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Research Article

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Posted Date: November 19th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11781942/v1

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Additional Declarations: No competing interests reported.

Operations research models for critical-mineral supply chains: a systematic review and an integrated stochastic programming and system dynamics framework for capacity investment

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Abstract Critical-mineral supply chains behave differently from the manufacturing networks for which most supply chain models were developed. Companion metals are produced as by-products of host metals, separation and refining capacity takes years to build, and secondary supply returns only when products reach the end of their service lives. These features shape prices, investment cycles and the outcome of resource policy. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement, we review 83 studies that build formal quantitative models of these chains, identified from 1,166 database records and 434 records found through citation searching. Dynamic material flow analysis (20 studies) and mathematical programming (14 studies) are the most common approaches. Three gaps stand out: no study formulates a two-stage stochastic programme with recourse, midstream separation is rarely modelled as a capacity investment decision, and only 18% of the studies report validation. To address the first two gaps, we couple a two-stage stochastic mixed-integer design model with a system dynamics model of capacity acquisition, prices and in-use stocks, using the neodymium–iron–boron magnet chain as an illustrative case. In the illustrative instance, planning on mean values raises expected cost by 35.2 million US dollars per year, or 1.5%. The simulations show that ignoring capacity under construction amplifies investment cycles, and that stronger collection of end-of-life products lowers peak prices but makes primary refining utilisation more volatile.

Keywords: Critical minerals, Rare earth elements, Capacity investment, Stochastic programming, System dynamics, Circular economy

MSC Classification: 90B06, 90C15, 90C11, 90-02, 91B76, 37N40

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1 Introduction

Critical minerals have become a question of industrial and resource policy as much as of supply chain management. Electric vehicles, wind turbines, grid storage and defence systems depend on materials whose processing is more concentrated than their extraction. The average market share of the three largest refining countries for energy minerals rose from 82% in 2020 to 86% in 2024, and a single country leads refining for 19 of the 20 minerals tracked by the International Energy Agency, with an average share of about 70% [1]. Export controls on gallium, germanium, antimony, graphite and several heavy rare earth elements have turned this concentration into a direct price and availability risk for manufacturers, and governments have responded with stockpiling and friend-shoring policies whose reach is limited by refining capacity [2].

These chains differ from discrete manufacturing in four ways that matter for investment and policy. Companion metals are by-products of host metals, so their supply responds weakly to their own price [3, 4]. Separation and refining plants take years to permit and build, so

investment reacts to past scarcity and tends to produce boom-and-bust cycles [5, 6]. Joint extraction ties together elements with very different demand, so one ore body yields surpluses of some elements and shortages of others [7]. Secondary supply arrives only after a product lifetime, so recycling policy affects primary markets with long lags [8]. Prices are therefore a slow and noisy guide to investment, and capacity decisions taken under uncertainty carry lasting costs.

Earlier reviews have treated supply security mainly through risk identification, criticality indicators and national strategy [9], or have set out an operations management agenda on resilience, opacity and ethics [10]. Reviews of network design under uncertainty [11] do not deal with by-product supply, construction delays or circular flows. What is missing is a systematic account of the formal models that are used, or could be used, to inform investment and policy decisions: which tiers and decisions they cover, how they represent uncertainty and feedback, and how far their results have been validated.

This paper addresses four questions. RQ1: Which commodities, supply-chain tiers and decisions have been modelled? RQ2: Which modelling paradigms are used, and how do they treat uncertainty, delays and feedback? RQ3: What do the models conclude about recycling and closed loops? RQ4: Which gaps remain, and how can optimisation and feedback simulation be combined to close them? The paper makes three contributions. It maps 83 quantitative models and shows where the evidence base for investment and policy decisions is thin. It proposes a framework that values midstream separation and recycling capacity under uncertainty while accounting for price formation and construction delays. Finally, it uses an illustrative case to estimate the cost of ignoring uncertainty and to show how supply-line accounting and extended producer responsibility affect prices, capacity cycles and refinery utilisation.

2 Review method

2.1 Protocol and reporting standard

The review follows the PRISMA 2020 statement [12] and guidance on literature reviews in logistics and supply chain management [13]. The protocol was not registered; it is reported in Online Resource 1 (Appendix A), and the completed PRISMA checklist is given in Online Resource 1 (Appendix E).

2.2 Information sources and search strategy

Twelve field-restricted queries were run in the scite.ai index [14] on 24 October 2026 for publications from 2012 onwards and returned 1,350 records. Backward and forward citation searching from eight seed studies added 722 records (Online Resource 1, Table A.1).

2.3 Eligibility criteria

We included peer-reviewed English-language journal articles that built or applied a formal quantitative model of the supply chain or market of a critical mineral. Static recycling estimates, pure demand projections, criticality scoring and battery logistics without material flows were excluded (Online Resource 1, Table A.2).

2.4 Selection process and use of large language models

Screening was carried out on titles and abstracts and then on full texts. A large language model (Claude, Anthropic) applied the written protocol to each record and assisted with data extraction; the authors checked all full-text decisions and extracted values against the source texts. The same tool helped generate code for the figures and illustrative models and assisted

