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Toward prospective dynamic criticality and resilience data**

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System dynamics modeling of the global nickel supply system at a mine-level resolution

Toward prospective dynamic criticality and resilience data

Jessie E. Bradley¹  | Willem L. Auping¹  | René Kleijn³  | Jan H. Kwakkel¹  |
Gavin M. Mudd⁴  | Benjamin Sprecher² 

¹Faculty of Technology, Policy and Management, TU Delft, Delft, The Netherlands

²Faculty of Industrial Design Engineering, TU Delft, Delft, The Netherlands

³Institute of Environmental Science, Leiden University, Leiden, The Netherlands

⁴British Geological Survey, Critical Minerals Intelligence Centre, Nottingham, UK

Correspondence

Jessie Bradley, Faculty of Technology, Policy and Management, TU Delft, Delft, The Netherlands. Email: J.E.Bradley@tudelft.nl

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Abstract

Securing the availability of enough metals to fulfill demand is a critical societal concern. Models of metal supply systems can help enhance our understanding of these systems and identify strategies to reduce material criticality and improve resilience. In this work, we introduce a novel approach to modeling metal supply systems, using nickel as a case study. Our approach combines system dynamics modeling, in which various feedback loops influence future outcomes, with the higher sectoral and geographical detail of industrial ecology (IE) methods and data on individual mines. We also include extensive uncertainty analyses through exploratory modeling and analysis. Using this combined modeling approach, we explore the development and resilience of the global nickel supply system between 2015 and 2060 under various uncertainties and policy levers. Our results show that incorporating feedback effects leads to more realistic demand behavior and resource depletion patterns compared to traditional dynamic material flow analysis. Market feedback enhances resilience, but cannot fully offset criticality risks. Sectoral disaggregation reveals increased criticality risks due to the energy transition, which can be mitigated by increasing opportunities for substitution, product lifetime extension, recycling, exploration, capacity expansion, and by-product recovery. Geographical disaggregation highlights the resilience benefits of diverse supply sources, as well as the effects of changing regional market shares on sustainability impacts, ore grade variability, and by-product dynamics. Our combined modeling approach is a step toward prospective, dynamic criticality assessment, in which system changes and future risks are accounted for when determining material criticality and policy recommendations.

KEYWORDS

critical materials, exploratory modeling and analysis, industrial ecology, nickel, prospective, system dynamics

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1 | INTRODUCTION

Securing a sustainable metal supply to meet demand is a critical societal concern, both short term and long term. In the short term, disruptions such as COVID-19 and the war in Ukraine have significantly stressed supply chains (Jowitt, 2020; Khurshid et al., 2023; van der Nest & van Vuuren, 2023). In the long term, pressures arise from increasing metal demand due to population growth, rising affluence, and socio-technological developments such as the energy transition. These factors are expected to further strain supply chains and exacerbate sustainability impacts (Sprecher & Kleijn, 2021; Watari et al., 2020, 2021; Zhang et al., 2022).

Nickel is of particular concern for the energy transition, as it is used in stainless steel for energy infrastructure, and in many batteries (Bloomberg New Energy Finance [BNEF], 2019; Nickel Institute, n.d.). Nickel was not considered critical (indicating both high economic importance and high supply risk) in most material criticality assessments (Schrijvers et al., 2020). However, criticality assessments are generally static snapshots that focus on the short term (Ioannidou et al., 2019), and multiple studies have indicated potential future nickel supply risks due to the energy transition (e.g., Moreau et al., 2019; Tokimatsu et al., 2018; Valero et al., 2018; Watari et al., 2018). Reflecting these future risks, the European Union classified nickel as a strategic metal (European Commission [EC], 2023a, 2023b).

Metal supply chains are part of highly complex systems. Such systems consist of multiple sub-systems, including metal demand, primary supply, secondary supply (recycling), price, and sustainability impacts, interconnected through various feedback loops (Auping et al., 2012; Bradley, 2021). Modeling can help grasp the complexity of these systems and make them easier to understand (Sterman, 1994), which allows for better identification of future risks and strategies for improving resilience.

Prospective metal supply system models vary in their complexity. Relatively simple demand projection models provide insight into potential future demand development and risks given current production, reserves, and resources. These models project significant increases in metal demand due to the energy transition (Liang et al., 2022; Watari et al., 2020, 2021; Zhang et al., 2022).

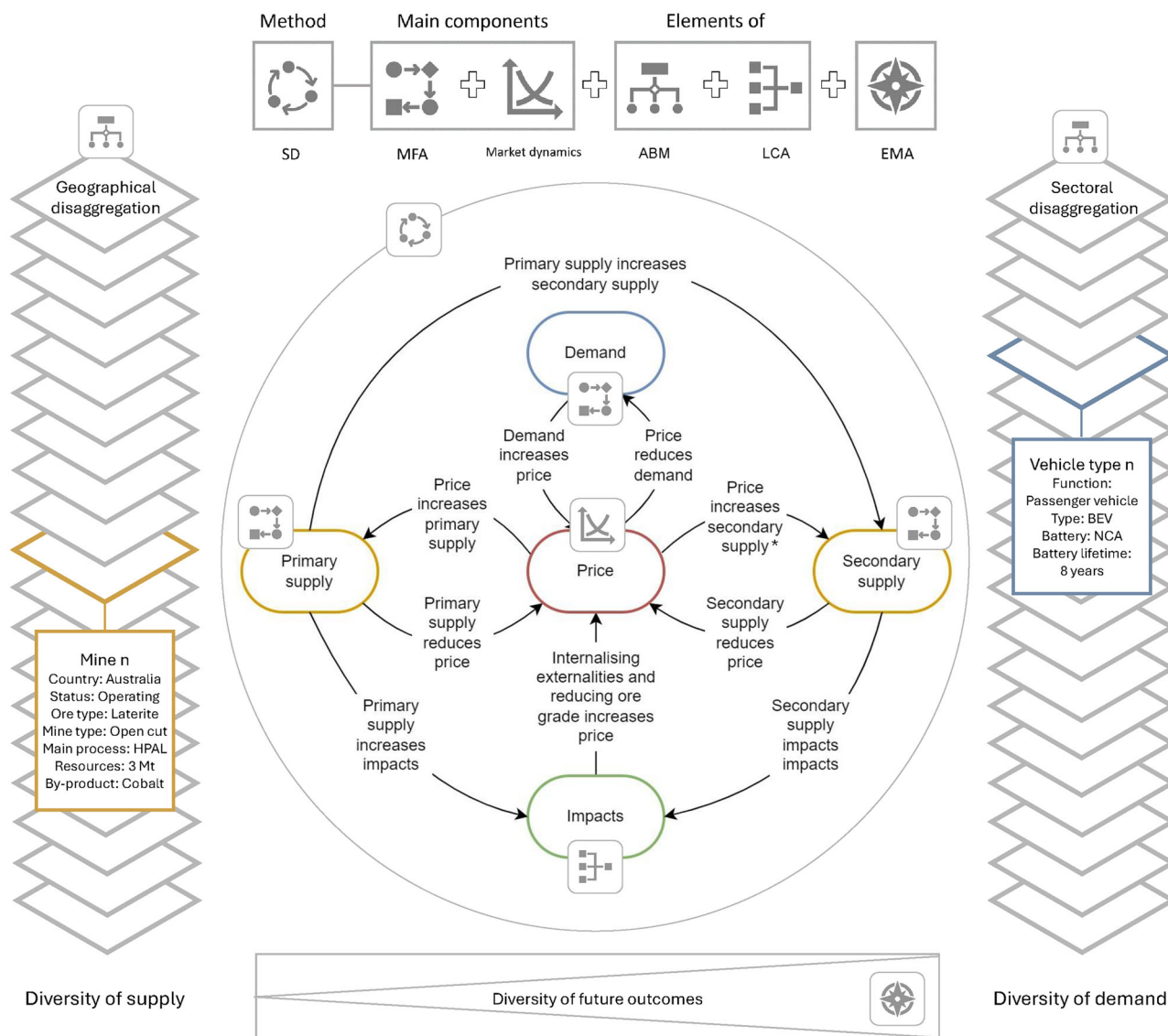
More detailed models include those based on the industrial ecology (IE) tools of material flow analysis (MFA), life cycle assessment (LCA), and environmentally extended input–output analysis (EE-IOA). These methods have traditionally been used mostly retrospectively (Muller et al., 2014; Pauliuk & Hertwich, 2016), but are increasingly employed for prospective modeling (e.g., de Koning et al., 2018; Elshkaki et al., 2016; Harpprecht et al., 2021). In addition to demand, these models include other elements of metal supply systems, such as primary supply, secondary supply, stocks, and sustainability impacts. However, they often overlook feedback effects between sub-systems.

