Geometallurgical Recovery Prediction Models for U.S. Critical Minerals: A Critical Review of Current Approaches for Copper, Cobalt, Lithium and Rare Earth Element Ore Systems

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Abstract: The United States is working hard to scale up domestic critical mineral production, and the goal is to reduce import dependence. Executive Order 14241 and the 2025 List of Critical Minerals set the federal framework, and that framework rests on credible domestic production projections. The projections then rest on the accuracy of recovery prediction models that operators run at mine level. This paper reviews the published geometallurgical recovery prediction literature for four critical mineral systems of U.S. strategic importance. The systems are copper, cobalt, lithium, and rare earth elements. It compares the geostatistical, machine-learning, and process-mineralogy methods that are now in use. And it identifies where the underlying physical complexity, the data availability, and the published methodology align to support credible federal projections. It also shows where they do not. The conclusion is that the methodology maturity is highly uneven across the four mineral systems, and that this unevenness has direct consequences for U.S. critical mineral supply chain credibility.

Keywords: *Geometallurgy; Recovery Prediction; Critical Minerals; Lithium; Cobalt; Copper; Rare Earth Elements; Geostatistics; Non-Additivity; U.S. Mining.*

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I. INTRODUCTION

Whether the United States can produce enough of its own critical minerals to reduce import dependence has become a central question of U.S. industrial policy. Executive Order 14241 was signed on 20 March 2025 (Federal Register, 90 FR 13673), and it requires immediate measures to increase domestic mineral production as a matter of national security (White House, 2025). The Final 2025 List of Critical Minerals was published on 7 November 2025 (Federal Register, 90 FR 50494), and the list names sixty mineral commodities that are essential to the national economy and national security (USGS, 2025b). The federal methodology that supports the list takes operator-reported production figures and turns them into national-scale supply-risk estimates (Nassar et al., 2025). So the credibility of the national projection depends directly on the credibility of the operator-level recovery numbers.

But federal policy ambition alone does not solve a technical problem. U.S. lithium resources occur in claystone formations at Thacker Pass, Nevada, and that is a non-traditional ore type at relatively low grades. U.S. cobalt resources are concentrated in metasedimentary cobalt-copper deposits in Idaho, and also in Proterozoic magmatic nickel-copper sulfide deposits in Michigan (USGS, 2025a). The Mountain Pass carbonatite in California is the principal active U.S. source of rare earth elements (MP Materials Corp., 2024). And U.S. copper resources come mainly from porphyry deposits with mineralogically zoned ore types. So each of these systems presents its own recovery prediction problem, because the physical and chemical controls on recovery are different in each case.

Geometallurgy integrates geological, mineralogical, and metallurgical information within a spatial framework, and the framework is usually a 3D block model. The purpose is to forecast metallurgical performance before the

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ore arrives at the plant (Lamberg, 2011; Dunham & Vann, 2007). At the heart of practice is the recovery prediction model. The model is a quantitative relationship between measurable ore characteristics and metallurgical recovery, and the simplest definition of recovery is given in Equation (1).

$$R = \frac{M_c}{M_f} \times 100 \tag{1}$$

Where R is recovery (%), M_c is the mass of metal in the concentrate, and M_f is the mass of metal in the feed. This simple ratio conceals a deep methodological problem: recovery, unlike grade, is not a spatially additive variable. The recovery of a blend of two ore parcels is not the average of their individual recoveries (Carrasco, Chilès, & Séguret, 2008) — a property that complicates the application of conventional geostatistical estimators such as kriging.

Geometallurgical recovery prediction has matured considerably for copper (Musafer, Thompson, Kozan, & Wolff, 2019; Adeli, Dowd, Emery, & Xu, 2021; González-García, Madani, & Emery, 2025). It is less mature for cobalt (Dehaine et al., 2021), and it is still in early stages for lithium and rare earth elements. This asymmetry matters. The credibility of federal production projections (Nassar et al., 2025) depends on what operating mines actually deliver in recovery against forecast, and that delivery depends on whether the underlying recovery prediction methods are well-validated for the specific ore type in question. So this paper reviews the published recovery prediction literature for copper, cobalt, lithium, and rare earth elements. It compares geostatistical, machine-learning, and process-mineralogy methods, and it identifies the practical gaps that affect U.S. supply credibility.