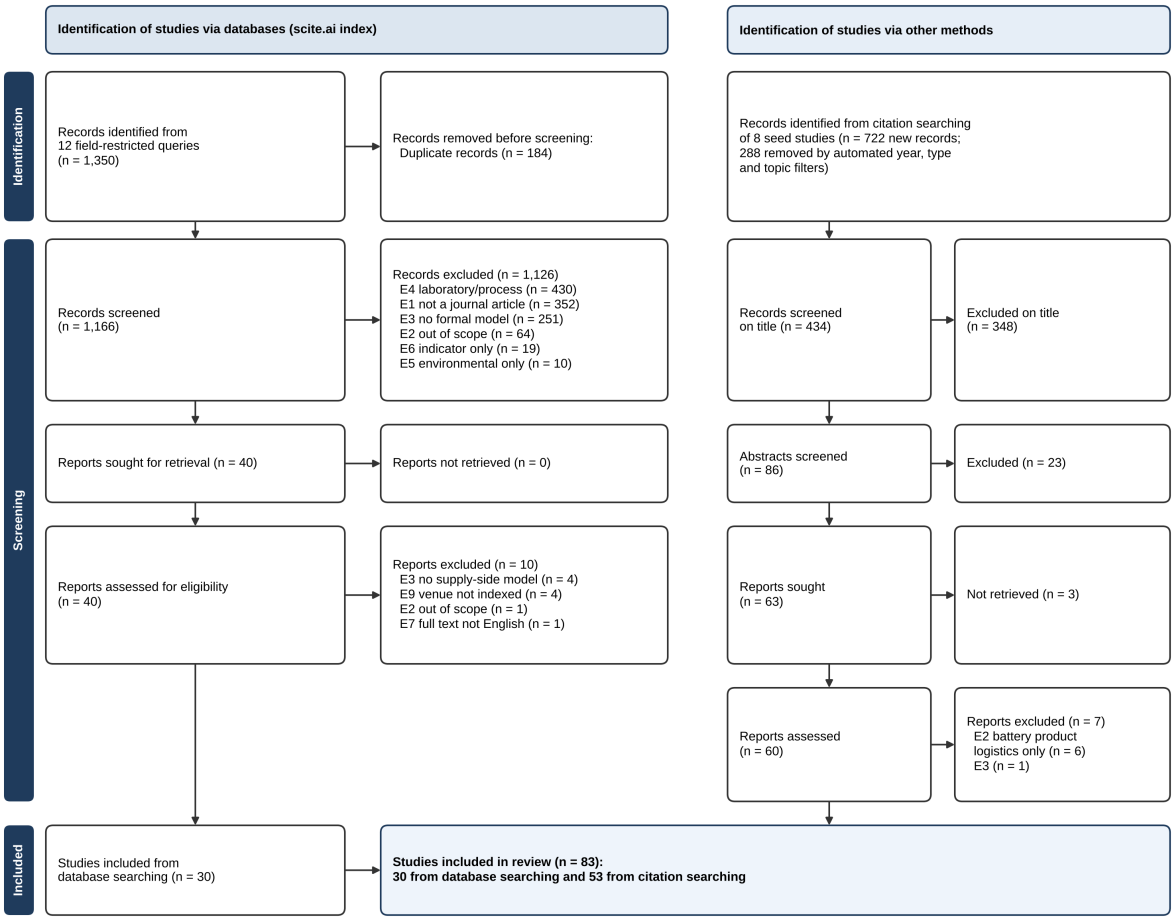


Fig. 1 PRISMA 2020 flow diagram of study selection

with drafting and language editing. The authors reviewed and edited all such output and take full responsibility for the content.

2.5 Data extraction, quality appraisal and synthesis

For each study we extracted the commodity, tier, method family, treatment of uncertainty, decision level and main finding. Quality was appraised against five binary criteria (stated problem, transparent formulation, data source or calibration, validation or verification, and sensitivity or scenario analysis) and used to describe the evidence base rather than to exclude studies. The synthesis is descriptive and narrative.

3 Profile of the evidence base

3.1 Study selection

After removal of 184 duplicates, 1,166 database records were screened and 1,126 were excluded. Forty reports were assessed in full and 30 were included. Of the 722 records from citation searching, 434 remained after automated year, type and topic filters; 60 reports were assessed in full and 53 were included. The review therefore covers 83 studies (Fig. 1; Online Resource 1, Appendix D).

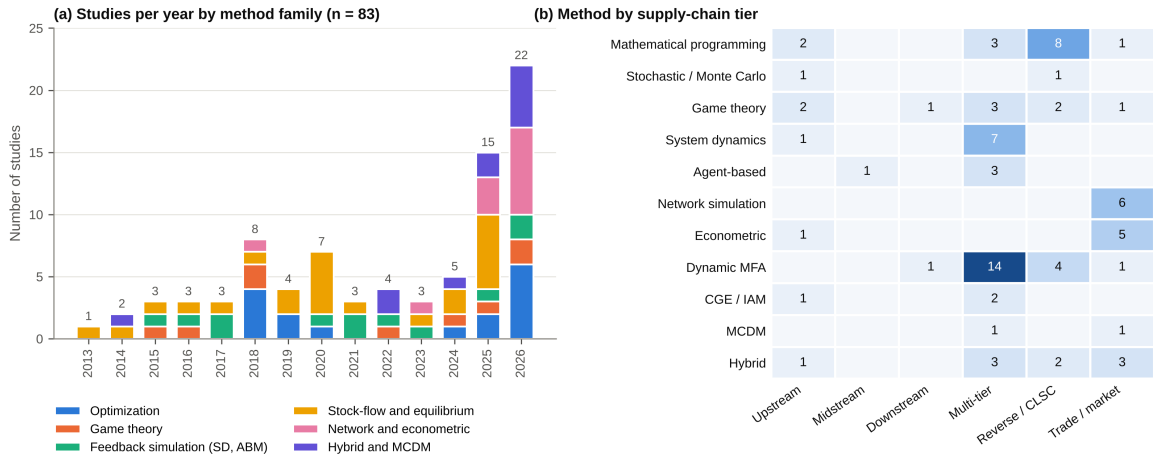


Fig. 2 Profile of the 83 included studies: (a) studies per year by method family; (b) method family by main supply-chain tier

3.2 Temporal, commodity and outlet profile

The field is young and growing quickly: 24 studies appeared up to 2019, 22 between 2020 and 2024, and 37 in 2025 and 2026 (Fig. 2a). Rare earth elements and permanent magnets are the subject of 45 studies (54%), lithium of 12, and nickel and cobalt of four each. Most studies appeared in resource-policy and industrial-ecology journals, led by Resources Policy and Sustainability (12 each), and only six in operations research, operations management or logistics journals (Online Resource 1, Appendix G). The topic thus sits within resource economics and policy, where the prescriptive tools of operations research are still little used.