More comprehensive models, such as system dynamics (SD) models, consider the entire system and its delays and feedback loops. These models show that price feedbacks can help reduce demand and increase supply in times of scarcity (e.g., Choi et al., 2016; Glöser-Chahoud et al., 2016; van Vuuren et al., 1999). Some SD models assume fixed resources (e.g., Sverdrup et al., 2017), while others account for resource expansion with rising prices (e.g., Auping et al., 2012). Although SD models generally consider a broader set of dynamics, they are often less detailed than IE models (Walzberg et al., 2021), and tend to treat all mines as a single “global mine” (e.g., Auping et al., 2012; van der Linden, 2020; van Vuuren et al., 1999). However, the heterogeneity among mines can lead to different behavior in disaggregated systems. Capturing these dynamics can provide a clearer picture of potential future developments in demand, supply, price, and sustainability impacts. Furthermore, understanding regional differences can better inform decision-making.

Combining the detail of IE with the comprehensiveness of SD can address several knowledge gaps in current prospective metal supply system models. These gaps include the underrepresentation of physical material flows combined with sustainability impacts and market mechanisms (Glöser-Chahoud, 2023; Helbig, 2023; Walzberg et al., 2021; Watari et al., 2020), the dynamic nature of resources, reserves, and ore grade (Northey et al., 2018), exploration and mining capacity limitations (Helbig, 2023), feedback loops impacting recycling (Helbig, 2023), inclusion of circularity improvements other than recycling (Helbig, 2023; Liang et al., 2022; Watari et al., 2020, 2021), inclusion of elemental linkages (Watari et al., 2020, 2021), and local sustainability aspects in global assessments (Northey et al., 2018). Additionally, there are calls for increased prospective, dynamic criticality assessment (Ioannidou et al., 2019; Knoeri et al., 2013).

Addressing these gaps provides a more realistic representation of metal supply systems, enabling better insight into supply risks and more effective decision-making. Song et al. (2022) previously demonstrated the benefits of integrating SD and IE for understanding critical material dynamics. Supply security depends on economic and geopolitical factors, requiring a model that endogenously connects demand, primary supply, secondary supply, price, and sustainability impacts, at a high geographical and sectoral resolution. We could not find any models including all these elements. Models that come closest include agent-based models (e.g., Cao et al., 2021; Riddle et al., 2021) and models by Rahimpour Golroudbary et al. (2023), Nguyen et al. (2021), and Northey et al. (2023). However, these models either exclude sustainability impacts or economics, or rely on hypothetical data.

In this work, we present a detailed SD model, that explores metal supply system dynamics at the level of individual mines, in a case study on nickel. The aim of our research is to explore the potential development of the global nickel supply system between 2015 and 2060 under various uncertainties and policy levers. We focus on the effects of including feedback loops combined with sectoral and geographical disaggregation, and the implications this has for criticality and resilience.



Legend: SD = System Dynamics, MFA = Material Flow Analysis, ABM = Agent-Based Modelling, LCA = Life-Cycle Assessment, EMA = Exploratory Modelling and Analysis, HPAL = High Pressure Acid Leaching, Mt = Megatonne, BEV = Battery Electric Vehicle, NCA = Nickel Cobalt Aluminium. *Included indirectly

FIGURE 1 Overview of the detail and comprehensiveness included in the model. Top: methods combined in the model. Middle: sub-system diagram (SSD) showing demand (blue), supply (orange), economics (red), and sustainability impacts (green), and their relationships, highlighting the comprehensiveness added by system dynamics. The icons indicate the focus of the individual methods. Left and right: geographical and sectoral layers (subscripts) representing model detail. Bottom: representation of the diverse futures explored using exploratory modelling and analysis. Note: Only elements of agent-based models and life cycle assessment are included, not the full methodologies.

2 | METHODS

Our modeling method integrates the greater comprehensiveness of SD modeling with the detail of traditional IE methods and mine data, and the extensive uncertainty inclusion of exploratory modeling and analysis (EMA) (Figure 1). Below, we first describe the method, followed by its relation to criticality and resilience. Finally, we describe the nickel case study, including sub-model structure and experimental setup. Further details, including verification and validation, can be found in Section 1 of Supporting Information S1 and in Bradley (2021) and Bradley et al. (2022). The model itself, including variables and equations, as well as input data, and code for EMA are available on GitHub (see Supporting Information S1 for the link).

2.1 | Modeling method

The primary method is SD, which, in the context of metal supply systems, can be seen as a dynamic material flow analysis (dMFA) combined with market dynamics (Glöser-Chahoud, 2023). SD models consist of stocks, flows, and variables connected by differential and integral equations, and

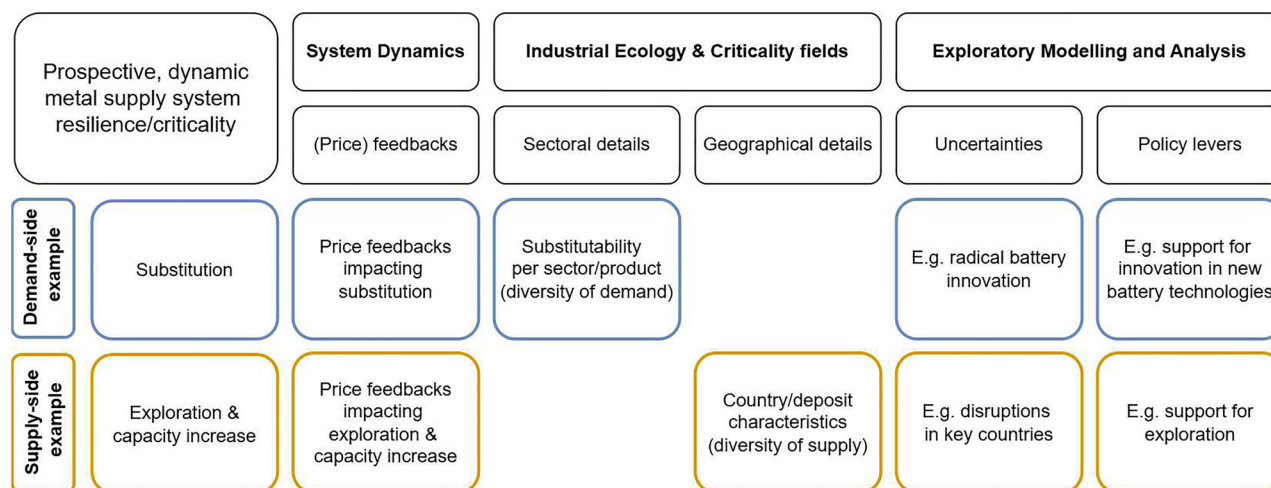


FIGURE 2 Factors influencing prospective, dynamic metal supply system resilience and criticality. Horizontal: contributions from the described methodological fields (system dynamics, industrial ecology, and exploratory modelling and analysis). Vertical: examples of demand- (blue) and supply-side (orange) factors included in the model and in resilience and criticality assessments. These factors reflect the combined effects of feedbacks, details, uncertainties, and policy levers. Omitting any of these aspects can change conclusions regarding criticality and resilience. Similar representations can be made for increasing time in use, recycling, and stockpiling (Helbig et al., 2021; Bradley et al., 2024; Sprecher et al., 2017).

often include multiple feedback loops, delay structures, and accumulations, allowing the simulation of complex behavior (Auping et al., 2024; Forrester, 1958, 1995; Pruyt, 2013). The endogenous connection of metal supply sub-systems through feedback loops distinguishes SD from the more isolated approach of traditional IE methods, like dMFA and life cycle assessment (LCA).

Our model is enhanced with sectoral and geographical details that are more common in traditional IE methods and agent-based modeling (ABM). It includes ABM elements through its resolution at the level individual mines competing for global market share, enabled by a detailed database on nickel deposits (earlier version of Mudd & Jowitt, 2022). Sectors are also disaggregated on both the demand and supply side, with a specific focus on the energy system. The model includes LCA elements by incorporating dynamic cradle-to-gate environmental impacts based on changing mine characteristics and regional electricity mixes.

Given the high uncertainty of the future, we include detailed uncertainty analysis through EMA. EMA accounts for deep uncertainty inherent in complex prospective, dynamic systems by running thousands of simulations with varying model structures and parameter values, generating a wide range of possible futures (Auping, 2018; Bankes, 1993). Analyzing the results helps identify factors contributing to the most and/or least favorable futures (Bryant & Lempert, 2010; Kwakkel & Jaza-Rozen, 2016). Within EMA, key uncertainties and outcomes can be organized using the XLRM framework. In this framework, X represents exogenous uncertainties that cannot be easily controlled, L refers to policy levers that can be controlled, R represents relationships within the system, and M refers to performance metrics (Bankes, 1993; Lempert et al., 2003).

