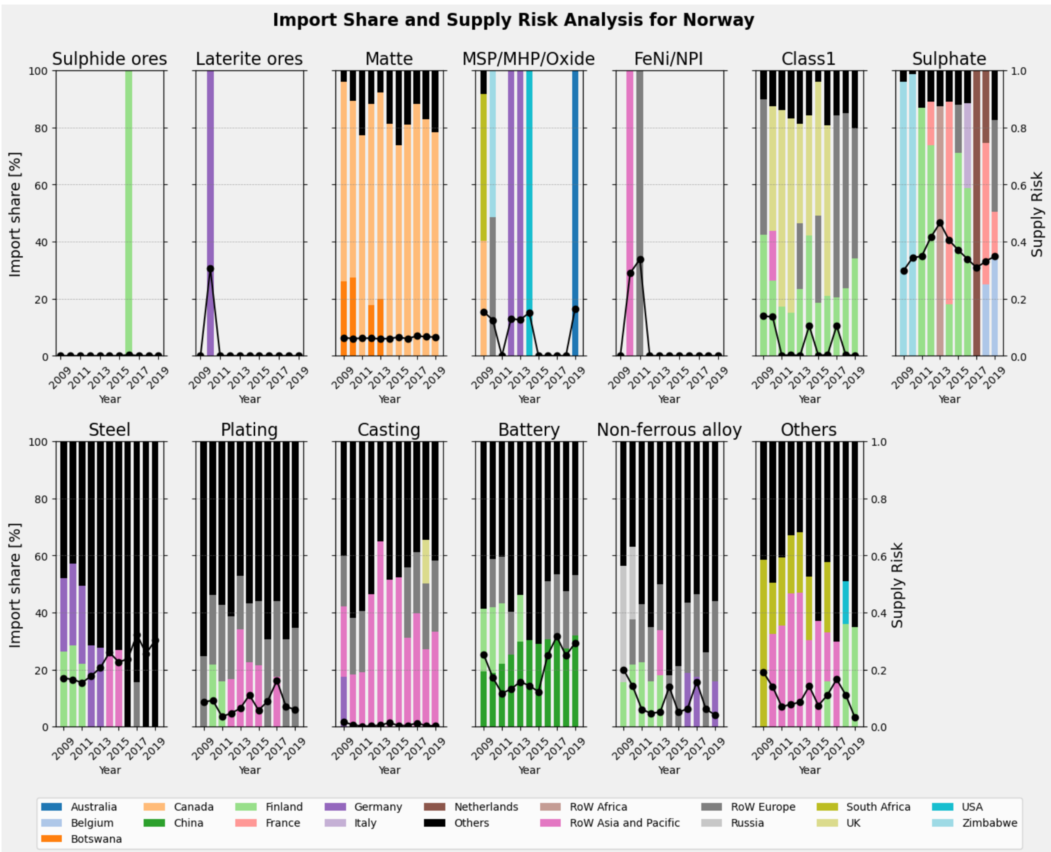

Figure S 12: Import Share and Supply Risk for Norway

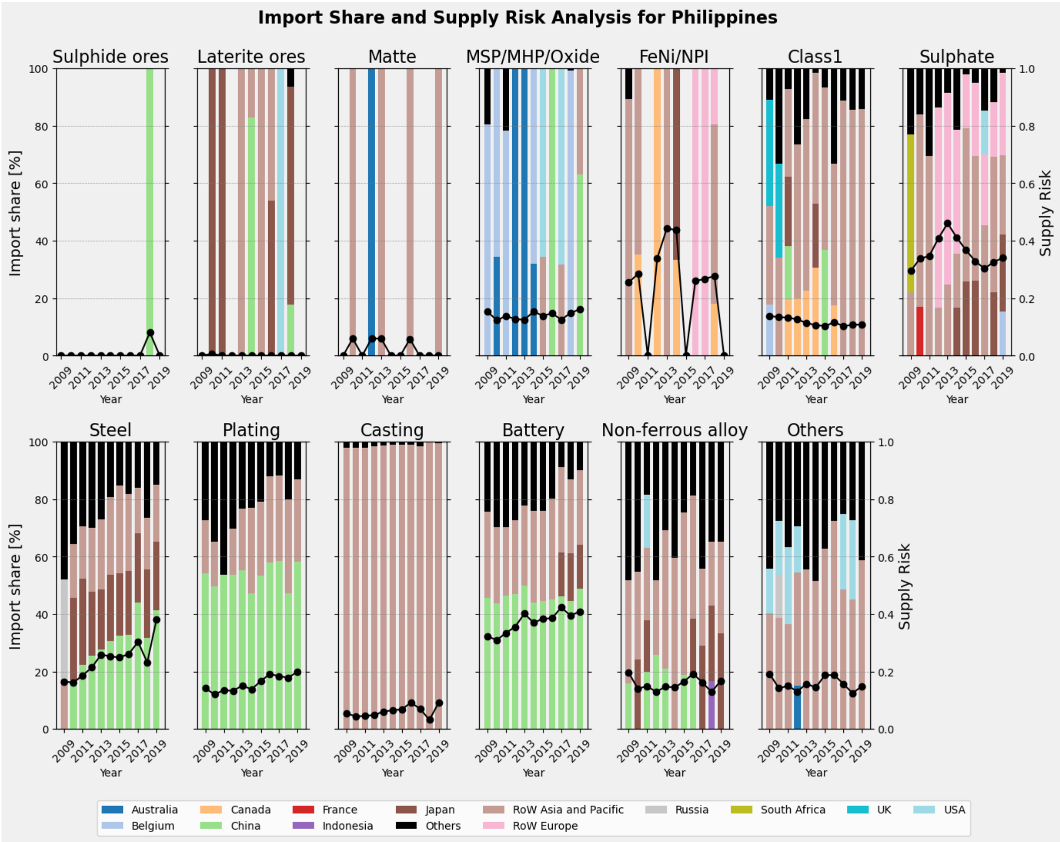

Figure S 13: Import Share and Supply Risk for Philippines

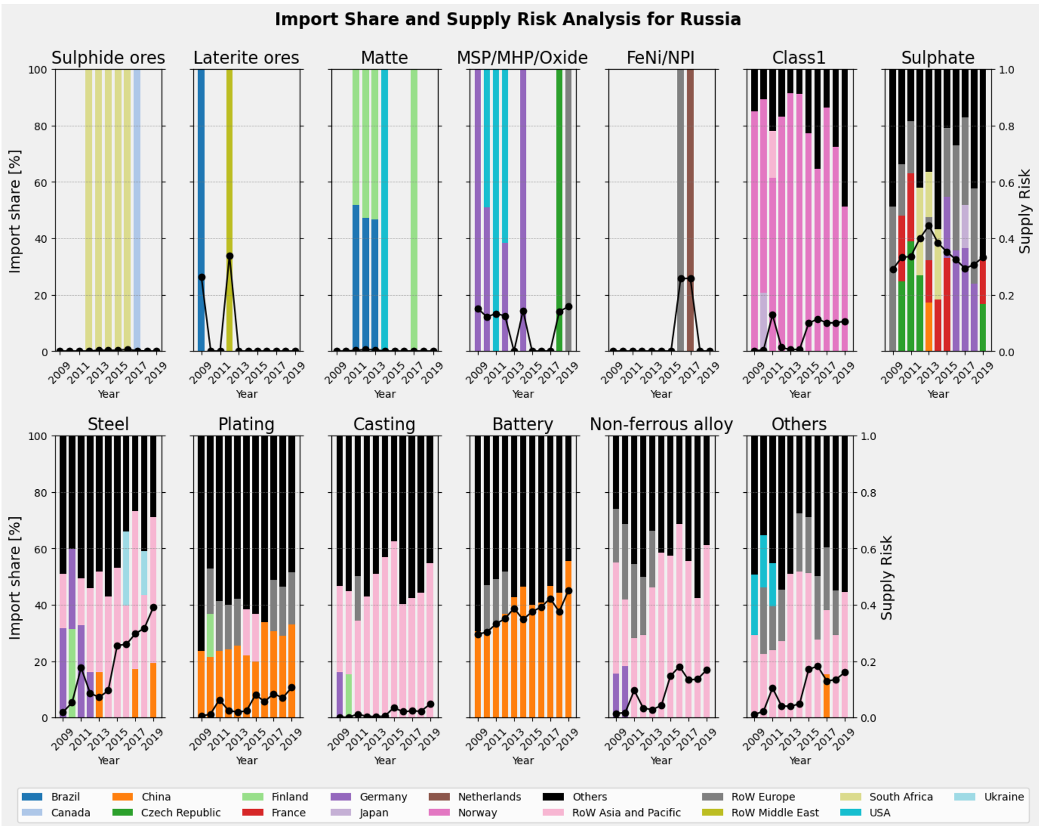

Figure S 14: Import Share and Supply Risk for Russia

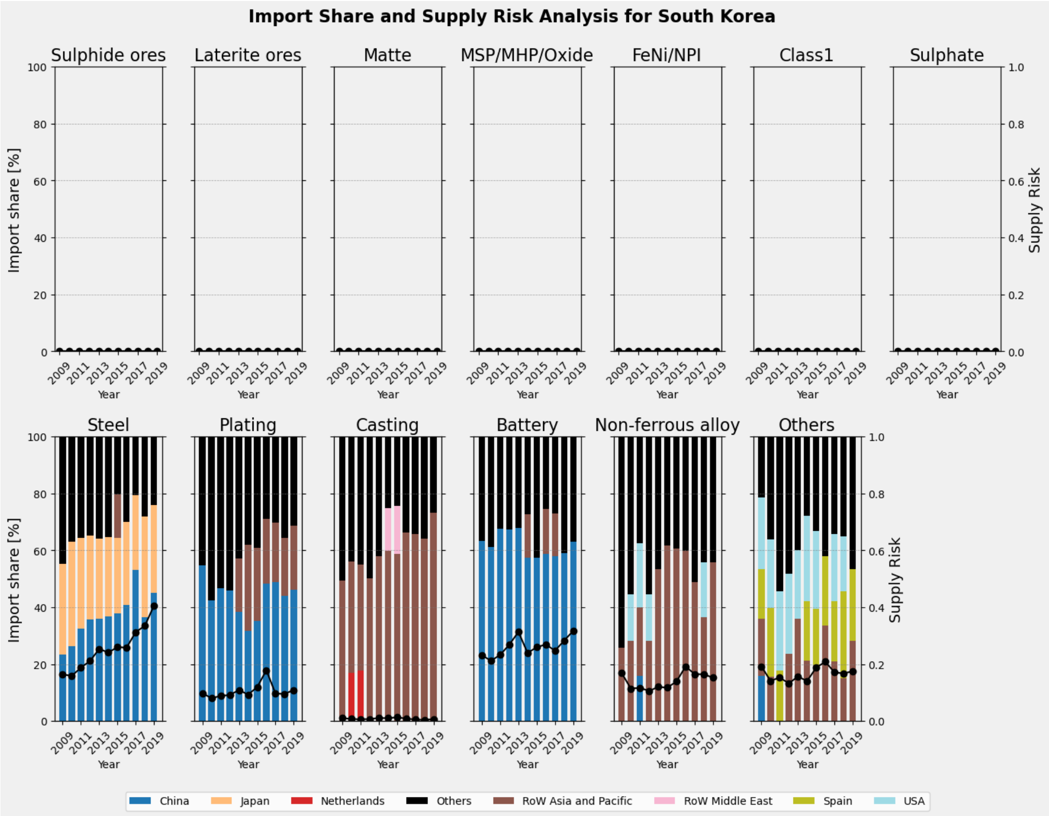

Figure S 15:Import Share and Supply Risk for south Korea

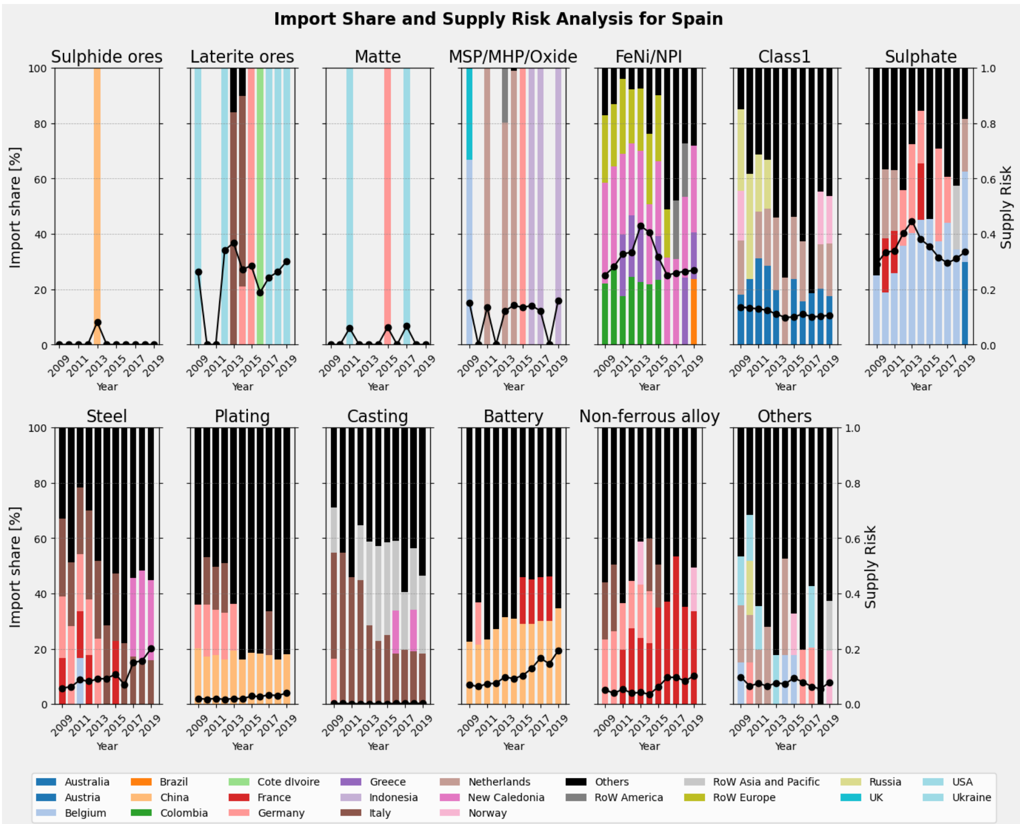

Figure S 16: Import Share and Supply Risk for Spain

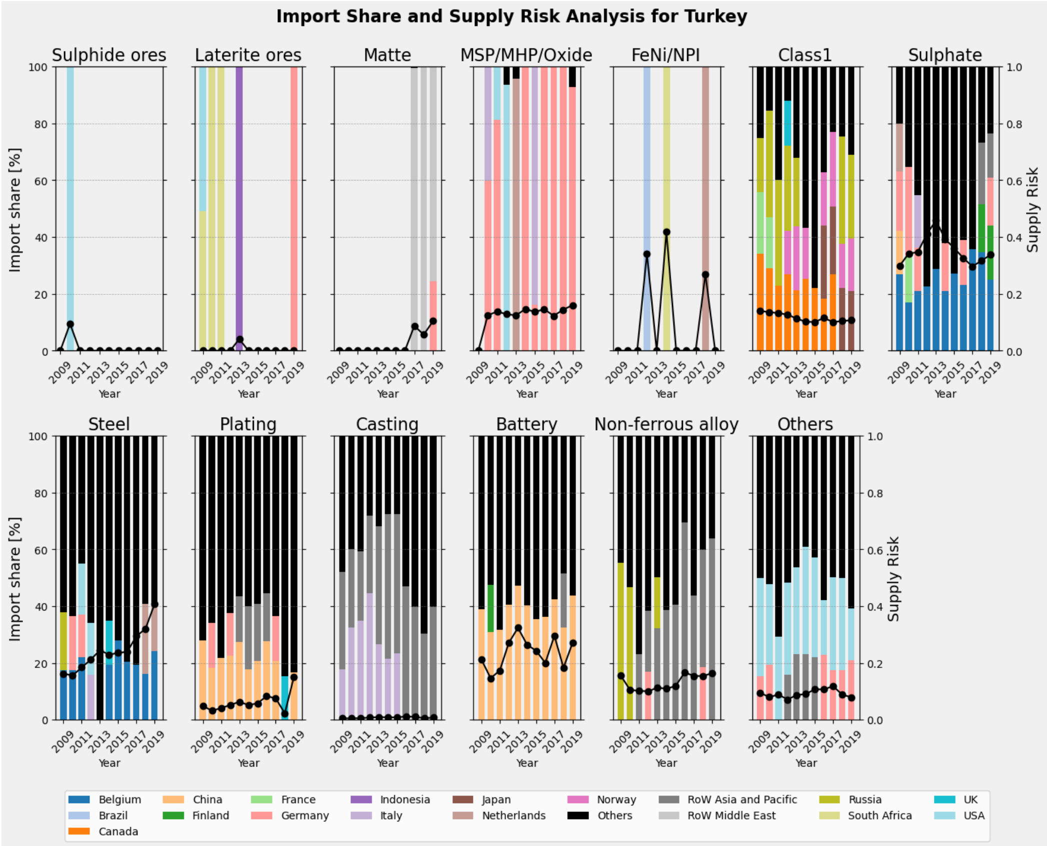

Figure S 17: Import Share and Supply Risk for Turkey

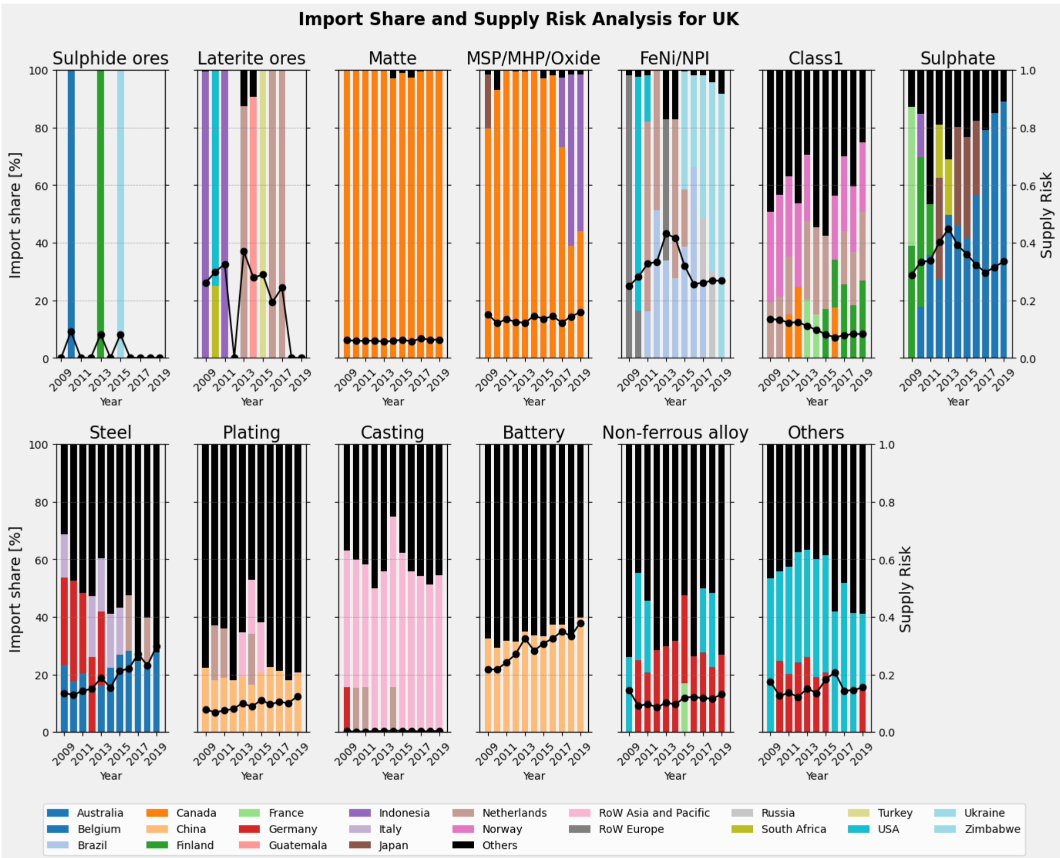

Figure S 18: Import Share and Supply Risk for UK

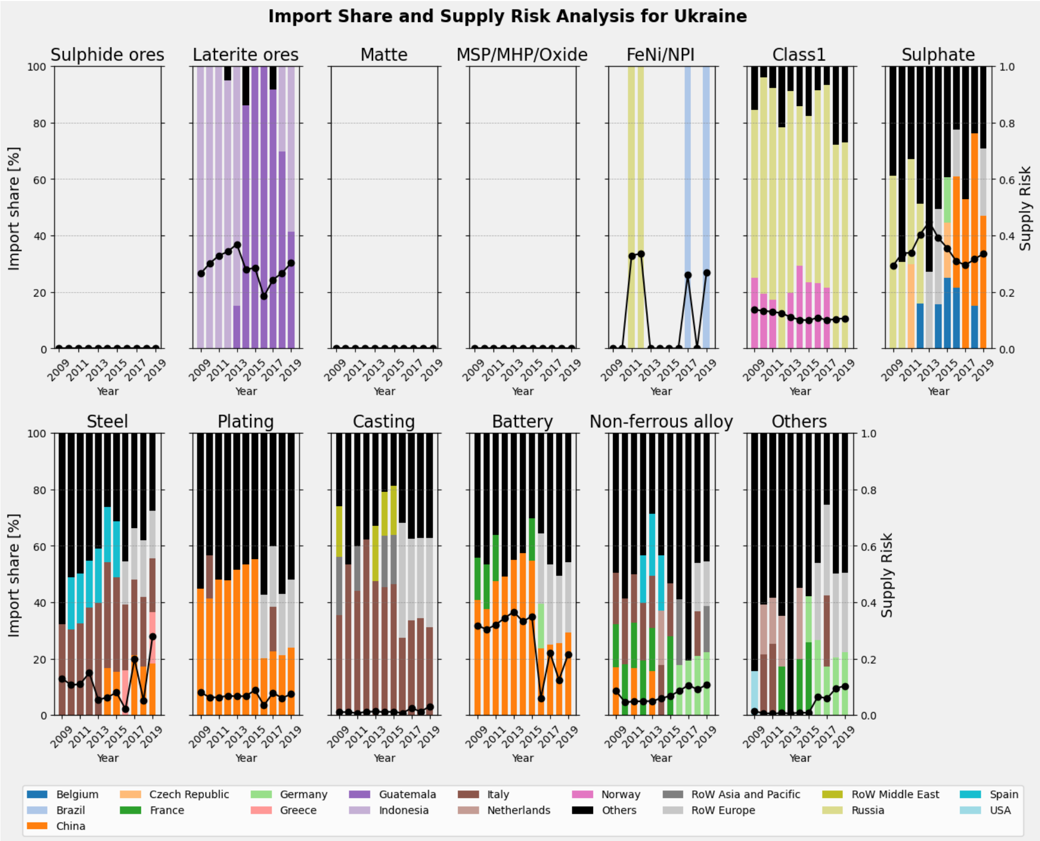

Figure S 19: Import Share and Supply Risk for Ukraine

Paper nº 3

Environmental Science & Technology

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Exploring the Impact of Recycling on Demand–Supply Balance of Critical Materials in Green Transition: A Dynamic Multi-Regional Waste Input–Output Analysis

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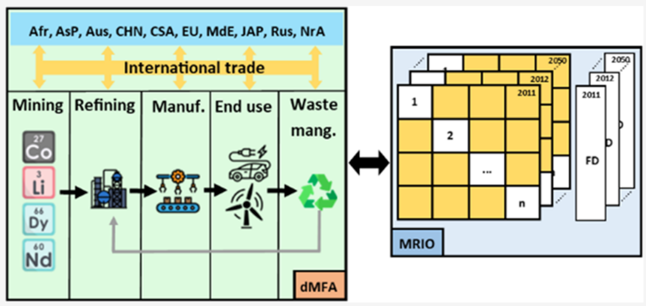
ABSTRACT: Addressing our climate urgency requires various renewable and low-carbon technologies, which often contain critical materials that face potential supply risks. Existing studies on the critical material implications of green transition have used various methodologies, each with pros and cons in providing a system understanding. Here, we integrated the dynamic material flow analysis and input–output modeling principles in an integrated multi-regional waste input–output model to assess the demand–supply balance and recycling potentials for cobalt, lithium, neodymium, and dysprosium under various energy scenarios projected to 2050. We show that although all four critical materials are likely to face strong growth in annual demand (as high as a factor of 25 compared to the 2015 level), only cobalt has a higher cumulative demand by 2050 than the known reserves. Nevertheless, considering the sheer scale of demand increase and long lead time of opening or expanding new mines, recycling efforts are urgently needed to supplement primary supply toward global green transition. This model integration is proven useful and can be extended to more critical materials and green technologies.