3.3 Methods, supply-chain tiers and decision levels

Dynamic material flow analysis ($n = 20$) and mathematical programming ($n = 14$) are the largest method families, followed by game theory ($n = 9$), hybrid models ($n = 9$), system dynamics ($n = 8$), econometric models ($n = 6$) and network models ($n = 6$) (Fig. 2b). Only one study treats midstream separation and refining as its main object. Policy analysis (58 studies) and strategic design (21) dominate, whereas tactical and operational decisions appear in only four studies.

3.4 Quality appraisal and treatment of uncertainty

Although 78% of the studies provide a transparent formulation, only 18% (15 studies) report validation or verification (Fig. 3a). Uncertainty is handled mostly through scenarios (65%), followed by deterministic set-ups (14%) and Monte Carlo simulation (8%) (Fig. 3b). No study formulates a two-stage stochastic programme with recourse, the standard approach to capacity decisions under uncertainty [15, 16].

4 Primary supply and multi-tier design

Thirty-one studies model primary supply, refining or integrated forward chains; study-level detail is given in Online Resource 1 (Appendix B, Table B.1).

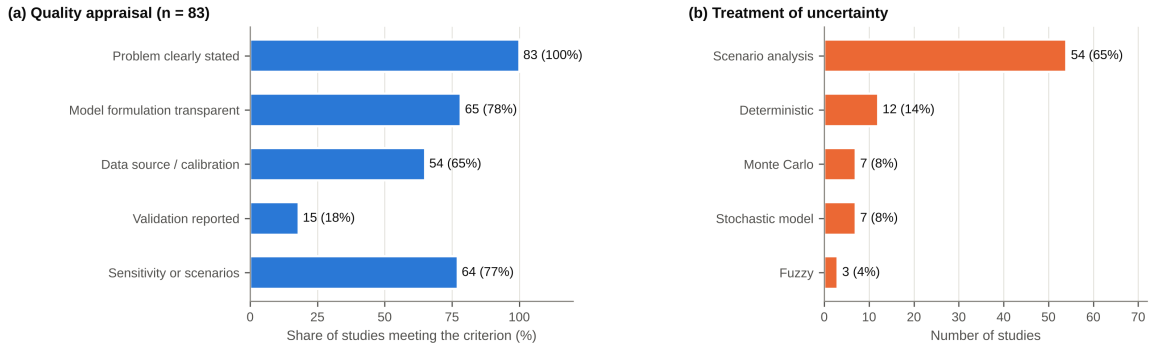


Fig. 3 Quality appraisal and treatment of uncertainty: (a) share of studies meeting each appraisal criterion; (b) studies by treatment of uncertainty

4.1 By-product dependence and co-production

Econometric evidence for 40 metal pairs shows that the supply of companion metals depends on host-metal economics rather than on their own prices [3], and simulation models confirm this for indium, cobalt and nickel [17, 4, 18]. Co-production yields surpluses and deficits at the same time, for example of europium, yttrium and terbium, and of heavy rare earths at regional level [7, 19, 20]. Material flow models show that meeting wind power targets would require an 11- to 26-fold expansion of neodymium and praseodymium supply [21], point to unrecorded mining [22] and reveal close interdependence between Chinese and US supply [23]. Because a separation plant earns revenue from a basket of elements with weakly related demand, models that ignore co-production misstate the value of separation assets.

4.2 Investment, delays and market power

Agent-based models show that disruption effects persist for years after physical supply recovers [5, 24], and new mines take six to nine years to commission [6, 25]. Game-theoretic models examine how quotas, taxes, industrial integration and Stackelberg leadership shape capacity and prices [26, 27, 28, 29]. In lithium, deadweight losses concentrate in refining [30], and strategic reserve policy follows threshold rules [31]. System dynamics and computable general equilibrium (CGE) models simulate quotas, environmental regulation and informal mining [32, 33, 34]. In these models capacity follows behavioural or equilibrium rules rather than cost-optimal design.

4.3 Network design for primary supply chains

Design models of primary chains focus on battery metals. A global mixed-integer programme finds that an emissions-minimising lithium network costs 6% more and emits 2% less than the cost-minimising design [35]. Other programmes assess lithium routes in Mexico and Brazil [36, 37], the import dependence of US clean-energy targets [38], flexible battery chemistries [39], dual sourcing under disruption [40], the effect of recycling on new mine requirements [41] and recovery routes for magnets [42]. All of them are deterministic or scenario-based, and none represents reagent supply.

5 Reverse flows and closed loops

Twenty-eight studies examine secondary recovery and closed-loop networks (Online Resource 1, Table B.2).

5.1 Secondary supply potential and timing

Stock-flow models show that secondary supply lags primary use by the lifetime of the product. Recycled neodymium and dysprosium were negligible up to 2020 [8] but could meet 18% to 26% of demand in magnet and wind applications over 2030 to 2050 [43, 21]. Similar timing effects are reported for vehicle and wind-turbine magnets [44, 45], lighting phosphors [46], dysprosium [47, 48, 49] and battery metals [50, 51, 52, 53, 54]. Two economic findings recur: lower material intensity often reduces criticality faster than recycling, and circular strategies shift primary dependence between metals, for example from cobalt to nickel. Secondary supply is therefore a long-term stabiliser rather than a short-term buffer.

5.2 Optimisation of reverse networks

Reverse-network models for permanent magnets cover location-allocation under fuzzy uncertainty, inventory control and multi-objective network design [55, 56, 57, 58], and superstructure optimisation finds vehicle-magnet recycling profitable but hard-disk recovery unprofitable [42]. In battery reverse logistics, decentralised black-mass production lowers network cost by 42% [59], and other models locate recycling plants or schedule production and recycling jointly [60, 61]. Further work adds stockpiles under extended producer responsibility (EPR) and pinch-analysis bounds on recovery [62, 63].