2.2 | Relation to criticality and resilience

When assessing criticality and resilience of metal supply systems in a prospective, dynamic manner, comprehensiveness (SD), detail (IE), and uncertainty consideration (EMA) are all important. In the context of metal supply systems, resilience can be defined as “the capacity to supply enough of a given material to satisfy the demands of society, and to provide suitable alternatives if insufficient supply is available” (Sprecher et al., 2015, p. 2). Improving resilience can reduce material criticality, which indicates high economic importance and supply risk (Graedel & Reck, 2016). Both resilience and criticality are dynamic and influenced by a combination of changing system characteristics (including feedback, sectoral, and geographical aspects), uncertainties, and policies (Figure 2).

Market feedbacks influence resilience by balancing supply and demand (Sprecher et al., 2015). During a supply deficit, supply can be increased through efficiency improvements, exploration, capacity increase, and recycling. Demand can be reduced through substitution, both material (switching between materials) and functional (switching between options to fulfil a function), and increasing time in use (Bradley et al., 2024). Such balancing feedback loops improve system stability, and there are also reinforcing feedbacks that can destabilize.

Sectoral details impact resilience by including effects of quality and diversity of demand. With “diversity of demand” we refer to the number of options available to fulfil a certain function, including market shares of different products, substitution options, and the diversity in product states (new, reused, refurbished, shared, etc.). Diversity of demand is related to the concept of flexibility in resilience research, which indicates how well a

system can meet demand under a disturbance by switching between alternatives (Sprecher et al., 2015). Sectoral details related to quality include the ease of implementing circularity (substitutability, reusability, and recyclability) and other efficiency improvements per product/sector. Common criticality indicators sensitive to sectoral details are related to substitutability and recyclability (Helbig et al., 2021).

Geographical details affect resilience by including effects of quality and diversity of supply. Diversity of supply relates to the number of supply options to fulfil demand (Sprecher et al., 2015), including the diversity of mines, processing plants, producing countries, and resource and reserve locations, as well as the diversity of sources, such as primary supply, secondary supply, unconventional sources (e.g. tailings and deep sea mining), and stockpiles. Diversity of supply is inversely related to the concept of supply concentration in criticality assessments (Helbig et al., 2021). Geographical details related to quality include the ease of finding new material, the quality, and the ore grades of deposits (Northey et al., 2018), as well as location-related risks. Common criticality indicators sensitive to geographical details are related to political instability, regulations, and by-product dependence (Helbig et al., 2021). Costs and delays for new capacity also depend on geographical details.

Including uncertainties showcases the diverse ways resilience can change over time. Many unplanned events can occur in the future, including radical innovation, natural disasters, geopolitical shifts, new societal and technological trends, and new deposit discoveries (Sprecher et al., 2015). Such events can challenge the resilience of the system, but can also change the resilience itself. Robust policy making requires understanding how policies perform under various circumstances (Kwakkel & Haasnoot, 2019).

2.3 | Nickel case study

Our nickel model consists of four interconnected sub-models, covering demand, supply (primary and secondary), price, and sustainability impacts. The demand sub-model includes energy system components (electricity generation capacity, stationary storage, and vehicles) in a detailed, bottom-up manner, the Rest of the Economy (RoE) in an aggregated, top-down manner, and price feedbacks on demand related to price elasticity, substitution, and nickel intensity changes. The supply sub-model includes stocks and flows in the nickel supply chain, mechanisms for exploration, changing mining capacity, and recycling. It also includes detailed geographically and technologically specific data on individual mines, including location, ore type, principal processing method, ore grade, and by-product composition (Mudd & Jowitt, 2022). The price sub-model includes data and mechanisms for determining costs, price, profit, and investment attractiveness. The impact sub-model includes sustainability impacts, specifically focusing on final energy use and greenhouse gas (GHG) emissions, based on LCA data, and changing regional energy mixes. A simplified overview of the model structure and other aspects of the XLRM framework applied to nickel are shown in Figure 3, with more detailed information in Tables 1 and 2.

We tested 27 uncertainties and policy levers on performance metrics related to nickel demand, price, recycling, ore grade, by-product production, and GHG emissions. We created the model, which we adapted from previous research (Auping, 2011; Van der Linden, 2020) in Vensim. We then used the EMA Workbench package in Python (Kwakkel, 2017) to simulate the model 1000 times from 2015 to 2060. Each model run reflects different uncertainties, policy levers, and policy combinations, of which the most important ones (Figure 3, Table 2) are described below. We use price as the main indicator for resilience. Price fluctuations inherently capture the dynamics of supply and demand, which allows us to assess the system's response to disruptions and the effectiveness of policy levers in maintaining stability.

We selected key uncertainties based on four quadrants related to slow, fast, demand-side, and supply-side disturbances (Sprecher et al., 2015). A slow, demand-side disturbance is represented by the energy transition, which we based on three shared socio-economic pathways (SSPs) that conform to a 1.5°C temperature increase target (SSP1-19, SSP2-19, and SSP5-19) and compared to a Business as Usual (BAU) scenario (SSP2-baseline) (International Institute for Applied Systems Analysis [IIASA], 2018). The scenarios were augmented with storage and vehicle projections (BNEF, 2019; International Energy Agency [IEA], 2017; Zerrahn et al., 2018). A fast demand-side disturbance is represented by radical battery innovation. When switched on, a new 0% nickel battery enters the market in 2035 and 2050, both times halving the substitution threshold (used to represent substitutability). A fast supply-side disturbance is represented by disruption in key supplying countries. When switched on, this disruption compromises the top supplying country for a year, in 2030 and 2045. A slow supply-side disturbance is represented by ore depletion, based on a range of rates at which ore grade is reduced. Two additional key uncertainties are related to the inclusion or exclusion of by-products and the inclusion or exclusion of price feedbacks on demand and exploration.

We selected key policy levers based on four quadrants related to efficiency, utility, demand-side, and supply-side strategies for reducing material criticality (Bradley et al., 2024). Demand reduction by using less material is represented by substitution, both functional and material. For functional substitution, different trajectories are described in the energy transition SSPs. For material substitution, we tested a range of substitution thresholds for batteries. Demand reduction by extending useful lifetime is represented by product lifetime. We tested EV battery lifetimes of 8 and 16 years. Supply increase by wasting less material is represented by end-of-life (EoL) waste management. We tested four EoL recycling strategies, three where battery recycling is worse, the same as, or better than other nickel products (excluding stainless steel), and one with an additional increase in collection rate. Supply increase by obtaining more material is represented by exploration, based on a range of sensitivities of exploration to price changes and expectations of the energy transition.

TABLE 1 Summary of the main aspects, components, and mechanisms included per sub-model.

Aspect	Components and mechanisms
<i>Demand sub-model</i>	
Electricity generation	- 11 types: Solar photovoltaics (PV), concentrated solar power (CSP), wind, geothermal, bio, hydro, ocean, nuclear, coal, natural gas, and oil - Inclusion of carbon capture and storage (CCS)
Electricity storage	- Non-battery storage: Pumped hydro storage (PHS) and concentrated solar power thermal energy storage (CSP TES) (assumed to be used before battery storage) - Vehicle to grid (V2G) storage (using EVs as stationary storage) and other forms of flexibility (ability to deal with variable renewable energy [VRE]) - Electric vehicle (EV) battery repurposing - Behind the meter and grid storage - 8 battery types: Nickel cobalt aluminum (NCA)+, NCA, nickel manganese cobalt (NMC) 811, NMC 622, NMC 532, NMC 422, NMC 111, and other (the numbers indicate the relative shares of the components)
Vehicles	- 5 vehicle types: Internal combustion engine (ICE), hybrid electric vehicle (HEV), plug-in hybrid electric vehicle (PHEV), battery electric vehicle (BEV), and fuel cell vehicle (FCV) - 3 vehicle functions: passenger, truck, and bus
Total demand (including the Rest of the Economy [RoE])	- Split between stainless steel, batteries, and other - Top-down calculations for the RoE using gross domestic product (GDP) and population data - Bottom-up calculations for the energy system, using nickel intensity and lifetime data per component and data on energy and transport developments - Price feedbacks related to price elasticity, substitution, and nickel intensity changes
<i>Supply sub-model</i>	
Primary supply	- 652 (potential) projects in 45 countries + international waters - 19 by-products and 2 ore types: sulfides and laterites - 4 mine types: open cut, underground, combined, and deep sea mining - 4 status types: greenfield development, brownfield development, operating, and mothballed - Possibility to recover tailings - 11 principal processing methods: High pressure acid leaching (HPAL), heap leaching (HL), atmospheric leaching (ATL), direct nickel (DNI), rotary kiln electric arc furnace (RKEF), blast furnace (BF), caron, hydrometallurgical sulfide, pyrometallurgical sulfide, direct shipping ore (DSO), and beneficiation - 2 energy types: fuel and electricity - Function for exploration based on historical data, price, and energy transition expectations - Reserves based on economic extractability of resources - Capacity addition based on reserves, investment attractiveness, and a limit for annual global capacity increase investment. - Mothballing based on length of time and degree of unprofitability - Various delays and losses at different points in the supply chain. - Functions for nickel and by-product ore grade reduction with increased mining
Secondary supply	- Split between class I (>99% nickel; batteries and other) and class II (<99% nickel; stainless steel) products each with their own end-of life recycling rate (EoL RR), consisting of EoL processing rate (EoL PR) and EoL collection rate (EoL CR) - Inclusion of both post-production (new scrap) and post-consumption (old scrap, EoL) recycling - Assumed to increase with decreasing ore grade
<i>Price sub-model</i>	
Costs	- Variable operating costs: energy for mining, processing and transport (based on ore grade, mine type, processing method, and country), royalties and taxes, reagents and other, and carbon costs. - Fixed operating costs: labor and other costs (estimated as 2% of capital costs) - Capital costs: estimated based on capacity - Mining costs (and impacts) allocated between nickel and recovered by-products - Processing costs (and impacts) allocated between nickel and other metals in class II products - Autonomous energy and carbon efficiency increase
Price, profit, and investment attractiveness	- Real nickel metal price based on marginal costs and scarcity (supply–demand gap) - Current profit calculations impacting mothballing - Current potential profit calculations impacting restarting - Future potential profit calculations impacting reserves, investment, and exploration - Investment attractiveness based on profit and corruption
<i>Impacts sub-model</i>	
Greenhouse gas emissions	- Electricity-related emissions: based on electricity use, electricity mix, and emissions of electricity generation technologies - Other emissions: based on processing method