II. GEOMETALLURGICAL RECOVERY MODELLING: PRINCIPLES AND CHALLENGES

Geometallurgical models integrate geological data (lithology, alteration, structure), mineralogical data (XRD, QEMSCAN, MLA), and geochemical assays through delineated geometallurgical domains. The integration then feeds a recovery prediction model, and the prediction model informs mine planning and process optimisation (Lamberg, 2011; Dunham & Vann, 2007). But there is one fundamental complication. Recovery is non-additive, and that means it does not behave like a grade. Two ore parcels with the same head grade but different mineralogy can give very different recoveries when they are processed through the same flowsheet. So the same flowsheet does not produce the same recovery for two parcels with the same grade. This non-additivity is the central reason geometallurgical prediction is harder than grade estimation, and it is also the reason direct kriging of recovery is biased (Carrasco, Chilès, & Séguret, 2008).

The standard geostatistical estimator at an unsampled location x_0 takes the linear form:

$$Z^*(x_0) = \sum_{i=1}^{n} \lambda_i Z(x_i) \tag{2}$$

Where $Z^*(x_0)$ is the estimated value, λ_i are kriging weights from the variogram, and $Z(x_i)$ are observations. For non-additive recovery this linearity yields estimates inconsistent with mass balance; Adeli, Dowd, Emery, and Xu (2021) circumvent this by separately estimating the additive mass variables M_f and M_c and computing recovery from the estimated values:

$$R^* = \frac{M_c^*}{M_f^*} \times 100 \tag{3}$$

Co-kriging adds further benefit when the mass variables are cross-correlated (Carrasco et al., 2008; Adeli et al., 2021). Machine learning has also entered the field (Merrill-Cifuentes, Cracknell, & Escolme, 2023; Tiu, Ghorbani, Lamberg, & Rosenkranz, 2024), but standard ML treats coordinates as numeric predictors and so it does not model spatial autocorrelation (Fouedjio & Arya, 2024). Hybrid frameworks have therefore emerged. Some of them combine ML response surfaces with geostatistical residuals (Fouedjio & Arya, 2024). Others use dual random fields to model dense covariates jointly with sparse response data (Riquelme, 2025). And others use joint simulation that respects inequality constraints between correlated variables, for example, total copper and soluble copper (Abildin, Madani, & Topal, 2019). So the modern literature has moved away from direct kriging of recovery, and it has moved toward indirect estimation of the underlying mass variables and toward methods that handle non-stationarity and non-additivity.

III. RECOVERY PREDICTION IN COPPER ORE SYSTEMS

➢ *Ore Variability and Recovery Controls*

Copper porphyry deposits show characteristic mineralogical zonation. From bottom to top, the zonation runs from a deep primary sulfide zone (chalcopyrite, bornite), through a transitional supergene-enriched zone (chalcocite, covellite), and then to a near-surface oxidation zone hosting secondary copper minerals such as malachite, chrysocolla, azurite, and tenorite (Sillitoe, 2010). Each zone presents distinct recovery characteristics. Chalcopyrite responds well to standard sulfide flotation, but chalcocite and covellite need modified flotation conditions because their surface chemistry is different. And oxide copper minerals do not respond to flotation at all, so they need leach-solvent extraction-electrowinning instead. The copper oxide ratio, or COR, is the key geometallurgical attribute, and González-García et al. (2025) define it formally as the ratio of acid-soluble copper to total copper in the rock.

➢ *Predictive Modelling Approaches*

Copper has the most mature recovery prediction literature of any commodity. Musafer, Thompson, Kozan,

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and Wolff (2019) applied D-vine copulas to predict copper recovery from indirect test measurements. The indirect measurements were the Bond mill index, the abrasion-breakage index, and the SAG power index. The work used 930 drill-core samples from a South American orebody, and the D-vine copula approach outperformed ordinary and generalised least-squares regression. Abildin, Madani, and Topal (2019) used joint simulation to honour the inequality constraint between total copper grade and soluble copper grade (the COR), because the constraint cannot be broken without producing physically impossible results. Adeli, Dowd, Emery, and Xu (2021) extended this work using a soft-data approach. And González-García et al. (2025) developed a method that combines spatial non-stationarity with machine-learning response surfaces, which is then applied to a porphyry case study.

$$COR = \frac{Cu_{oxide}}{Cu_{total}} \times 100 \tag{4}$$

Where Cu_oxide is the acid-soluble content and Cu_total the total copper grade. Modelling COR as a transformed-domain variable, conditioned on geological interpretation, produces more accurate block-level predictions than direct simulation, with downstream value for separating sulfide flotation feed from oxide leach feed. Complementary methods include Bayesian Hilbert-kriging (Nelis, Gamboa, & Costa, 2022), foundational domain-delineation case studies (Deutsch et al., 2016), and texture-aware hyperspectral imaging (Merrill-Cifuentes et al., 2023).