5.3 Incentives and coordination in the reverse chain

Game-theoretic models show that competition for scarce resources can push firms towards recycling [64], that recycling subsidies expand secondary output without lowering primary margins [65], and that environmental taxes curb extraction but may hurt remanufacturing unless combined with subsidies [66]. Combining EPR, taxation and green procurement raises the magnet recycling rate to 52.3%, a level that single instruments do not reach [67]. In all of these models end-of-life inflows are exogenous, so the feedback from prices to product demand and future scrap is missing.

6 Modelling paradigms: feedback, networks and uncertainty

Table 1 compares the paradigms found in the 83 studies.

6.1 Feedback models

System dynamics models represent delays and market feedback under trade restrictions, quotas and supply shocks [32, 6, 33, 68, 69, 70, 71]. At mine-level resolution, endogenous market feedback gives more realistic depletion paths for nickel than static material flow analysis [18]. Agent-based models represent heterogeneous market participants [5, 24, 4], recently with agent rules derived from large language models [72, 73]. None of these models optimises network design.

6.2 Network and econometric models

Network models trace how shocks spread through trade [74, 75, 76, 77, 78]. Diplomatic cooperation, for example, multiplies rare earth trade by 3.29 [79], and a 25% export tariff reduces global rare earth trade by more than 10% [80]. Econometric studies estimate the behavioural parameters that simulation models need: stockpiling responses, export cycles, price transmission, demand effects, shipping risk and the cost of decoupling [2, 81, 82, 83, 84, 85]. Neither group prescribes network decisions.

Table 1 Comparison of modelling paradigms in the corpus ($n = 83$)

Paradigm	n	Main tiers (n)	Main uncertainty treatment (n)	Valid.[1]	Strength	Limitation
Dynamic material flow and stock-flow (DMFA)	20	multi-tier (14), reverse (4)	scenario (13), deterministic (4)	2	Stocks, retirement delays, secondary potential	No decisions; prices exogenous
Mathematical programming (MP)	14	reverse (8), multi-tier (3)	scenario (8), deterministic (5)	1	Location, capacity and flow decisions	Deterministic inputs; no feedback
Hybrid (HYB)	9	trade (3), multi-tier (3)	scenario (9)	2	Links behaviour and flows	Ad hoc couplings; hard to validate
Game theory (GT)	9	multi-tier (3), reverse (2)	scenario (6), deterministic (2)	2	Market power, incentives, coordination	Static; stylised networks
System dynamics (SD)	8	multi-tier (7), upstream (1)	scenario (7), Monte Carlo (1)	1	Delays, feedback, capacity cycles	No design optimisation
Econometric (ECO)	6	trade (5), upstream (1)	stochastic (4), deterministic (1)	2	Behavioural parameters for calibration	Not prescriptive
Network simulation (NET)	6	trade (6)	scenario (5), stochastic (1)	1	Shock propagation in trade	No decision variables
Agent-based (ABM)	4	multi-tier (3), midstream (1)	scenario (3), Monte Carlo (1)	3	Heterogeneous agents, persistence of shocks	Calibration and validation burden
General equilibrium and integrated assessment (CGE/IAM)	3	multi-tier (2), upstream (1)	scenario (3)	0	Economy-wide and energy-system effects	Coarse supply-chain detail
Stochastic evaluation (SP/RO)	2	upstream (1), reverse (1)	Monte Carlo (1), stochastic (1)	1	Probabilistic evaluation of supply or policies	No recourse decisions
Multi-criteria (MCDM)	2	multi-tier (1), trade (1)	fuzzy (2)	0	Structured weighting of criteria	No supply-chain dynamics

6.3 Integrated models and the treatment of uncertainty

Multi-criteria models rank trade partners and barriers [86, 87]. Integrated assessment and market models link mineral constraints to the energy transition: bottlenecks could halve clean power deployment by 2060 [88], and recycling and substitution reduce the prevalence of price risk from 90% to under 10% [89]. An energy-system model finds that lithium criticality is economic and geopolitical rather than geological [90], while supply-gap and input-output models identify deficits in battery metals and limits to niobium circularity [91, 92]. Across all paradigms uncertainty is handled mainly through scenarios, and recourse decisions are absent.