TABLE 2 Main uncertainties, policy levers, and policy combinations tested in the model.

Uncertainty/policy lever	Type	Categories or range	Elaboration	Sources
<i>Main uncertainties</i>				
Energy transition (SSPs and connected transport scenarios)	Slow, demand-side disturbance	4	Three SSPs that comply with 1.5°C (SSP1-19, SSP2-19, and SSP5-19; which are referred to as the energy transition scenarios) and one BAU scenario (SSP2-baseline). These SSPs influence electricity generation capacity, electricity demand, electricity mix, variable renewable energy share, population, GDP, and carbon price. The 1.5°C scenarios are connected to a faster EV transition and SSP2 base is connected to a BAU EV transition.	IIASA, 2018; BNEF, 2019; IEA, 2017
Radical battery innovation	Fast, demand-side disturbance	2	Either on or off. When this switch is turned on, a radical new battery technology is discovered that does not require nickel. It occurs in 2035 and in 2050 and halves the substitution threshold for batteries.	Assumption
Disruption in key countries	Fast, supply-side disturbance	2	Either on or off. When this switch is turned on, a supply disruption occurs for 1 year starting in 2030 and in 2045. The disruption affects the country that at that time has the largest share of nickel mining and it shuts down all mines in that country for a year.	Assumption
Power for ore grades	Slow, supply-side disturbance	0.1–0.5 (dmnl)	Determines how quickly average ore grade declines (see Section 1.1.5 of Supporting Information S1 for the ore grade equation)	Van der Linden (2020)
By-product inclusion	Structural uncertainty	2	Either on or off. Option to include or exclude by-products in determining costs and profit of the mines.	Assumption
Inclusion of price feedbacks on demand and exploration	Structural uncertainty	2	Either on or off. When this switch is turned on, price feedbacks impact demand, influencing intensity changes, price elasticity changes, and substitution. In addition, exploration is included and influenced by price.	Van der Linden (2020)
<i>Main policy levers</i>				
Battery substitution threshold	Demand reduction by using less	2.5–5 (dmnl)	Batteries are assumed to be easiest to substitute. Half of the substitution threshold for stainless steel is assumed (see the model on GitHub for the substitution equations)	Van der Linden (2020)
Improved battery lifetime	Demand reduction by extending life	2	Either on or off. When this switch is turned on the EV battery lifetime doubles from 8 to 16 years, the assumed lifetime of the vehicles.	See Table 1.1 of Supporting Information S1
EoL battery waste management	Supply increase by wasting less	4	Four EoL recycling strategies. One where the EoL waste management of batteries is worse than traditional uses of class I (>99% nickel), one where it is the same, one where it is better and one where there is further increased effort in managing battery waste.	See Bradley (2021), appendix G3.2
Power for price-based exploration	Supply increase by obtaining more	0.5–1 (dmnl)	Gives more or less weight to the price and energy transition anticipation-based elements of determining exploration (see Section 1.1.5 of Supporting Information S1 for the exploration equation. A higher value means less exploration).	Assumption
<i>Policy combinations</i>				
None	None	-	Energy transition (SSP5-19) runs with low battery substitutability, battery lifetime, battery EoL recycling, and exploration. Settings: SSP5-19, battery substitution threshold >3.75, improved battery lifetime = off, EoL battery waste management = worse or same, power for price-based exploration >0.7	Assumption
Demand side	Demand reduction	-	Functional substitution to SSP2-19 runs with high battery substitutability and lifetime, but low battery EoL recycling and exploration. Settings: SSP2-19, battery substitution threshold ≤3.75, improved battery lifetime = on, EoL battery waste management = worse or same, power for price-based exploration >0.7	Assumption

(Continues)

TABLE 2 (Continued)

Supply side	Supply increase	-	Energy transition (SSP5-19) runs with low battery substitutability and lifetime, but high battery EoL recycling and exploration. Settings: SSP5-19, battery substitution threshold >3.75 , improved battery lifetime = off, EoL battery waste management = better or improved, power for price-based exploration ≤ 0.7	Assumption
All	Demand reduction and supply increase	-	Functional substitution to SSP2-19 runs with high battery substitutability, battery lifetime, battery EoL recycling, and exploration. Settings: SSP2-19, battery substitution threshold ≤ 3.75 , improved battery lifetime = on, EoL battery waste management = better or improved, power for price-based exploration ≤ 0.7	Assumption

Notes: The full list of uncertainties can be found in Section 1.3 of Supporting Information S1. Type indicates whether the uncertainties and policy levers fit within one of the quadrants described by Sprecher et al. (2015) or Bradley et al. (2024), and which quadrant this is, or whether the uncertainty is another type of parametric or structural uncertainty. The categories or range column indicates either the number of categories included for categorical parameters or the min and max value when a range is tested. The units are included in brackets for ranges. Abbreviation: Dmnl, dimensionless.