KEYWORDS: *critical materials, green technologies, material flow analysis, dynamic waste input–output, multi-regional input–output, recycling*

1. INTRODUCTION

The transition to a net-zero carbon economy is becoming increasingly urgent in the global and national policy agendas to curb climate change and reduce dependency on fossil fuels. Green technologies such as electric vehicles (EVs) and wind turbines (WT), for example, play a key role in cutting CO_2 emissions and ensuring the low-carbon transition of the energy and transport sectors. However, these green technologies often have higher material intensity relative to conventional technologies[1,2] and depend essentially on a wide range of critical materials.[3] Indeed, the cost reduction of green technologies and the consequent increase in their adoption in recent years have led to a surge in the demand for critical materials such as cobalt[4] and lithium,[5] which are fundamental for lithium-ion batteries, and rare earth elements (REEs) such as neodymium and dysprosium,[6] which are key components for permanent magnets (PMs) used in WT and EVs.

As a result, the critical material implications of such a renewable and low-carbon transition have gained increasing attention in the past decade.[3] A growing number of studies have examined the future demand and potential supply bottlenecks for critical metals used in green energy and transportation technologies.[7] The main methodologies include, among others, material flow analysis (MFA),[8−10] system dynamics (SD) modeling,[11,12] life cycle assesment[7] (LCA), and input–output analysis[13,14] (IO).

MFA is one of the most utilized methods to estimate the historical and future flows and stocks of metals, from either a top-down or a bottom-up perspective. The bottom-up MFA has been mostly applied to evaluate the material requirement of a specific technology (e.g., WTs) or a sector (e.g., transport), while the top-down MFA has been employed to study the material demand at aggregate level (e.g., national economy wide) or for all end-use applications.[15] Due to data limitation, practical MFA models often do not provide information on interindustry flows within one country's socioeconomic system or across nations,[16] and they usually address one material at a time and do not consider the simultaneous flows of interconnected materials used in one or several end-use sectors.[17]

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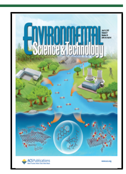

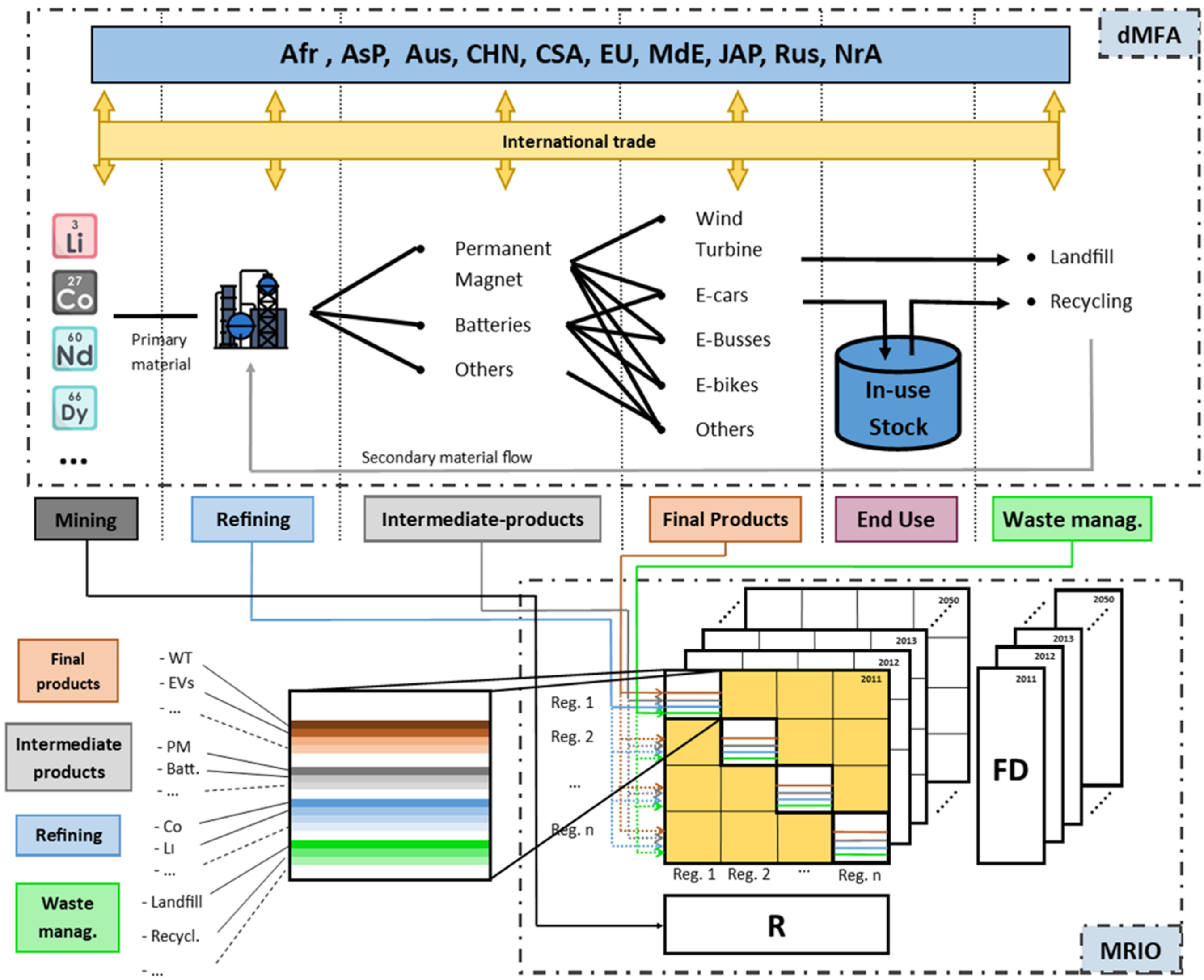

Figure 1. System definition for the dynamic multi-regional waste input−output (dMRWIO) modeling framework. Afr: Africa; AsP: Asia Pacific regions; Aus: Australia; CHN: China; CSA: Central & South America; EU: Europe; MdE: Middle East; JAP: Japan; Rus: Russia; NrA: North America. WT: wind turbines; EVs: electric vehicles; PM: permanent magnets. FD: final demand.

These limitations can be mitigated through the introduction of an IO model. The IO approach was first developed as a quantitative economic model that represents the interdependencies between different sectors of a national economy.[18] Due to the widely available national IO tables and multi-regional IO (MRIO) database, IO analysis has been extended to address resource and environmental issues in recent decades. In particular, it helps characterize interindustry flows across increasingly fragmented national and international supply chains,[19] and when combined with MFA, trace multiple material flows from extraction to waste management.[20]

Such an integration of MFA and IO has been proposed recently to study the potential bottlenecks in critical metal supply for various green technology applications for example, Soulier et al.[21] combined a dynamic MFA (dMFA) with a single-region IO model to trace copper through the Chinese economy. They accounted for recycling and thus secondary copper provision in the model but did not consider the international trade and future demand and dynamics. Tisserant and Pauliuk[22] estimated the future global cobalt demand by integrating MRIO modeling and dynamic stock models and incorporating mining risks into a resource depletion model, but without explicitly considering the potential effect of recycling. De Koning et al.[13] coupled an MRIO model with an LCA model to explore the global metal requirements under long-term socioeconomic scenarios. These initial attempts in the literature often lack comprehensive consideration of the recycling sector and the dynamics of in-use stocks that have already been widely regarded important for metal demand and recycling potential estimation.[8−10]

In this study, we aim to address the above-mentioned knowledge gaps by integrating dMFA with MRIO modeling principles. This builds on the dynamic waste input−output (dWIO) modeling method developed by Nakamura and Kondo,[23] which can capture the dynamics of waste generation and recycling (often the focus of MFA models) using an IO model structure.[24] The dWIO model is capable of considering the following aspects of recycling: the supply−demand balance of secondary materials, quality issues due to the unintentional mixing of materials, and the flow of goods and services such as energy and chemicals (which are not of primary interest in a typical MFA). We extend this dWIO framework to a multi-

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regional level as a dynamic multi-regional waste input−output framework (dMRWIO) to assess the demand of various critical materials under low-carbon-energy scenarios and quantify the potential of the recycling sector for alleviating the pressure on primary critical materials. This dMRWIO model framework has been exemplified to evaluate the future demand−supply balance of the four critical materials (i.e., Co, Li, Nd, Dy) employed in the referred green technologies (WT and EVs) under different energy-related scenarios derived from the World Energy Outlook 2020 (WEO20) by the International Energy Agency (IEA).[25] Recycling scenarios were created to analyze how the demand of virgin materials is affected by the secondary material flows.

2. METHODS AND MATERIALS

The system of our integrated modeling framework is defined as shown in Figure 1. The dMFA and MRIO modeling principles have been integrated through the following three aspects: (i) international trade of refined metals, intermediate products, and final products between relevant industries within and across multiple regions, (ii) relevant waste management industries and the forecasted amount of waste, and (iii) transactions of resources between economies and the environment, providing information regarding raw material extraction in each studied region. The integration of the two modeling approaches is illustrated through colored arrows that represent all of these elements and is elaborated in the following sections.

2.1. Dynamic Multi-Regional Waste Input−Output Model (dMRWIO). The basis of our integrated model is the dWIO model,[23] which was created by incorporating the MaTrace-alloy[26] model into the static WIO[27] framework. Unlike the classical IO model, which is an economic model, the dWIO model is hybrid with matrices containing data in both monetary units and physical units. A brief introduction to the dWIO model is given in Section 1 in the Supporting Information (SI).

In this study, building upon the dWIO, we created a dynamic multi-regional WIO (dMRWIO) to account for international trade of raw materials, intermediate, and final products that contain the observed critical metals across different regions and the dynamic effects of the waste management sector on the primary demand for the studied critical metals. This was made possible through the integration of dWIO and MRIO modeling techniques. The MRIO modeling technique allows to track the inputs, outputs, and impacts of producing a "typical product output" of economic sectors throughout its global value chain and to quantify the contributions to the value of the product from different economic sectors in various countries represented in the model. Detailed information and mathematical explanation of the dMRWIO model can be found in Section 1 in the SI.

2.2. Sector Disaggregation and Aggregation. The base MRIO tables adopted in this study are from the *Exiobase v.3*[28,29] database. This version of the database contains the monetary MRIO tables for 49 national economies (of which 5 Rest of the World regions), 163 industries per economy, and several environmental extensions covering the years from 1995 through 2011. *Exiobase* has been chosen primarily because it provides the highest resolution for metal-related sectors including six different metal production sectors and seven different metal mining sectors.

As a first step, the 49 regions were aggregated into 10 macroregions that represent the entire world economy, i.e., Africa (Afr), Asia Pacific (AsP), Australia (Aus), China (CHN), Central and South America (CSA), Europe (EU), Middle East (MdE), Japan (JAP), Russia (Rus), and North America (NrA). *Exiobase*'s high sector resolution was not required for this study since the technologies and materials examined are only present in a small number of sectors. An acceptable sectoral aggregation level has been established as the optimal trade-off between model size and results accuracy, with the 163 industries being aggregated into 39 major sectors as detailed in the SI. The four materials studied are not listed in the *Exiobase* database but are part of "*Other nonferrous metal ores and concentrates*". Disaggregating an MRIO table to trace critical materials involves assumptions about homogeneous product mixes, as the aggregation level of IO tables is usually so high that it does not allow us to distinguish specific critical metals from the bulk of nonferrous metals (e.g., the share of cobalt in "*Other nonferrous metal ores and concentrates*"). The magnitude of critical material flows is usually much smaller than the magnitude of the aggregated nonferrous metal flows which those critical material flows are a part of. Hence, as suggested by Tisserant and Pauliuk,[22] the flows of critical materials contained in the nonferrous metals sector can be considered as perturbation or extension of this sector. In this study, the share of the analyzed metals in the total output of other nonferrous metals sector was less than 6% (Price of Nd, Dy, Co, and Li in 2011 from USGS Minerals yearbook and Joint Research center:[30,31] Nd = 180269.1 €/ton, Dy = 1084892 €/ton, Co = 31145.32€/ton, Li = 3144.604 €/ton; and total global supply of other nonferrous metals in EXIOBASE is 142510 M€). Therefore, instead of disaggregating the X matrix, it was sufficient to hybridize it by adding the data on the physical metal requirements of the different consuming sectors.

The 2011 environmentally extended MRIO (EE MRIO) table of Exiobase v.3 has been hybridized by adding four industries in each region to produce the materials under study, i.e., "*refining of cobalt,*" "*refining of lithium,*" "*refining of neodymium,*" and "*refining of dysprosium,*" with each supplying one main product, i.e., "*refined cobalt,*" "*refined lithium,*" "*refined neodymium,*" and "*refined dysprosium*". Global sector-specific use of these materials was estimated for the year 2011 using data from the European Joint Research Center (JRC)[30,32] and US Geological Survey (USGS)[31] to match the global demand and use patterns. JRC and USGS provide information on the global end-uses divided by the main sectors of use.

The JRC provides information on the uses of Nd and Dy in PMs only at an aggregate level. A breakdown of applications with the approximate percentages of rare earth materials used in PMs was acquired from the study by Constantinides.[33] Through this data, we have divided the demand for Nd and Dy used in PMs that are employed in different applications (e.g., WTs and EVs). To allocate the share of sector uses by region, we used the regional market share extrapolated from *Exiobase*. More information on such assumptions and allocation can be found in the SI.

It was assumed that PMs are produced primarily by China (83.3%) and Japan (10.25%), while North America and Europe supply 5.12 and 1.28% of the remaining production, respectively.[34] Since *Exiobase* v.3 does not contain specific sectors for e-bikes and WTs, we hybridized the MRIO table by adding 2 industries for each region (i.e., "*manufacturing of Wind Turbines*" and "*manufacturing of e-bikes*") each supplying one main product ("*Wind Turbines*" and "*e-bikes*," *respectively*). To calculate the material flows directed to the green technologies considered in this study, we have first derived the material intensity coefficients of each technology from the relevant literature and reports and multiplied these coefficients by the installed capacities for WTs and EVs. More detailed information regarding the technologies and their associated material intensities of the studied critical metals is provided in the SI.

2.3. End of Life and Waste Treatment. The recycling of critical materials includes several steps. The critical materials containing end-of-life (EoL) products first need to be collected, and then disassembled, where the scraps are generated. Such scrap is subsequently processed by refineries, where the recycled material is extracted and sent back to the production sectors. Data on the collection rate (CR) for each material has been acquired from a report published by Bio by Deloitte.[35] The disassembler efficiency rate (γ) and refinery efficiency rate (ε) were determined for each product from a study conducted by the European Rare Earth Magnet Recycling Network (EREAN).[36] The secondary material flows reenter the manufacturing cycle via the refineries at the end of the recycling phase. The recycling content rate (RR) is defined as the ratio of total recycled material to the total final demand for such material.

To calculate the material outflow at the end-of-product lifetime in 2011, we first identified the products that can be recycled. PMs were the only products eligible for the recycling of Nd and Dy. In fact, the use of these materials in other applications is either dissipative or their concentrations in the final product is too low to be recycled.[37] While certain cobalt products such as pigments, ceramics, and paints are dissipative, cobalt used in superalloys, hard metals, batteries, or even spent catalysts can be collected, reused, and recycled.[38] For lithium, only LIB-related products can be recycled using current technologies and prices. The recycling of these products mainly aims at recovering cobalt and nickel elements.[39]

Once the products eligible for recycling were identified, we created a historical stock of these products based on the dMFA modeling principle[8−10] and data obtained from the USGS. To track different age cohorts, a survival function based on the Weibull distribution was used to estimate the number of products and appliances that were purchased in year t_0 and have survived after t years (t_{0+t}).

It was assumed that there are two refineries, one that treats the scraps of PMs to recycle Nd and Dy, and one that recycles Co and Li. In addition, there are one landfill sector and two disassembler sectors, one for PMs, and one for products that contain Co and Li. We hybridized the MRIO table adding these 5 waste sectors in each region, i.e., "*Refinery of Nd and Dy from permanent magnet*", "*Refinery of Co and Li*", "*Disassembler of permanent magnet*", "*Disassembler of EoL products containing Co and Li*", and "*Landfill*". Detailed information is provided in Section 3 in the SI.

2.4. Scenarios. For this study, we defined three main scenarios, i.e., baseline scenarios (BLS), stated policies scenario (SPS), and sustainable development scenario (SDS), based on the 2020 World Energy Outlook (WEO2020) by the International Energy Agency (IEA).[25] The SPS is based on today's policy settings and on an assumption that the COVID-19 pandemic is brought under control in 2021. The BLS is based on the SPS, with the additional assumption that policy goals are reached with 3 years of delay due to problems caused by the pandemic. The sustainable development scenario (SDS), which is based on the same economic and public health viewpoint as the SPS, works backward from common long-term climate, clean air, and energy access goals by analyzing what steps would be required to attain those goals. Detailed information on the development of the scenarios was provided in Section 5 in the SI.

2.5. Final Demand Projection and Supply Potentials. The annual demand of the studied materials has been assumed to be driven by the green technology scenarios and by the final demand (FD) for the other sectors. The projection of the FD is based on the approach used by Tisserant and Pauliuk,[22] where the FD was increased according to GDP growth projections. These projections were retrieved from the WEO2020 for each region, except for Australia (which was assumed based on the world average GDP growth rate). Using the time series data for multi-regional FD for the years 2000 and 2011, the historic sector-specific growth rates were determined for 11-year periods. These growth rates were used as a proxy to determine the future income elasticities to distribute the overall GDP growth in a country across all of the sectors considered in this study. More detailed information is provided in Section 4 in the SI.

The cumulative demand for each studied metal was estimated for 2050 using the described dMRWIO model and then compared with the reserves and resources. Reserves are a subset of resources that can currently be economically extracted.[40] Data were taken from Junne et al.,[6] who estimated the reserves and resources including a range of data from different studies. We considered the average values of reserves and resources estimated in the referred study.