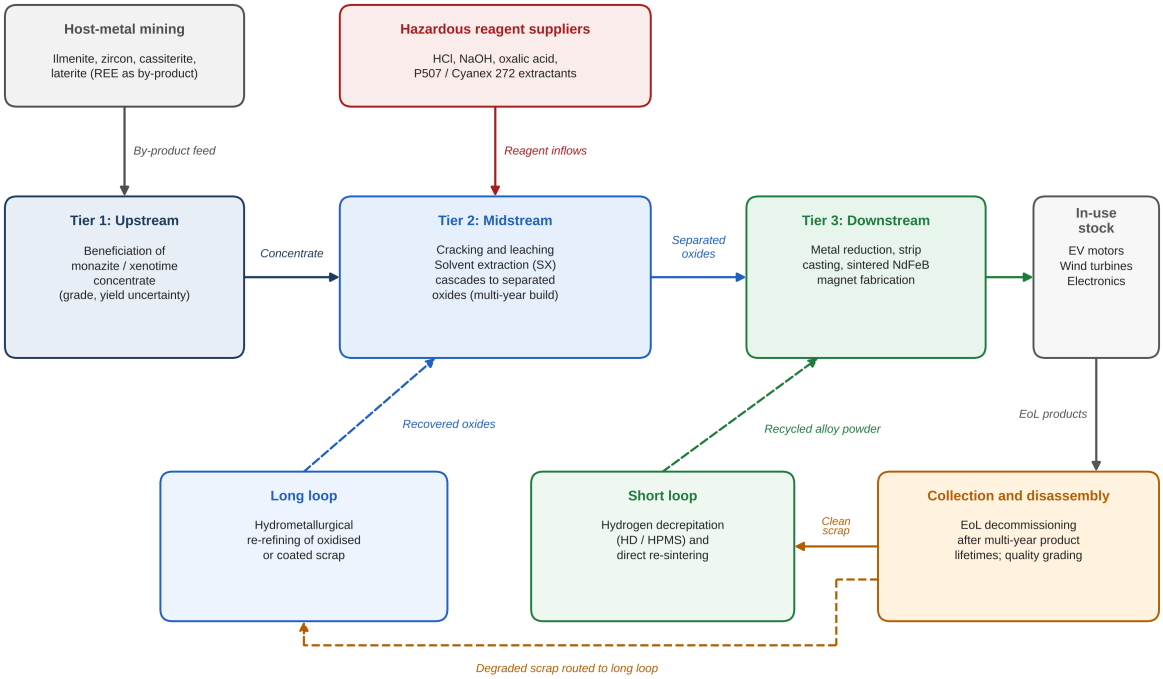


Fig. 4 Multi-tier and closed-loop architecture of the NdFeB magnet supply chain used as the reference case. Solid arrows denote forward and reagent flows; dashed arrows denote secondary flows

7 An integrated stochastic programming and system dynamics framework

The review points to a structural mismatch: optimisation models choose locations and capacities but take feed, prices and scrap as given, whereas feedback models capture delays and price formation but cannot choose network structure. We combine two-stage stochastic programming, the standard method for design under uncertainty [15, 16, 11], with system dynamics [93], so that capacity is valued against a distribution of supply and demand conditions generated by a model of market dynamics. Persistent disruptions in rare earth markets [24] are one instance of the ripple effects that such a framework must capture [94, 95].

7.1 Architecture of the framework

Figure 4 shows the reference chain for neodymium–iron–boron (NdFeB) magnets. Concentrate is recovered as a by-product and separated into oxides by solvent extraction (SX), which consumes hazardous reagents. Oxides are reduced to alloys and fabricated into magnets. End-of-life magnets return through a short loop (direct re-sintering) or a long loop (hydrometallurgical re-refining). The framework links a stochastic mixed-integer design layer to a stock-flow simulation layer that supplies the scenario distribution and end-of-life volumes.

7.2 Design layer: two-stage stochastic mixed-integer programme

In the first stage the planner decides which separation hubs j and recycling plants s to open (Y_j, Y_s) and how much capacity to install (CAP_j, CAP_s). In the second stage a scenario ω with probability p_ω is revealed, and concentrate, reagent, oxide, product and scrap flows are

chosen. The objective minimises annualised investment cost plus expected recourse cost:

$$\min Z = \sum_{j \in J} \left(F_j Y_j + C_j \, CAP_j\right) + \sum_{s \in S} \left(F_s Y_s + C_s \, CAP_s\right) + \sum_{\omega \in \Omega} p_\omega \Phi_\omega \tag{1}$$

where the recourse cost of scenario ω is

$$\begin{aligned} \Phi_\omega = & \sum_{i,j} c_{ij} X_{ij\omega} + \sum_{u,j} \left(c^G_{uj} + \kappa_u\right) G_{uj\omega} + \sum_{j,k} c_{jk} W_{jk\omega} + \sum_{k,m} c_{km} V_{km\omega} \\ & + \sum_{m,r} c^{\mathrm{rev}}_{mr} Q_{mr\omega} + \sum_{r,s} c^{\mathrm{rev}}_{rs} R_{rs\omega} + \sum_{s,j} c^{\mathrm{rec}}_{sj} S_{sj\omega} + \sum_{m} \pi_m \, SHORT_{m\omega} \end{aligned} \tag{2}$$

The recourse cost includes a handling surcharge κ_u on hazardous reagents and a penalty π_m on unmet demand, which can be read as the cost of shortfalls to downstream users. The constraints limit purchases to scenario-specific concentrate availability, apply SX yields and minimum reagent inputs, balance oxide supply with demand, and cap recycling by the end-of-life outflow passed from the dynamic layer; the full formulation (Eqs. C.1 to C.8) and notation (Table C.1) are given in Online Resource 1 (Appendix C). The economic value of planning under uncertainty is measured by two standard quantities [15]:

$$\mathrm{VSS} = \mathrm{EEV} - \mathrm{RP} \geq 0, \qquad \mathrm{EVPI} = \mathrm{RP} - \mathrm{WS} \geq 0 \tag{3}$$

where RP is the expected cost of the stochastic solution, EEV the expected cost of implementing the mean-value design, and WS the expected cost when each scenario is known in advance. The value of the stochastic solution (VSS) is the expected loss from planning on mean values, and the expected value of perfect information (EVPI) is an upper bound on what a planner should be willing to pay for better information on supply, reagent availability and demand.

7.3 Dynamic layer: system dynamics model

The in-use magnet stock $S(t)$ grows with shipments $I(t)$ and declines with retirements $O(t)$, obtained by convolving past shipments with a Weibull lifetime density $f(x)$ [93]:

$$\frac{\mathrm{d}S(t)}{\mathrm{d}t} = I(t) - O(t), \qquad O(t) = \int_0^t I(\tau) f(t-\tau)\,\mathrm{d}\tau, \qquad f(x) = \frac{\varphi}{\lambda}\left(\frac{x}{\lambda}\right)^{\varphi-1} \mathrm{e}^{-(x/\lambda)^\varphi} \tag{4}$$

Separation capacity $K(t)$ is adjusted through capacity starts $CS(t)$ that replace retirements $CR(t)$ and close the gaps in installed capacity and in the supply line $SL(t)$ of capacity under construction, following an anchoring-and-adjustment rule:

$$CS(t) = \max\left\{0,\; CR(t) + \frac{K^*(t) - K(t)}{T_a} + w_{SL}\,\frac{SL^*(t) - SL(t)}{T_a}\right\} \tag{5}$$

where $w_{SL} \in [0,1]$ is the weight that investors give to capacity already under construction. The indicated oxide price $P^*(t)$ responds to inventory coverage $c(t)$, and the market price adjusts to it with a lag:

$$P^*(t) = P_{\mathrm{ref}} \min\left\{P_{\max},\; \left(\frac{c^*}{c(t)}\right)^{\varepsilon}\right\}, \qquad \frac{\mathrm{d}P(t)}{\mathrm{d}t} = \frac{P^*(t) - P(t)}{T_P} \tag{6}$$

Primary output is limited by desired output, installed capacity, feed availability and reagent supply:

$$Q_{\mathrm{prim}}(t) = \min\left\{Q^*(t),\; u_{\max} K(t),\; \alpha A(t),\; \frac{G(t)}{\gamma}\right\} \tag{7}$$

Equation (6) is the channel through which scarcity feeds back into demand, investment and, a product lifetime later, scrap availability; Eq. (7) makes reagent supply an explicit constraint on refinery output.

