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Securing India's Critical Mineral Supply Chains:

A Machine Learning Framework for Disruption Prediction and Strategic Reserve Sizing

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About the Author

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Abstract

India’s commitments to the energy transition and to net-zero by 2070 rely, in large part, on the availability of critical minerals. Global demand for these minerals has risen, and with supply concentrated in a limited number of exporting countries, fears of the weaponisation of trade loom large. This poses a major challenge to India's national security. In this context, the paper adopts modern machine learning algorithms to predict supply chain disruptions of critical minerals, particularly lithium, cobalt, nickel, graphite, and vanadium. Furthermore, the study aims to estimate strategic reserve sizing for these minerals to ensure a smooth response in the event of a supply choke. The author utilises monthly critical mineral import data from UN Comtrade for India between 2011 and 2025, producing a balanced panel dataset of 48,780 dyadic trade observations.

The analysis employs an XGBoost predictive architecture, evaluated via strict temporal block splitting, achieving a test ROC-AUC of 0.855 and a critical recall of 0.989. Additionally, the study utilises governance fragility, industrial output, and Maritime Domain Awareness (MDA) metrics for predictive purposes. Applying a Value-at-Risk (VaR) sovereign autonomy filter, the study calculates strategic reserves for the critical minerals mentioned, amounting to USD 633 million in initial capital expenditure, which scales up to USD 910 million over a 5-year lifecycle. This is essential for energy security and represents 2.7% of India’s defence capital budget. The findings augur well for a dynamic, machine-learning-based supply chain vulnerability prediction system that can highlight countries and minerals at risk. The study also suggests anchoring any energy security framework on institutions that deal with both energy and security, in this case, Khanij Bidesh India Ltd. (KABIL) and the National Security Council Secretariat (NSCS).

Introduction

The 21st-century geopolitical landscape is fraught with the weaponisation of trade, particularly of critical minerals, thereby limiting the global green energy transition (Baffes et al., 2021). Over time, the definition of national security has also evolved to include the secure and consistent supply of critical minerals such as lithium, cobalt, nickel, graphite, and vanadium (IEA, 2021). In India specifically, we observe these security concerns manifest as maritime disruptions in the Indian Ocean Region (IOR), as well as other bottlenecks in the region (Brewster, 2014). These bottlenecks pose a significant challenge to the growth of developing economies, which often rely on imported technology and processed resources for their industrial foundations.

However, the biggest hurdle on the journey towards self-reliance is the insufficient domestic supply to meet the escalating demands of advanced manufacturing and defence production (Chadha et al., 2025). Consequently, India needs to balance a general attitude of collaborative stewardship of global resources with the need to overcome maritime logistics constraints and geopolitical friction. Traditional stockpile equations seem redundant in the face of real-time disturbances, the weaponisation of trade, and non-linear relationships in the global environment (Martinez, 2025). For that reason, we must develop systems that can dynamically assess geopolitical conditions, quantify supply-chain vulnerabilities, and transform reserve sizing and composition from a reactive to a predictive science.

In this paper, mapping of maritime transit risks (MDA) and upstream governance data is provided to give policymakers the probability of disruption in supply chains for these critical minerals, along with vulnerable hotspots, before they impact the industrial base. The paper also aims to quantify the benefits of the proposed strategically located transhipment hub, such as the Galathea Bay facility, which has the potential to act as a buffer against supply disruptions at chokepoint locations (PIB, 2026). Through the large-scale deployment of such predictive models, India can transition from a reactive stage to proactive stewardship, ensuring true self-reliance by measuring the risk of various suppliers and adjusting backups and reserves accordingly.

Literature Review

Resource literature identifies concentration and scarcity in upstream extraction, which plays into the monopolistic leverage of dominant suppliers (IEA, 2023; World Bank, 2023). In this context, China is known to control over 90% of refined rare earths and rare earth magnets, while also contributing largely to graphite and dysprosium (IEA, 2023). Developing countries that are resource-rich often face significant restrictions on ore extraction and export due to regulatory friction, causing global disruption in supply (OECD, 2025).

Additionally, maritime literature extensively documents vulnerabilities in Sea Lines of Communication (SLOCs). It highlights chokepoints such as the Strait of Hormuz and the Strait of Malacca as critical to a frictionless global supply chain for resources (UNCTAD, 2026). In this context, Maritime Domain Awareness (MDA) is crucial for mitigating asymmetric disruptions from grey-zone tactics (IMO, 2023). MDA provides data through real-time vessel tracking and threat understanding (IMO, 2023). However, without integrating this data with appropriate supply chain risk models, the objective remains only partially fulfilled.

Critical minerals are highly concentrated globally; a small number of suppliers dominate the industry, posing supply chain risks (Schrijvers et al., 2020). In India, research by Govinda et al. (2022) highlights that India's partner countries in the critical mineral supply chain often rank below the median in political stability, while Patel (2026) indicates the possibility of a fivefold increase in demand for lithium in India by 2030. These structural and procedural issues pose accelerating threats to India’s mineral security.

However, the current discourse on developing strategic reserves relies on deterministic approaches that do not incorporate probabilistic disruption risk. In this context, machine learning (ML) and its architectures, such as XGBoost, can help. ML can synthesise multiple metrics and indices into a single probabilistic failure forecast for buyers (Chen et al., 2017). This can support stockpiling and thereby reduce the risk of shock magnification in the event of a supply chain disruption (Acemoglu & Tahbaz, 2025).

Additionally, Brintrup et al. (2020) indicate that combining structural data, such as governance, with macroeconomic signals, such as price volatility, can improve disruption prediction by 12-18 percentage points, helping to frame the feature engineering portion of the study. Work by Heckmann et al. (2015) is critical in establishing thresholds for identifying a disruption. The cost asymmetry approach adopted in this paper draws heavily on the work of Hendricks and Singhal (2005), which reports that the average abnormal stock return plummets by 40% in the event of a disruption.

Three gaps persist: no study has produced a machine-learning-based probabilistic prediction model for these five critical minerals simultaneously; no study integrates global and national indices, such as GSCPI, IIP, LSCI, and Spot Prices (Table 1), as conditioning variables; no study tracks longitudinal import data and tests it on the post-COVID and post-Ukraine commodity shock period.

Methodology

To develop a supply chain vulnerability prediction system for the specific use case of India, the study utilises the sources listed in Table 1. These sources yield a balanced panel dataset of 48,780 rows spanning 271 bilateral trade pairs over a 15-year period from 2011 to 2025. This period was chosen specifically for the availability of monthly trade data. The dataset is rich in mineral types, including lithium, cobalt, nickel, graphite, and vanadium (Figure 1). The study also trains the model on geopolitical events, including chokepoints and tension events that threaten the SLOCs.