3. RESULTS

3.1. Cumulative Demand vs Reserves and Resources. Figure 2 shows that the cumulative demand for cobalt

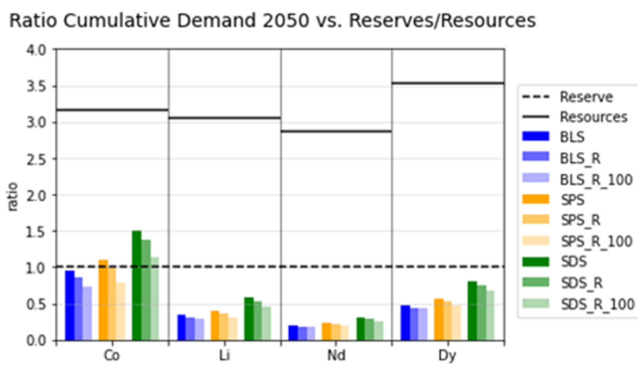

Figure 2. Global cumulative demand in 2050 under different scenarios compared with reserves and resources. The color scale represents the recycling scenarios.

exceeded the known reserves, given the assumptions under SPS and SDS. This finding is consistent with other similar studies,[4,41−46] showing that cobalt could face a possible supply bottleneck in the near future. This, in turn, may potentially affect the market price of cobalt, the related penetration of Li-ion batteries that contain cobalt, and eventually, the evolution of electromobility. Increasing cobalt recycling can significantly impact its cumulative demand (bars with brighter shaded colors), reduce the consumption of virgin cobalt, and avoid the overcoming of reserves. The cumulative demand for lithium

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Environ. Sci. Technol. 2023, 57, 10221−10230

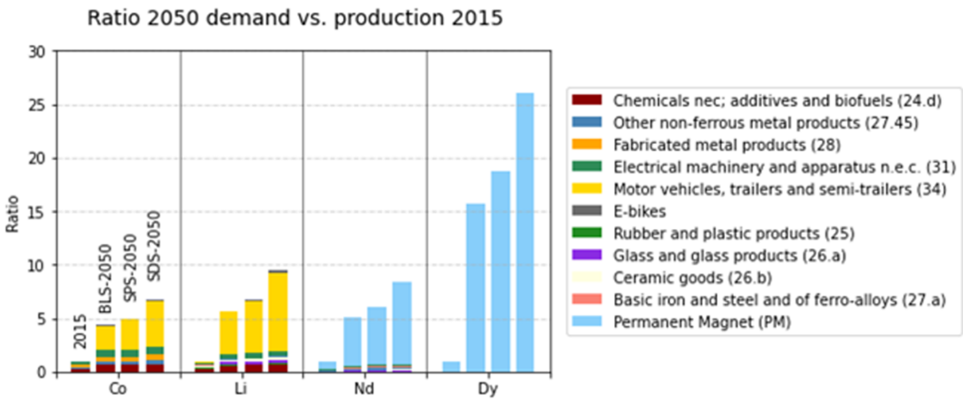

Figure 3. Ratio between demand in 2050 under the three scenarios vs production in 2015.

could reach 12 million metric tons by 2050 under SDS, consuming almost 60% of the reserves. Li is less critical compared to cobalt since the reserves were not expected to get depleted before 2050. As for the studied REEs, the expected cumulative demand for Nd was the lowest, reaching a maximum of 27% of the reserves extracted in 2050. Dy showed a higher supply risk compared with Nd since its cumulative demand was projected to consume about 80% of the total known reserves in 2050 under the SDS. The effect of increasing the recycling rate was more evident for lithium and cobalt due to the higher recycling efficiency of these two materials. On the other hand, the effect of recycling of Nd and Dy was observed to be minimum in comparison to other studied metals, as the efficiency rate in the waste management of these two critical metals was lower due to the difficulties in recycling PMs.

3.2. Demand in 2050 vs Production in 2015 by Sector. Figure 3 shows a comparison between the production of the studied materials in 2015,[6] and the demand for these materials in 2050 under the three modeled scenarios. There will be an increase in the demand for Li, Co, and Nd by a factor of 5 up to 10, while Dy sees a growth factor of 15 under the BLS and up to 25 under the SDS. As shown in Figure 2, the reserves of Dy are enough to meet the global demand until 2050; however, the faster increase in the demand for this material could potentially cause a supply shortage in the near future, since it is difficult to predict whether the mining sector will be able to meet the ever-growing demand. The main driver of this increase in the demand for Co and Li are the lithium-ion batteries deployed in EVs, where their market penetration was assumed to reach 70−75% of the total vehicle demand in 2050. The demand for Nd and Dy comes mainly from the PMs sector since they are used in several products (e.g., WTs, EVs, and e-bikes). Figure S8 in the SI shows how the demand for PMs is also driven by the EV sector, while the share of WTs in the total demand for PMs increases, making it the second most consuming sector of the studied critical metals under SPS and SDS.

3.3. Domestic Material Consumption Shares by Region. Figure 4 illustrates the annual domestic material consumption shares by region of the studied metals in the years 2020, 2030, 2040, and 2050. This result highlights that China (represented in dark green) is the largest consumer of these critical materials due to the ambitious national policies established by the government and its large population. Even if China remains as a major consumer of the studied critical metals until 2050, its share is expected to decrease due to the

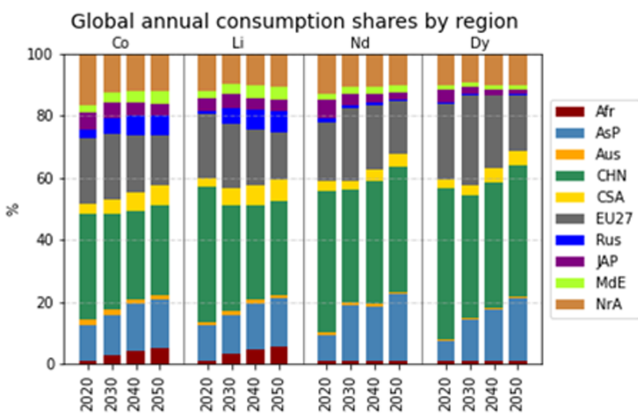

Figure 4. Global annual consumption shares of Co, Li, Nd, and Dy by region in SDS.

expected rise of developing regions such as Asia Pacific, Africa, and Central and South America. The EU27 region is the second largest consumer and follows the same decrease as China. North America, the third region for the annual demand for these metals in 2020, is likely to see its position overtaken by the Asia Pacific region due to the expansion of green technology investments in developing countries such as India.

It should be noted that the reported annual domestic material consumption does not consider the import/exports of raw materials or materials embedded in products directed to other regions; it only considers the material necessary to satisfy the domestic final demand. With the use of more detailed data on the supply chain (i.e., import/export of raw materials and products), it would be possible to give a better view of the annual demand of a region and of different levels of the supply chain. For example, China is the largest importer and refiner of cobalt,[47] and a major exporter of Co-containing final products (e.g., Li-ion batteries). This gives China a larger share of the global demand for cobalt.

3.4. Annual Demand and Recycling Content Rate. Figure 5 shows how the annual demand and the recycling content rate (RR) are affected by the increase of the collection rate (CR). Cobalt was the only metal among the studied metals that already has a high rate of recycling from super alloy or hard materials. In 2011, its RR was around 17%. The value of the RR in the R_100 scenario (dotted line) decreases until around 2035 and then rises again to reach 40% in 2050. The demand for EVs and WTs grows dramatically in 2020, increasing the stock of these technologies in use, which will

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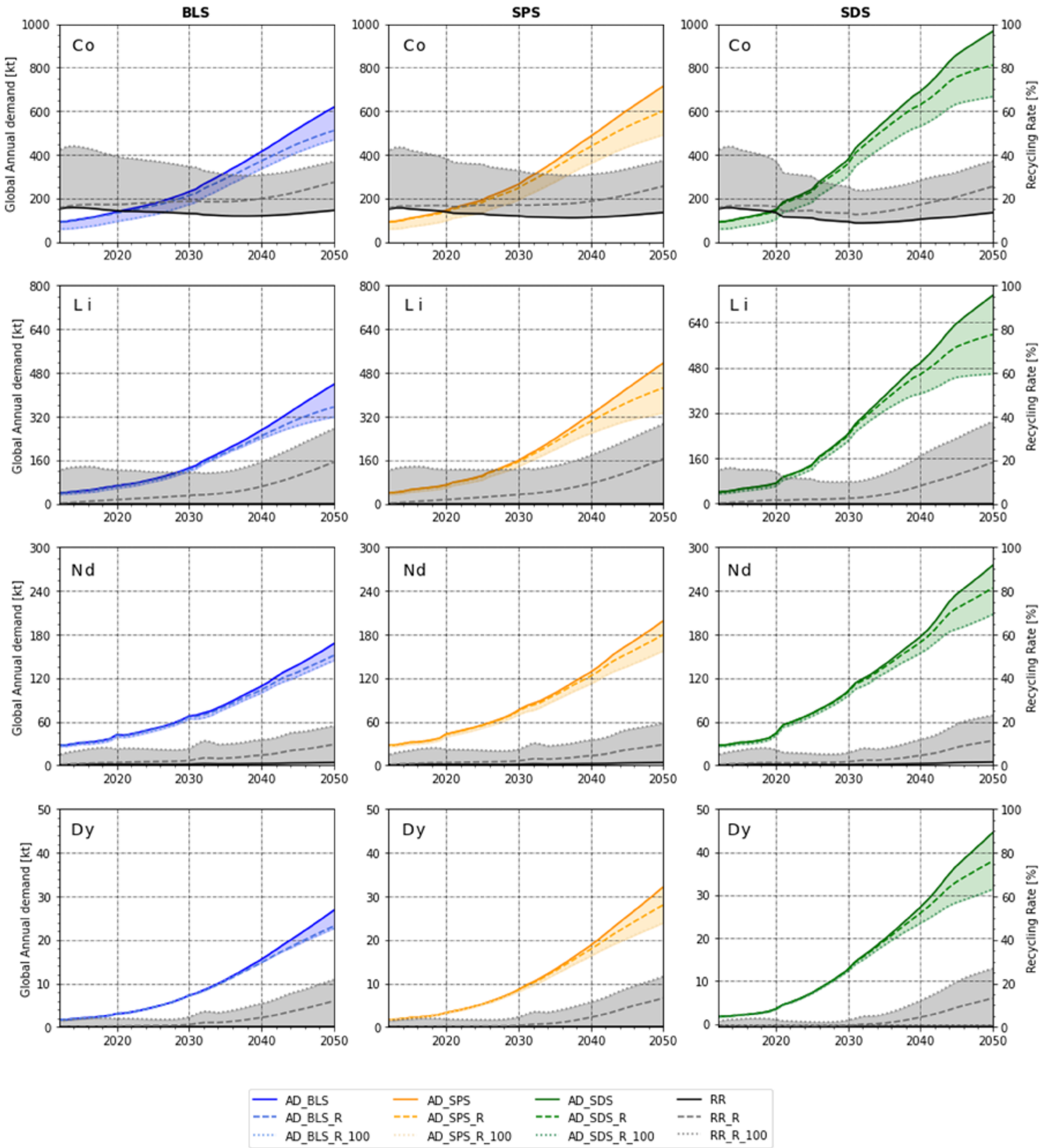

Figure 5. Global annual demand and recycling content rate. The line style identifies the different recycling scenarios: solid = baseline scenarios; dashed = R; dotted = R_100. The gray lines, reported on the right *y* axis, refer to the RR content.

become available at the end of life increasing the RR after 2035.

As for Li, Nd, and Dy, the effects of increasing recycling (even in the 100% scenario, i.e., the maximum CR possible) on the annual demand for these materials were observed to be minimal until 2030. This is due to the long lifetime of the products, in which they are contained (e.g., EVs and WTs), as well as the constant increase in demand for these technologies. We observed that after 2035, the increase in RR (gray shadow areas in Figure 5) reaches a potential RR of 40% for Li and almost 25% for Nd and Dy in 2050. This difference is due to the difficulty of recovering PMs from e-waste[34] and the low disassembling efficiency of wind turbines compared to the high theoretical material recovery rate of lithium batteries.[48,49] The results on annual demand and RR at the regional level are reported in the SI.

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4. DISCUSSION

Our study has investigated the extent to which the recycling of the studied critical metals (Co, Dy, Li, and Nd) can alleviate the future demand for these materials under various low-carbon-energy scenarios. Comparing the cumulative demand to the global reserves is one of the first assessments when analyzing the supply chain disruption of critical materials as it helps understand whether the reserves of these materials are enough to satisfy the demand driven by different energy scenarios (particularly the rapid expansion of the EV market and the increasing adoption of WT across the world). Our results show that the cumulative Co demand could exceed the known reserves of 12 million tons prior to 2050 under the SDG and SDS scenarios. Despite differences in methodology and assumption, these results are in line with similar studies,[1,6,45,46] where the reserves of Co are depleted around 2035 under the most ambitious scenarios. The cumulative demand for Nd is expected to reach between 1.5 and 8 million tons in 2050 and is not expected to outnumber the known reserve of 16 M tons, as also reported by other scholars.[1,6,13,45,46] The results regarding the future demand for Li and Dy differ significantly from other studies,[6,45,46] where the cumulative demand for these two materials is likely to exceed the reserves (21 M ton of Li and 0.85 M ton of Dy). In comparison, we have estimated that 50 and 80% of the reserve of Li and Dy will be consumed under the most ambitious scenarios, respectively. In this study, the annual demand for Nd is expected to grow up to a factor of 25 in 2050 with respect to the supply in 2015. Previous studies by other scholars[4,6,13,45,46,50] reported similar results, but a comprehensive comparison is difficult since different reference years of demand and supply are taken into consideration.

Rapidly increasing demand could affect the supply chain in the coming years. Even if the reserves are enough to satisfy the demand, opening/expanding new mines often take many years, making this kind of investment risky and costly. Most critical materials are produced as byproducts of other host materials (e.g., Co as co-host for copper and nickel) and require a long lead period (i.e., 5−10 years) to start a new mine,[51] posing a higher supply risk for certain materials as to expand the mining capacity of those host materials at the same rate as the deployment of green technologies.[52] Such an investment may not be an easy decision as it poses economic, political, and environmental risks for investors, local and national governments, and neighboring communities.[53]

Our results highlighted the innovation of production technologies, such as cobalt-free Li-ion batteries, and an increase of recycling can significantly alleviate the supply risks of the four materials studied. In particular, recycling EoL products as a secondary supply would be essential to supplement primary supply. It would gradually help relieve the pressure on the mining sector from an ever-increasing demand for critical metals and reduce geopolitical dependency in this regard, as more EVs and WT reach the end of their useful life. Today, businesses exist that recycle lithium-ion batteries at the commercial level, such as Umicore, but these technologies are still in early stages, and they do not have the capacity to handle the expectedly increasing volume of EoL lithium-ion batteries. Therefore, expanding the technological capacity to follow the rapid increase in the volume of EoL products will be also a key factor to increase the secondary flow of critical materials. However, such an expansion also necessitates time and investment from public or private organizations.

These results suggest that the integrated dMRWIO framework proposed in this study can help better understand the future demand, recycling potentials, and potential bottlenecks of critical materials in the global green transition. We leveraged the advantages of MFA and IO to address common limitations found in the literature, particularly limited geographical boundaries, narrow technology or material focus, and the static nature of modeling. This integration enables us to forecast the demand for critical materials in various low-carbon-energy scenarios, including energy and transportation sectors. Additionally, thanks to dWIO, we can comprehensively incorporate waste management sectors into the developed dMRWIO model, explicitly considering the supply−demand balance of secondary materials. Utilizing such an integrated dMRWIO model for similiar studies offers several advantages. First, it provides a holistic perspective and global economic coverage, capturing the fate of critical materials across different economic sectors often missed by other models. Second, it allows for estimating future demand for critical materials, aiding decision-making in a dynamic future. Third, it encompasses a wide range of technologies and materials, ensuring a comprehensive analysis beyond specific subsets.

Nevertheless, there are a few unavoidable shortcomings in this study due to methodological limitations and data gaps. We identify the major ones as follows:

- First, the material intensity and the penetration rate of the considered green technologies have been kept constant. Intensities of material usage will likely change over time as a consequence of technological optimization.[54] As shown by previous studies,[4,6,54] different penetration rates of these technologies are likely to affect the material demand, reducing the risk of supply chain disruption. This limitation could be addressed by testing different material intensity and technology penetration rate assumptions since they are exogenous parameters of the dMRWIO model.
- Second, waste management operations should be characterized with more accurate data and extended with the inclusion of different EoL management and circular economy strategies other than recycling. These could be remanufacturing and reuse of products, e.g., batteries reused for grid stability and energy storage.[55,56] Data on international trade of waste products are needed to better understand the secondary material flows at the global level and the dynamic effect of the growing stock of EoL products. Trade of waste products (especially for e-waste[57]), in which different critical materials are embedded, has been growing in recent years. Effective handling of waste products can have a positive effect on environmental quality and efficient use of resources by reducing the demand for virgin materials.[58]
- Last but not least, a key limitation in the dMRWIO modeling principle is that the technical coefficients in matrix A are assumed constant. This consideration excludes that the efficiency of production in any sector of the global economy will improve in the future and may result in the overestimation of the material demand. Efficiency trends for each region and economic sectors present in *Exiobase* could be projected using MRIO

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Environ. Sci. Technol. 2023, 57, 10221−10230

tables from previous years, to attenuate the limitation previously explained.[13]

Further research can extend the model to include environmental and social impact analysis using the Environmentally Extended (EE) MRIO tables. Providing insights into the energy demand of mining, manufacturing, and waste management operations would help with more accurate assessments of the potential climate change impacts of the green transition from the life cycle perspective. This technique provides a simple and robust means to evaluate the linkages between economic consumption activities within and across nations. Understanding how the consumption in one country causes environmental and social impacts in multiple other countries is fundamental to taking effective measures and creating policies to make the green transition sustainable. Another important next step would be to further include other green technologies (e.g., solar energy and fuel cells) and related critical materials (e.g., platinum) to create more elaborated material demand scenarios and comparative impact analysis. This would further contribute to choosing adequate strategies to achieve net-zero carbon emissions with optimal resource use in the coming decades.

In summary, this study has demonstrated the effectiveness of the developed dMRWIO model in addressing the existing gaps in the literature regarding the modeling of future demand, in-use stock, and recycling potentials of critical materials at a multi-regional level. The multi-regional and sector-specific information could facilitate the identification and evaluation of more effective natural resource and waste management strategies that can efficiently reprocess the expectedly increasing amounts of inflows of EoL green technologies and thus prevent possible supply chain disruption of such critical materials caused by resource depletion or geopolitical risk (e.g., war). As a result, the dMRWIO model holds significant potential to enable industries and governments to adopt evidence-based approaches to forecasting the future volume of EoL products at the national level, assessing the environmental, economic, and social impacts of different recycling practices and technologies, and subsequently formulating policies that incentivize the adoption of best practices for managing future waste flows of green technologies, as well as the expansion of mining and refining capacity to mitigate future supply−demand imbalances.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.2c09676.

Details on methodology, data sources, and complementary figures and tables (PDF)

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Notes

The authors declare no competing financial interest.

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Supporting Information for

Exploring the impact of recycling on demand-supply balance of critical materials in green transition: A dynamic multi-regional waste input-output analysis

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Summary information:

Number of pages: 42

Figures: Figure S1 – S18

Tables: Table S1 – S16

Contents

1. Dynamic Waste Input-Output

In this chapter we explain briefly the dWIO, introducing in part 1.1. and 1.2. the fundamental concepts of the Waste Input-Output model and the MaTrace-Alloy model, the core parts that are integrated in the dWIO. Finally, In part 1.3. the dWIO is explaind.

1.1. Waste Input-Output model

The Waste input-output (WIO) developed by Nakamura and Kondo[1] is a modelling technique that extends the standard IO analysis by incorporating waste flows and waste treatment processes into the core IO table to account for the end-of-life (EoL) phase of products[2]. Such an extension allows to include the end-of-life phase of products involving waste management and recycling into IOA, making it applicable to all the stages in a product lifecycle which are production, use, and EoL.

	Products (n_1)	Waste tratment (n_2)	Final Demand (n_y)
Products (n_1)	X_1	X_2	y_1
Waste (n_w)	W_1	W_2	w_y

Table S1: A schematic WIO account

Table 1 presents a schematic WIO account with: n_1 producing sectors (each producing a single product), n_2 waste treatment sectors, $n_y=1$ final demand sector, n_w waste categories.

The set of n_1 products is denoted by "1" and that of n_2 waste treatment sectors by "2". X_1 refers to the flows of goods and services among production sectors while y_1 to the final demand (F.D.)

The other elements of the model refer to the flows associated with waste and waste treatment, with:

- W_1: flow of waste generated and/or absorbed by production sectors, with its (i, j) element, *ij w*, W_1 >0 if sector *j* generates waste *i*, W_1 <0 if sector *j* uses (recycles) waste *i*.
- W_2: amount of generated waste (treatment residue) minus the amount of recycled waste by treatment sector in a year.
- X_2: flow of goods and services that are necessary for this transformation including products obtained from treatment processes (electricity from the waste heat of waste incineration facilities), or material recycled from refinery, which occur as negative inputs.
- w_y that refers to the generation of waste from final demand, garbage, wastewater, and EoL products).

Denoting by x_1 the quantity of n_1 products produced and by w the quantity of n_w waste for treatment, we can write the following balance:

$$\begin{pmatrix} X_1 & X_2 \\ W_1 & W_2 \end{pmatrix}\begin{pmatrix} \iota_1 \\ \iota_2 \end{pmatrix} + \begin{pmatrix} y_1 \\ w_y \end{pmatrix} = \begin{pmatrix} x_1 \\ w \end{pmatrix} \quad (S1)$$

where ι_1 refers to $n_a \times 1$ vector of ones used for summation, where the symbol α represents a set of sectors, products, scrap, or waste. Denoting by x_2 the activity level of treatment sectors (that refers to the quantity of waste treated in each treatment sector), the input coefficient matrices A (as the technical coefficient matrix as we have seen before) and waste generation coefficients G are given by:

$$A_1 = X_1 * \hat{x}_1^{-1}\,; A_2 = X_2 * \hat{x}_2^{-1} \quad (S2)$$

$$G_1 = W_1 * \hat{x}_1^{-1}\,; G_2 = W_2 * \hat{x}_2^{-1} \quad (S3)$$

Where $\hat{v} = diag(v)$ refers to a diagonal matrix, the element of which is the i-th element of a vector v. Introducing the allocation matrix S that allocates waste to treatment processes of order $n_2 = n_w$ it is possible to obtain:

$$x_2 = Sw \quad (S4)$$

By applying the matrix **S** to the system of equation (**Error! Reference source not found.**) After the substitution with equations **Error! Reference source not found.** and **Error! Reference source not found.** it is possible to write the solution of the system as:

$$\begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \begin{pmatrix} 1 - A_1 & -A_2 \\ -SG_1 & I - SG_2 \end{pmatrix}^{-1} \begin{pmatrix} y_1 \\ Sw_y \end{pmatrix} \quad (S1)$$

The WIO is a static model because it does not involve any index referring to different times: it is not a system of difference/differential equations.

1.2. MaTrace alloy model

Based on their previous work, Nakamura et al.[3] in 2014 developed the MaTrace-Alloy model, a dynamic Material Flow Analysis (dMFA) model capable of tracing the fate of materials (metals) over time across products involving the mixing of materials over repeated recycling[4]. The model is based on the following assumption:

- **Products, alloy, and metal**: A product consists of alloys. Alloys consist of metals.
- **EoL products and scrap**: EoL products are disassembled into several types of scrap, each of which consists of alloys.
- **Refinery**: A refinery sector produces a secondary alloy from scrap, and it is the only sector (process) in which the metal composition of scrap (a combination of alloys) can be altered.