Table 2 Illustrative results of the design layer (27 scenarios; costs in million USD per year, flows in kt per year)

Indicator	Stochastic solution (RP)	Mean-value solution (EV)
Hubs opened	H1, H3	H1, H3
Separation capacity by hub	H1: 60.0; H3: 31.3	H1: 30.6; H3: 56.5
Total separation capacity	91.3	87.1
Recycling plant and capacity	S2: 15.3	S2: 15.3
First-stage cost	606.6	619.3
Expected total cost under uncertainty	2285.2 (RP)	2320.3 (EEV)
Expected unmet demand	14.2	14.8
Expected secondary feed	13.5	13.5
Wait-and-see cost (WS)	2208.2	
VSS = EEV − RP	35.2 (1.5% of RP)	
EVPI = RP − WS	76.9 (3.4% of RP)	

7.4 Coupling of the two layers

The layers are linked by fixed-point iteration. The dynamic simulation generates scenario parameters and end-of-life volumes; the design model returns capacities; these capacities update the capacity targets in the simulation; and the procedure repeats until the relative change in capacities falls below a tolerance (Online Resource 1, Eq. C.9).

7.5 Illustrative results: design layer

The illustrative instance has three mines, three candidate hubs and two candidate recycling plants, and its 27 scenarios combine three levels each of concentrate availability, demand and reagent availability (Online Resource 1, Appendix C). Table 2 summarises the results obtained with the open-source HiGHS solver.

Both designs open the same hubs and recycling plant but size and place capacity differently. The stochastic solution installs 91.3 kt per year of separation capacity, 4.8% more than the mean-value design (87.1 kt per year), and places most of it at hub H1 rather than H3. Implementing the mean-value design raises expected cost by 35.2 million USD per year (VSS, 1.5% of RP), which equals 5.8% of the annualised first-stage investment cost. The EVPI of 76.9 million USD per year (3.4% of RP) bounds the value of better information. The recycling plant has the same size (15.3 kt per year) in both solutions because it is limited by the end-of-life outflow from the dynamic layer, not by demand uncertainty.

7.6 Illustrative results: dynamic layer

Figure 5 shows the causal loop diagram; its eight feedback loops are listed in Online Resource 1 (Table C.2). Loop R4, for example, captures scrap-base erosion: a supply deficit raises prices, which reduces magnet demand and, a product lifetime later, the scrap available for recycling. The stock-flow model (parameters in Online Resource 1, Appendix F) was run under four scenarios: S0, base case with $w_{SL} = 0.3$; S1, full supply-line weighting ($w_{SL} = 1.0$); S2, EPR collection raised by 40 percentage points from 2030; and S3, no concentrate shock.

Figure 6 and Table 3 show three results. First, when investors underweight capacity under construction (S0), utilisation follows cycles of about 12 years, its standard deviation is four times that under S1 (0.043 against 0.011), and peak capacity under construction is 38% higher (761 against 552 kt per year). This is the capacity cycle described in earlier models [5, 6]. Second, stronger EPR collection (S2) lowers the peak price index from 1.63 to 1.30 and raises the secondary share of shipments to 20.4% by 2060. Third, the same policy raises the volatility of primary refinery utilisation (standard deviation 0.062), because secondary oxide displaces

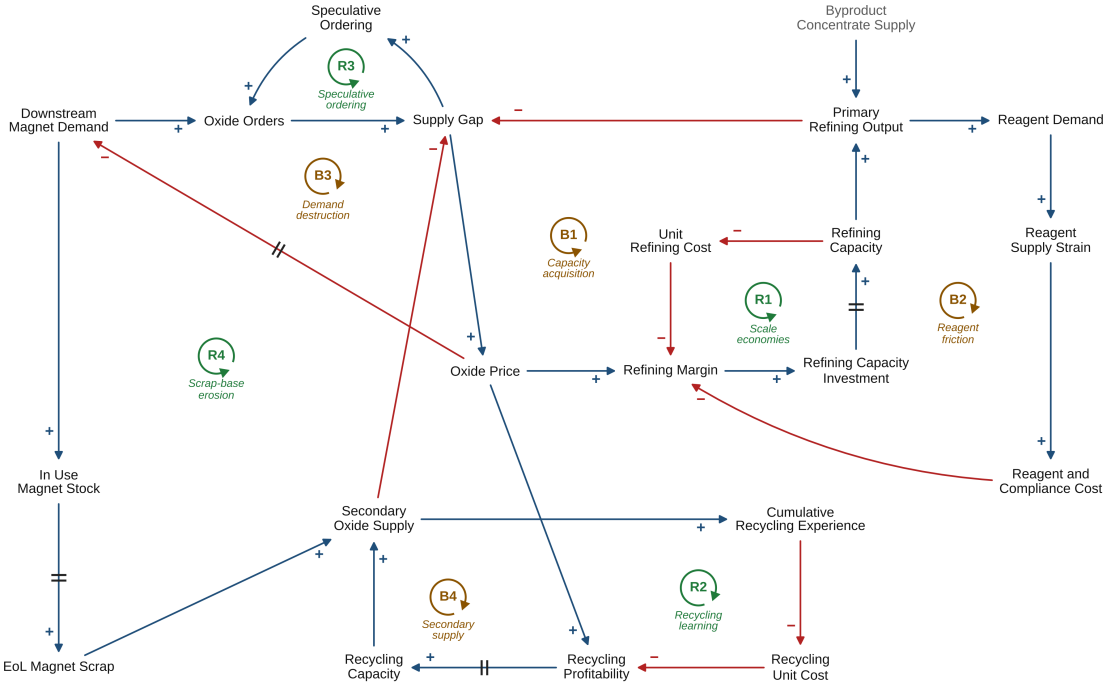


Fig. 5 Causal loop diagram of the reference chain with link polarities, delay marks and the eight feedback loops (the Vensim file is provided in Online Resource 3)