To ensure the integrity of the model, a temporal split of the data is employed. The model is trained on data from 2011 to 2021, validated on 2022, and tested on exclusively post-2022 data (excluding 2025). These divisions were chosen over random cross-validation to ensure the model learns to recognise specific disruption events that would otherwise not be present in a stable dataset (such as the COVID disruption, Red Sea disruptions, and the Russia-Ukraine conflict).

To reflect real-world geopolitical frictions, the following three statistical techniques have been used:

- Structural zero-filling: trade data can be sparse, with supplier countries not supplying materials for a few months; we treat these gaps as deliberate “zeroes”, rather than “missing data”. This limits the statistical noise the model would otherwise learn and treats persistent missing data as true disruption, distinguishing it from infrequent zeroes.
- Inverse Probability Weighting (IPW): this technique forces the algorithm to pay closer attention to rare but significant supply chain disruption events. The idea is to prevent bias towards stability that arises from years of stable data.
- SHAP (SHapley Additive exPlanations): this helps interpret and translate the model’s “black box” decisions into transparent features that can inform policy recommendations. It is particularly useful for understanding which factors trigger a specific risk alert.

Under all this, the fundamental architecture relies on an eXtreme Gradient Boosting (XGBoost) algorithm. The advantage of using this algorithm over a traditional linear model is the use of an additive tree-ensemble approach, where the prediction $\hat{y}_i$ for a given dyad is the sum of K regression trees:

$$\hat{y}_i = \phi(x_i) = \sum_{k=1}^{K} f_k(x_i), \quad f_k \in \mathcal{F}$$

where $\mathcal{F}$ represents the space of all possible regression trees. In addition, to provide a binary output (disruption or continuity) based on the probabilistic score [P(Di,t)] produced by the model, a logistic link function in the final ensemble output is used:

$$P(D_{i,t}) = \frac{1}{1 + e^{-\hat{y}_i}}$$

These algorithms and architectures are used for one simple reason: to identify and interpret the non-linear relationships that disrupt global trade. The model can now capture complex interaction effects, such as increased import share by a supplier country and a reducing governance score - something a linear model would miss.

Calculating the strategic reserve is another novel contribution of the paper, and a temporal decay function is used to account for the degradation of stockpiled materials. A Value-at-Risk (VaR)-style piecewise mandate is used to elevate the estimation beyond static expected-value heuristics and to ensure sovereign baseline coverage:

$$\text{Reserve}_i = \frac{\text{Annual\_Import}_i \times \gamma_i \times \text{TEBW}_i}{365}$$

$$\text{where} \quad \gamma_i = \begin{cases} 1.0 & \text{if } \max_j P(D_{ij}) \geq \tau_{\text{sov}} \\ 0.25 & \text{otherwise} \end{cases}$$

Here, the ***Annual_Import*** is the total amount in tonnes imported per year for each mineral; ***Time-to-Export-Bottleneck-Window (TEBW)*** is the total number of days during which a sector can maintain its operations when its input supply has been completely cut off. ***τ,*** on the other hand, is the sovereign security threshold, calculated endogenously through the Gaussian Mixture Model (GMM). This gives lower and upper bounds of 0.255 and 0.824, respectively. The final threshold is chosen as a midpoint between the two: ***0.50***. Any disruption probability above this threshold deems a 100% TEBW Reserve allocation.

In addition, the study employs Youden's J statistic and a Dynamic Prevalence Cost Ratio to determine the optimal model deployment threshold (Springer, 2024). Both methods converge on $p \geq 0.11$. Thus, whenever the probability of a disruption exceeds 0.11, the model triggers the T+1 early warning system. Similarly, a restrictive threshold of 0.85 is derived endogenously, representing the 85th percentile of the predicted probability of disruption across the entire balanced panel. Any value of p above this threshold is deemed CRITICAL.

Additionally, the model recognises strategic competitors who may deliberately sabotage supply for geopolitical gain. To this end, a floor of >5% in bilateral imports and >10% in global production shares (e.g., China-graphite and Russia-vanadium) has been introduced, with a mandated probability floor of 0.85 (the same as the CRITICAL category for the Vulnerability Index), ensuring they are always triggered. This reflects a preference for security over logistical convenience. For any supplier with a disruption probability below the threshold, a 25% fractional buffer is applied.

A caveat must be noted here for Nickel specifically, which applies a 0.30 metallurgical recovery factor, as the metal is priced at a pure level, whereas it is largely imported as ferroalloys and unwrought nickel in India.

Note: the various thresholds used, along with their rationale, are stated in Table 0.

Results and Findings

1. SHAP Analysis and the OOD Ablation Pattern

SHAP (SHapley Additive exPlanations) analysis highlights the exceptional importance of input features such as import share (1.50) and the global production Herfindahl-Hirschman Index (HHI) (0.68) in explaining vulnerability to disruption and predicting future disruption events. This is perhaps the strongest evidence for the importance of concentration-based indices in forecasting supply chain fragility. Additionally, the exchange rate plays a critical role, with a high SHAP value of 0.20, indicating that fluctuations in disruption could be attributed to the weakening INR.

For robustness, a feature ablation study reveals a universal Out-of-Distribution (OOD) degradation pattern. When the Macro & GSCPI, Bilateral Premiums, Tier-2 Governance, Diplomatic Buffers, Spatial & Maritime, or Policy and Monopoly features are removed, the OOD test-AUC marginally improves (by 0.010 to 0.024). This should not be interpreted as a model failure; rather, it indicates the structural regime change in the supply market for these 5 critical minerals post-2022.

Further, the Adversarial AUC of 1.000 indicates that pre-2022 baselines, such as stable governance indices and historical premium prices, map onto post-2022 data in a distorted manner (Appendix A1). Both findings indicate that since the advent of the Russia-Ukraine conflict, the global trade environment has shifted towards a more weaponised state: it is less free and globalised, and more protectionist. Regardless, the full feature set for structural interpretability has been retained.

2. *Model Performance and Empirical Risk Patterns*

When evaluated on an out-of-distribution test set (2023-2025 data), the model achieves a Test ROC-AUC of 0.855 and a Brier Score of 0.1516 (Figure 2), both indicating strong discriminative power and calibration (expanded in Table 2).

The model's predictions reveal three important patterns. First, import concentration is the primary driver of supply chain vulnerability, as indicated by the high SHAP values for import share and global production HHI (Table 3). Second, not only the origin but also transit nodes are critical points of potential vulnerability: countries such as Ireland, Finland and Belgium are not producers but act as transhipment hubs and refiners, yet rank among vulnerable suppliers (Table 4). Thirdly, the model identifies 0.11 as the "Threshold Cliff", separating idiosyncratic noise from genuine supply chain disruptions. This is validated by retrospective trigger alerts for China's Graphite Export Controls ($p=0.585$) and Russia-Ukraine Nickel Sanctions ($p=0.877$), along with the correct non-trigger for the 2022 Chilean Lithium price peak ($p = 0.073$), demonstrating the model's ability to distinguish between supply collapse and pure financial speculation (Table 5).