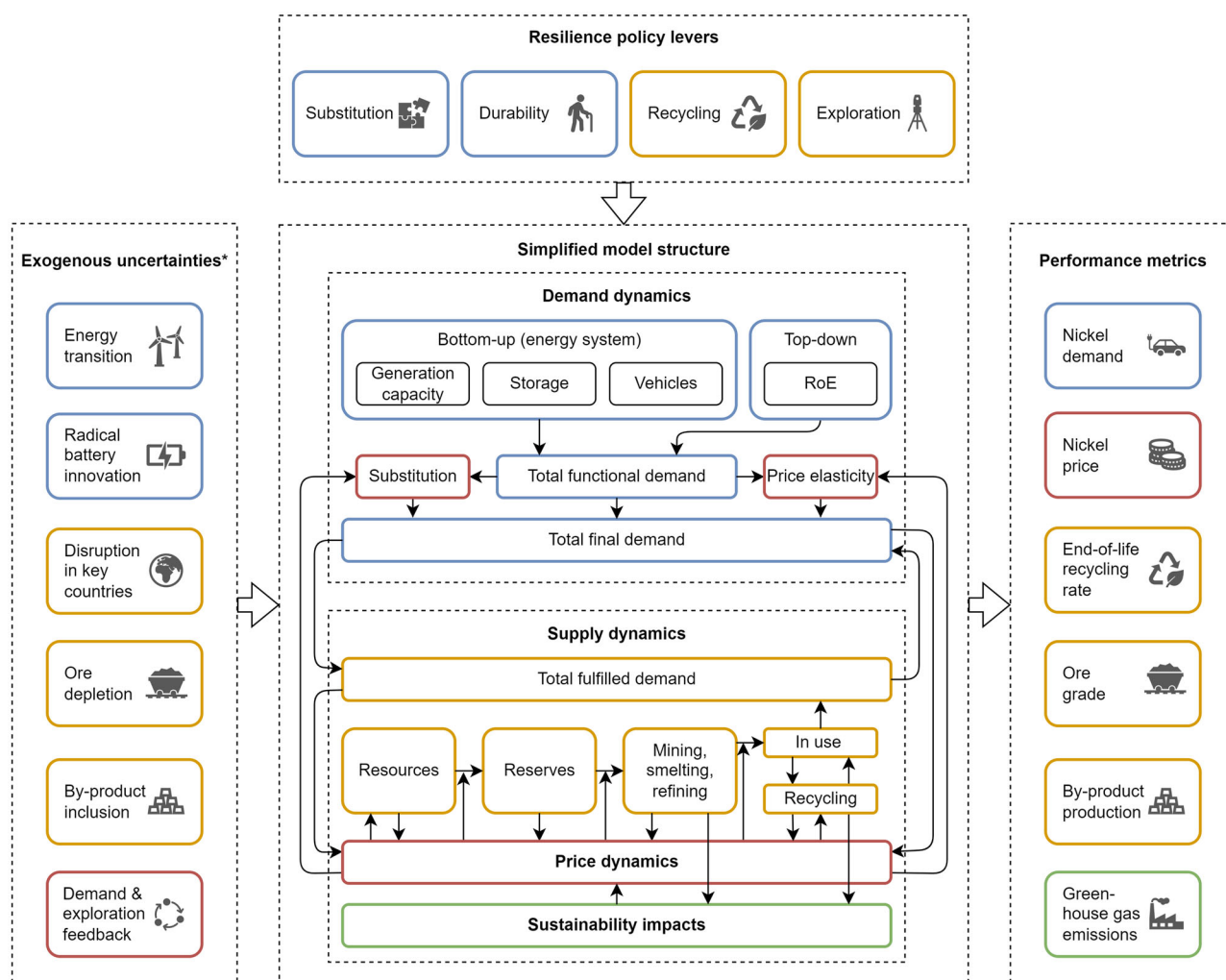


FIGURE 3 XLRM framework applied to the nickel case study. Blue, demand; orange, supply; red, economics; green, sustainability impacts. RoE, Rest of the Economy. *Additional uncertainties are included in Section 1.3 of Supporting Information S1.

3 | RESULTS

In this section, we describe the case study results per performance metric: demand, price, EoL RR, ore grade, by-product production, and GHG emissions. We focus on the effects of uncertainties and policy levers with the largest contribution, and policy combinations. Other factors and details are in Section 2 of Supporting Information S1 and Bradley (2021, section 3).

3.1 | Nickel demand

Nickel demand is generally higher during the energy transition than under BAU, though not always (Figure 4a; Figure 2.1 of Supporting Information S1). Under BAU, demand is projected at 6–18 million tonnes/year by 2060, with a cumulative total of 200–320 million tonnes (2015–2060). In 1.5°C energy transition scenarios, demand reaches 7–38 million tonnes/year by 2060, with a cumulative total of 270–670 million tonnes.

The energy transition initially increases demand both directly, by requiring more nickel in products, and indirectly, by reducing average time of nickel products in use. Directly, higher GDP and population (in SSP1 and SSP5), faster EV adoption, and more nickel-intensive energy infrastructure raise demand. Additionally, an increase in variable renewable energy share could increase battery storage demand, though this could be covered by improving energy system flexibility, such as using grid-connected EVs for storage. Indirectly, demand increases due to shorter lifespans of renewable energy infrastructure (and early retirement of non-renewable capacity), and an increasing share of batteries, which have a shorter lifespan than stainless steel. An average battery lifetime of 8 years significantly increases demand compared to 16 years (Figures 2.1 and 2.5 of Supporting Information S1). Batteries overtake stainless steel as the largest contributor to nickel demand around 2035–2040 in the energy transition scenarios, if no substitution occurs.

However, when feedback effects are included, there are circumstances where nickel demand becomes lower during the energy transition, mainly through substitution. As price increases, demand decreases through market-driven price elasticity and substitution. Additionally, policy levers and disruptions can accelerate substitution, which is especially visible in runs with radical battery innovation (Figure 4c). The highest demand (median of about 29 million tonnes/year by 2060) occurs in scenarios with only supply-side policies, which suppress prices more than scenarios with no policies, leading to less market-based substitution (Figure 4e,f). Without policies, substitution can reduce demand to as low as 7 million tonnes/year by 2060. However, low demand (8–17 million tonnes/year by 2060) combined with less extreme prices generally occur when policies stimulating higher substitutability, longer battery lifetimes, and less nickel intensive 1.5°C pathways (SSP2-19) are included.

3.2 | Nickel price

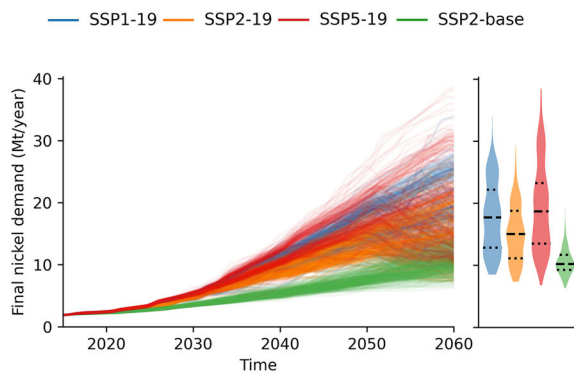
Nickel prices are influenced by costs and demand–supply imbalances, which both increase during the energy transition. Costs increase due to factors such as faster declining ore grades and carbon pricing (Figures 2.2 and 2.3 of Supporting Information S1). For most runs, average prices cycle around 30,000 2005\$/tonne under the energy transition and around 15,000 2005\$/tonne under BAU. However, price extremes can occur due to demand–supply imbalances.

On the demand-side, the greatest contributors to price are the energy transition, especially SSP5-19 (Figure 4b), and radical battery innovation (Figure 4d). During the energy transition, large demand increases can cause extreme prices when supply is unable to keep up. However, price stability improves with radical battery innovation. When demand-side policies are implemented, the median price drops from 90,000 2005\$/tonne (no policies) to around 40,000 2005\$/tonne by 2060 (Figure 4f).

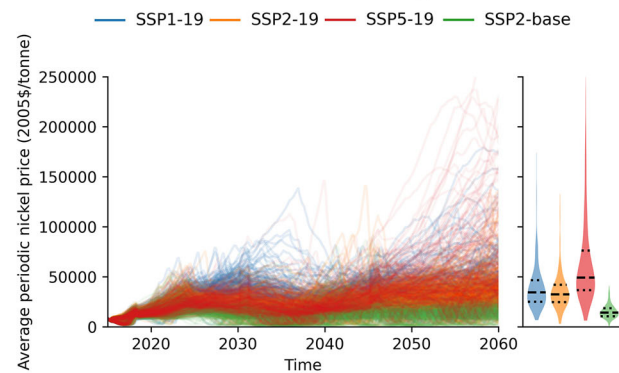
On the supply-side, short-term supply disruptions in key supplying countries result in small price peaks in 2030 and 2045 (Figure 4b,d,f). These disruptions generally do not lead to sustained price increases due to the resilience provided by a large diversity of primary supply, allowing other countries to compensate (see Figure 2.9 of Supporting Information S1 for country shares for a single run). Substitution also occurs as price increases, leading to additional balancing.

The most important long-term supply-side contributors are the inclusion and degree of exploration (Figures 2.4 and 2.6 of Supporting Information S1). Without exploration, current resources start to run out by 2050–2060 in the energy transition scenarios. However, the figures shown here all include feedback effects and exploration. As prices rise, exploration increases, and the larger the influence of price on exploration, the more stable the prices. Other supply-side factors that improve price stability include by-product consideration, higher maximum capacity increase, and improved battery recycling (Figures 2.7 and 2.8 of Supporting Information S1). During the energy transition, the largest price reduction occurs when both demand- and supply-side policies are combined, leading to a median of about 25,000 2005\$/tonne by 2060 (Figure 4f).

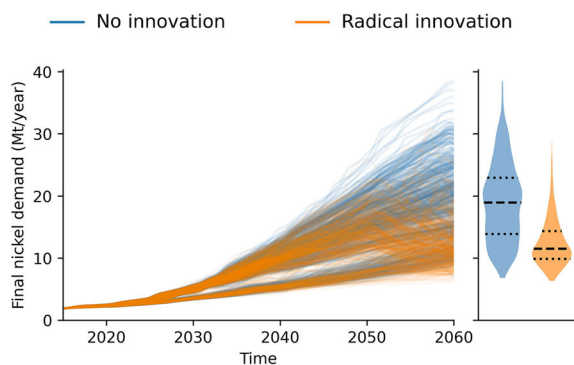
(a) Nickel demand: energy transition



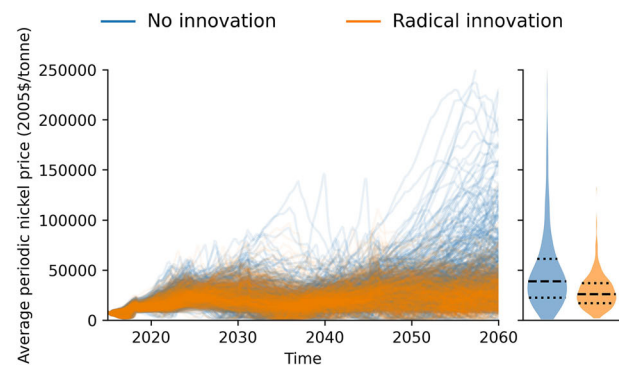
(b) Nickel price: energy transition



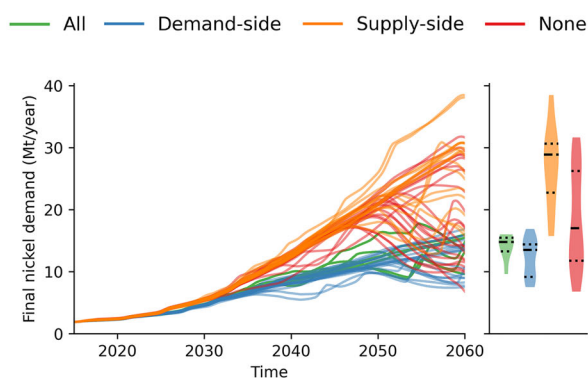
(c) Nickel demand: radical battery innovation