The $\boldsymbol{n_1}$ producing sectors are categorized as follows: $\boldsymbol{n_q}$ durable final products, $\boldsymbol{n_p}$ parts and component, $\boldsymbol{n_a}$ alloys, $\boldsymbol{n_m}$ metals, $\boldsymbol{n_o}$ other goods and service.

The producing sectors is the sum of all the other sectors mentioned above. The $\boldsymbol{n_2}$ waste sector, that is equal to $\boldsymbol{n_2} = \boldsymbol{n_r} + \boldsymbol{n_d} + \boldsymbol{n_l}$ where $\boldsymbol{n_r}$ refers to refineries; $\boldsymbol{n_d}$ to disassemblers and $\boldsymbol{n_l}$ other waste treatments and landfill

and nw waste categories, are equal to nw = ne + ns + nz where $\boldsymbol{n_e}$ refers to the EoL products, $\boldsymbol{n_s}$ to scrap types and $\boldsymbol{n_z}$ to treatment residues and other waste type.

The MaTrace-alloy model represents the development of the durable final product $\boldsymbol{y_q(t)}$ over time and is based on the following system of differential equations:

$$y_q(t) = (\Delta \odot D(t)\, diag\,((R^T \odot \Omega\Gamma\, V(t))\iota_m))\iota_m \tag{S6}$$

$$V(t) = \sum_{r=0}^{t} \hat{u}(t,r) C^T(t-r) \tag{S7}$$

$$u(t,r) = B(t-r)\delta(t-r)\phi(t-r) \tag{S8}$$

Where:

• $\odot$: Hadamard product[5]

• C($\boldsymbol{n_m} \times \boldsymbol{n_a}$): metal composition of alloys [kg-metal/kg-alloy]

• B($\boldsymbol{n_a} \times \boldsymbol{n_q}$): alloy composition of final products [kg/$]

• Γ($\boldsymbol{n_s} \times \boldsymbol{n_a}$): scrap transformation of alloys recovered from EoL products [dimensionless quantity]

• Ω($\boldsymbol{n_r} \times \boldsymbol{n_s}$): allocation scrap to refinery processes [dimensionless quantity]

• R($\boldsymbol{n_m} \times \boldsymbol{n_r}$): yield of metals at the refining of scrap into secondary alloys [dimensionless quantity]

• D($\boldsymbol{n_q} \times \boldsymbol{n_r}$): allocation of secondary alloys to products [dimensionless quantity]

• Λ($\boldsymbol{n_q} \times \boldsymbol{n_r}$): manufacturing yields products [dimensionless quantity]

• δ($\boldsymbol{n_q} \times \mathbf{1}$): recovery yields of EoL products products [dimensionless quantity]

• ϕ(r)($\boldsymbol{n_q} \times \mathbf{1}$): fraction of products that is discarded after r years of use products [dimensionless quantity]

The logic behind the (**Error! Reference source not found.**) is as follow: the term **u** gives the amount of alloys recovered in year **t** from EoL products that were produced in (t × r) and discarded in **t**. Multiplying by the material composition of alloys, $\boldsymbol{C}$, and summing over all $\boldsymbol{r}$ such that **r** < **t**, the transpose of the term **V**($\boldsymbol{n_a} \times \boldsymbol{n_m}$) gives the metal composition of EoL alloys recovered in the year. The EoL alloys are then allocated to scrap categories via **Γ**, and scrap is further allocated to refinery processes via **Ω**. Once the metals in scrap are submitted to refinery processes, they are rearranged via $\boldsymbol{R}$ into new alloys, which are subsequently allocated to new products via **D**. For further details please refer to reference[6].

1.3. Dynamic Waste Input-Output model (dWIO)

By integrating the MaTrace-Alloy model, a dynamic Material Flow Analysis (dMFA) model capable of tracing the fate of materials (metals) over time across products involving the mixing of materials over repeated recycling, in the WIO, Nakamura and Kondo developed the Dynamic Waste Input-Output model (dWIO)[7]. The dWIO is the base used to build the model developed for this study because it takes into account the recycling process of products, that depends on their past production, incorporated in an IO analysis.

	q	p	a	m	o	r	d	l	y
q	0	0	0	0	0	0	0	0	y_q
p	X_{pq}	X_{pp}	0	0	0	0	0	0	0
a	X_{aq}	X_{ap}	0	0	0	X_{ar}^{Θ}	0	0	0
m	0	0	X_{ma}	0	0	0	0	0	0
o	X_{oq}	X_{op}	X_{oa}	X_{om}	X_{oo}	X_{or}	X_{od}	X_{ol}	y_o
e	0	0	0	0	0	0	0	0	w_{ey}
s	0	0	0	0	0	0	W_{sd}	0	0
z	W_{zq}	W_{zp}	W_{za}	W_{zm}	W_{zo}	W_{zr}	W_{zd}	W_{zl}	0

Table S2: WIO account of the flows in the dWIO model.

Where the classification is the following: **q** as final product; **p** as parts and components; **a** as alloys; **m** as metals; **o** as others. Treatment sectors consist in: **e** as EoL products; **s** as scraps; **z** as residues; **r** as refineries; **d** as disassemblers; **l** as landfill.

In the dWIO the amount of secondary alloys is represented by X_{ar}^{Θ} , with a negative sign indicate its substitution for competing primary alloys. For the sake of simplicity, it is assumed that process waste is internally recycled (no occurrence as a waste item), that EoL final durable products are the only waste items generated from the final demand, that there is a one-to-one correspondence between final durable products and EoL products ($n_q = n_e$) and that there is a single disassembling sector ($n_d = 1$), and a landfill sector ($n_l = 1$). The balance equation for the Table 2 can be written as follow:

$$\begin{pmatrix} A_1 & A_2 \\ G_1 & G_2 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} + \begin{pmatrix} y_1 \\ w_y \end{pmatrix} = \begin{pmatrix} x_1 \\ w \end{pmatrix} \tag{S9}$$

With:

$$x_1 = \begin{pmatrix} x_q \\ x_p \\ x_a \\ x_m \\ x_o \end{pmatrix}; \quad x_2 = \begin{pmatrix} x_r \\ x_d \\ x_l \end{pmatrix}; \quad w = \begin{pmatrix} w_e \\ w_s \\ w_z \end{pmatrix}; y_1 = \begin{pmatrix} y_q \\ y_p \\ y_a \\ y_m \\ y_o \end{pmatrix} = \begin{pmatrix} y_q \\ 0 \\ 0 \\ 0 \\ y_o \end{pmatrix}; w_y = \begin{pmatrix} w_{ey} \\ w_{sy} \\ w_{zy} \end{pmatrix} = \begin{pmatrix} w_{ey} \\ 0 \\ 0 \end{pmatrix}; \tag{S10}$$

$$A_1 = \begin{pmatrix} A_{qq} & A_{qp} & A_{qa} & A_{qm} & A_{qo} \\ A_{pq} & A_{pp} & A_{pa} & A_{pm} & A_{po} \\ A_{aq} & A_{ap} & A_{aa} & A_{am} & A_{ao} \\ A_{mq} & A_{mp} & A_{ma} & A_{mm} & A_{mo} \\ A_{oq} & A_{op} & A_{oa} & A_{om} & A_{oo} \end{pmatrix} == \left(\begin{matrix} 0 & 0 & 0 & 0 & 0 \\ A_{pq} & A_{pp} & 0 & 0 & 0 \\ A_{aq} & A_{ap} & 0 & 0 & 0 \\ 0 & 0 & A_{ma} & 0 & 0 \\ A_{oq} & A_{op} & A_{oa} & A_{om} & A_{oo} \end{matrix} \right. \tag{S11}$$

$$G_1 = \begin{pmatrix} A_{qr} & A_{qd} & A_{ql} \\ A_{pr} & A_{pd} & A_{pl} \\ A_{ar} & A_{ad} & A_{al} \\ A_{mr} & A_{md} & A_{ml} \\ A_{or} & A_{od} & A_{ol} \end{pmatrix} = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ A_{ar} & 0 & 0 \\ 0 & 0 & 0 \\ A_{or} & A_{od} & A_{ol} \end{pmatrix}; \quad (S12)$$

$$G_2 = \begin{pmatrix} G_{eq} & G_{ep} & G_{ea} & G_{em} & G_{eo} \\ G_{sq} & G_{sp} & G_{sa} & G_{sm} & G_{so} \\ G_{zq} & G_{zp} & G_{za} & G_{zm} & G_{zo} \end{pmatrix} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ G_{zq} & G_{zp} & G_{za} & G_{zm} & G_{zo} \end{pmatrix} \quad (S13)$$

Here it is possible to note that the production of final products is always equal to the final demand for it ($x_q = y_q$) and that the EoL products are solely generated by the final demand sector ($w_e = w_{ey}$). The allocation matrix **S** is needed in order to transform the system in a solvable form.

The EoL products are allocated to disassembling via ($S_{de} = \delta T$) to which recovery yields of EoL products are applied, and then via ($S_{rs} = \Omega$) the scrap is allocated to refineries. It is assumed that "residue" is entirely allocated to "landfill," and none of it is recycled. The resulting allocation matrix is shown in the following equation:

$$S = \begin{pmatrix} S_{re} & S_{rs} & S_{rz} \\ S_{de} & S_{ds} & S_{dz} \\ S_{le} & S_{ls} & S_{lz} \end{pmatrix} = \begin{pmatrix} 0 & \Omega & 0 \\ \delta^T & 0 & 0 \\ (\iota_q - \delta)^T & 0 & \iota_q^T \end{pmatrix} \quad (S14)$$

Thus, by applying the matrix **S** to the system the following equations are obtained:

$$\begin{pmatrix} x_r \\ x_d \\ x_l \end{pmatrix} = \begin{pmatrix} 0 & \Omega & 0 \\ \delta^T & 0 & 0 \\ (\iota_q - \delta)^T & 0 & \iota_q^T \end{pmatrix} \begin{pmatrix} w_e \\ w_s \\ w_z \end{pmatrix} = \begin{pmatrix} \Omega w_e \\ \delta^T w_s \\ (\iota_q - \delta)^T w_e + \iota_q^T w_z \end{pmatrix} \quad (S15)$$

The last step for the integration of the MaTrace-Alloy with the WIO is done by establishing links between their elements. The amount of EoL products in year t is given by:

$$w_{ey}(t) = \sum_{r=0}^{t} \phi(t-r) y_q(r) \tag{S16}$$

Where $\phi(r)(nq \times 1)$ [dimensionless quantity] is the fraction of products that is discarded after r years of use products. The disassembling process transforms na alloys constituting EoL products into n_s types of scrap, resulting in an $n_s \times 1$ matrix of the flow of scraps:

$$W_{sd}(t) = \Gamma \sum_{r=0}^{t} B(r)\delta(t)\phi(t-r) y_q(r) \tag{S17}$$

Where:

$$B(r) = A_{aq}(r) + A_{ap}(r)(I - A_{pp}(r))^{-1} A_{pq}(r) \tag{S18}$$

The quantity of recovered EoL products intended to for disassembling xd is:

$$x_d(t) = \delta(t) w_{ey}(t) \tag{S19}$$

The matrix G_{sd} is given by:

$$G_{sd}(t) = W_{sd}(t) x_d^{-1}(t) \tag{S20}$$

Being that the activity level of the refinery sector is:

$$x_r = \Omega G_{sd} \delta(t) w_{ey}(t) \tag{S21}$$

This implies that x_r depends on the past values of y_q not only through w_{ey} but also through G_{sd}. The quantity of scrap treated by refinery processes is given by:

$$x_r = \Omega\Gamma \mathrm{V}(t)\iota_m \tag{S22}$$

Where V(t) indicates the metal composition of EoL products in alloy, and is given by:

$$V(t) = \sum_{r=0}^{t} diag(B(r)\delta(t)\phi(t-r) y_q(r)) C^T(r) \tag{S23}$$

By multiplying the quantity of metal that enters the refineries by the yield of the process we obtain the metal that has been recycled:

$$x'_r = (R^T \odot \Omega\Gamma\mathrm{V}(t))\iota_m \tag{S24}$$

Therefore, the terms $X_{ar}^{\ominus}$ and $A_{ar}^{\ominus}$ can be obtained as:

$$X_{ar}^{\ominus}(t) = \begin{pmatrix} -x'_r \\ 0 \end{pmatrix} = \begin{pmatrix} -diag((R^T \odot \Omega\Gamma\mathrm{V}(t))\iota_m \\ 0 \end{pmatrix} \tag{S25}$$

$$A_{ar}^{\ominus}(t) = X_{ar}^{\ominus}(t)x'_r(t) = \begin{pmatrix} x'_r(t)x_r^{-1}(t) \\ 0 \end{pmatrix} \tag{S26}$$

where the $(n_a \times n_r) \times n_r$ matrix of zeros added at the bottom corresponds to the alloys that are not produced by the refineries. The dWIO model overcomes the limitation of the MaTrace-Alloy because the supply-demand balance of secondary materials is properly considered, and the flow of goods and services other than the material of primary interest is captured. There is nevertheless a drawback in this model: the additional requirement of data necessary for its implementation, such as a time series of the final demand for durable products together with their material composition and the lifetime distribution. For further details about the dWIO please refer to reference[7].

1.4. Dynamic Multi-Regional Waste Input-Output model (dMRWIO)

Table 2 shows, by using a two-regions example, a schematic view of the dMRWIO model employed in this study.

		Region 1		Region 2		Final Demand	
		Industries (n_i)	Waste (n_w)	Industries (n_i)	Waste (n_w)	F.D. (n_y)	F.D. (n_y)
Reg. 1	Industries (n_i)	X_1^{11}	X_2^{11}	X_1^{12}	X_2^{12}	y_1^{11}	y_2^{12}
	Waste treatment sectors (n_{wts})	W_1^{11}	W_2^{11}	W_1^{12}	W_2^{12}	w_1^{11}	w_1^{12}
Re	Industries (n_i)	X_1^{21}	X_2^{21}	X_1^{22}	X_2^{22}	y_1^{21}	y_2^{22}

	Waste treatment sectors (n_{wts})	W_1^{21}	W_2^{21}	W_1^{22}	W_2^{22}		w_1^{21}	w_2^{22}

Resources (n_r)	R^{11}	0	R^{22}	0

Table S3: A schematic dMRWIO account. (ni:number of industries; nwts: number of waste treatment sectors; nw number of waste categories; ny =1 number of final demand; nr: number of resources). The superscripts refer to the region 1 and region 2. The matrices colored in yellow refer to the international trades of goods, services, and waste between the regions.

For the sake of simplicity, only two regions are displayed, though it may easily be extended to multiple regions. The matrices X and y refer to the flows of goods and services among production sectors and the final demand, respectively, while the matrix W refers to the flows associated with waste produced as a result of industrial activities from the industries and the activities in all the waste management sectors. More specifically, W_1 refers to the flows of waste generated and/or absorbed by the sectors of a national economy, W_2 refers to the flows of outputs that result from waste management sectors. Due to a lack of data and the fact that the involved nations are working to reduce and control the trade of e-waste and are instead focusing on recycling, reusing, and repair within their own borders, the international flows (i.e., trade) of waste between regions have not been taken into consideration[30]. For this reason, the matrix W that refer to the international trade is equal to zero. It has been assumed that the waste management sectors do not extract resources and that all the waste produced in a region is treated inside that region. The matrix R refers to the raw material extracted from the natural environment (i.e, mining). In the matrix FD, y_1^{11} and y_1^{22} refer to final demand within each region, $y_1^{21}$and y_1^{12} refer to the demand for imported/exported goods in each region. Accordingly, the total final demand for goods in region 1 and region 2 can be formulated as in the following equation:

$$y_1^1 = y_1^{11} + y_2^{12} \, ; y_1^2 = y_1^{22} + y_2^{21} \qquad (S27)$$

As in equation (S1), it is possible to write the following balance equation:

$$\begin{pmatrix} X_1^{11} & X_2^{11} & X_1^{12} & X_2^{12} \\ W_1^{11} & W_2^{11} & 0 & 0 \\ X_1^{21} & X_2^{21} & X_1^{22} & X_2^{22} \\ 0 & 0 & W_1^{22} & W_2^{22} \end{pmatrix} \begin{pmatrix} \iota_1 \\ \iota_2 \\ \iota_1 \\ \iota_2 \end{pmatrix} + \begin{pmatrix} y_1^1 \\ w_y^1 \\ y_1^2 \\ w_y^2 \end{pmatrix} = \begin{pmatrix} x_1^1 \\ w^1 \\ x_1^2 \\ w^2 \end{pmatrix} \tag{S28}$$

In the equation above, w_y^1 and w_y^2 refer to the generation of waste from final demand, such as garbage, wastewater, and EoL products for region 1 and region 2, respectively. The matrices w^1 and w^2 refer to the quantity of waste for treatment for the two regions. ι_a refers to an $n_a \times 1$ vector of 1s used for summation.

This system cannot be solved unless each waste is exclusively assigned to a single treatment process, which hardly reflects the reality of waste management. For instance, any solid waste can be landfilled, while several treatment methods can be applied to a given waste: organic waste can be landfilled, incinerated, or composted. Introducing the technical coefficient matrix **A** and the waste generation coefficients **G**, as defined before, it is possible to write the following balance equation:

$$\begin{pmatrix} A_1^{11} & A_2^{11} & A_1^{12} & A_2^{12} \\ G_1^{11} & G_2^{11} & 0 & 0 \\ A_1^{21} & A_2^{21} & A_1^{22} & A_2^{22} \\ 0 & 0 & G_1^{22} & G_2^{22} \end{pmatrix} \begin{pmatrix} x_1^1 \\ x_2^1 \\ x_1^2 \\ x_2^2 \end{pmatrix} + \begin{pmatrix} y_1^1 \\ w_y^1 \\ y_1^2 \\ w_y^2 \end{pmatrix} = \begin{pmatrix} x_1^1 \\ w^1 \\ x_1^2 \\ w^2 \end{pmatrix} \tag{S29}$$

To solve this system, the allocation matrices S that allocates each kind of waste to one or more different treatment processes is needed, as shown in eq. (S10). The solution to the system is:

$$\begin{pmatrix} x_1^1 \\ w^1 \\ x_1^2 \\ w^2 \end{pmatrix} = \begin{pmatrix} (I - A_1^{11}) & -A_2^{11} & -A_1^{12} & -A_2^{12} \\ -S^1 G_1^{11} & \left(I - S^1 G_2^{11}\right) & 0 & 0 \\ -A_1^{21} & -A_2^{21} & (I - A_1^{22}) & -A_2^{22} \\ 0 & 0 & -S^2 G_1^{22} & \left(I - S^2 G'^{11}_2\right) \end{pmatrix} \begin{pmatrix} y_1^1 \\ S^1 w_y^1 \\ y_1^2 \\ S^2 w_y^2 \end{pmatrix} \tag{S30}$$

The terms that represent the metals that are recycled and introduced again in the production system with a negative sign are inside the matrices A_2^{11}, A_2^{12}, A_2^{21} and A_2^{22}. If the region does not produce the material that is recycled, the effect is not counted, since the total production assumes a negative sign. To overcome this problem and assuming no domestic production, it has been assumed that all the flows of recycled metals will substitute the imported counterparts. Otherwise, if the metal is both produced and imported, they will substitute the domestic production and the import. In order to make the model dynamic, we followed the same steps for the creation of the dWIO[24], as previously elaborated.

Defining α^{11}, α^{12}, α^{21} and α^{22} as the allocation vectors for the recycled metals, Eq. (S24) given in the SI becomes:

$$x'^{11}_{r}(t) = \widehat{\alpha^{11}}((R^{11})^{T} \odot \Omega^{11}\Gamma^{11}V^{11}(t))\iota_{m} \tag{S31}$$

which represents the metal recycled in region 1. This is repeated for region 2, $x'^{22}_{r}(t)$. Therefore, it is possible now to calculate $X^{11\,\ominus}_{ar}$ (defined in SI which refers to the recycled materials that directly enter the production system in the region 1, and $X^{12\,\ominus}_{ar}$, which refers to the recycled materials that is exported. The same calculation applies to region 2 through $X^{22\,\ominus}_{ar}$ and $X^{21\,\ominus}_{ar}$. In this way, the model created becomes dynamic as the quantity of products reaching the EoL each year is a function of the products lifetime and the past final demand.

2. Critical materials considered in the model

Neodymium and Dysprosium

Data on demand of Nd and Dy in 2011 are taken from[8,9]. They are given in ton of oxide; using the conversion factor in tons of metal/tons of oxide that is equal to 0.857 for Nd and 0.871 for Dy[10] it is possible to calculate the amount of metal. In the table below we can see the allocation in the Exiobase sectors. The sector manufacture of Permanent Magnet (m.P.M.) does not exist in Exiobase, since it is a part of m.27.a "Manufacture of basic iron and steel and of ferro-alloys and first products thereof". In 2011 more than 76% of the Nd extracted is used for Permanent magnet, or the neodymium-iron-boron (NdFeB) permanent magnet. Due to their magnetic strength and higher torque, 2.5 times stronger than SmCo magnets[11,12] these magnets are the heart of motors and generators. They are indeed smaller and lighter than alternative materials/devices. As permanent magnets are used in different products and in different quantities, the addition of a new industry "manufacture of Permanent Magnet" (m.P.M.) is required.

A breakdown of applications with approximate percentages of rare earth magnets going into each was made by Constantinides[13]. Through this data it is possible to divide the demand of Nd for P.M. in the different applications (see Table 3). The data refers to 2010, we assume the same division per application for 2011.