Table 1 summarizes the principal recovery controls for each of the four commodity systems reviewed.

Table 1 Principal Ore Variability Drivers and Recovery Controls by Critical Mineral System

Commodity	**Principal U.S. deposit type**	**Dominant recovery controls**	**Indicative reference**
Copper	Porphyry (sulfide / transitional / oxide)	Copper oxide ratio; pyrite-to-Cu sulfide ratio; texture and hardness	Sillitoe, 2010; González-García et al., 2025
Cobalt	Metasedimentary IOCG (Blackbird, ID); magmatic Ni-Cu sulfide (Eagle, MI)	Oxidation state of cobalt minerals; grain size and intergrowth with pyrite and chalcopyrite	Dehaine et al., 2021; USGS, 2025a
Lithium	Spodumene pegmatite; lithium claystone (Thacker Pass, NV)	Spodumene-clay alteration extent; grain-size heterogeneity; gangue mineralogy	Sahoo et al., 2024; Tadesse et al., 2024
Rare earths	Carbonatite (Mountain Pass, CA)	Distribution of REEs across mineral phases (bastnäsite vs monazite)	USGS, 2025a; Nassar et al., 2025

Source: Author's Synthesis from the Cited Primary Literature.

IV. RECOVERY PREDICTION IN COBALT ORE SYSTEMS

➢ *Ore Variability and Recovery Controls*

Cobalt is almost never the primary target of a mining operation. Globally, the majority of cobalt is produced as a by-product of copper mining or nickel mining. So cobalt-specific testwork is typically less comprehensive than the testwork for the primary metal, and cobalt recovery models often inherit assumptions from the primary circuit (Dehaine, Michaux, Pokki, Kivinen, & Koivistoinen, 2021). But the U.S. has two cobalt resources where cobalt is at least co-primary, and those are the Blackbird district in Idaho and the Eagle mine in Michigan. Blackbird is a metasedimentary cobalt-copper deposit hosted in iron-oxide-copper-gold-type mineralisation. Eagle is a magmatic nickel-copper sulfide deposit, and the cobalt occurs as a by-product of nickel sulfide processing. The two cases have very different mineralogy, and they also have very different processing routes.

The oxidation state and the host mineralogy are the dominant recovery controls for cobalt. In sediment-hosted copper-cobalt deposits, cobalt occurs in heterogenite (a hydrated cobalt oxide) in the oxide zone, and it occurs in carrollite and other cobalt sulfides at depth (Dehaine et al., 2021). Recovery of cobaltite from Blackbird specifically requires selective sulfarsenide flotation, and that recovery is sensitive to the grain size and the intergrowth with pyrite and chalcopyrite. In magmatic nickel-copper sulfide deposits, the cobalt is hosted mainly in pentlandite, and the recovery follows the nickel circuit. So the cobalt recovery in a magmatic system is determined by the nickel flotation conditions and not by independent cobalt circuit design.

➢ *Predictive Modelling Approaches*

Geometallurgical modelling for cobalt lags copper modelling, and the main reason is economic. The economic incentive to invest in cobalt-specific recovery optimisation has been limited, because cobalt is normally a by-product credit and not a primary revenue stream. Dehaine et al. (2021) identify the principal challenges. They include the variability of cobalt mineralogy across deposit types, the absence of a standardised cobalt grindability test, the strong dependence of recovery on the circuit chemistry of the primary metal, and the limited cobalt-specific testwork in industry practice. So the published recovery prediction methods for cobalt remain limited. The geometallurgical literature for the U.S. cobalt operations is particularly thin, and there is no public-domain spatial recovery prediction model for either Blackbird or Eagle. The federal supply-risk methodology in Nassar et al. (2025) therefore relies on operator-reported figures without an independent prediction framework against which to check them.