3. Base Scenario Lifecycle Costing and Risk Typologies

The model follows a Value-at-Risk (VaR)[1] mandate, under which any disruption with a probability of $p>0.50$ will trigger full 100% Time-to-Export-Bottleneck-Window (TEBW) coverage. In our case, all the minerals cross this threshold, thereby triggering full temporal coverage, with an initial Capital Expenditure (CapEx) of USD 633 Million, scaling to a 5-Year Lifecycle Cost of USD 910 Million (Table 6).

The T+1 Disruption Forecasts for 2026 (Table 7), as produced by the model, highlight countries with the most risk-prone imports. It should be noted that while VI uses a $p>0.85$ threshold for 'CRITICAL', the T+1 uses a $p>0.70$ threshold for the same. This reflects the premise that, while VI is long-term and can afford to be more lenient, the disruption prediction is a more time-relevant indicator and needs to be stricter in its classification for policy purposes. Table 7 also differentiates the risk

[1] Derivation expanded in the Appendix

type: transit and origin-specific. Both are important to acknowledge and tackle for energy security, but the policy response for each will differ, hence the segregation.

It must be noted that countries like Ireland (p = 0.970) are ranked higher than natural producers such as Argentina (p = 0.883) for Lithium. This is because Argentina's direct trade with India is relatively insignificant; the mineral trade goes through intermediaries such as Norway, Finland, Ireland, and Belgium, and reaches India after processing and refining. The model recognises this relationship and subsequently links the Vulnerability Index of these countries accordingly.

4. Galathea Bay Actuarial Simulation and Strategic ROI

As a supplementary application of the model, the study runs an actuarial simulation of the savings resulting from the proposed Galathea Bay Transhipment Hub on Great Nicobar Island. The idea is that such a port would reduce sovereign supply risks by routing East Asian supplies through this node. The model predicts savings of around $17.3 million in CapEx avoidance for the reserve, driven by reduced expected lost tonnage. This is a one-off saving, unrelated to the unmodelled recurring annual flow benefits that the project would otherwise entail (Tables 8 and 9).

While it may seem like a small amount, the amount is restricted to only 5 critical minerals. Extrapolating this to the 30 identified by NCMM (Ministry of Mines, 2025) and over 50 by the USGS (USGS, 2025), as well as the broader import commodities such as semiconductors, automobiles, and electronics, would magnify the macroeconomic benefits into the billions of dollars. The mentioned extrapolation, however, is beyond the scope of this paper. This only goes to show the benefits and security that the construction of this infrastructure project could reap for India. Thus, expediting its timeline becomes a critical aspect of the energy transition and green development.

Policy Recommendations

1. Structural Reconfiguration of Supply Chains

Empirical analysis reveals India's heavy reliance on sensitive nodes such as Russia and Indonesia for fundamental inputs, including unwrought nickel and free-alloys (UN COMTRADE, 2024). Sectors such as steel and battery manufacturing depend heavily on these inputs; thus, pivoting from heuristic stockpiling to algorithmic, Value-at-Risk (VaR) principles of risk aversion becomes critical (IEA, 2023). To ensure sufficient stock at all times, a dual-threshold coverage policy must be adopted, mandating 100% Time-to-Export-Bottleneck-Window (TEBW) for thresholds above 0.50 and 25% coverage for values below it. This ensures that downstream manufacturing is always protected against succumbing to alert fatigue (Ministry of Mines, 2025).

2. Institutional Operationalisation and Data Integration

The government has already initiated efforts towards critical minerals acquisitions and exploration through the Khanij Bidesh India Ltd. (KABIL) (PIB, 2019). It is recommended that KABIL be designated the nodal authority for implementing this predictive model and for algorithmic stockpiling of critical minerals. This will ensure the model receives real-time sectoral information, integrating bilateral trade flows. Additionally, the National Security Council Secretariat (NSCS) should be actively involved in the quarterly assessment of the model’s performance, particularly how the SHAP drivers or anticipated TEBW exceedances might affect energy security. This will enable dynamic adjustment of parameters such as thresholds and spot-market interventions before a disruption occurs.

3. Geopolitical Leverage and Maritime Domain Awareness

The threat does not stem from a single point of origin but follows a sequence: origin node to transit node and refining chokepoints. Each stage presents distinct challenges, requiring separate diplomatic buffers. FTAs/MoUs with Australia, Argentina, and Japan, for example, help mitigate some of these (UKTPO, 2025). This is further supported by the SHAP values for shielded exposure (interaction between diplomatic status and trade intensity) at 0.0411, with a maximum negative impact of -0.58, implying that, ceteris paribus, having diplomatic status (FTAs/MoUs) with a country that has a high import share of critical minerals for India reduces the disruption probability by 58 percentage points. Thus, quick turnaround for such agreements and special clauses for critical minerals are critical. The Ministry of External Affairs (MEA) must ensure the length, breadth, and speed of FTAs/MoUs to help alleviate India's energy security needs.

Additionally, developing the Galathea Bay Transhipment Hub on Great Nicobar Island is crucial to neutralising grey-zone trade weaponisation and solving the "Malacca Dilemma" in India's favour, thereby addressing asymmetric coercion (Warsaw Institute, 2021).

4. Energy Security and Industrial Shielding

India's energy transition depends on the continued supply of critical minerals. Index of Industrial Production (IIP) data confirm robust growth in basic metals and chemical manufacturing. This leaves the downstream Indian manufacturing sector exposed to upstream supply and price transmission shocks (CSEP, 2025). The prescribed USD 633 million CapEx and USD 910 million 5-year lifecycle cost for strategic reserves serve as long-term insurance against sudden shocks.

5. Self-Capacity Development and Multilateral Resilience

The model may predict which supplier is at the greatest risk in the coming year and thus help India prepare for it; however, true Atmanirbharta still lies in domestic capacity building. While domestic production cannot be increased overnight, India must invest heavily in metallurgical processing and refining infrastructure, for which it currently relies on European and East Asian partners as transit nodes. Eventually, this model will account for all critical minerals, particularly Rare Earth Elements. India must leverage existing technology and develop a strategic mineral reserve-sharing agreement with the Global South and the Indian Ocean Rim Association (IORA) countries to ensure Indo-Pacific resilience and foster cooperative governance (DFAT, 2024; IEEFA, 2025).