Applications	% Nd	% Dy	Exiobase sector
motors, industrial, general auto	24.36%	37.25%	m.29
HDD	14.35%	0%	m.30
E-bikes	8.72%	13.33%	e.b.
Transducers, Loudspeaker	9.33%	0%	m.32
unidentified	6.82%	3.17%	m.32
magnetic separation	5.01%	4.85%	m.30
MRI	4.20%	1.93%	m.33
Torque-coupled	3.82%	5.84%	m.31
sensors	3.36%	1.55%	m.31
Hysteresis clutch	3.01%	2.92%	m.31
generators	2.63%	6.82%	m.31
energy storage system	2.29%	3.52%	m.31
wind power	1.99%	3.06%	w.t.
air conditioning	1.91%	2.92%	m.29
EV	0.73%	2.81%	m.34
others	7.48%	10.02%	m.28

Table S4: Demand of Nd and Dy for P.M. in each application in 2010 [%]

As for P.M., other sectors were added (e.b. referring to e-bikes and w.t. to wind turbine), since the high aggregation of sectors in Exiobase does not allow to characterize the future demand of these to technologies. EV are allocated in the sector m.34 “Manufacture of motor vehicles, trailers and semi-trailers”. Some applications do not use Dy, this is because Dy is essential to enable the use of NdFeB magnets at elevated temperatures. As Y. Yang and colleagues stated in their study[14], the global NdFeB magnet production is dominated by China that is by far the dominant magnet-producing country with about 83,3 % of market share. Japan is following with around 10,25% of market share[14].

Cobalt

Demand of cobalt in 2011 was 82400 tons[15]. As depicted in Table 4, in 2011 roughly a third of cobalt worldwide was used in batteries. The increasing demand for portable electronic devices since the 1980s boosted the demand for high-capacity rechargeable batteries in which cobalt is used. 19% of cobalt was used in superalloys that is historically the major end-use of cobalt. Cobalt is alloyed mostly with nickel but also with iron to provide superior thermal performance, corrosion, and wear resistance in a wide range of alloys used in applications such as jet engines, turbines, space vehicles or chemical equipment[8]. Another 13% of cobalt worldwide enters hard metals where it is used as a powerful binder for manufacturing of carbide and diamond tools used in metal cutting, drilling, mining, and construction.

It is used in the oil and gas sector in hydrodesulphurization (a catalytic chemical process widely used to remove Sulphur from natural gas and from refined petroleum products such as gasoline or petrol), where the catalyst must be Sulphur-resistant. Pigments and decolorizers, magnets, soaps and dryers are other minor end-uses.

Application	%			Exiobase sectors
Batteries	30%	24720	ton	m.31
Superalloys	19%	15656	ton	m.27.45
Hard materials	13%	10712	ton	m.28
Catalysts	9%	7416	ton	m.24.d
Pigments	9%	7416	ton	m.24.d
Magnets	7%	5768	ton	m.28
Hard facing/HSS and other alloys	5%	4120	ton	m.28
Tyre adhesives, soaps, driers(paint/ink)	5%	4120	ton	m.24.d
Feedstuffs, biotech, anodising	3%	2472	ton	m.24.d
	Total	82400	ton	

Table S5: End-uses of cobalt in 2011 [tons], and sector allocation in Exiobase

Lithium

In 2011 the global demand of lithium amounted to 34000 tons, of which 29% was used in ceramic and glass, and 27% in batteries. Similarly, to cobalt, the demand for lithium increased due to the development in lithium-ion battery industry. The other sectors that require lithium are showed in Table 4, data taken from USGS. Since 29% of lithium is used for ceramic and glass, we need to split this quantity in the two sectors m.26.a, m.26.b, but no more information is given. It is assumed that this quantity is divided in two equal parts between ceramic and glass.

Application	%			Exiobase sectors
Primary aluminium production	2%	680	ton	m.27.42
Continues casting	5%	1700	ton	m.27.a
Ceramic and glass	29%	9860	ton	m.26.a, m.26.b
Catalyst, absorber, sanitation, solution	16%	5440	ton	m.24.d
Lubricant and greases	12%	4080	ton	m.24.d
Batteries	27%	9180	ton	m.31
Rubber and thermoplastic	3%	1020	ton	m.25
Pharmaceuticals	2%	680	ton	m.24.d
Air treatment	4%	1360	ton	m.24.d
	Total	34000	ton	

Table S6: End-uses of lithium in 2011 [tons] and sector allocation in Exiobase

3. Green technologies considered in the model

Wind turbines

Permanent magnets are used in direct drive configuration wind turbine, due to their lighter and more compact turbine design, achieved by the very strong magnetic field, and a greater efficiency at low blade-rotation speeds in low winds. Moreover, permanent magnet synchronous generator PMSGs are also used in mid-speed (coupled with a 1 or 2 stage gearbox) or in high-speed (coupled with a traditional 3 or 4 stage gearbox) transmissions[16]. In this study we considered 2 models:

- Model 1: high-speed and mid-speed PMSG technologies
- Model 2: low-speed DD-PMSG

The global market share of DD-PMSG in 2015 was estimated at 4% for high-speed and mid-speed PMSG technologies and 19% for low-speed DD-PMSG (by installed capacity)[9].

EVs (cars, ebus and e-bikes)

Electric cars will play a key role in the decarbonization of the transportation sectors. They can be divided in two main categories: battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV). In the public transportation e-busses are gaining importance, especially in big cities where are becoming the favorite solution to reduce CO2 emission and traffic. As for e-car, also the e-busses are available in two types: battery electric busses (BEB) and plug-in hybrid electric busses (PHEB). In the world of two-wheels the e-bikes are becoming more popular thanks to the decrease of price, increase in performance and practice as bike sharing.

Thanks to the ability to offer low weight, compact size, high efficiency and easier control synchronous motors with NdFeB permanent magnets (PMs) are present in most of the electric vehicles; it is estimated that by 2025 between 90 and 100% of EV sales will be based on this technology. For this study is assumed that all electric vehicles considered use NdFeB permanent magnets. The material intensity for BEV and PHEV is assumed after a review of several scientific papers[14,17–25].

Lithium-ion batteries

Over the last decade, LIBs have been introduced in EVs. With more than two decades of improvements in energy and power density, safety, cost, and cycle life, LIBs have become the preferred battery system adopted by leading EV manufacturers such as General Motors, Honda, Nissan, Ford, BMW, and BYD. While some hybrid electric vehicles still use nickel metal hydride batteries, LIBs are more attractive for plug-in hybrid vehicles and battery electric vehicles (BEVs) due to their light weight, much higher energy density, longer cycle life, and ability to provide deep discharges[26]. There are several different chemistries, and they contain different elements and/or different proportions of the elements. Lithium-cobalt oxide (LCO) was the first commercialized lithium chemistry to reach the mass market, in the 1990s. Due to safety and lifetime concerns, LCO batteries have since lost market share to nickel cobalt-aluminum (NCA), nickel–manganese-cobalt (NMC) and lithium-iron-phosphate (LFP) batteries[27]. In the table below the material intensity of the batteries considered in this study are reported.

kg/kWh	Li	Co
NCA	0.1	0.13
NMC111	0.15	0.4
NMC433	0.14	0.35
NMC532	0.14	0.23
NMC622	0.13	0.19
NMC811	0.11	0.09

Table S7: material intensity for lithium-ion batteries

Today, NMC 111 (with nickel- cobalt-manganese in the proportion of 1:1:1) is the most used with a market share of 42 %, NMC 433 with 5%, NMC 532 with 7% and finally 14% of market share for NCA. The last share concern batteries without cobalt[28].

For this study it is assumed that all the EV use Lithium-ion batteries. Due to their low price compared with lithium-ion batteries, the lead-acid battery (LAB) is very common in e-bikes in China, 90% of them being composed of LAB. It is assumed that only 10% of e-bikes in China use lithium-ion batteries[29].

Lithium-ion batteries, besides EV, are used in a wide range of products such as laptops or smartphones. To keep track of cobalt and lithium flow in these devices, it is presumed that the material that enters the sector m.31 is used to produce batteries for cellphones, digital cameras, laptops, smartphones, and tablets, with the share as reported in Table 7. The share is calculated with the data found in[30].

	%
Cell Phone	0.168
Digital Camera	0.016
Laptop	0.384
Smartphone	0.344
Tablet	0.088

Table S8: Share of battery uses by devices

3.1. End of Life product

Permanent magnets are the only products eligible for the recycling of Nd and Dy. Indeed, in other applications the use of this material is dissipative or the concentration in the final product is too low to be recycled[14]. All the products listed in Table 8 are therefore potentially recyclable.

Product
Motors, industrial, general auto
HDD, magnetic separation
Torque-coupled, sensors, hysteresis cluth, generators, energy storage system
Transducer, loudspeaker
Magnetic resonance imaging (MRI)
Electric cars and busses
Wind turbine
E-bikes
Superalloy, catalysist, magnets, hard materials, chemical & others
Lithium-ion battery
Others

Table S9: Recyclable products

The cobalt used in pigments, ceramics, paints, etc, cannot be recycled since is used in a dissipative way, but it can be collected, reused or recycled from products such as superalloys, hard metals, batteries or even spent catalysts[28].

For lithium, only LIB-related products can be recycled using current technology and prices. The recycling of these products mainly aims at recovering cobalt and nickel elements[31].

With this information we defined the EoL product and the scraps that are reported in Table 9.

End of Life and scraps sectors	
Code	**Name**
EoL_m.28	End of Life of fabricated metal products (28)
EoL_m29	End of Life of machinery and equipment n.e.c. (29)
EoL_m30	End of Life of office machinery and computers (30)
EoL_m31	End of Life of electrical machinery and apparatus n.e.c. (31)

EoL_m32	End of Life of radio, television and communication equipment and apparatus (32)
EoL_m33	End of Life of medical, precision and optical instruments, watches and clocks (33)
EoL_m34	End of Life of motor and electric vehicles, trailers and semi-trailers (34)
EoL_w.t.	End of Life of wind turbine
EoL_e.b.	End of Life of e-bikes
EoL_Co	End of Life of product containing Co
EoL_batt	End of Life of lithium-ion batteries
s_m.28	scraps of sector m.28
s_m29	scraps of sector m.29
s_m30	scraps of sector m.30
s_m31	scraps of sector m.31
s_m32	scraps of sector m.32
s_m33	scraps of sector m.33
s_m34	scraps of sector m.34
s_w.t.	scraps of wind turbine
s_e.b.	scraps of e-bikes
s_Co	scraps of products containing Co
s_batt	scraps of lithium-ion batteries
z	Residue
Waste treatment sectors	
r_PM	Refinery of Nd and Dy from permanent magnet
r_Co_Li	Refinery of Co and Li
d_PM	Disassembler of permanent magnet
d_Co_Li	Disassembler of products containing Co and Li
l	Landfill

Table S10: EoL secotrs and scraps and waste treatment sectors

3.2. Product lifespan

Product lifetime or product lifespan is the time interval from when a product is sold to when it is discarded. We build survival functions for each product, based on the Weibull distribution, used to calculate how many products and appliances purchased in year t0 survive after t years. The survival function (SF) equals 1 minus the cumulative distribution function (CDF) of the product lifetime distribution and is expressed as follows:

$$SF(t) = e^{\left(\frac{t}{\lambda}\right)^{\alpha}} \qquad (S32)$$

where t is time, λ is the Weibull Scale parameter, and α is the Weibull shape parameter[32]. The survival function gives us the fraction of the products purchased in year *t0* that are still in use in year *t*. For each model year (*t*), for each model region (r) and for each product (p), we can determine the total number of surviving products (SP) from all previous years (t') given the quantity of products (q) produced in the previous year:

$$\mathrm{SP}_{r,p}(\mathrm{t}) = \sum_{t'=0}^{t} q_{r,p}(t') * SF_{r,p}(t-t') \qquad (S32)$$

After deriving the amount of surviving products, we can calculate the amount of waste generated (WG) in the year *t* with the following equation:

$$\mathrm{WG}_{r,p}(\mathrm{t}) = \mathrm{SP}_{r,p}(\mathrm{t}-1) - \mathrm{SP}_{r,p}(\mathrm{t}) \qquad (S33)$$

The waste generated is equal in the model to the products at EoL, so:

$$\mathrm{WG}_{r,p}(\mathrm{t}) = w_{y}^{r,p} \qquad 3.2.3$$

For simplification, it is assumed that the lifetime of the magnets is determined by the lifetime of the appliances containing them. In the following table the Weibull Scale parameter, and the Weibull shape parameter are reported.

Products	**λ**	**α**
Industrial motor	13	3.25
Air conditioner	12	3
HDD	6	1.5
Magnetic separation	10	2.5
Torque-coupled	10	2.5
Sensor	10	2.5
Hysteresis clutch	10	2.5
Acoustic transducer	8	2

Unidentified	10	2.5
Cell phone	4	1.8
Digital camera	6.5	1.6
Laptop	5.5	1.8
Smartphone	2.1	1.5
Tablet	5.1	1.8
Wind turbine	22.5	22.4
Electric cars	11.9	5.5
Electric busses	15	5.5
E-bikes	5	1.25

Table S11: Products Weibull Scale parameter and Weibull shape parameter

3.3. Waste management

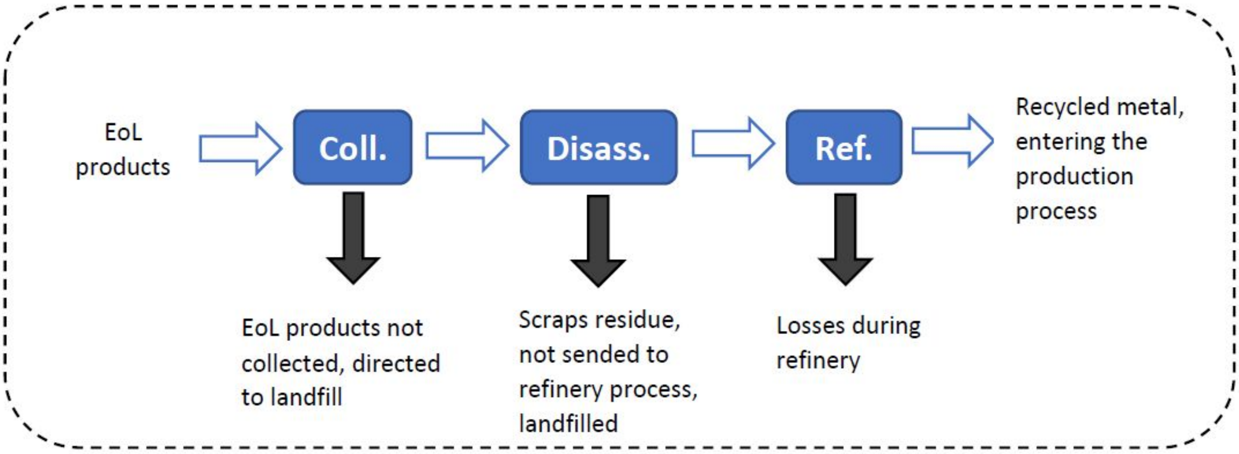

Figure S1: Schematic illustration of the recycling process

Figure S1 illustrates the recycle process where the EoL products enter the collector sector (Coll.). A collection rate (*CR*) is assumed for each material to estimate which fraction of the appliances is collected for recycling. The products collected enter in the disassembly sector (Disass.). In the case of PM losses during sorting and disassembling may occur if the magnets are deeply embedded in the devices and cannot be easily extracted, if they are too small or not suited as an input material. An efficiency rate of the disassembler is assumed for each product (γ). Then through the Refinery (Ref.) the scraps are recycled and enter again the production process as recycled metal, with an efficiency of refinery (ε).

In Table S12 we reported the assumption made in this study on the efficiency of the disassembler and the refinery. These data are drawn from research of the European Rare Earth Magnet Recycling Network (EREAN)[33].

The Collection Rate (CR) for 2011, reported here in the Table S11, are derived from a report from Bio by Deloitte[34].

	CR
Cobalt	0,380036
Lithium	0,001209
Neodymium	0,06986
Dysprosium	0

Table S12: Collection Rate

The recycling content rate (*RR*) of a material is defined as the ratio between the total recycled material that enter again in the production process and the total final demand of the material.

We defined 2 disassembler sectors, one for P.M. and one for products containing Co and Li. The scraps produced from the disassemblers goes in two different refineries, one dedicated for the scraps of PM that produce recycled Nd and Dy and a second one for scraps containing Co and Li and produce the two materials as recycled products.

Products	**Disass. Eff. (γ)**	**Refinery Eff. (ε)**
Industrial motor	40%	92%
Air conditioner	90%	92%
Magnetic separation	80%	92%
HDD	60%	92%
Torque-coupled	10%	92%
Sensor	10%	92%
Hysteresis clutch	10%	92%
Acustic transducer	50%	92%
Unidentified	10%	92%
Cell phone	90%	90%
digital camera	90%	90%
Laptop	90%	90%
Smartphone	90%	90%
tablet	90%	90%
Wind Turbine	90%	90%
Electric cars	90%	90%
Electric busses	90%	90%
E-bikes	90%	90%

Table S13: Efficiency rate waste management sectors

4. Final demand projection

To project future metal demand for the sectors present in the Exiobase table, a similar approach to Tisserant and Pauliuk[35]used, based on a final demand increase according to GDP growth projections. Regional projections for total GDP growth between 2007 and 2050 were retrieved from the World Energy Outlook 2018 of IEA [10], and had to be broken down from the aggregated sectors. Using the time series for multi-regional final demand for the years 2000 and 2010[36] the tables were aggregated to the 10 regions used in this study. The ratio (R_n) of the final demands (noted for a given year FD_{year}), were calculated as follows for sector n:

$$R_n = \frac{FD_n^{2010}}{FD_n^{2000}} \tag{S34}$$

Assuming that future regional economic development will follow the same trend in the future as in this limited historic period might be misleading, because of new technology but also lifestyle, level of development and income level. To take into account and attenuate those effects, for this study R_n were assumed at the world level ratios.

The increase is calculated for 10 years, it is assumed that the relative yearly increase was:

$$R_n = R_n^{\frac{1}{10}} \tag{S35}$$

In this way, an average historical growth rate for each sector was determined. Then the estimations of future total GDP growth with the historic sector specific growth data are combined.

First, the 2011 final demand vector was projected into the future using the historic sectoral growth ratios (r_n), to determine $FD^{elastic}$. For the "Production of electricity" sectors, the different growth rate for each technology is taken from the IEA projection for each scenario.

Then, the average region-specific GDP growth from the IEA is used to determine the average growth of each sector in each region $FD_n^{GDP,\,t}$. From the historic data the share of growth attributed to sector n was calculated for each scenario:

$$s_n = \frac{FD_n^{elastic}}{\sum_n^{sectors} FD_n^{elastic}} \tag{S36}$$

The sector-specific estimate for final demand $FD'_n$was calculated by distributing a certain amount of the total GDP growth to the sector, using s_n as distribution coefficient of total growth.

$$FD_n^t = FD_n^{2011} \cdot s_n \sum_{n}^{sectors} FD_n^{GDP,t} \tag{S37}$$

These equations provide the model to project the final demand of the background economic sectors. It is considered that there is no final demand for the studied materials as they are only used by industries to produce goods.

5. More scenario assumptions

Wind turbines

Data on the cumulative installed capacities of wind turbines in each region were obtained from WEO2020. Since these scenarios are drawn until 2040, we calculated the average installed capacity growth rate for the period 2011-2040 for each region and used it to derive the scenarios until 2050. Two different Model of WT were considered in this work: the high-speed and mid-speed permanent magnet synchronous generator (PMSG) technologies; the low-speed Direct Drive-PMSG. For more information, please refer to SI.

The market share for the two WT models here considered, have been obtained from the Pavel et al.[43]. Due to data unavailability, the market share of these two wind turbine technologies from 2040 through 2050 has been assumed to remain the same as their market shares for the period 2030-2040. The share of the two different wind turbine models is the same for all the scenarios. Once the scenarios for the installed capacity are developed, it is possible to derive the annual installed capacity using the survival function to estimate how many wind turbines need to be installed to meet the projected demand for WT over the course of the duration of the considered scenario.

Electric cars

IEA projected the number of E-cars deployed globally to reach 140 million under the SDS and 245 million under the SPS at the global level by 2030. To build our scenarios for EPV until 2050, we first projected the world population based on the data provided by the United Nations[1] to estimate global vehicle stock. We assumed a maximum motorization rate (MR) of 471 cars/ 1000 persons for each region by 2050. Based on the historical data on MR[44], we calculated an annual average growth rate for each region to project the MR through 2050. Multiplying the population by the MR, we obtained a projection of car stock in each region from 2011 through 2050. We created an S-shaped curve to represent the adoption of E-cars (i.e., the share of E-cars in total number passenger vehicles) in each region. These adoption curves have been generated based on the historical data on E-cars stocks provided by Global Electric Vehicles Outlook 2020 (GEVO20) of IEA, and the data from the WEO20. In this study we divided the E-cars in two categories: Battery Electric Vehicles (BEV) and Plug-In Hybrid Electric Vehicles (PHEV). The share of BEV and PHEV for the projected scenario were derived from the GEVO20.

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(1) Link: https://population.un.org/wpp/Download/Probabilistic/Population/

Electric Busses

Data on historical and projected stock for 2025 and 2030 were extrapolated from the WEO20 and the GEVO20. We assumed a linear grow rate to forecast the stock of e-busses until 2050. To estimate the annual sales of E-busses we used the survival function to estimate how many E-busses need to be produced to meet the demand over the course of the duration of the considered scenario. As for E-car, we considered 2 different types of E-busses: the Battery Electric Busses (BEB) and the Plug-In Hybrid Electric Busses (PHEB). The share of BEB and PHEB for the scenarios is derived from the GEVO20.

E-bikes

To derive the scenarios for the sales of e-bikes, we assumed a constant growth rate for the e-bike stocks based on the data taken from the WEO 2018[45]. Accordingly, 920 million e-bikes are expected by 2040 under SDS, while this number goes down to 740 million under SPS, and to 500 million under BLS. Data on the e-bike sales between 2011 and 2015 were taken from the Ref.[46]. Calculating the annual growth rate between 2015 and 2040, we simply extended the scenarios until 2050, deriving the annual sales from the stock with the SF.

Table 1 summarizes the scenarios assumed for the analysis. Figures related to the scenarios are presented in SI.