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V. RECOVERY PREDICTION IN LITHIUM ORE SYSTEMS

➢ *Ore Variability and Recovery Controls*

Lithium extraction from hard-rock sources has expanded rapidly as battery demand outpaces brine-based supply, and the principal hard-rock source is spodumene-bearing pegmatite. Spodumene (LiAlSi2O6) is the principal hard-rock ore mineral, and it is processed via dense-medium separation, magnetic separation, and froth flotation (Sahoo, Tripathy, Nayak, Hembrom, Dey, Rath, & Mohanta, 2024). The beneficiation challenge is twofold. First, the spodumene grain size and the spodumene-mica intergrowth control the recovery, because mica reports to the spodumene concentrate and lowers its grade. Second, the variable proportion of altered spodumene phases (cookeite, holmquistite) reduces the recovery of lithium-bearing minerals. So a robust recovery prediction model must capture both the mineral assemblage and the texture, and it must also capture the alteration state of the pegmatite.

The Thacker Pass project in Nevada represents a non-traditional U.S. lithium ore type. The lithium is hosted in claystone (chiefly hectorite and illite) and not in spodumene, and the processing route is acid-leach and not flotation. As of 31 December 2024, the proven and probable reserves are 14.3 million tonnes of lithium carbonate equivalent at 2,540 ppm Li, and that figure is an increase of 286% relative to the November 2022 reserve estimate (Lithium Americas Corporation, 2025). The expansion came mainly from the redefinition of the cut-off grade, because more of the claystone became economic at the higher cut-off. So the recovery prediction problem at Thacker Pass is fundamentally about acid-leach kinetics on a clay matrix, and not about spodumene flotation. And the published methods for spodumene flotation do not transfer.

➢ *Predictive Modelling Approaches*

Published geometallurgical recovery prediction models for lithium ores are rare. The existing literature focuses on beneficiation process optimisation, and it does not focus on spatial recovery prediction from drill-core data. The recent reviews of Sahoo et al. (2024) and Tadesse et al. (2024) cover beneficiation routes and spodumene flotation chemistry, but they do not cover spatial prediction. The pilot-scale results of Wang et al. (2023) on spodumene flotation extend the chemistry knowledge, but they do not address spatial variability across a deposit. So no published spatial recovery prediction framework is available for U.S. lithium operations. The Thacker Pass project would need a framework that captures the spatial variability of clay mineralogy and the spatial variability of acid-leach kinetics, and no such framework has been published. The federal projection for U.S. lithium production therefore relies on operator-reported numbers, because no independent spatial model is available to check those numbers.

VI. RECOVERY PREDICTION IN RARE EARTH ELEMENT ORE SYSTEMS

➢ *Ore Variability and Recovery Controls*

REEs present the most complex geometallurgical challenge of the four mineral groups considered here, and the reason is mineralogical. The economically recoverable fraction is determined not by the total REE grade alone, but by the distribution of REEs across mineral phases. The 2025 List of Critical Minerals includes sixteen individual rare earth elements (USGS, 2025b), and federal supply chain analysis identifies REEs among the highest-risk commodities (Nassar et al., 2025). So the credibility of any U.S. supply forecast for REEs depends heavily on the accuracy of recovery prediction at the few active or planned domestic operations, and Mountain Pass is the principal one.

The principal U.S. REE producer is the Mountain Pass carbonatite deposit in California, and the REEs there are hosted predominantly in bastnäsite. In a carbonatite system, REEs may be distributed among bastnäsite, monazite, parisite, and other accessory minerals. The recovery of REEs through gravity-flotation circuits is much higher for bastnäsite-hosted REE than for monazite-associated REE, because monazite requires different chemistry and a different flowsheet. So the recovery prediction at Mountain Pass depends not only on the total REE grade, but also on the bastnäsite-to-monazite ratio across the deposit. And the ratio varies geologically. MP Materials Corp. (2024) reports the resource estimate but not a spatial recovery prediction framework, and the SEC Technical Report Summary uses a single overall recovery factor in the resource economics.

Figure 1 presents verified 2024 operating data from the two principal active U.S. critical mineral mines reviewed in this paper. Panel (a) shows Mountain Pass operating performance for January–September 2024 (ore feed grade, bastnaesite concentrate grade, and TREO recovery). Panel (b) shows the updated proven and probable lithium reserves at Thacker Pass, reflecting the 31 December 2024 S-K 1300 Technical Report.