(d) Nickel price: radical battery innovation



(e) Nickel demand: policy combinations



(f) Nickel price: policy combinations

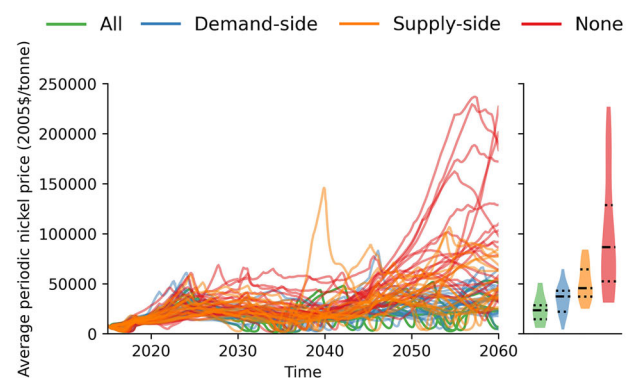
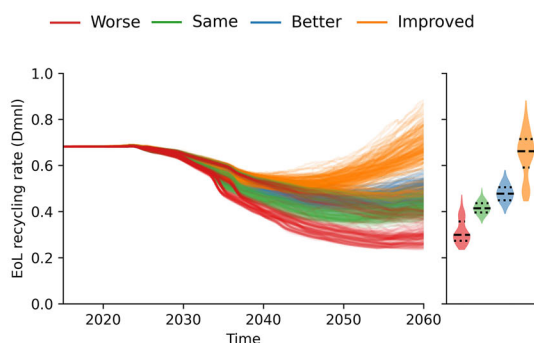
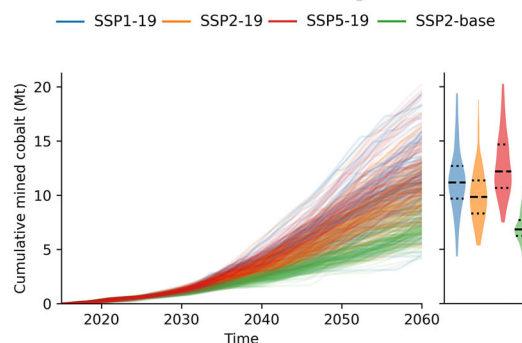


FIGURE 4 (a–d) Model output for final nickel demand and average periodic price for the energy transition (energy transition scenarios: SSP1-19, SSP2-19, and SSP5-19; Business as Usual scenario: SSP2-base) and radical battery innovation. Note: The inclusion of price feedbacks on demand and exploration is technically the greatest contributor to price, but results excluding these feedbacks are not shown here (see Section 2.2 of Supporting Information S1). (e–f) Model results for policy combinations (see Table 2). For a clearer view of the impact of individual policy levers and combinations of policy levers for a single set of uncertainties, see Figure 2.15 of Supporting Information S1. None = SSP5-19 with low recycling, exploration, substitutability, and lifetime. Supply-side increases recycling and exploration. Demand-side increases substitutability and lifetime and functional substitution to SSP2-19. All combines supply-side and demand-side. Violin plots (right side of the main plots) show the density, median, and range of outcomes for 2060. Mt, megatonne (million tonnes). These plots were generated with the data and code available on GitHub (see Supporting Information S1 for the link).

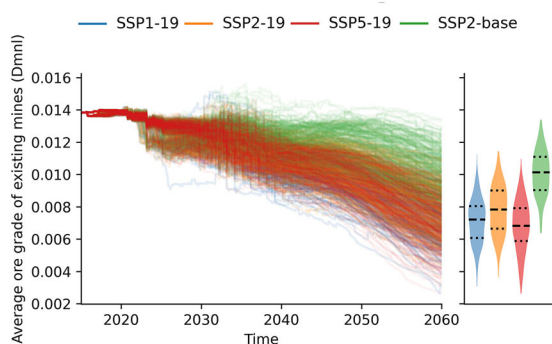
(a) End-of-life recycling rate: battery recycling strategy



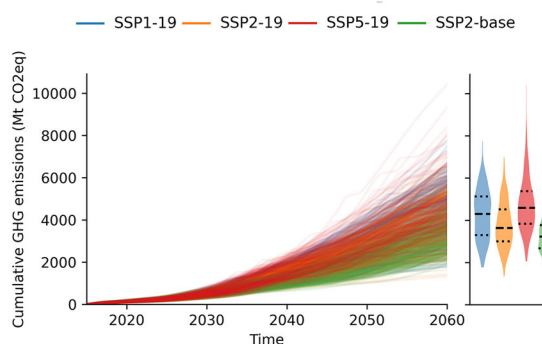
(b) Cumulative mined cobalt: energy transition



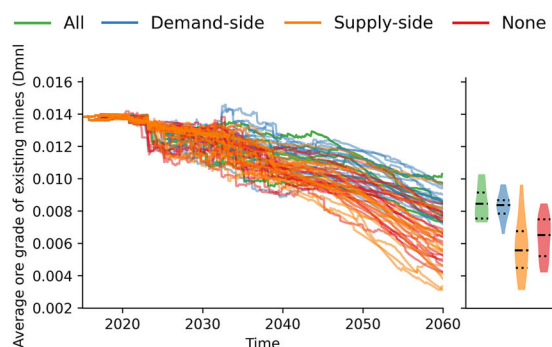
(c) Nickel ore grade: energy transition



(d) Cumulative greenhouse gas emissions: energy transition



(e) Nickel ore grade: policy combinations



(f) Cumulative GHG emissions: policy combinations

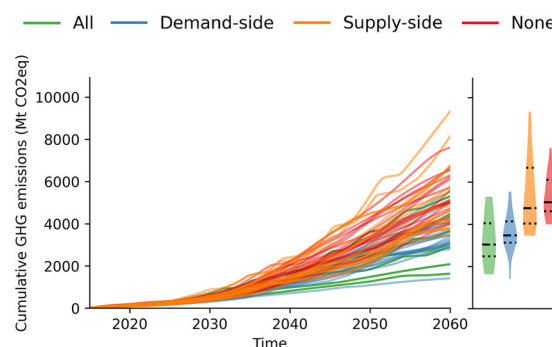


FIGURE 5 (a–d) Model output for end-of-life recycling rate (EoL RR), ore grade, cobalt mining, and GHG emissions for the greatest contributors to each of these performance metrics. Note: Figure 5b only includes the runs with inclusion of by-products. SSP1-19, SSP2-19, and SSP5-19 represent energy transition scenarios. SSP2-base = Business as Usual. Worse, same, better, and improved refer to EoL battery waste management strategies in comparison to other uses of class I (>99% nickel). (e–f) Final nickel demand and average periodic price under policy combinations (Table 2). None = SSP5-19 with low recycling, exploration, substitutability, and lifetime. Supply-side increases recycling and exploration. Demand-side increases substitutability and lifetime and functional substitution to SSP2-19. All combines supply-side and demand-side. Violin plots (right side of the main plots) show the density, median, and range of outcomes for 2060. Mt, megatonne (million tonnes). These plots were generated with the data and code available on GitHub (see Supporting Information S1 for the link).

3.3 | Nickel recycling

The nickel EoL RR initially decreases from 68%, then stabilizes or increases, ending up between 23% and 88% by 2060, depending on the battery recycling strategy (Figure 5a). The initial decrease is driven by an increasing share of battery scrap, which has a lower EoL RR than stainless steel. EoL RR can then increase again if primary production becomes less attractive due to declining ore grades and/or if battery recycling improves. A larger battery share also reduces efficiency in the forward supply chain due to higher losses in battery production compared to stainless steel.

The energy transition accelerates both the decrease and subsequent increase in EoL RR for most recycling strategies. The decrease is accelerated due to a faster transition toward more batteries, which also means the EoL RR remains lower than under BAU when battery recycling is worse than other applications. However, when battery recycling is improved, EoL RR ends up higher than under BAU due to lower ore grades, which increases recycling attractiveness (Figure 2.10 of Supporting Information S1).