Limitations and Future Scope

While the current model is robust in validating prior disruption events and predicting future ones, it faces various limitations in its present form. Firstly, the model is highly constrained by historical data limitations: UN Comtrade, although reliable, does not provide monthly trade data prior to 2011 (UN COMTRADE, 2023), and any adjustments using other datasets in this regard would have posed severe data credibility issues for the study. Without other "black swan" events such as the GFC 2008 in the dataset, the model is limited in predicting unexpected turns of events.

Secondly, the model relies on static data, albeit for illustrative purposes. Geopolitics and geoeconomics dynamically dictate global trade; blockades are decided within weeks, which often don't reflect in hardcoded or static datasets. Here, the absence of micro-level Automatic Identification System (AIS) telemetry or subsea cable disruption metrics is deeply felt (Z2 Data, 2025).

Thirdly, Chinese data is often flagged as under- or over-reported, thereby undermining the accuracy of any such predictive model. Fourthly, the model, in its current form, is limited to 5 critical minerals out of the 30 identified by the National Critical Minerals Mission (NCMM) (Ministry of Mines, 2025); the inclusion of the rest is an obvious extension of the study. Finally, the absence of India-relevant and production-index equivalents to the Global Supply Chain Pressure Index (GSCPI) limits the policy recommendations that could be made specifically for maritime routes and the partner countries involved in the region (NBER, 2022).

As far as future avenues are concerned, the abovementioned limitations must be addressed. Government-backed monthly data dating back to the 1990s could improve the model's performance and reliability. Including metals and minerals beyond the 5 discussed, and even non-minerals (such as electronics and natural resources), could provide a generalist model aimed at assessing diversified suppliers. Additionally, the integration of real-time events will be the single biggest addition: live news analysis through the GDELTS database, sentiment analysis and its inclusion, as well as UN agreements and developing FTA/MoU discussions could add an unprecedented dynamic edge (GDELTS, 2024).

Conclusion

This study lies at the intersection of geopolitics, energy security, and machine learning, offering a potential pathway to securing India's critical mineral supply chain and, thereby, its energy transition in the 21st century. The findings corroborate the existing literature on supplier concentration and then build on it to produce an algorithmic strategic resilience model.

Based on the outcomes of the study, several key policy actions are recommended:

- Model Institutionalisation: The predictive model should first be institutionalised within a broader framework to facilitate fine-tuning in real-world contexts. Achieving maximum utility requires integration with Khanij Bidesh India Ltd.'s (KABIL) procurement data and protocols, as well as the National Security Council Secretariat's (NSCS) review process.

- Phased Stockpiling: The prescribed physical stockpiles should be phased in gradually by allocating the required USD 633 million in initial Capital Expenditure (CapEx).

- Logistical Resilience: Transhipment hubs, such as Galathea Bay, should be operationalised to reduce India's vulnerability to supply chain fragility.
- Multilateral Governance: These predictive capabilities should be utilised to foster multilateralism, reinforce global maritime governance, and promote fair access to critical minerals, thereby protecting against the weaponisation of trade.

Ultimately, predicting threats represents only the initial phase. India must chart a pragmatic course transitioning from identification to action to preserve its energy security and advance toward self-reliance.

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Appendix

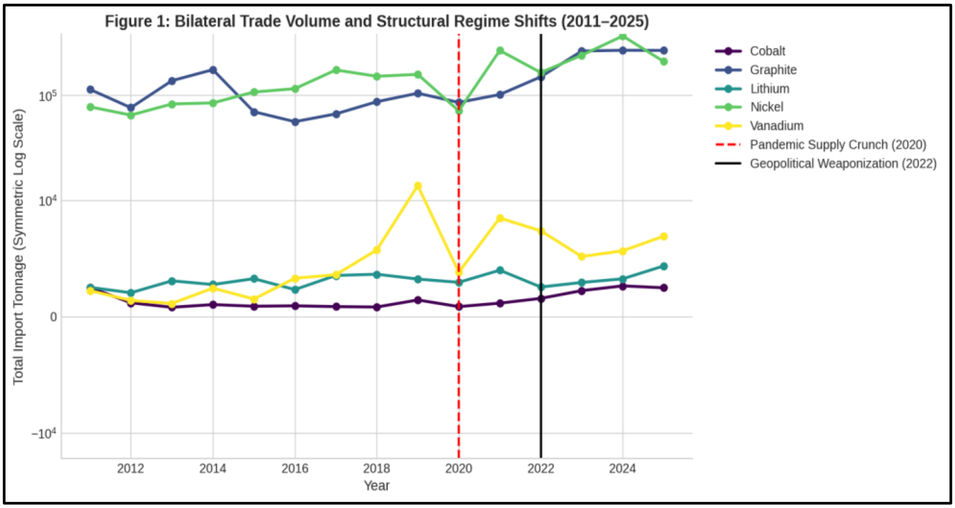


Figure 1: Bilateral Trade Volume and Structural Regime Shifts (2011–2025)
Total Import Tonnage (Symmetric Log Scale)
10^5
10^4
0
-10^4
2012
2014
2016
2018
2020
2022
2024
Year
Cobalt
Graphite
Lithium
Nickel
Vanadium
Pandemic Supply Crunch (2020)
Geopolitical Weaponization (2022)

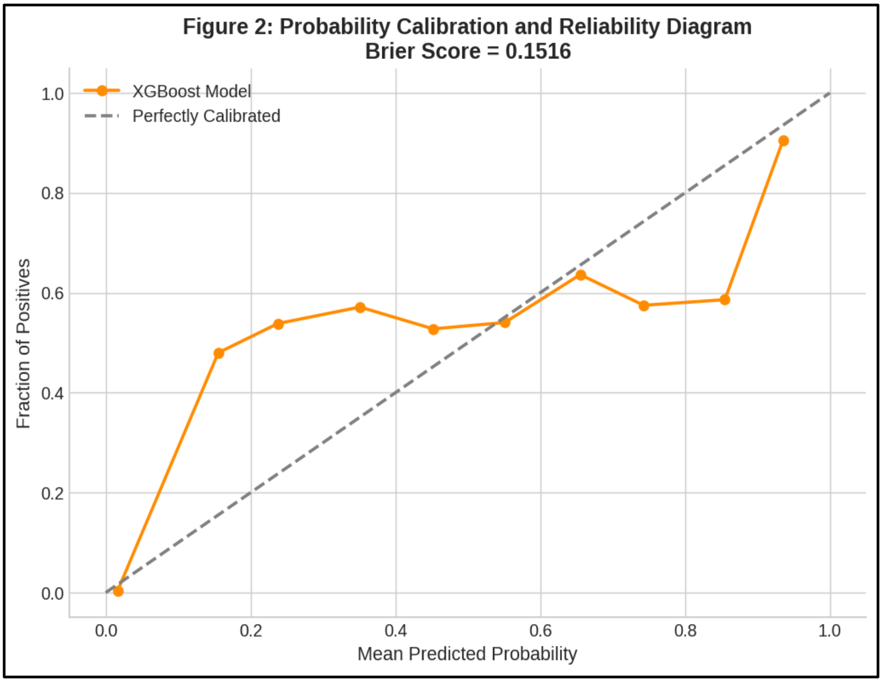


Figure 2: Probability Calibration and Reliability Diagram
Brier Score = 0.1516
XGBoost Model
Perfectly Calibrated
Fraction of Positives
Mean Predicted Probability
0.0
0.2
0.4
0.6
0.8
1.0