Table 3 Simulation indicators, 2025 to 2060

Indicator	S0	S1	S2	S3
Peak price index (year)	1.63 (2032)	1.63 (2032)	1.30 (2031)	1.22 (2060)
Minimum utilisation, 2030 to 2060	0.68	0.72	0.66	0.67
Standard deviation of utilisation, 2035 to 2060	0.043	0.011	0.062	0.041
Peak capacity under construction (kt per year)	761	552	616	706
Secondary share of shipments in 2060	4.1%	4.1%	20.4%	4.1%

primary output [50].

8 Managerial and policy implications

8.1 Implications for capacity investment and policy

The results are illustrative, but they point to five implications. First, investment in separation and recycling capacity should be appraised against explicit probability distributions of feed, reagent supply and demand; in the illustrative case the mean-value design is not only more expensive but also places capacity at the wrong hub. For public agencies that co-finance midstream plants, the VSS measures what is lost when appraisal relies on central forecasts, and the EVPI bounds the value of public information such as geological surveys, market monitoring and disclosure of stockpile levels.

Second, reagent logistics belong to the economics of midstream capacity: hazardous reagent supply, permitting and transport can bind output (Eq. (7)), so subsidies for separation capacity that do not secure reagents may deliver less oxide than planned.

Third, recycling capacity should be sized to the retirement profile of in-use stocks rather

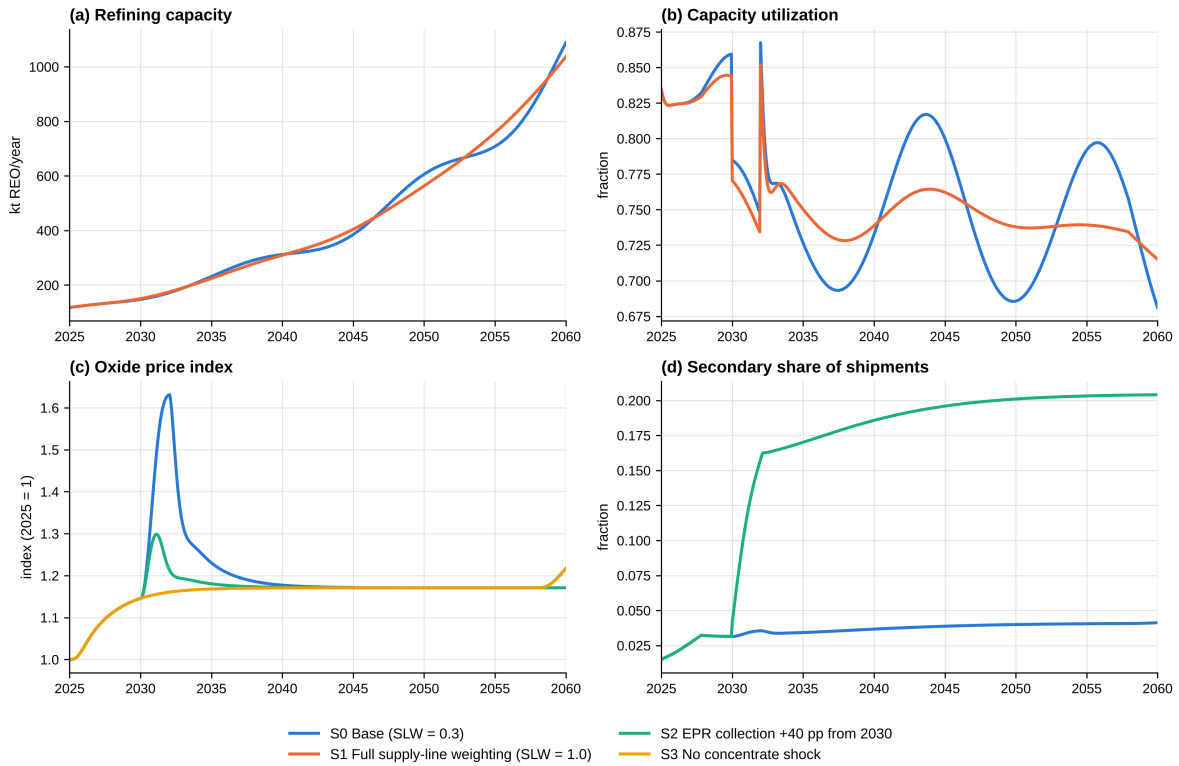


Fig. 6 Behaviour of the stock-flow model under four scenarios (illustrative parameters): (a) separation capacity and (b) capacity utilisation for S0 and S1; (c) oxide price index for S0, S2 and S3 (S1 coincides with S0); (d) secondary share of shipments for S0 and S2

than to current demand, because secondary supply arrives one product lifetime after the original sale [8, 21]. The identical recycling capacity in both design solutions illustrates this point.

Fourth, circularity policy has distributional effects within the supply chain. EPR collection dampens price spikes and raises secondary supply, but it moves part of the adjustment burden onto primary refiners, whose utilisation becomes more volatile. Collection mandates may therefore need to be paired with measures that reduce investment risk for primary refiners, for example long-term offtake arrangements or coordinated capacity planning.