		2011	2019	2030			2040			2050			
				BLS	SPS	SDS	BLS	SPS	SDS	BLS	SPS	SDS	**unit**
E-cars	BEV	0.1	4.8	80.9	81.2	140.0	337.6	335.6	500.0	652.0	659.1	803.7	M units
	PHEV	0.0	4.2	45.6	47.4	64.7	226.3	220.0	295.3	501.5	509.5	616.7	M units
E-busses	BEB	4.3	433.9	2113.8	3217.7	4972.0	5112.9	5925.2	9433.6	7820.4	8632.6	13895.3	t units
	PHEB	0.3	77.6	298.9	3217.7	650.8	552.8	6353.5	1219.8	829.9	9489.3	1788.7	t units
E-bikes		162.0	300.5	377.5	387.9	490.0	433.0	485.9	793.3	556.2	664.8	1334.7	M units
Wind turbine	Inst. Cap.	220.0	622.2	1449.6	1786.0	2539.0	1786.0	2640.0	4167.0	2122.4	3494.0	5795.0	GW
	Model 1	0.0	0.1	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	0.3	%
	Model 2	0.2	0.3	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	0.4	%

Table S14: Scenario information

Recycling scenarios

Among the recycling scenarios developed for this study, only the CR is changed, while the efficiency rate of the disassembler (γ) and the refinery (ε) are kept constant. We considered three scenarios: (i) the Business As Usual (BAU) scenario, where the CR is held constant at 2011 values; (ii) the medium scenario, identified as "R", the CR linearly increases by 50 percent point until 2050, compared with the value in 2011; and (iii) the maximum scenario, identified as "R_100" scenario, the CR is fixed at 100%.

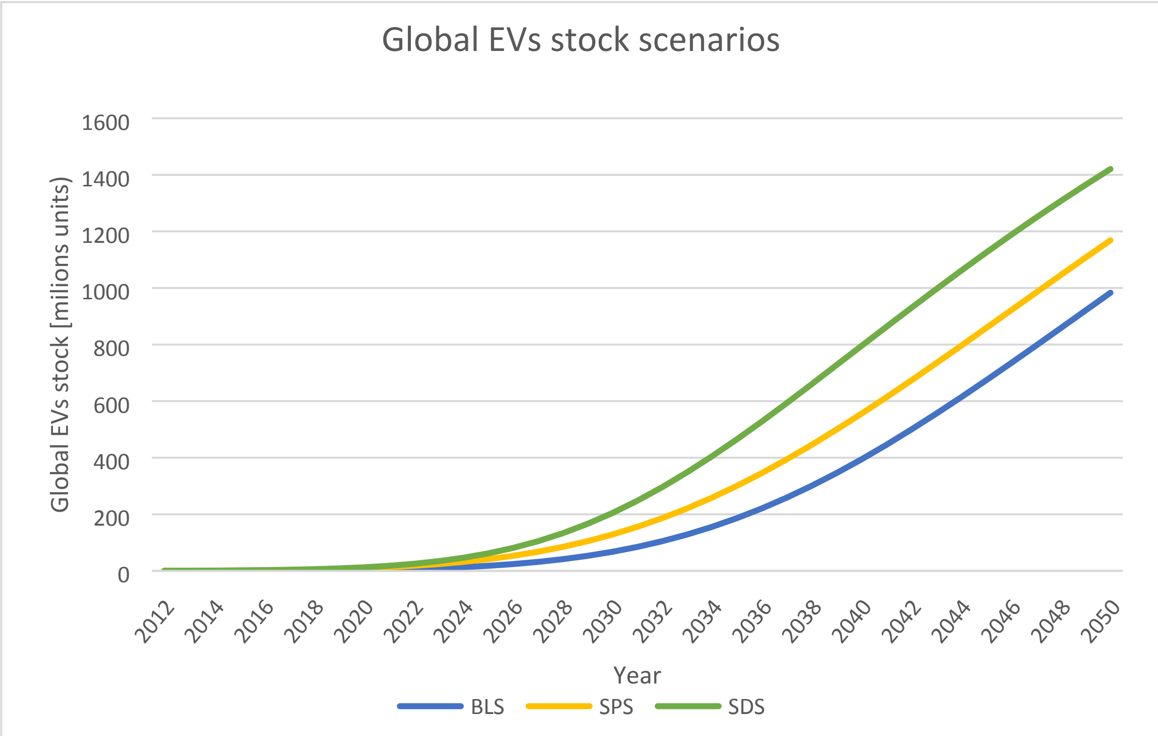

Figure S2: Global EVs stock scenarios

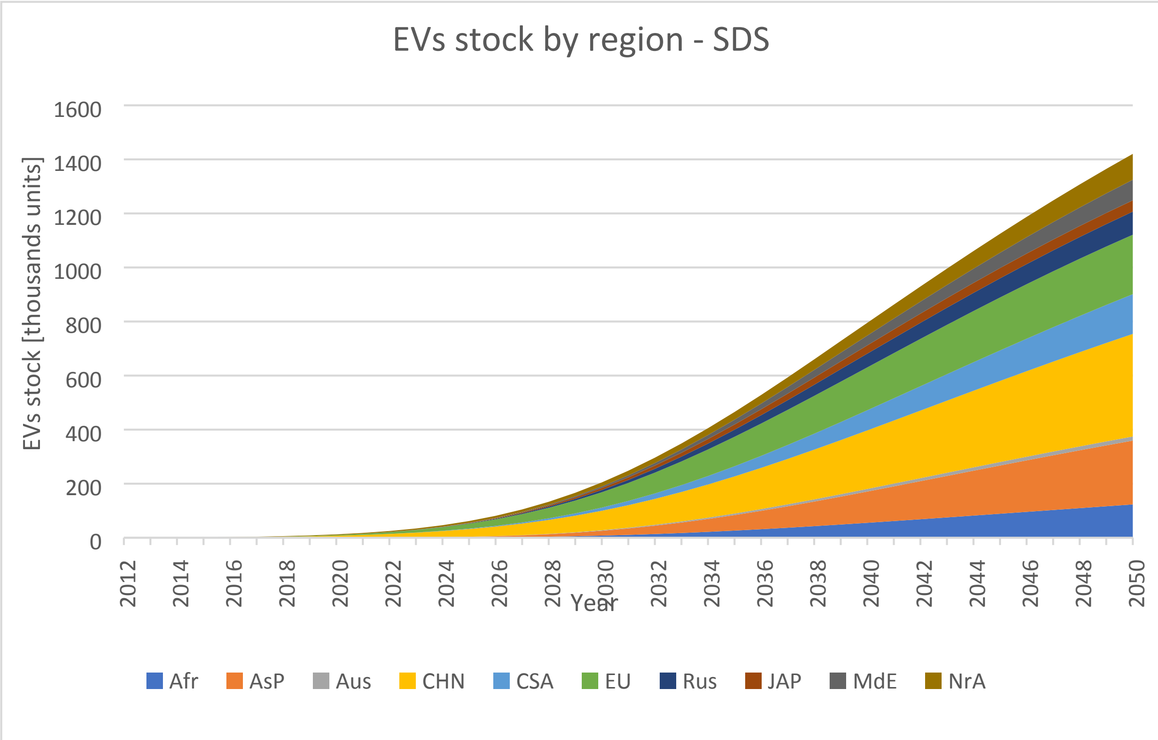

Figure S3: EVs stock by region - SDS

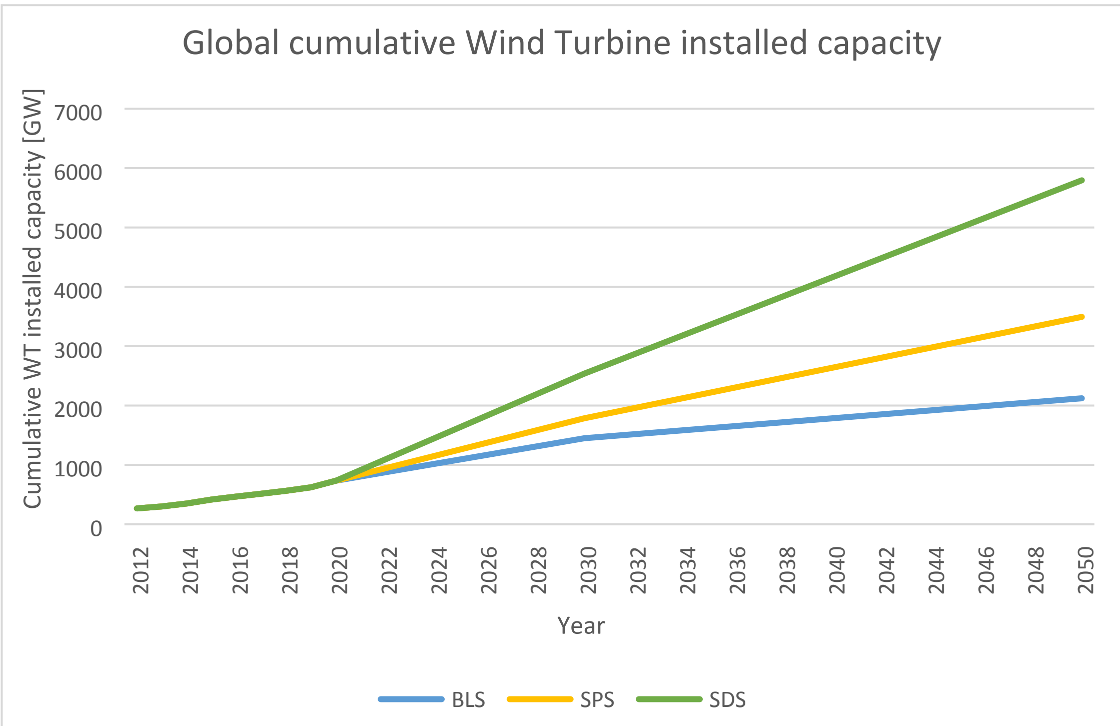

Figure S4: Global cumulative Wind Turbine installed capacity

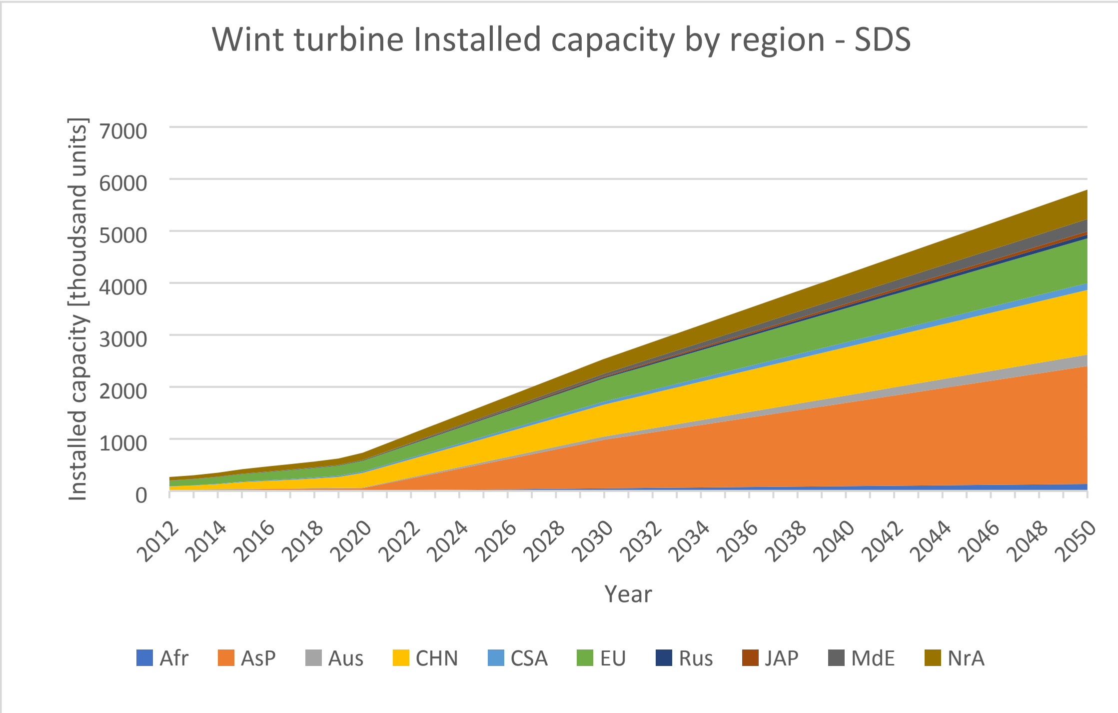

Figure S5: Wind Turibine installed capacity by region - SDS

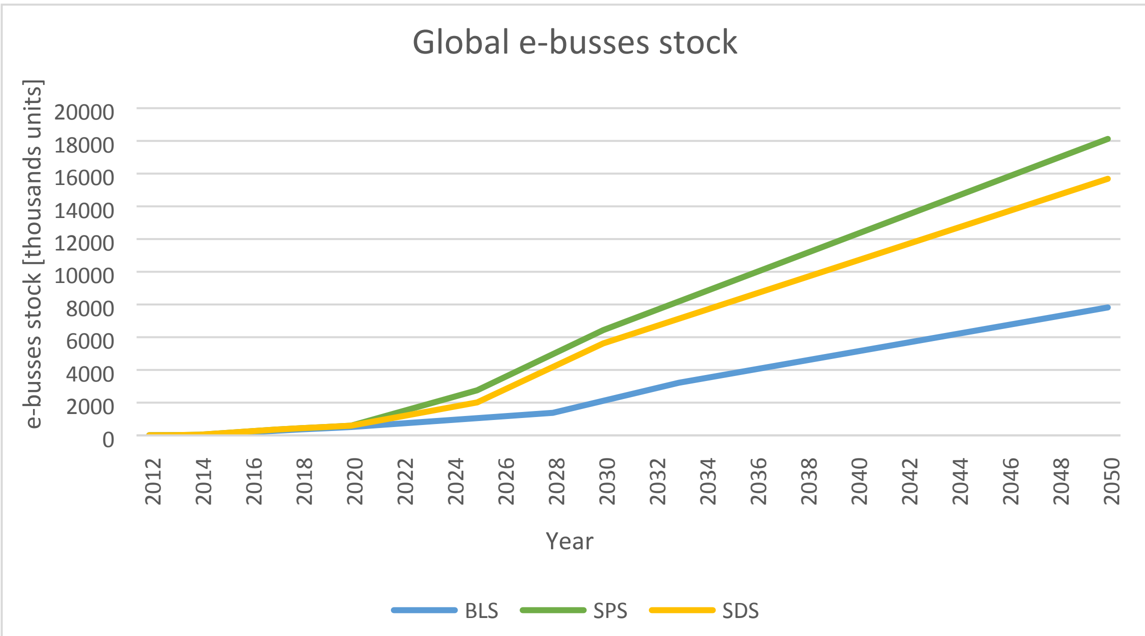

Figure S6: Global e-Busses stock by scenario

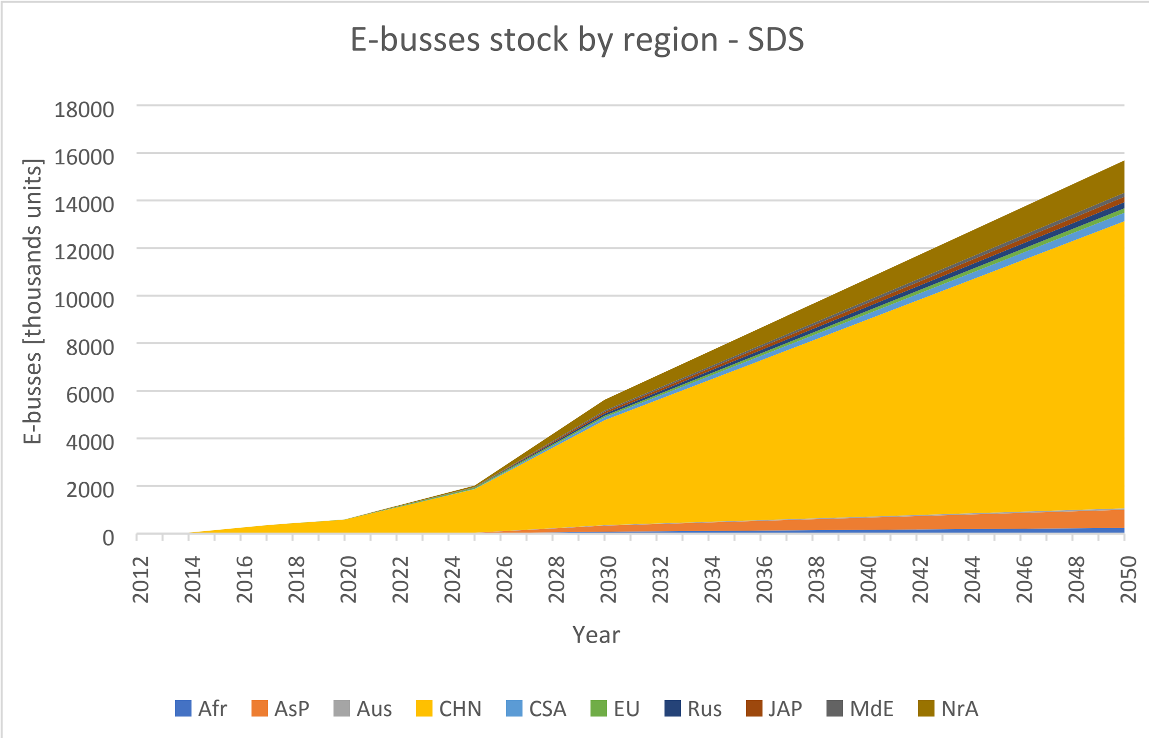

Figure S7: E-busses stokc by region - SDS

6. Additional results

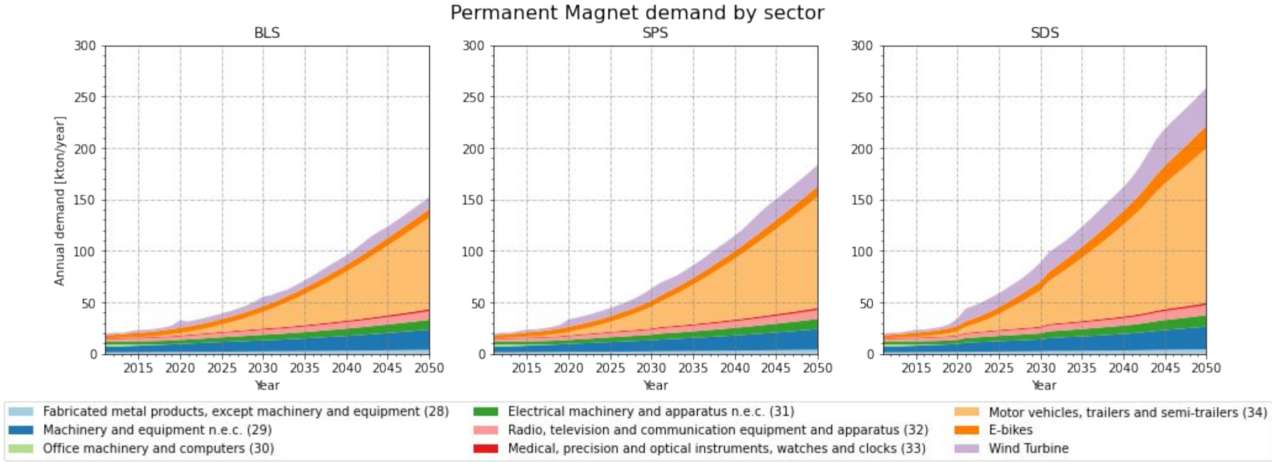

Figure S8: Permanent magnet annual demand by sectors

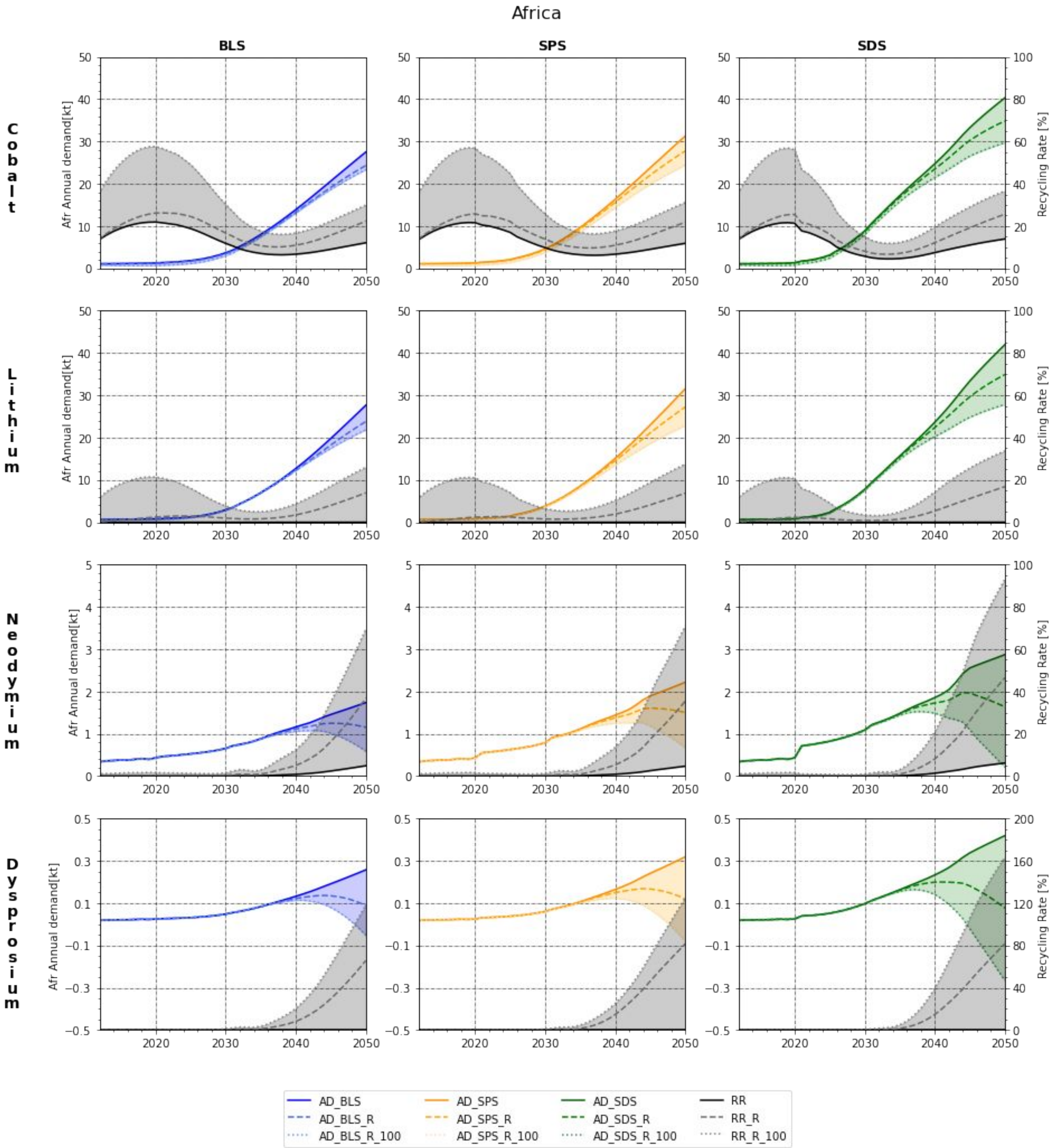

Figure S9: African annual demand & Recycling content Rate.