Figure 3: The Graphite Anomaly: Bilateral Premium vs. Global Benchmark (2023)

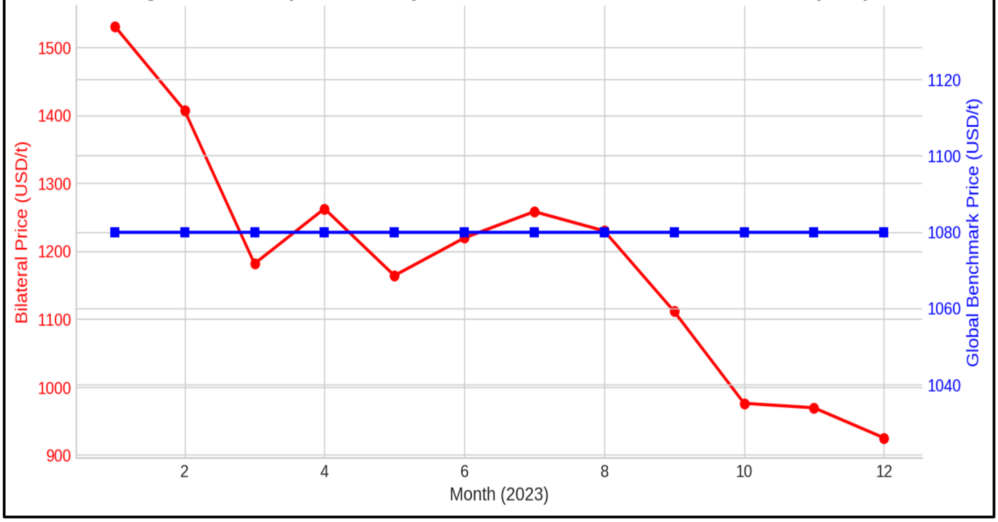
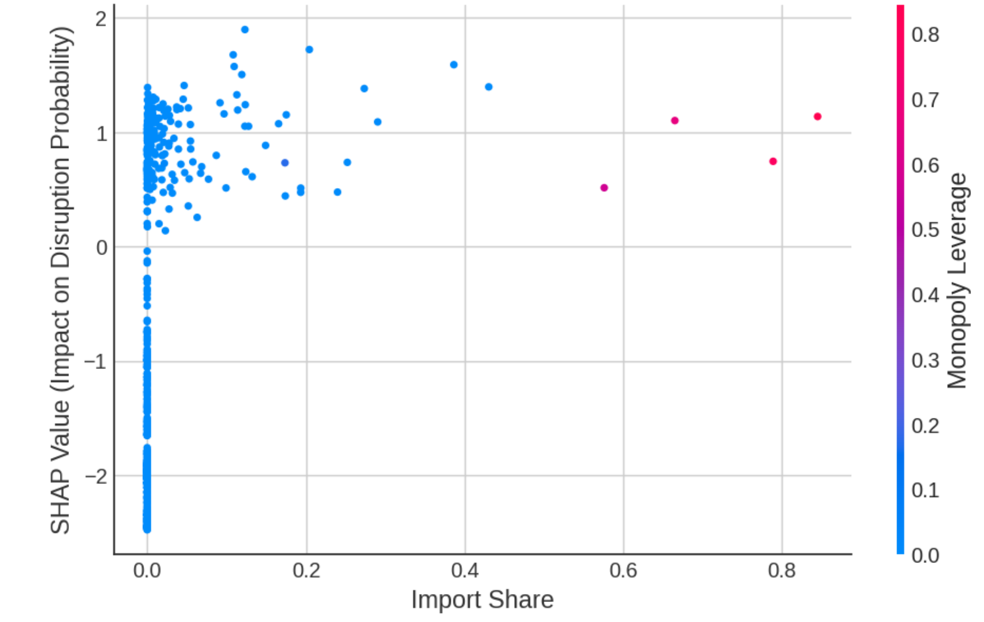
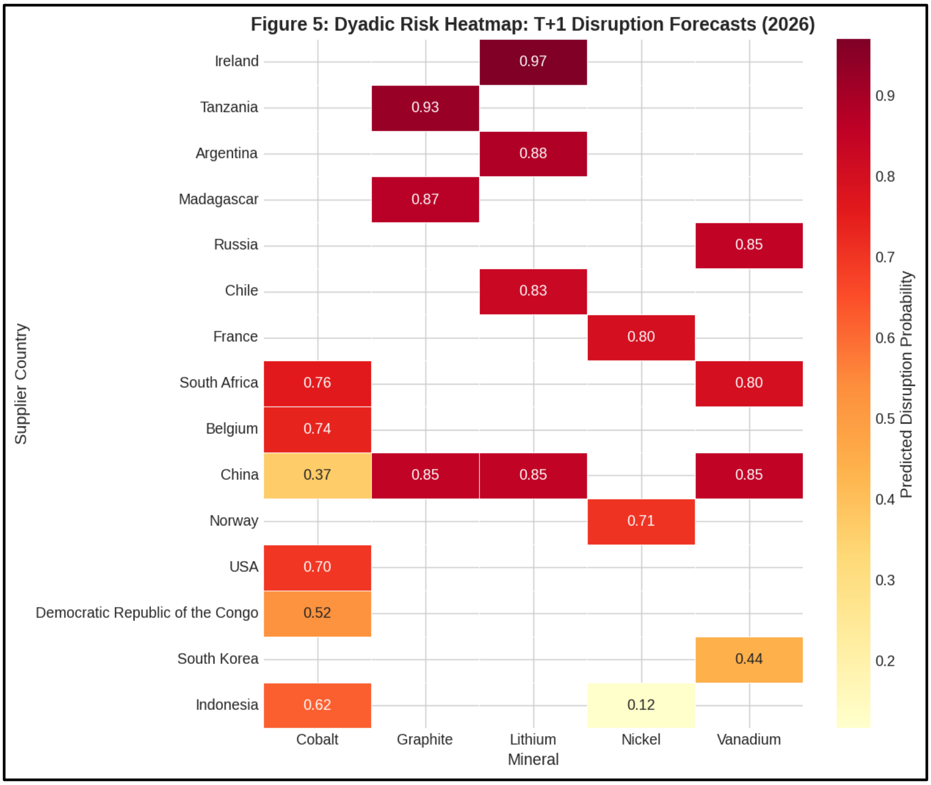