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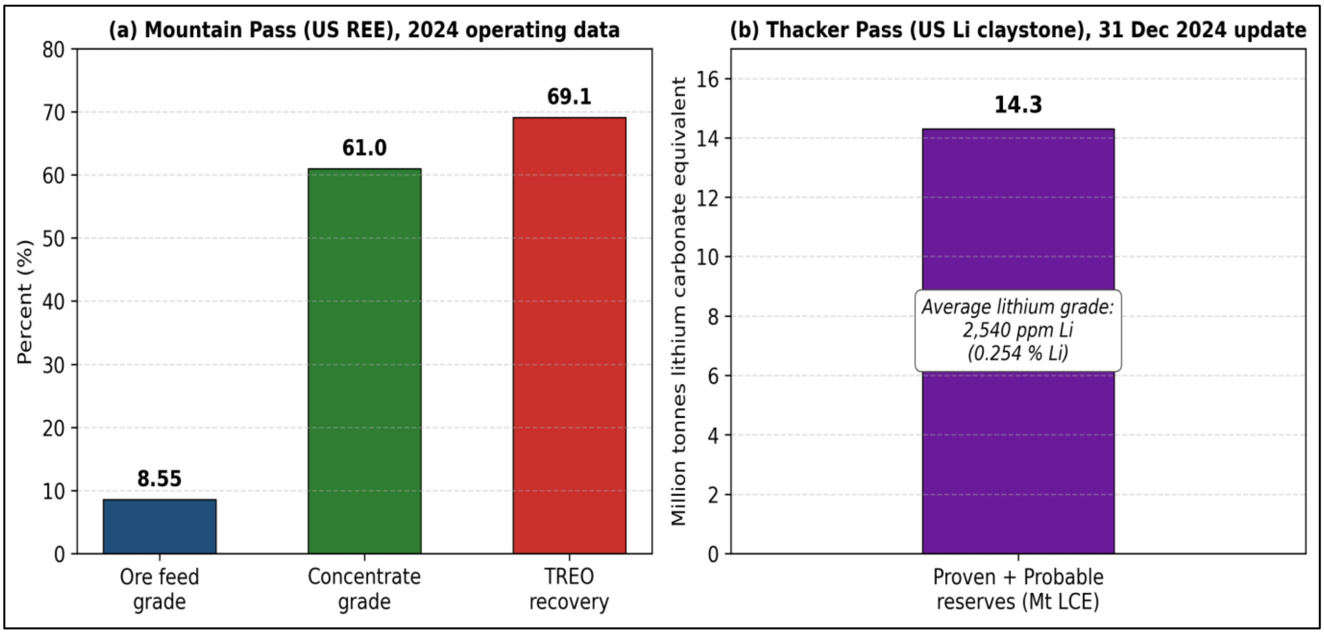

Fig 1 Operating Performance of Two Flagship U.S. Critical Mineral Mines: (a) Mountain Pass REE Operation, January–September 2024 Operating Data; (b) Thacker Pass Lithium Claystone Project, Proven and Probable Reserves as of 31 December 2024.

(Source: Mountain Pass Values from MP Materials Corp. (2024), SEC Technical Report Summary (S-K 1300), Mountain Pass Rare Earth Mineral Resources and Mineral Reserves Estimate, Effective 1 October 2024. Thacker Pass Values from Lithium Americas Corporation (2025), S-K 1300 Technical Report Summary on the Thacker Pass Project, Humboldt County, Nevada, USA, effective 31 December 2024. Figure prepared by the author from the cited primary sources.)

➢ *Predictive Modelling Approaches*

Geometallurgical modelling for rare earth ores is in its infancy. The majority of global rare earth production occurs in China, and the dominant Chinese resource is ion-adsorption clay deposits that supply heavy REE through a fundamentally different processing route, which is in-situ leach with ion-exchange. The published Western-language case-study literature on this Chinese practice is limited. For Mountain Pass specifically, the public-domain literature is even thinner. The published methods reviewed for copper, cobalt, and lithium therefore have no direct counterpart for U.S. REE operations, because no full spatial recovery prediction framework exists in the public domain for any U.S. REE deposit. So the federal supply projections for U.S. rare earth output rest entirely on operator-reported recovery numbers, and no independent prediction model is available to validate them.