3.4 | Nickel ore grade

Although the average nickel ore grade of operating and mothballed mines generally decreases over time, there are also point instances of increase (Figure 5c; Figure 2.11 of Supporting Information S1). Ore grades decline faster during the energy transition due to increased mining, reaching a median of about 0.0075 tonne/tonne ore by 2060, compared to 0.010 tonne/tonne ore under BAU. Scenarios with increased exploration lead to the lowest ore grades (Figure 5e; Figure S2.14 of Supporting Information S1). Higher prices during the energy transition make lower-grade mines profitable, while low prices can make such mines unprofitable, resulting in eventual decommissioning. These dynamics lead to average ore grade variability. The average ore grades of nickel by-products can also fluctuate. Since nickel dynamics have the largest impact on which mines open and close, there are cases where average by-product ore grades related to nickel mining continue to increase (Figure 2.12 of Supporting Information S1).

3.5 | Nickel by-products

Nickel by-products impact deposit profitability, changing the order in which mines become profitable and, thereby, the overall development of ore grade, emissions, costs, and prices. By-products enable lower-grade deposits to remain profitable longer. Additionally, allocation of some of the costs and impacts to by-products can reduce those of nickel production. The order of the deposits becoming profitable can, in turn, impact by-product production.

Of the 19 by-products in the model, cobalt and palladium depend most on nickel mining (Nassar et al., 2015). Therefore, these metals and their prices are more connected to nickel scarcity and more can be said about their potential future supply. More cobalt is mined between 2015 and 2060 in the energy transition scenarios (about 6–20 million tonnes) compared to BAU (about 4–11 million tonnes), due to the higher nickel demand (Figure 5b; see Figure 2.13 of Supporting Information S1 for palladium).

3.6 | Nickel greenhouse gas emissions

Cumulative GHG emissions from 2015 to 2060 range from 1.5 to 10 billion tonnes CO₂eq in energy transition scenarios and from 1.9 to 5.8 billion tonnes CO₂eq under BAU. Cumulative emissions are generally higher during the energy transition but can be lower for SSP1-19 and SSP2-19 (Figure 5d). Initial emission increases are driven by higher demand and faster ore grade decline. Despite this ore grade decrease, energy efficiency improvements lead to relatively stable average final energy use over time, although it can increase significantly after 2045 for some energy transition runs. Other factors these runs have in common include low exploration, a high rate of ore grade reduction with increased mining, and by-product consideration (Figure 2.14 of Supporting Information S1). Final energy use impacts GHG emissions. However, average emissions are generally slightly lower by 2060 due to increased renewable energy in the electricity mix. This effect may be even more pronounced if fuel use for mining also becomes more renewable.

Demand-side policies slow ore grade decline and reduce emissions, while supply-side policies can lead to faster ore grade decrease and higher emissions (Figure 5e,f). The supply-side policies consist of a combination of increased recycling and exploration, which have opposite effects. Increased recycling leads to less mining, higher ore grade and lower emissions, whereas increased exploration leads to more mining, lower ore grade, and more emissions. Combining all policy levers leads to the highest ore grades (median = 0.0085 tonne/tonne ore by 2060 compared to 0.0065 tonne/tonne ore for no policies) and lowest emissions (median = 3 billion tonnes CO₂eq from 2015 to 2060 compared to 5 billion tonnes CO₂eq for no policies).

GHG emissions (and related energy use and costs) also vary by country, depending on factors such as mine type, ore grade, and processing method for the active mines at a certain point in time, as well as regional electricity mix, which changes as the energy transition progresses. Figure 6 shows country-specific average GHG emissions per tonne of primary nickel production in 2015 and 2060 for a single BAU and energy transition run. The countries with active mines change over time and on average emissions per tonne are lower during the energy transition by 2060. In 2060, there are 26 countries with operating mines in the BAU run and the five with the largest share of operating capacity are Indonesia (16%), South Africa (12%), Cuba (11%), Russia (10%), and New Caledonia (8%). In the energy transition run, there are 34 countries with operating mines by 2060 and the top five are Indonesia (17%), Russia (15%), Australia (14%), Philippines (7%), and Cuba (6%). Other model runs lead to different active mining countries and emission levels, reflecting model uncertainties.

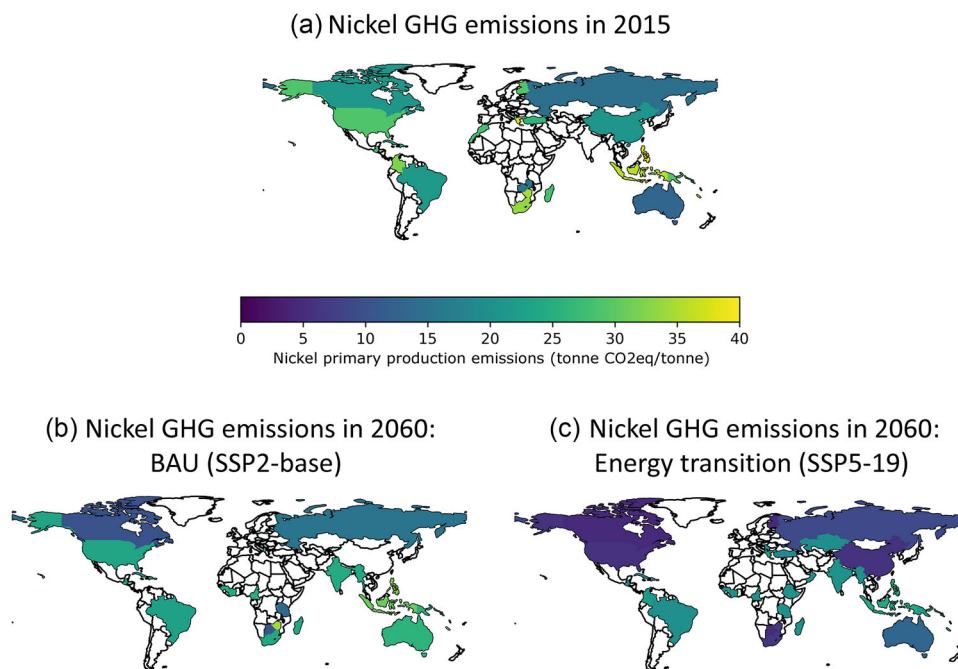


FIGURE 6 Average country-specific greenhouse gas emissions per tonne of primary nickel production in 2015 and 2060, for a single Business as Usual and energy transition run with base settings (see Table 1.24 of Supporting Information S1). Countries with no color have no operating mines in that year. (a) Behind 2015. (b) Behind Business as Usual. (c) Behind energy transition. Note: Refining was assumed to occur in the mining country although this is not always the case in reality. Figures like this can be made for each time step. This figure was generated with the data and code available on GitHub (see Supporting Information S1 for the link).

4 | DISCUSSION

Combining the greater comprehensiveness of SD with the detail of IE methods and individual mine data is a step toward prospective, dynamic criticality and resilience assessment. This integrated approach produces more realistic behavior and offers insights into regional disruptions, impacts, and by-product dynamics. Below, we discuss insights from our nickel case study to illustrate the effects of feedbacks, sectoral disaggregation, and geographical disaggregation. We also address implications for criticality and resilience, and limitations and recommendations for future research. For additional discussion points and details, see Bradley (2021, section 4).

4.1 | Feedback effects

Nickel demand generally increases during the energy transition, but may reach BAU levels by 2060 due to price feedback, mainly related to substitution. Unlike traditional dMFA and demand projection studies, which assume continuous demand growth as the energy transition progresses, or include changes such as substitution as exogenous factors (Elshaki & Graedel, 2013; Helbig, 2023; IEA, 2024; Xu et al., 2020), our approach incorporates price as an endogenous factor, better reflecting real market dynamics (Glöser-Chahoud, 2023; Kwakkel et al., 2013). For example, the recent resurgence of lithium iron phosphate (LFP) batteries, driven by high nickel and cobalt prices (IEA, 2024), contrasts with older projections assuming a growing share of nickel-containing batteries (BNEF, 2019). While our model also includes such older assumptions, price feedback overrides these, driving substitution toward both existing technologies, such as LFP, and emerging technologies when radical innovation occurs. This example highlights our model's flexibility to changing conditions. Although we modeled feedback between price and demand directly, we did not explicitly include the effects of price on time in use or functional substitution. Rising prices could incentivize increased product durability and circularity strategies (Zink et al., 2016), but also hinder EV and renewable energy adoption. We expect that including such feedbacks in future research could show a further balancing of nickel demand, though the latter may also jeopardize climate ambitions (Wang et al., 2023).