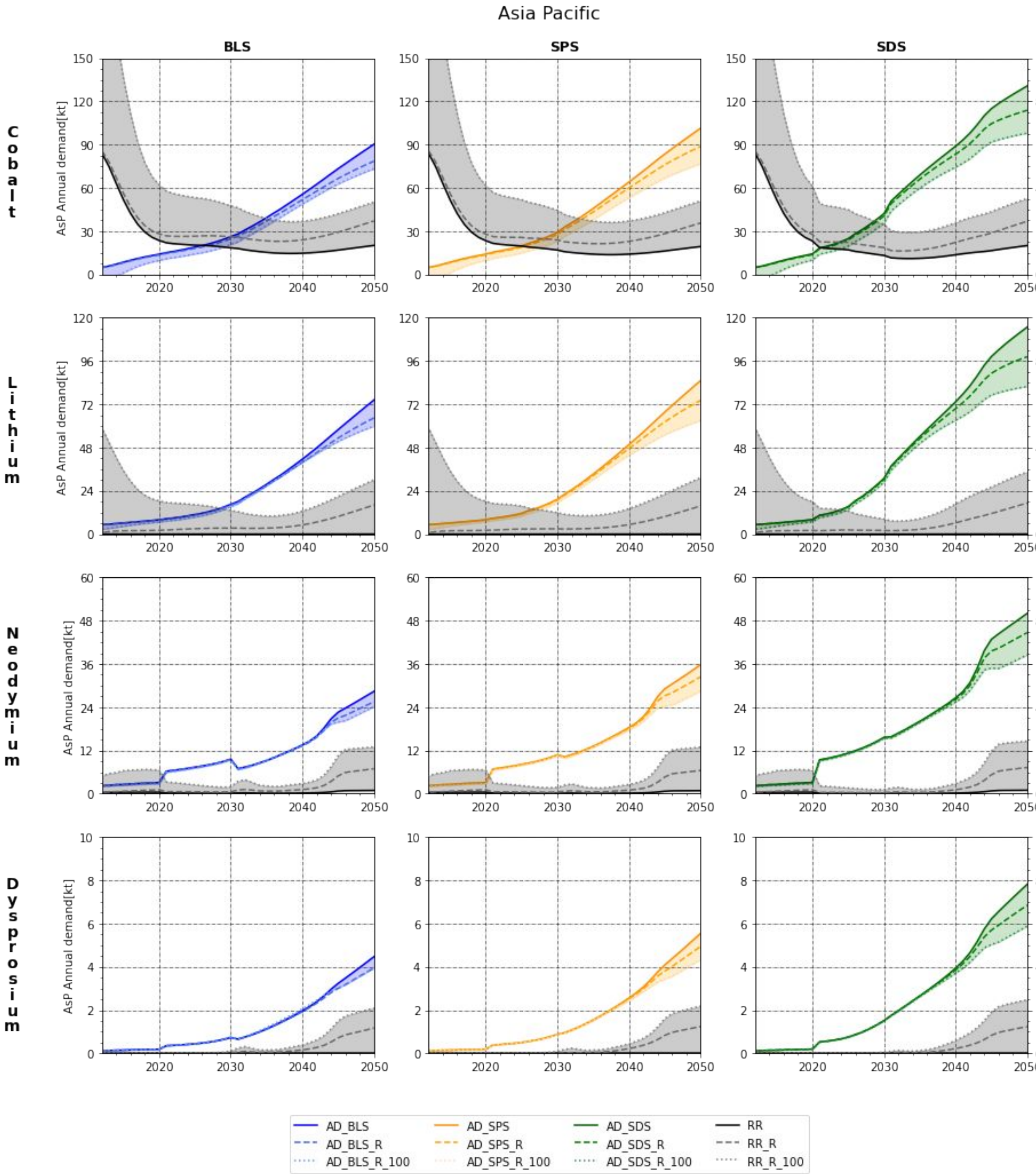

Figure S10: Asian Pacific annual demand & Recycling content Rate.

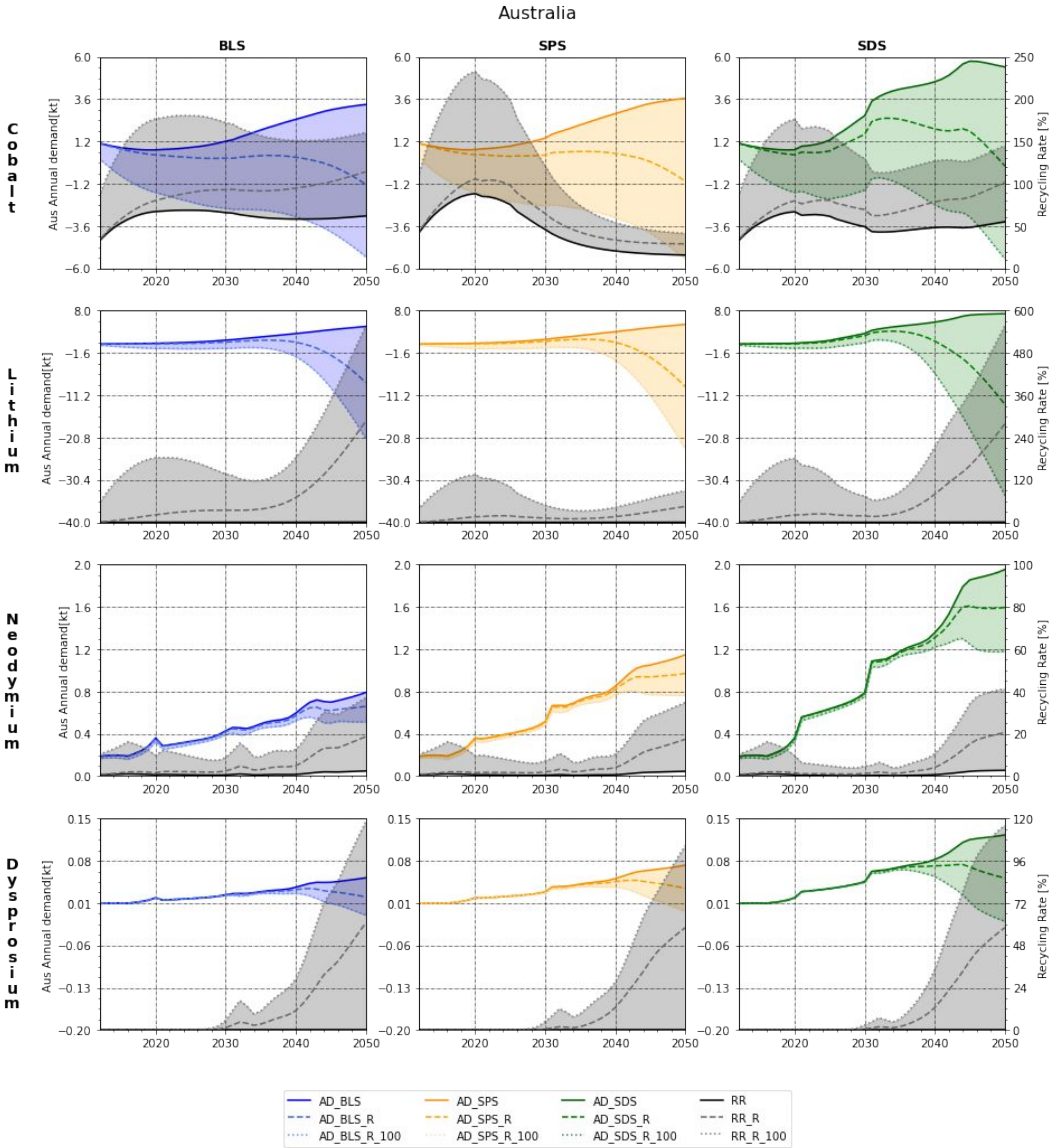

Figure S11: Australian annual demand & Recycling content Rate.

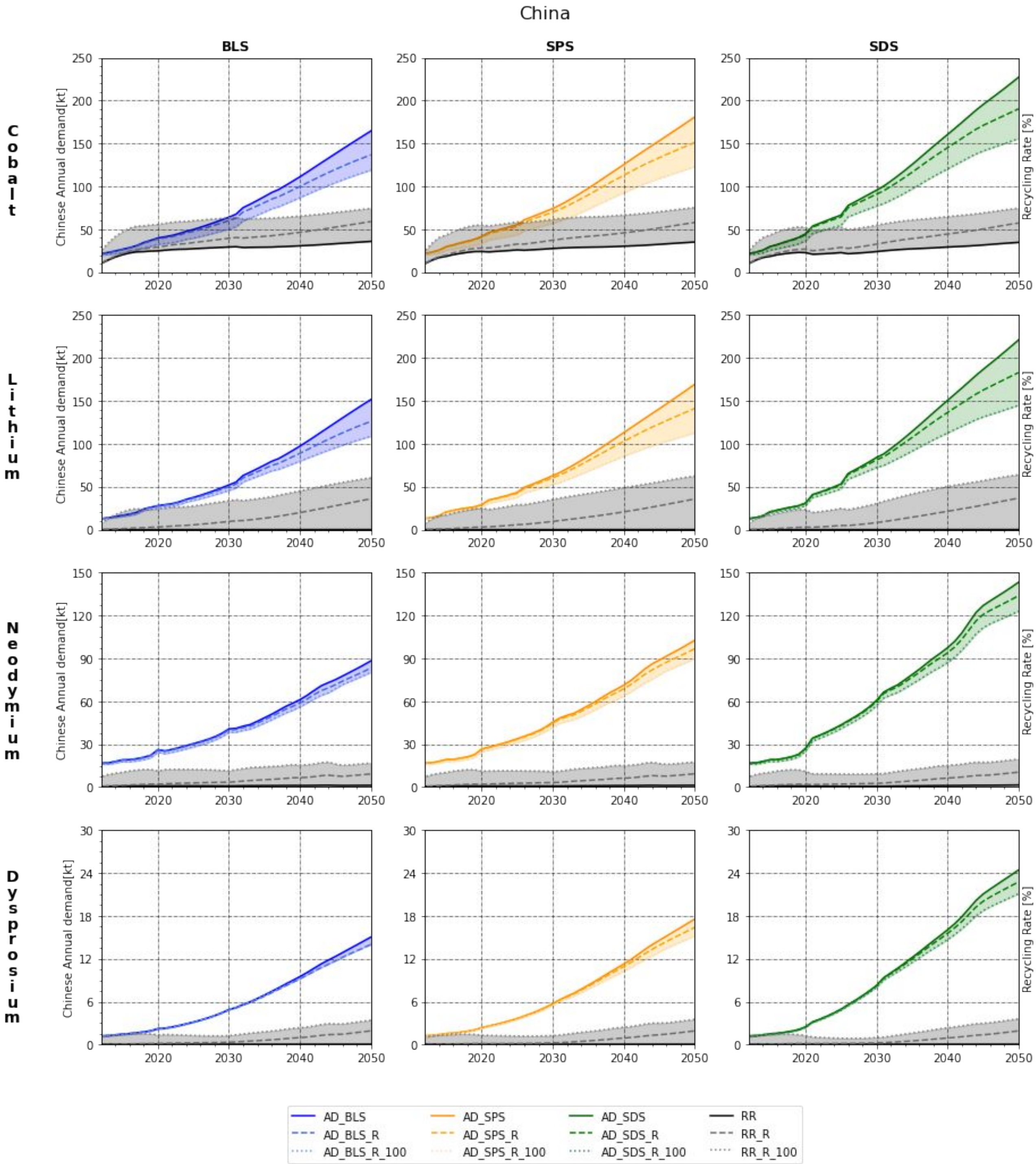

Figure S12: Chinese annual demand & Recycling content Rate.

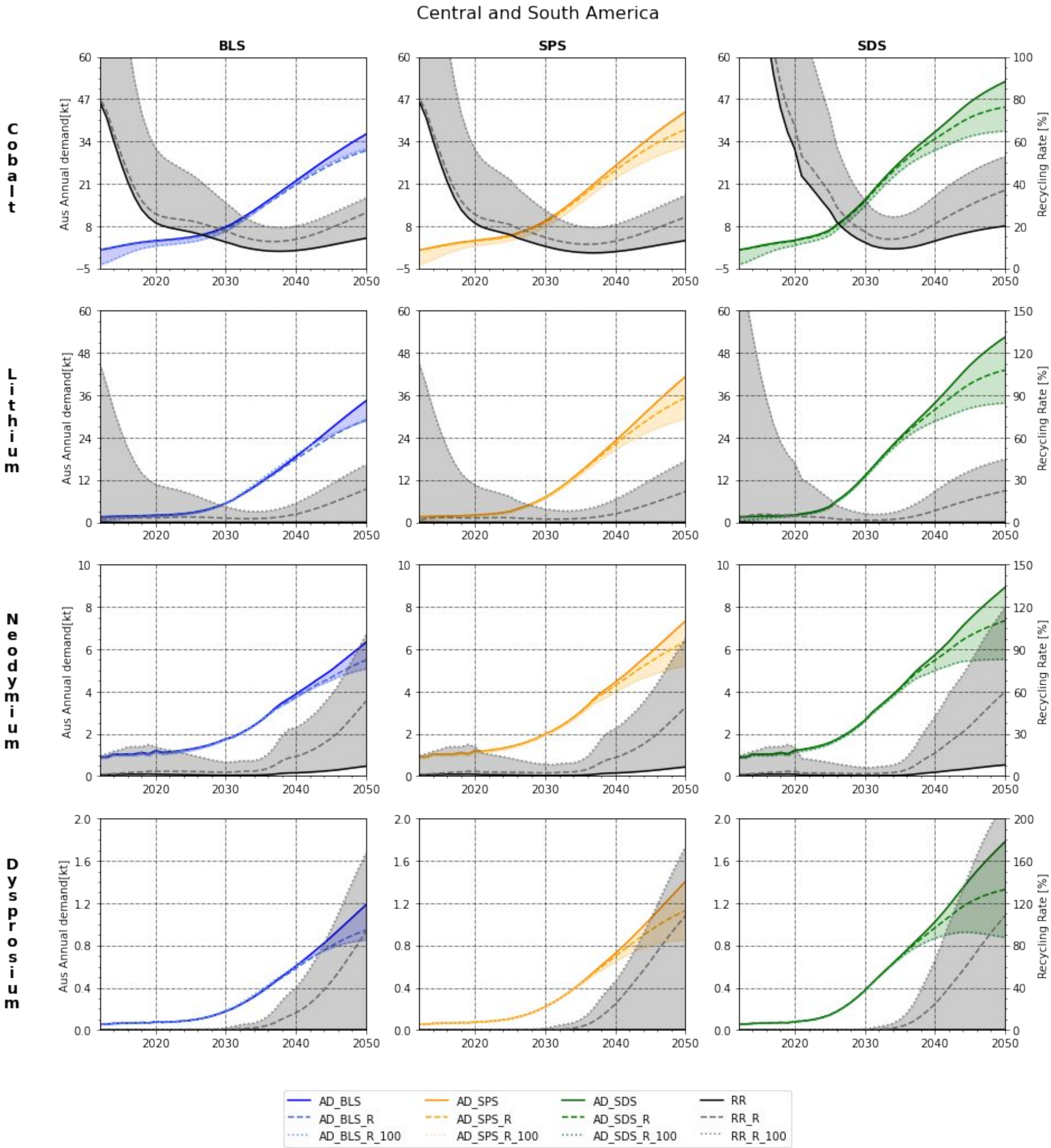

Figure S13: Central and South American annual demand & Recycling content Rate.

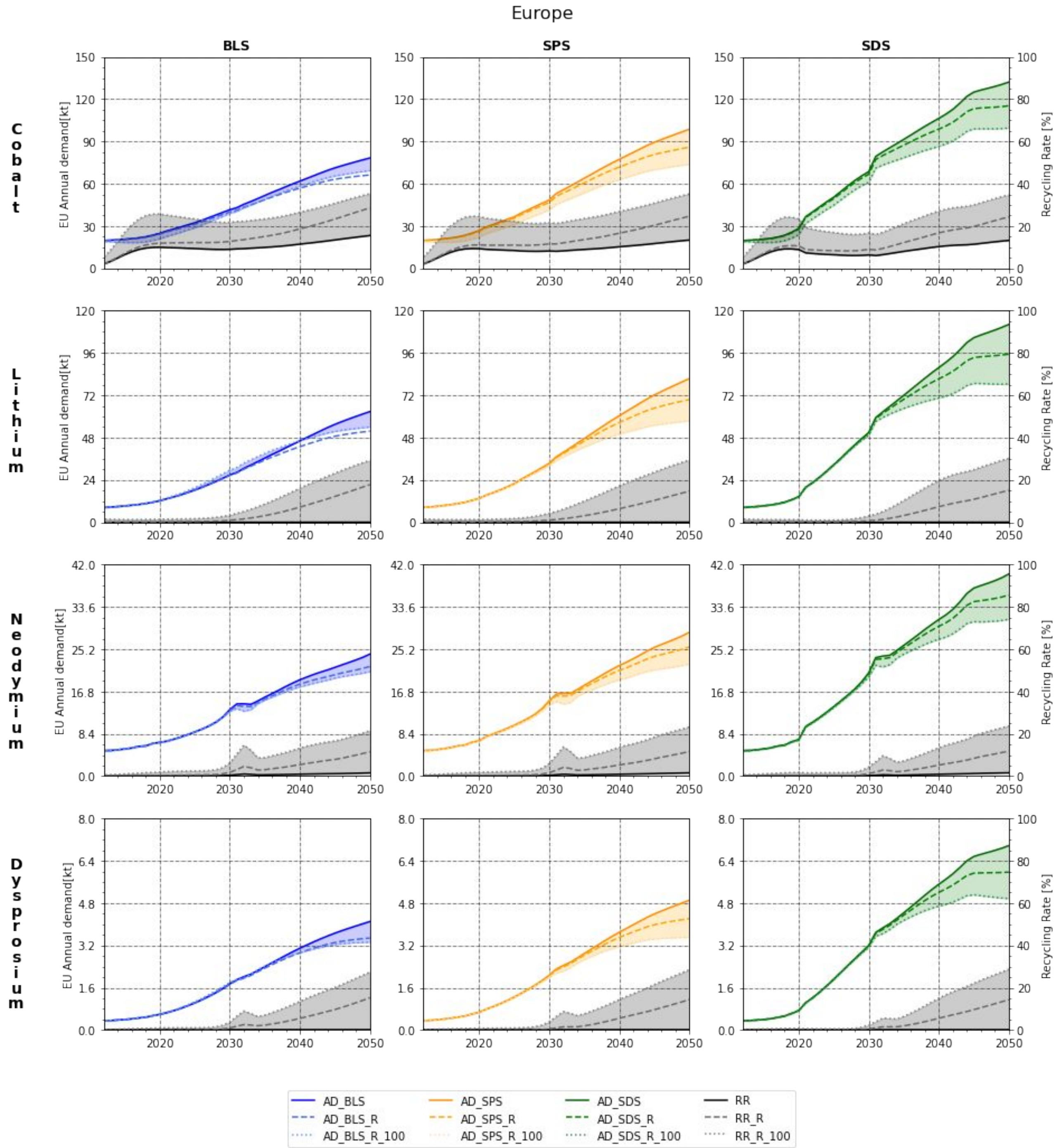

Figure S14: European annual demand & Recycling content Rate.

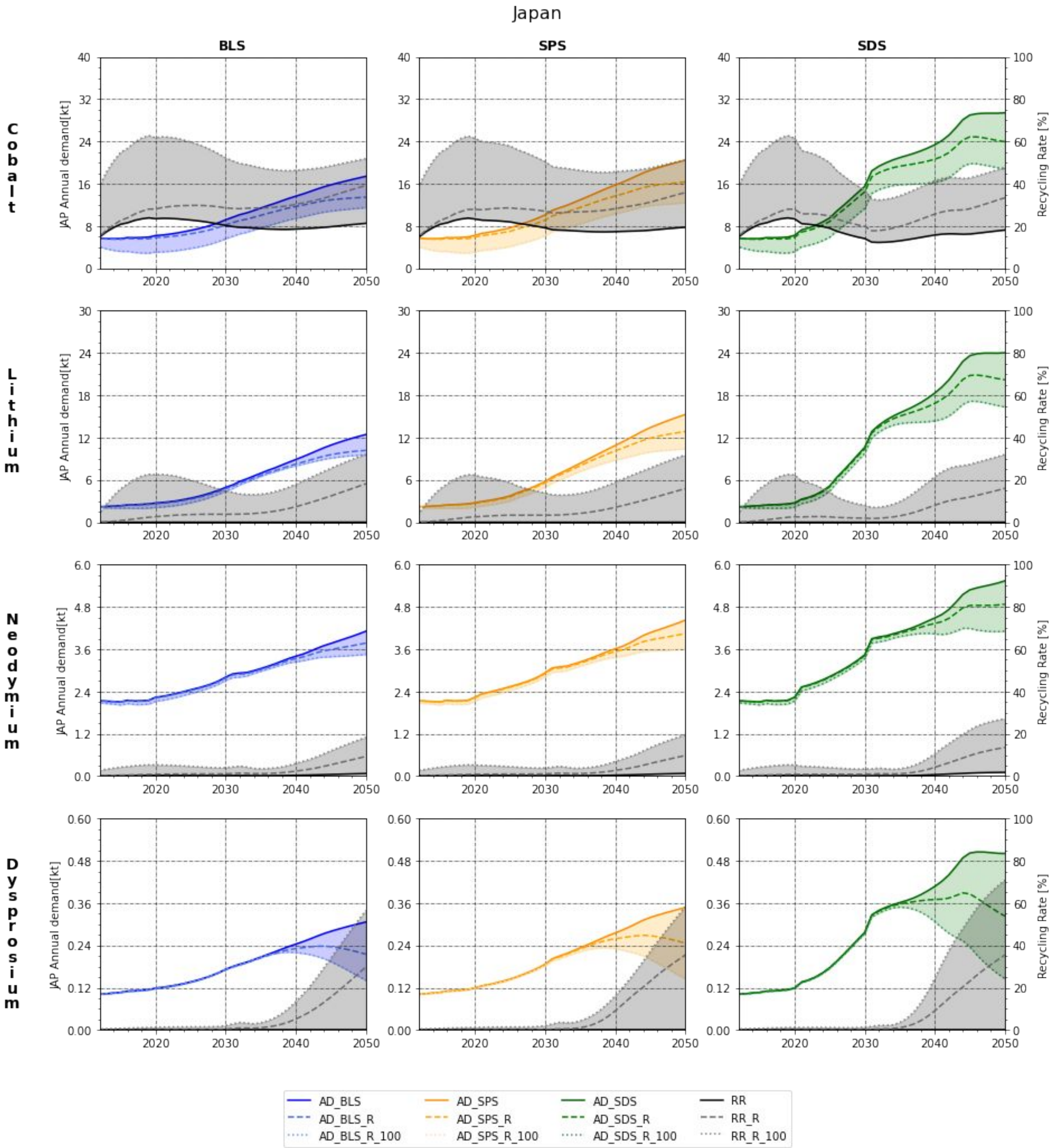

Figure S15: Japanese annual demand & Recycling content Rate.