Figure 4: Import Reliance and Monopoly Leverage as Primary Risk Drivers





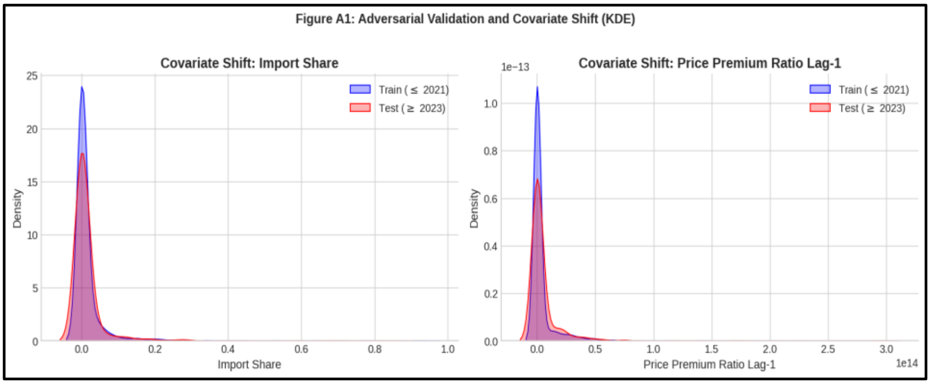


Figure A1: Adversarial Validation & Regime Shift (KDE) - representative of the structural regime shift pre and post-2022. Forces the model to rely on structural features that are time-invariant, as indicated in SHAP analysis.

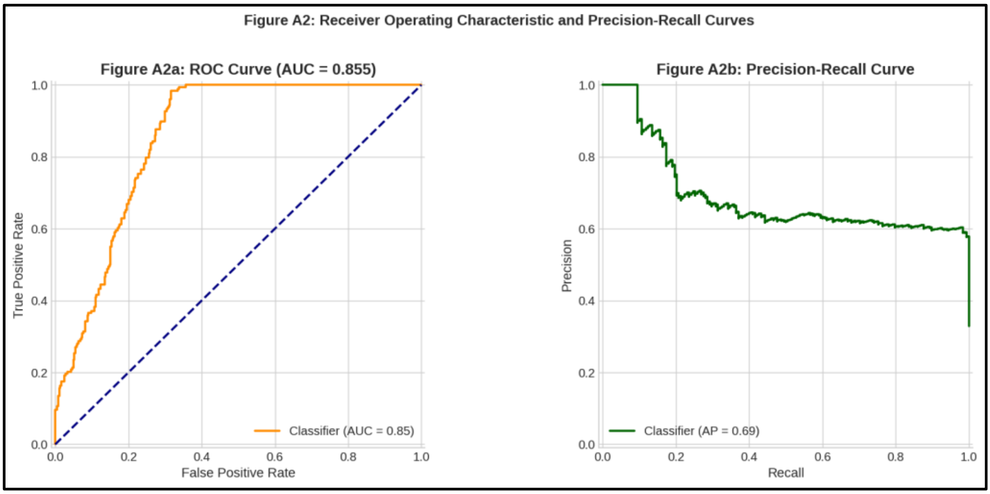


Figure A2: Receiver Operating Characteristic and Precision-Recall Curves
Figure A2a: ROC Curve (AUC = 0.855)
True Positive Rate
False Positive Rate
Classifier (AUC = 0.85)
Figure A2b: Precision-Recall Curve
Precision
Recall
Classifier (AP = 0.69)

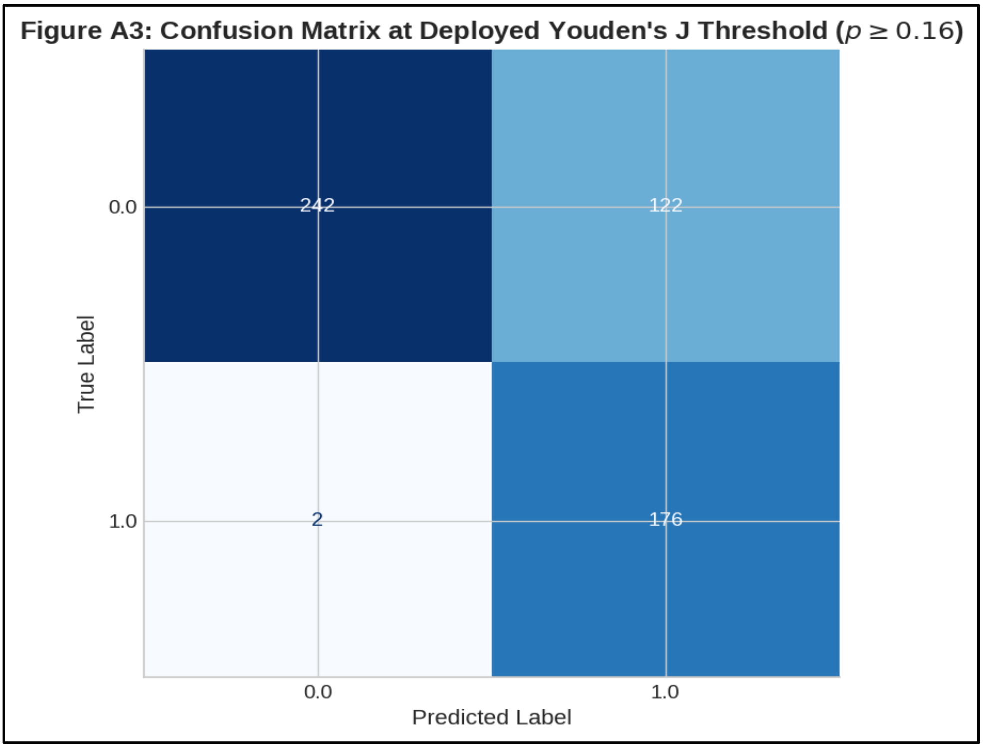


Figure A3: Confusion Matrix at Deployed Youden's J Threshold ($p \geq 0.16$)
True Label
Predicted Label
0.0
1.0
242
122
2
176