Nickel resources generally decrease faster during the energy transition, but are not depleted by 2060 when exploration is considered and impacted through price feedback. When this feedback is not considered, resources are eventually depleted (Olafsdottir & Sverdrup, 2021) and extreme prices can occur (Bradley, 2021; van der Linden, 2020). However, when feedback effects are included, supply risks are reduced and price behavior follows a "hog cycle" that is also seen in historical prices (Trading Economics, 2024). Historically, depleted resources have always been replaced through exploration. However, resource quality does diminish (Northey et al., 2018). In our research, this is illustrated by a decreasing ore

grade, which can increase energy and emissions, and related costs, thereby still leading to higher (albeit less extreme) prices. In our model, recycling was impacted by changing ore grades, however, we did not include a direct feedback between price and recycling. We expect that adding this feedback, as well as feedback related to stockpiling, could lead to additional balancing of prices (Sprecher et al., 2015).

The included market feedbacks lead to a more resilient nickel system, but this is not enough in all runs, especially those related to the energy transition. These runs have more price instability due to demand–supply imbalances. Sectoral and geographical details and other uncertainties, such as the ease of substitution, exploration, and recycling, as well as various delays, can make it more difficult for supply to keep up with demand, despite market feedbacks.

4.2 | Sectoral disaggregation

Sectoral disaggregation reveals increased risks for nickel due to the energy transition on both the demand and supply side. First, demand increases, both by requiring more nickel, and by reducing average time of nickel products in use. Second, supply efficiency is reduced at multiple points of the supply chain, including recycling efficiency. Each sector has its own dynamic EoL RR, and as market shares change, so does average EoL RR. Average EoL RR initially decreases because battery recycling improvement does not outweigh the overall efficiency reduction due to a lower stainless steel market share. This behavior contrasts with more aggregated models, where overall EoL RR increases due to assumed general efficiency improvements in all sectors, without considering relative shares (e.g., Teseletso & Adachi, 2022; van der Linden, 2020; van Vuuren et al., 1999). Important here is that sectoral disaggregation also applies to supply and not just to demand. The increased risk due to sectoral changes makes it extra important to focus on improving resilience during the energy transition.

During the energy transition, demand-side factors related to functional and material substitution, and extending time in use, improve nickel price stability. Functional substitution improves resilience when configuring the energy system more in line with SSP2-19 compared to other 1.5°C pathways. Based on such findings, critical material dynamics could be used to enhance other methods for optimizing energy systems, such as those based on costs (Brown et al., 2018) and environmental impacts (Theodosiou et al., 2015). Material substitution in batteries improves resilience by mitigating some of the demand increase due to the energy transition. Similarly, increasing battery lifetime partially counteracts the effect an increasing battery share has on average nickel product lifetime. Such insights can inform product design considerations to mitigate future risks (Graedel & Nuss, 2014; Peck et al., 2015). Substitution does lead to (potentially higher) impacts in other supply chains (Baars et al., 2021; Graedel, 2002). However, the larger the diversity of functional and material substitutes (within and across sectors), the more risks are spread, increasing resilience in general (Sprecher et al., 2015).

On the supply side, price stability is increased by improved recycling, exploration, capacity expansion, and by-product recovery. Improving battery recycling partially counteracts the effect an increasing battery share has on average nickel EoL RR, which reduces mining and slightly lowers prices. However, the impact of recycling is constrained by the rate at which metals exit use, and recycling alone cannot keep up with the rising demand (Tercero Espinoza, 2021). Therefore, more primary supply is necessary. The system remains more resilient when exploration is increased sooner, and new resource discoveries at volumes exceeding current mining help to anticipate the higher future demand. Given enough exploration, a higher global maximum capacity increase enhances resilience. Additionally, recovering by-products can improve deposit profitability and spread costs and risks across multiple metals. For clearer conclusions regarding by-products, more of their dynamics should be incorporated in future research. Other research suggests that multi-product production has greater stabilizing benefits in the short term than in the long term (Campbell, 1985). Combining all aforementioned demand- and supply-side factors yields the greatest improvement in overall resilience.

4.3 | Geographical disaggregation

Geographical disaggregation reveals the relatively small impact of short-term supply disruptions due to continued diversity of supply. Nickel deposits are spread across many countries (Mudd & Jowitt, 2022), and although mines dynamically open and close in different regions, supply diversity and related resilience remain. Although our model starts in 2015, it is entirely prospective, so no historical disruptions were included in the main runs. We did, however, test a disruption in Russia due to the Russia–Ukraine war in a single run and it led to a similar average price increase as seen in reality (Trading Economics, 2024).

While overall supply remains diverse, country-specific market shares change over time, affecting energy use and GHG emissions. Total emissions can vary depending on the timing of mine operations and the dynamic energy mixes of the countries involved. The characteristics of each deposit and country influence dynamic competitive advantage, which can change depending on whether externalities such as GHG emissions are considered in the costs. In turn, new mine locations determine where future local impacts will occur. In some criticality assessments, environmental factors influence criticality (Graedel & Reck, 2016; Schrijvers et al., 2020). Therefore, insight into regional impacts can be relevant for understanding the overall system dynamics and resilience, in addition to having merit on its own. In future research, more local impacts, such as land and water use,

can be assessed to address potential regional problems as nickel production evolves (Werner et al., 2019). Additionally, geopolitical risks can be explored in more detail.

The dynamic activation of different mines also influences nickel-dependent by-product production, and average nickel and by-product ore grades. In contrast to models with mine aggregation, which show continuous ore grade decrease (e.g., Sverdrup, 2016; Van der Linden, 2020; Van Vuuren et al., 1999), our model reflects real-world ore grade variability (Mudd & Jowitt, 2014). The general trend is still downward, but the average ore grade can temporarily increase. Average nickel-related by-product ore grades show even more variability and can even show an upward trend. By-product insights are especially relevant for by-products, with a relatively large dependency on nickel, such as cobalt and palladium (Nassar et al., 2015). Based on our projections, by-product production from nickel mining could meet previous demand projections for cobalt (Giurco et al., 2019; Månberger & Stenqvist, 2018; Watari et al., 2018) and palladium (Moreau et al., 2019; Valero et al., 2018), though potential supply chain losses and increased demand due to the energy transition should be considered. Distinguishing between mines is essential for understanding by-product development and criticality, particularly for metals primarily mined as by-products.

4.4 | Toward prospective, dynamic criticality assessment

By combining feedback effects with sectoral and geographical disaggregation, our approach paves the way toward prospective, dynamic criticality assessment. Our findings illustrate how sectoral details, such as shifts in the EoL RR during the energy transition, increase future nickel supply risks, while geographical factors, such as continued supply diversity, and price feedback effects help mitigate them. Nickel demand, prices, and impacts fluctuate widely under different uncertainties and policy levers, emphasizing the importance of extensive uncertainty analysis. Neglecting these aspects may obscure key trends that could alter a metal's criticality, and accounting for future risks is essential for anticipating disruptions and developing robust, adaptive policies. Song et al. (2022) also stress the importance of dynamically assessing criticality as technologies and regional conditions change. This anticipation is particularly relevant for long-term shifts like the energy transition, where recognizing changes early enables proactive mitigation. For nickel, market-based responses alone may be insufficient due to systemic delays, reinforcing the need for policies that encourage exploration, circularity, and innovation in battery material composition and lifetime to enhance resilience.

Our analysis is exploratory in nature and provides an initial qualitative assessment of future global nickel supply risks, however, further steps are needed to obtain more quantitative, regional results. To assess regional risks, further demand-side and secondary production geographical disaggregation is needed. Future research should incorporate such disaggregation and trade mechanisms (as done by, e.g., Song et al., 2022), enabling the testing of actual policy plans, such as the European Critical Raw Materials Act (EC, 2023c). Geographical and sectoral disaggregation provides the level of detail necessary to determine quantitative data for common supply risk indicators, such as the Herfindahl–Hirschman index (HHI), end-of-life recycling input rate (EoL RIR), and import reliance (IR) (EC, 2023a; Helbig et al., 2021). However, these indicators would have to be adapted for a dynamic context, perhaps by basing them on demand rather than on supply to account for risks during supply deficits (see Figure 2.18 of Supporting Information S1). Similar models could then be developed for other metals, and ideally linked, to capture the feedback between metal systems and determine relative criticality. Simplifying these models by removing redundancies in our current approach could further enhance usability. By addressing these factors, dynamic and interconnected models will provide deeper insights into the future criticality and resilience of metals, enabling more effective and forward-looking policies.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that supports the findings of this study are available in the supporting information of this article and openly available on GitHub at https://github.com/JessieBradley/Nickel_SD_model_JB

ORCID

Jessie E. Bradley  <https://orcid.org/0000-0002-1452-5866>

Willem L. Auping  <https://orcid.org/0000-0003-1898-643X>

René Kleijn  <https://orcid.org/0000-0001-5227-5119>

Jan H. Kwakkel  <https://orcid.org/0000-0001-9447-2954>

Gavin M. Mudd  <https://orcid.org/0000-0001-7115-1330>

Benjamin Sprecher  <https://orcid.org/0000-0002-0136-5656>

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