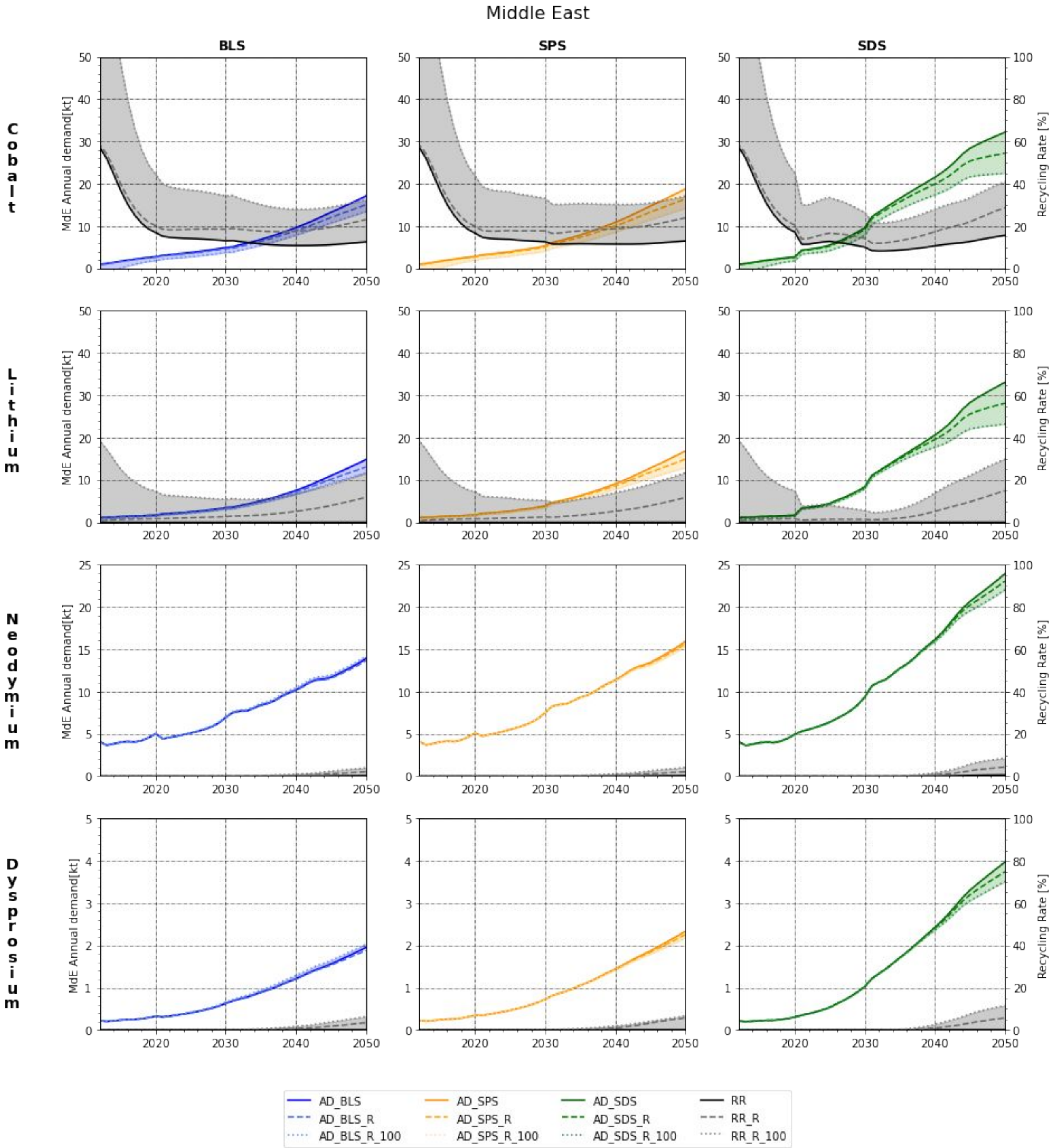

Figure S16: Middle Eastern annual demand & Recycling content Rate.

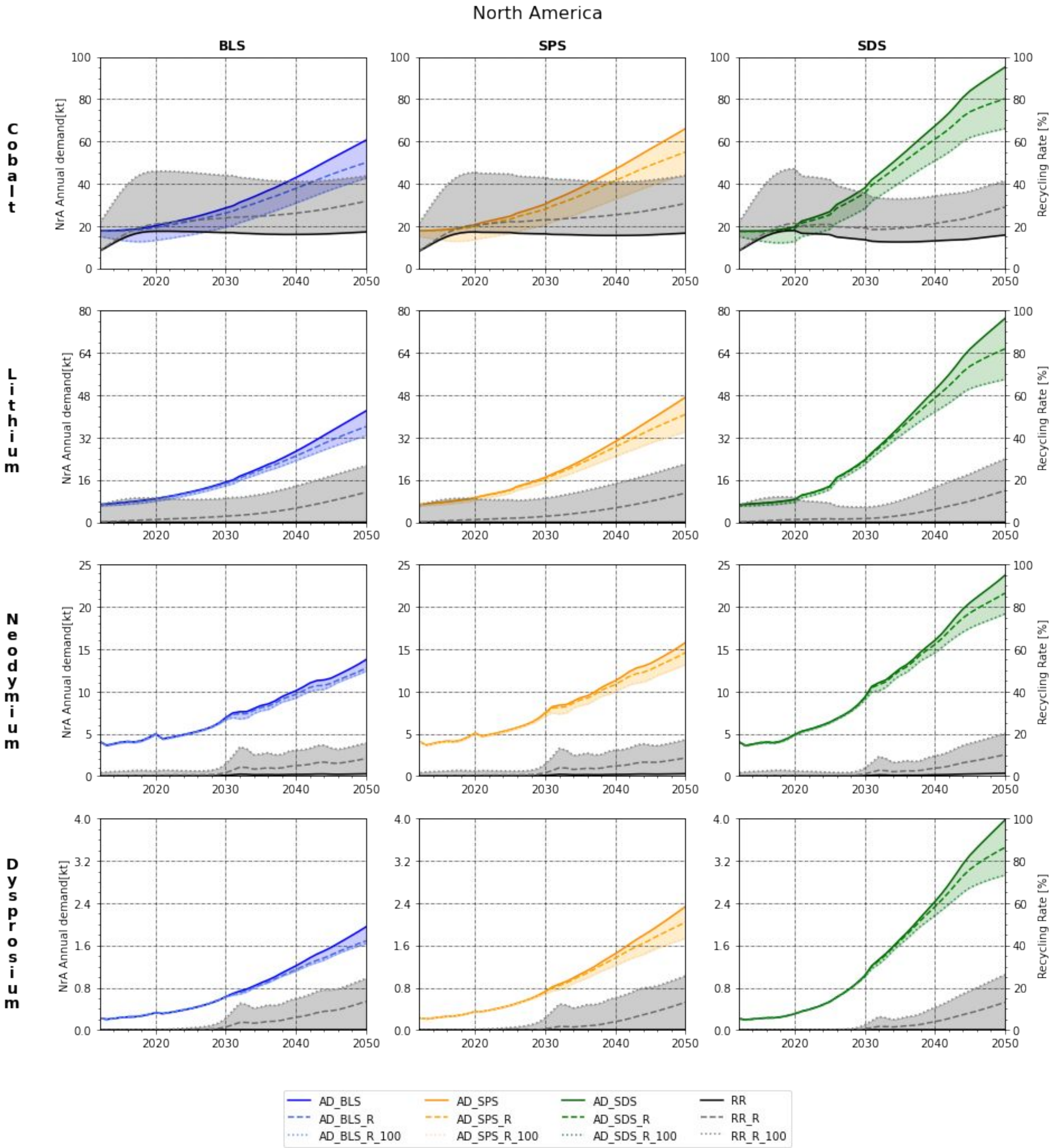

Figure S17: North American annual demand & Recycling content Rate.

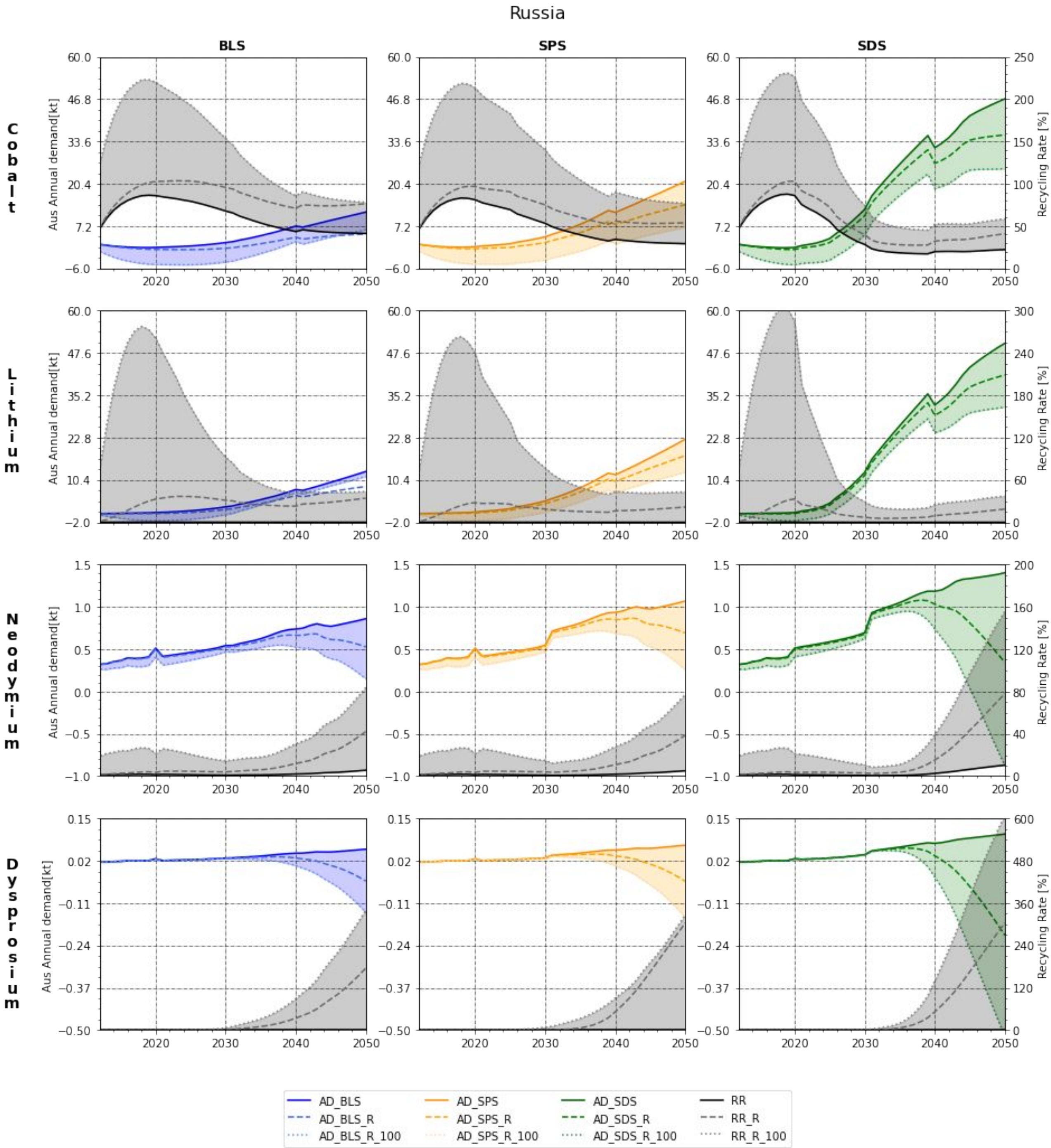

Figure S18: Russian annual demand & Recycling content Rate.

7. Exiobase sector codes

Industry/sector	Exiobase code	Aggregation code
Paddy rice	p01.a	AtB
Wheat	p01.b	AtB
Cereal grains nec	p01.c	AtB
Vegetables, fruit, nuts	p01.d	AtB
Oil seeds	p01.e	AtB
Sugar cane, sugar beet	p01.f	AtB
Plant-based fibers	p01.g	AtB
Crops nec	p01.h	AtB
Cattle	p01.i	AtB
Pigs	p01.j	AtB
Poultry	p01.k	AtB
Meat animals nec	p01.l	AtB
Animal products nec	p01.m	AtB
Raw milk	p01.n	AtB
Wool, silk-worm cocoons	p01.o	AtB
Manure (conventional treatment)	p01.w.1	AtB
Manure (biogas treatment)	p01.w.2	AtB
Products of forestry, logging and related services (02)	p02	AtB
Fish and other fishing products; services incidental of fishing (05)	p05	AtB
Coal, lignite and peat	p10	C.1
Crude petroleum and services related to crude oil extraction, excluding surveying	p11.a	C.2
Natural gas and services related to natural gas extraction, excluding surveying; inclulding liquid gas	p11.2	C.3
Other Hydrocarbons	p11.c	C.3
Uranium and thorium ores (12)	p12	C.4

Iron ores	p13.1	C.4
Copper ores and concentrates	p13.20.11	C.4
Nickel ores and concentrates	p13.20.12	C.4
Aluminium ores and concentrates	p13.20.13	C.4
Precious metal ores and concentrates	p13.20.14	C.4
Lead, zinc and tin ores and concentrates	p13.20.15	C.4
Other non-ferrous metal ores and concentrates	p13.20.16	C.4
Stone	p14.1	C.4
Sand and clay	p14.2	C.4
Chemical and fertilizer minerals, salt and other mining and quarrying products n.e.c.	p14.3	C.4
Products of meat cattle	p15.a	C.5
Products of meat pigs	p15.b	C.5
Products of meat poultry	p15.c	C.5
Meat products nec	p15.d	C.5
products of Vegetable oils and fats	p15.e	C.5
Dairy products	p15.f	C.5
Processed rice	p15.g	C.5
Sugar	p15.h	C.5
Food products nec	p15.i	C.5
Beverages	p15.j	C.5
Fish products	p15.k	C.5
Tobacco products (16)	p16	C.6
Textiles (17)	p17	C.6
Wearing apparel; furs (18)	p18	C.6
Leather and leather products (19)	p19	C.6
Wood and products of wood and cork (except furniture); articles of straw and plaiting materials (20)	p20	C.6
Wood material for treatment, Re-processing of secondary wood material into new wood material	p20.w	C.6
Pulp	p21.1	C.6

Secondary paper for treatment, Re-processing of secondary paper into new pulp	p21.w.1	C.6
Paper and paper products	p21.2	C.6
Printed matter and recorded media (22)	p22	C.6
Coke oven products	p23.1	D.1
Refined Petroleum	p23.2	D.2
Nuclear fuel	p23.3	D.3
Plastics, basic	p24.a	D.4
Secondary plastic for treatment, Re-processing of secondary plastic into new plastic	p24.a.w	D.4
N-fertiliser	p24.b	D.4
P- and other fertiliser	p24.c	D.4
Chemicals nec; additives and biofuels	p24.4	m.24.d
Rubber and plastic products (25)	p25	m.25
Glass and glass products	p26.a	m.26.a
Secondary glass for treatment, Re-processing of secondary glass into new glass	p26.w.1	D.4
Ceramic goods	p26.b	m.26.b
Bricks, tiles and construction products, in baked clay	p26.c	D.4
Cement, lime and plaster	p26.d	D.4
Ash for treatment, Re-processing of ash into clinker	p26.d.w	D.4
Other non-metallic mineral products	p26.e	D.4
Basic iron and steel and of ferro-alloys and first products thereof	p27.a	m.27.a
Secondary steel for treatment, Re-processing of secondary steel into new steel	p27.a.w	D.4
Precious metals	p27.41	D.4
Secondary preciuos metals for treatment, Re-processing of secondary preciuos metals into new preciuos metals	p27.41.w	D.4
Aluminium and aluminium products	p27.42	m.27.42

Secondary aluminium for treatment, Re-processing of secondary aluminium into new aluminium	p27.42.w	D.4
Lead, zinc and tin and products thereof	p27.43	D.4
Secondary lead for treatment, Re-processing of secondary lead into new lead	p27.43.w	D.4
Copper products	p27.44	D.4
Secondary copper for treatment, Re-processing of secondary copper into new copper	p27.44.w	D.4
Other non-ferrous metal products	p27.45	m.27.45
Secondary other non-ferrous metals for treatment, Re-processing of secondary other non-ferrous metals into new other non-ferrous metals	p27.45.w	D.4
Foundry work services	p27.5	D.4
Fabricated metal products, except machinery and equipment (28)	p28	m.28
Machinery and equipment n.e.c. (29)	p29	m.29
Office machinery and computers (30)	p30	m.30
Electrical machinery and apparatus n.e.c. (31)	p31	m.31
Radio, television and communication equipment and apparatus (32)	p32	m.32
Medical, precision and optical instruments, watches and clocks (33)	p33	m.33
Motor vehicles, trailers and semi-trailers (34)	p34	m.34
Other transport equipment (35)	p35	D.4
Furniture; other manufactured goods n.e.c. (36)	p36	D.4
Secondary raw materials	p37	D.4
Bottles for treatment, Recycling of bottles by direct reuse	p37.w.1	D.4
Electricity by coal	p40.11.a	E.1.a
Electricity by gas	p40.11.b	E.1.b
Electricity by nuclear	p40.11.c	E.1.c
Electricity by hydro	p40.11.d	E.1.d

Electricity by wind	p40.11.e	E.1.e
Electricity by petroleum and other oil derivatives	p40.11.f	E.1.f
Electricity by biomass and waste	p40.11.g	E.1.g
Electricity by solar photovoltaic	p40.11.h	E.1.h
Electricity by solar thermal	p40.11.i	E.1.i
Electricity by tide, wave, ocean	p40.11.j	E.1.j
Electricity by Geothermal	p40.11.k	E.1.k
Electricity nec	p40.11.l	E.1.l
Transmission services of electricity	p40.12	O
Distribution and trade services of electricity	p40.13	O
Biogasand gas; distribution of gaseous fuels through mains	p40.2	D.4
Steam and hot water supply services	p40.3	D.4
Collected and purified water, distribution services of water (41)	p41	O
Construction work (45)	p45	D.4
Secondary construction material for treatment, Re-processing of secondary construction material into aggregates	p45.w	D.4
Sale, maintenance, repair of motor vehicles, motor vehicles parts, motorcycles, motor cycles parts and accessoiries	p50.a	O
Retail trade services of motor fuel	p50.b	O
Wholesale trade and commission trade services, except of motor vehicles and motorcycles (51)	p51	O
Retail trade services, except of motor vehicles and motorcycles; repair services of personal and household goods (52)	p52	O
Hotel and restaurant services (55)	p55	O
Railway transportation services	p60.1	I
Other land transportation services	p60.2	I
Transportation services via pipelines	p60.3	I

Table S15: Exiobase sector classification, with sector aggregation

Symbol	Name	Aggregation code
AT	Austria	EU
BE	Belgium	EU
BG	Bulgaria	EU
CY	Cyprus	EU
CZ	Czech Republic	EU
DE	Germany	EU
DK	Denmark	EU
EE	Estonia	EU
ES	Spain	EU
FI	Finland	EU
FR	France	EU
GR	Greece	EU
HR	Croatia	EU
HU	Hungary	EU
IE	Ireland	EU
IT	Italy	EU
LT	Lithuania	EU
LU	Luxembourg	EU
LV	Latvia	EU
MT	Malta	EU
NL	Netherlands	EU
PL	Poland	EU
PT	Portugal	EU
RO	Romania	EU
SE	Sweden	EU
SI	Slovenia	EU
SK	Slovakia	EU
GB	United Kingdom	EU
US	United States	NrA

JP	Japan	JAP
CN	China	CHN
CA	Canada	NrA
KR	South Korea	AsP
BR	Brazil	CSA
IN	India	AsP
MX	Mexico	NrA
RU	Russia	Eur
AU	Australia	Aus
CH	Switzerland	EU
TR	Turkey	Eur
TW	Taiwan	AsP
NO	Norway	EU
ID	Indonesia	AsP
ZA	South Africa	Afr
WA	RoW Asia and Pacific	AsP
WL	RoW America	CSA
WE	RoW Europe	EU
WF	RoW Africa	Afr
WM	RoW Middle East	MdE

Table S16: Regional classification of Exiobase and regional aggregations of this study

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