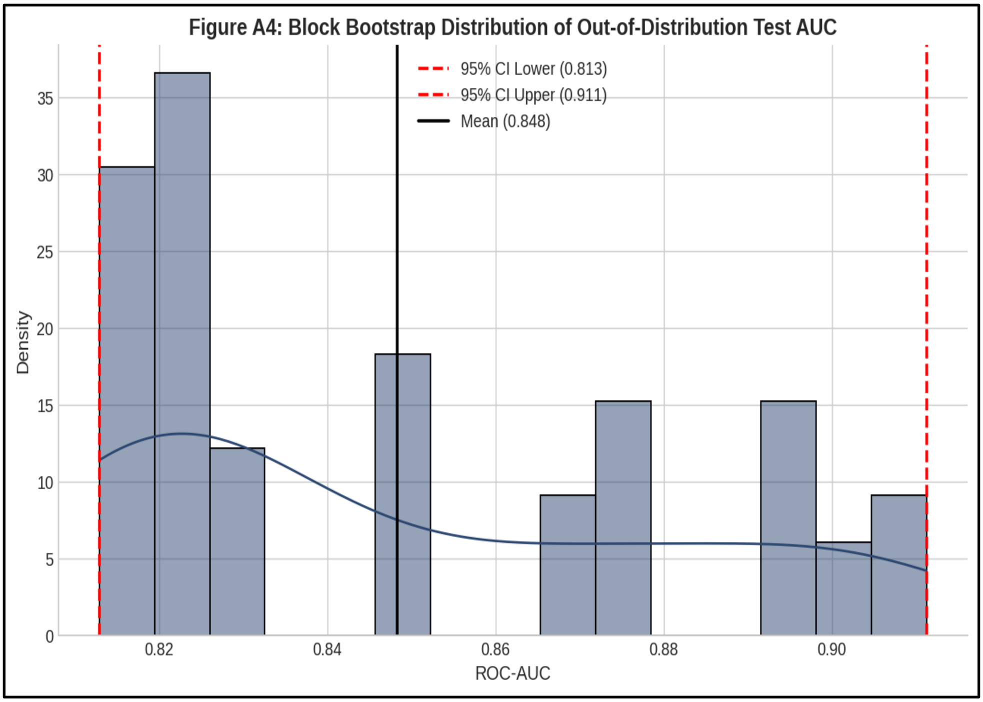


Figure A4: Block Bootstrap Distribution of Out-of-Distribution Test AUC

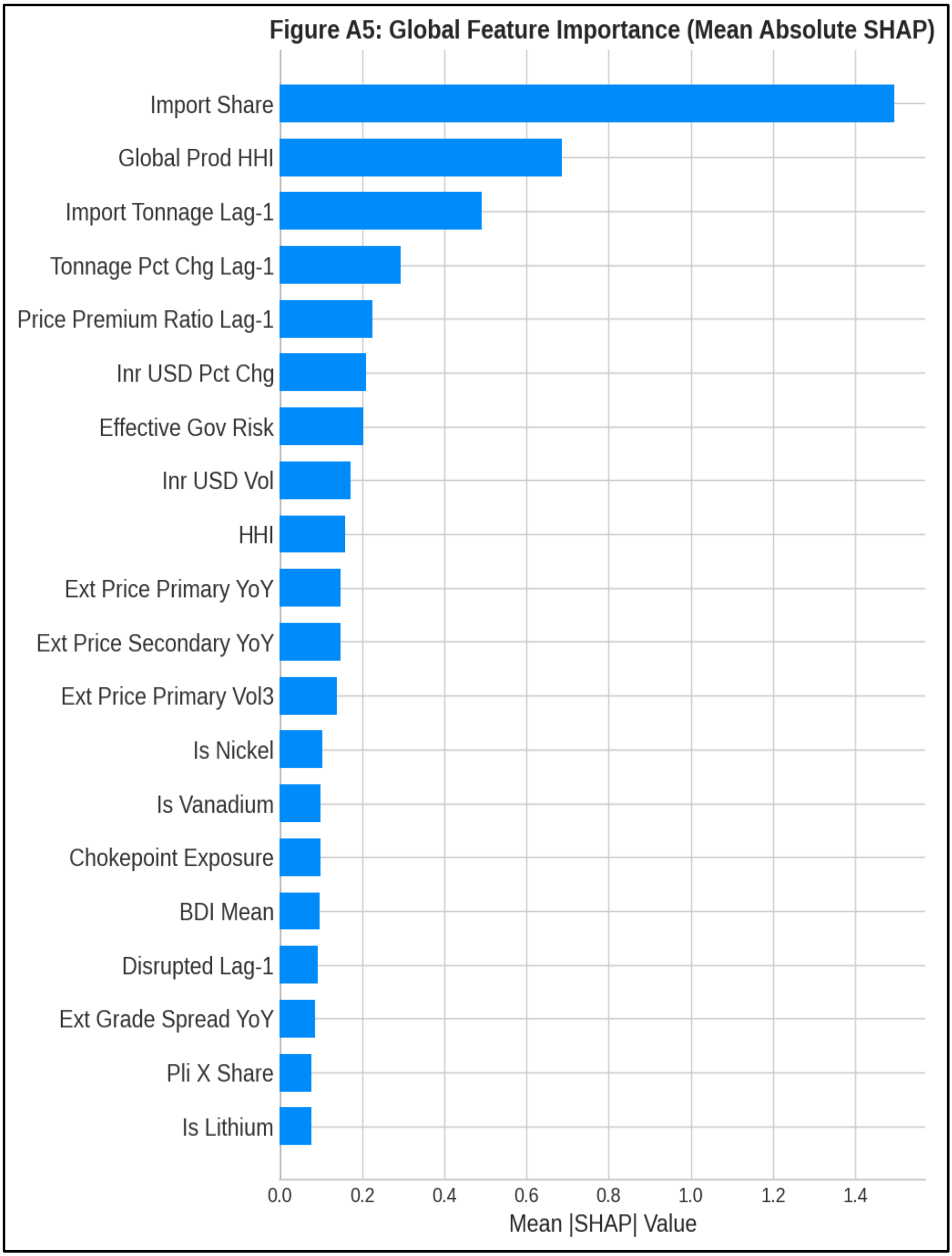


Figure A5: Global Feature Importance (Mean Absolute SHAP)
Import Share
Global Prod HHI
Import Tonnage Lag-1
Tonnage Pct Chg Lag-1
Price Premium Ratio Lag-1
Inr USD Pct Chg
Effective Gov Risk
Inr USD Vol
HHI
Ext Price Primary YoY
Ext Price Secondary YoY
Ext Price Primary Vol3
Is Nickel
Is Vanadium
Chokepoint Exposure
BDI Mean
Disrupted Lag-1
Ext Grade Spread YoY
Pli X Share
Is Lithium
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
Mean |SHAP| Value

Table 0: Highlighting the thresholds used		
Threshold	**Tier / Category**	**Description**
p≥0.11	Tactical Dashboard	Youden's J deployment threshold for the T+1 early warning system, triggering spot-market monitoring and diplomatic demarches.
p≥0.50	VaR Mandate Floor	GMM-derived boundary triggering the mandatory 100% physical Time-to-Export-Bottleneck-Window (TEBW) strategic reserve coverage.
p≥0.70	T+1 CRITICAL Tier	Standard early-warning classification for immediate, high-probability supply shocks.
p≥0.85	Structural CRITICAL Tier & Procurement Trigger	84th-percentile threshold identifying weaponizable monopolies. Breaching this tier triggers mandatory KABIL procurement actions and long-term strategic decoupling initiatives.