VII. DISCUSSION AND CROSS-CUTTING THEMES

The review reveals a pronounced asymmetry in recovery prediction maturity. Copper has multiple peer-reviewed frameworks that are validated for porphyry systems (Musafer et al., 2019; Abildin et al., 2019; Adeli et al., 2021; González-García et al., 2025). Cobalt occupies an intermediate position. Dehaine et al. (2021) identify the recovery controls clearly, but the U.S. operating-mine literature is sparse. Lithium has a rich beneficiation literature but very little spatial prediction work, and the Thacker Pass claystone presents a non-traditional ore type for which no published model exists. REEs have the thinnest published recovery prediction literature of the four, and there is no public-domain spatial prediction model for Mountain Pass. So the methodology maturity across these four mineral groups is highly uneven, and the unevenness maps directly onto the credibility of federal supply projections.

$$\sigma_K^2(x_0) = C(0) - \sum_{i=1}^{n} \lambda_i C(x_i - x_0) + \mu \tag{5}$$

Where σ^2_K is the kriging variance, $C(0)$ the variogram sill, $C(x_i - x_0)$ the covariance between sample i and estimation point, and μ the Lagrange multiplier. This variance is a function of data configuration and variogram model only and is not a posterior measure of local prediction error (Adusei-Gyamfi et al., 2024); probabilistic simulation and Bayesian methods (Nelis et al., 2022) provide the proper uncertainty-propagation framework.

A second theme is the tension between ML and geostatistics. ML captures non-linear relationships, but it does not exploit spatial autocorrelation (Fouedjio & Arya, 2024). The hybrid frameworks of Fouedjio and Arya (2024), Dutta and Emery (2024), and Riquelme (2025) are the most credible response to this tension, but none of them has yet been validated on U.S. critical mineral deposits. So the most promising methods exist in the literature, but they have not been tested against U.S. operating data. A third theme is the scarcity of public-domain geometallurgical data for U.S. critical mineral deposits. The corporate technical reports from MP Materials Corp. (2024) and Lithium Americas

Corporation (2025) provide resource estimates but not the underlying drill-core geometallurgical data, and academic publication of U.S. critical mineral geometallurgical data is rare. So independent validation of recovery prediction methods on U.S. ore is presently not feasible.

Figure 2 presents the 2024 U.S. net import reliance for six selected critical mineral commodities, with the share of consumption met by imports from China shown alongside total reliance.