Fifth, much of the boom-and-bust behaviour of refining capacity comes from how investors account for projects already under construction. Public reporting of capacity pipelines could dampen these cycles, much as information sharing reduces the bullwhip effect in manufacturing chains. Scenario sets for such analyses should draw on econometric evidence on stockpiling and trade responses [2, 81].

8.2 Research agenda

Table 4 brings together the seven gaps identified in the corpus and the corresponding research directions.

Five directions follow from the table. Design models should represent uncertainty explicitly, through stochastic, distributionally robust or chance-constrained formulations with scenario sets informed by econometric evidence. Midstream refining should be modelled as a decision tier, with SX capacity, co-production balances and reagent logistics as endogenous choices [7, 20]. Tactical and operational decisions, which 79 of the 83 studies leave aside, deserve attention, including stockpile release rules, dual-sourcing contracts [40] and recovery scheduling under uncertain scrap quality [56]. Validation by behaviour reproduction and back-casting

Table 4 Research gaps, supporting evidence and research directions

Gap	Evidence in the corpus ($n = 83$)	Research direction
G1 Uncertainty in design	Scenario analysis in 54 studies, deterministic models in 12; no two-stage or multi-stage stochastic programme	Two-stage and multi-stage stochastic, distributionally robust and chance-constrained design models
G2 Midstream as decision stage	Separation and refining are the main object of 1 study; no design model with reagent capacity	SX capacity planning, co-production balances and hazardous-reagent logistics
G3 Decision level	Policy 58, strategic 21, tactical 3, operational 1	Stockpiling rules, procurement contracts, dual sourcing and inventory control
G4 Validation	Validation or verification reported in 15 studies (18%)	Behaviour-reproduction and back-casting tests; open code and data
G5 Integration of paradigms	No study couples network-design optimisation with an endogenous feedback model	Coupled optimisation and simulation frameworks (Section 7)
G6 Commodity coverage	Rare earths and magnets in 45 studies; none centred on Ga, Ge, Sb, graphite, W or PGMs	Extension to materials under export controls
G7 Disciplinary outlet	Six studies in OR, OM or logistics journals	Engagement of the OR and OM community with critical-mineral chains

should become standard, particularly where large language models specify agent behaviour [72, 73]. Finally, coverage should extend to gallium, germanium, antimony, graphite, tungsten and platinum-group metals. Large instances of the coupled framework can be solved with multicut L-shaped methods or progressive hedging (Online Resource 1, Appendix H).

9 Limitations

The review has several limitations. Database searching used a single citation index; citation searching reduced but may not have removed the risk of missing records, and it was limited to one generation. Screening was assisted by a large language model, which may introduce selection bias even though all full-text decisions were checked by the authors. Where full texts were not openly accessible, quality appraisal relied on abstracts. Studies not written in English were excluded, and the protocol was not registered. Finally, the numerical results in Section 7 use illustrative, uncalibrated parameters; they show the structural behaviour of the framework and should not be read as forecasts for any firm or country.

10 Conclusions

This review examined 83 quantitative models of critical-mineral supply chains published since 2012. The field is growing quickly but remains fragmented: dynamic material flow analysis and mathematical programming dominate, rare earth elements are the main commodity, and most studies support policy analysis rather than investment or operational decisions. Models that capture feedback rarely optimise network design, and models that optimise design leave out delays and price formation.

Three gaps stand out: the absence of two-stage stochastic programming, the neglect of midstream separation as a capacity decision, and the limited validation of published models. The framework proposed here addresses the first two by coupling a two-stage stochastic programme with closed mass balances to a stock-flow simulation of capacity, prices and in-use stocks. In the illustrative case, stochastic planning lowers expected cost relative to mean-value planning, recycling capacity is governed by the retirement of in-use stocks, and both investor behaviour

and collection policy change the stability of primary refining. Calibration with industry and trade data, and application to materials under export controls, are the natural next steps.

Acknowledgements

The authors acknowledge the research library facilities that provided institutional and methodological resources for this work.

Declarations

- **Funding** This research did not receive any specific grant from funding agencies in the public, commercial or not-for-profit sectors.

- **Competing interests** The authors have no relevant financial or non-financial interests to disclose.

- **Ethics approval and consent to participate** Not applicable. The study does not involve human participants or animals.

- **Consent for publication** Not applicable.

- **Data availability** The search queries, exclusion counts, extraction matrix for the 83 included studies, PRISMA checklist and model parameters are provided in Online Resources 1 and 2. Record-level screening decisions are available from the corresponding author on reasonable request.

- **Materials availability** Not applicable.

- **Code availability** The Vensim models of the causal loop diagram and the stock-flow model, and the Python code of the illustrative stochastic programme, are provided in Online Resource 3.

- **Author contributions** Conceptualization: Denny Noviansyah, Abdullah Ade Suryobuwono; Methodology: Denny Noviansyah; Formal analysis: Denny Noviansyah; Investigation: Denny Noviansyah; Data curation: Abdullah Ade Suryobuwono; Software: Denny Noviansyah, Abdullah Ade Suryobuwono; Validation: Abdullah Ade Suryobuwono; Visualization: Denny Noviansyah; Resources: Denny Noviansyah, Abdullah Ade Suryobuwono; Writing – original draft: Denny Noviansyah; Writing – review and editing: Abdullah Ade Suryobuwono; Supervision: Abdullah Ade Suryobuwono. All authors read and approved the final manuscript.

Supplementary Information

Online Resource 1 (ESM_1.pdf): appendices A–H (search strategy, extended synthesis, full design-layer formulation, list of included studies, PRISMA 2020 checklist, model parameters, corpus profile and solution methods). Online Resource 2 (ESM_2.xlsx): data tables (search queries, eligibility criteria, extraction matrix of the 83 studies, PRISMA counts, system dynamics parameters and results underlying Tables 2 and 3). Online Resource 3 (ESM_3.zip): Vensim model files and Python code of the illustrative stochastic programme.

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