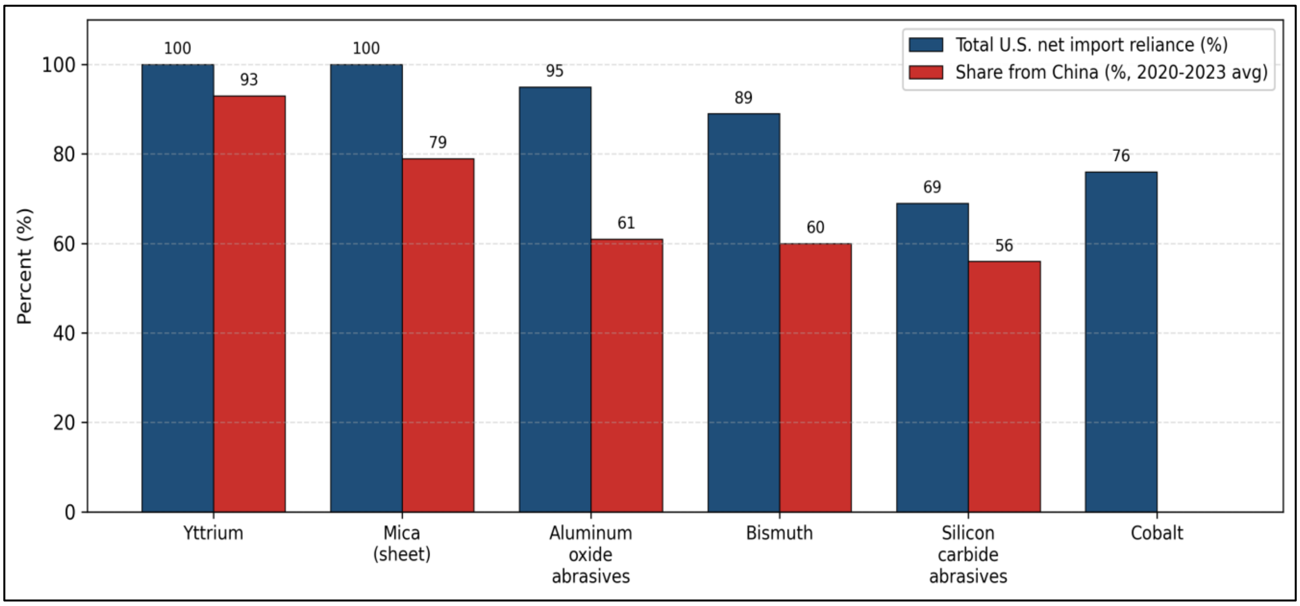

Fig 2 2024 U.S. Net Import Reliance for Selected Critical Mineral Commodities, with Share of Total Consumption Met by Imports from China (2020–2023 average). Cobalt Imports are Primarily from Norway, Finland, and Canada (not China).
(Source: U.S. Geological Survey (2025), Mineral Commodity Summaries 2025, https://doi.org/10.3133/mcs2025 ; Commodity-Specific Net Import Reliance Values from Individual MCS 2025 Commodity Chapters; China Import Shares from USGS (2025), "Mineral Commodities with Net Import Reliance on China" (USGS Media Gallery, March 2025). Figure Prepared by the Author from Values in the Cited USGS Publications.)

Table 2 summarises the principal published methodological contributions reviewed in this paper.

Table 2 Summary of Principal Methodological Contributions Reviewed

Reference	Methodology	Contribution
Carrasco et al. (2008)	Non-additivity analysis	Foundational demonstration that direct kriging of recovery is biased
Musafer et al. (2019)	D-vine copula regression on copper	Outperformed OLS/GLS on 930-core South American dataset
Abildin et al. (2019)	MAF-TBSIM hybrid co-simulation	Joint simulation respecting tCu-sCu inequality constraint
Adeli et al. (2021)	Co-kriging of mass variables	Indirect estimation of M_c and M_f to avoid non-additivity
González-García et al. (2025)	Soft-data + COR change-of-variable	Soft-data conditioning addresses non-additive COR
Fouedjio & Arya (2024)	Locally varying geostatistical ML	Combines spatial non-stationarity with ML response surfaces
Riquelme (2025)	Dual random fields	Joint UQ for dense inputs and sparse response outcomes
Mehrali (2026)	Multivariate EnKF block-model updating	Real-time recalibration as production data arrive

(Source: Author's Synthesis from the Cited Primary Literature. tCu/sCu = total/soluble copper; COR = copper oxide ratio; UQ = uncertainty quantification; EnKF = ensemble Kalman filter.)

VIII. CONCLUSIONS

This paper has reviewed the current state of geometallurgical recovery prediction for four critical mineral systems of strategic importance to the United States, and the picture is uneven. A pronounced asymmetry exists in the published methodology. Cobalt prediction is conceptually understood but the U.S. operating-mine literature is sparse. Lithium prediction has a strong beneficiation literature, but the spatial prediction work is limited, and the Thacker Pass claystone is a non-traditional ore type for which no published model exists. And REE prediction has the thinnest published literature of the four, with no public-domain spatial prediction model for Mountain Pass. So the federal supply-risk methodology inherits the asymmetry. Where the published methodology is mature, the federal projection has support. But where the published methodology is thin, the federal projection rests on operator-reported numbers, and no independent framework is available to check them. The closure of these gaps will require both methodological work and public-domain release of geometallurgical data from U.S. critical mineral operations.

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* *Competing Interests:*

The author declares no competing financial or personal interests.

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* *Data Availability:*

No primary data were generated or analysed. The Mountain Pass operating performance values plotted in Figure 1(a) are reproduced from MP Materials Corp. (2024), SEC Technical Report Summary (S-K 1300), effective 1 October 2024. The Thacker Pass mineral reserves plotted in Figure 1(b) are reproduced from Lithium Americas Corporation (2025), S-K 1300 Technical Report Summary, effective 31 December 2024. The values plotted in Figure 2 are reproduced from USGS Mineral Commodity Summaries 2025, https://doi.org/10.3133/mcs2025. All cited sources are publicly accessible.

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