Table 1: Data sources		
Dataset / Source	**Granularity & Scope**	**Primary Use in Model (Engineered Features & Targets)**
Master Trade Data (UN Comtrade / DGCIS)	Dyad-Month (2011–2025); 271 active supplier dyads	Target Variable: Disruption labels via volume drops (>40% YoY) and structural zero cutoffs. Features: import_share, hhi, price_premium_ ratio, supply_continuity, tonnage_ pct_chg_lag1.
Global Mineral Prices (Fastmarkets / IMF Proxies)	Mineral-Month (2011–2025); 5 priority minerals	Target Variable: Price spike labels via 12-month rolling Z-scores (>2.0σ). Features: ext_price_primary_yoy, ext_price_secondary_yoy, ext_price_primary_vol3.

Table 1: Data sources		
Dataset / Source	**Granularity & Scope**	**Primary Use in Model (Engineered Features & Targets)**
Worldwide Governance Indicators (WGI) (World Bank)	Country-Year (2011–2024); Political, Regulatory, Corruption	Features: gov_risk_score (inverted mean of WGI metrics). Tier-2 Upstream: Aggregated into effective_gov_risk for transshipment/processor hubs.
Policy Buffers & Diplomatic Agreements (MEA / Bilateral Treaties)	Country-Year (2011–2025); FTAs and Critical Mineral MoUs	Features: diplomatic_buffer_score (weighted sum of active FTAs/MoUs). Interaction: shielded_exposure (import_share × buffer score).
Global Supply Chain Pressure Index (GSCPI) (Federal Reserve Bank of NY)	Global-Month (2011–2025); Macro freight & logistics stress	Features: Macro control variables gscpi_mean and gscpi_volatility to capture systemic global logistics shocks independent of bilateral relations.
Index of Industrial Production (IIP) (MOSPI, Govt. of India)	Sector-Month (2011–2025); Manufacture of Basic Metals	Features: iip_basic_metals_yoy to control for domestic demand-side shocks and isolate pure supply-side disruptions.
Liner Shipping & Freight Indices (UNCTAD LSCI / Baltic Dry)	Global / Country-Year; Maritime connectivity & bulk freight	Features: bdi_mean, bdi_vol (freight volatility). Spatial: Informs chokepoint_exposure and maritime_chokepoint_risk.
Global Mine Production Data (USGS / IEA / WMD Schema)	Country-Year (2011–2025); Upstream extraction volumes	Features: global_prod_hhi, global_prod_share, compound_concentration (CR2). Flags: is_monopoly, is_hegemon, is_processor_hub.

Table 2: Model Parameters and Configurations

Category	Metric / Parameter	Value / Configuration
Category	**Metric / Parameter**	**Value / Configuration**
Panel Architecture	Balanced Panel Structure	48,780 rows (271 active dyads * 180 months)
	Feature Space	38 features (Includes IIP, LSCI, INR/USD macro variables)
	Target Definition (IEA-Anchored)	>2.0σ Price Spike AND >40% YoY Volume Drop, OR Structural Cutoff
Temporal Splits	Training Set	≤ 2021 (Pre−weaponization era)
	Validation Set	2022 (Black Swan Buffer: Russia-Ukraine, China regulatory shifts)
	Test Set (OOD)	≥ 2023 (Out−of−Distribution: Export controls, Red Sea crisis)
Model Performance	Algorithm	XGBoost Classifier (IPW-weighted to correct covariate shift)
	Test ROC-AUC	0.855 (95% Bootstrap CI: [0.815, 0.910])
	Test Brier Score	0.1516 (Indicates highly calibrated probabilities)
	Test Recall	0.989 (Only 2 missed disruptions in OOD test set)
	Adversarial Validation AUC	1.000 (Full) / 1.000 (Physics): Confirms structural regime break
Endogenous Thresholds	Youden's J [DEPLOYED]	$p \geq 0.11$ $p \geq 0.11$ (Maximizes Sensitivity

Table 2: Model Parameters and Configurations		
Category	**Metric / Parameter**	**Value / Configuration**
		`+ Specificity)`
	Geopolitical Override (CART)	Enforces 0.85 floor for weaponizable monopolies (>5% bilateral / >10% global share)
Algorithmic TEBW	Nickel	115.5 days (Weighted: 85% Steel, 15% Alloys/Batteries)
	Vanadium	113.2 days (Weighted: 85% Steel, 10% Alloys, 5% Other)
	Lithium	110.2 days (Weighted: 87% Batteries, 13% Other)
	Cobalt	104.2 days (Weighted: 70% Batteries, 15% Alloys, 15% Chemicals)
	Graphite	92.2 days (Weighted: 30% Steel, 55% Batteries, 15% Other)
Strategic Sizing (VaR)	GMM Sovereign Policy Floor	τ=0.50 τ=0.50 (Midpoint of Friction [0.255] and Crisis [0.824] clusters)
	Total Initial CapEx	USD 633.0 Million (Across Li, Co, Ni, Graphite, V)
	5-Year Lifecycle Cost	USD 910.6 Million (Includes carrying costs & degradation)
Actuarial Simulation	Galathea Bay Hub Savings	USD 17.3 Million (One-time CapEx avoidance via expected lost tonnage mitigation)

Table 3: Top 10 SHAP Drivers	
Mean Absolute SHAP Value	
Import Share	1.4958
Global Production HHI	0.6853
Import Tonnage (Lag-1)	0.4903
Tonnage % Change (Lag-1)	0.2948
Price Premium Ratio (Lag-1)	0.2253
INR/USD % Change	0.2088
Effective Governance Risk	0.2026
INR/USD Volatility	0.1712
Import HHI	0.1585
External Primary Price YoY	0.1476

Table 4: Vulnerability Index

Mineral	Supplier Country	Vulnerability Index	Risk Tier	Disruption Prob.	Import Share	Global Prod. %
Cobalt	Finland	36.20	HIGH	0.280	27.6%	0.0%
Cobalt	USA	33.62	HIGH	0.697	11.0%	0.0%
Cobalt	China	33.61	MEDIUM	0.365	22.4%	0.0%
Graphite	China	59.00	CRITICAL	0.850	72.1%	69.9%
Graphite	Tanzania	37.33	CRITICAL	0.926	7.6%	0.0%
Graphite	Madagascar	34.74	CRITICAL	0.869	6.9%	6.8%

Table 4: Vulnerability Index						
Mineral	**Supplier Country**	**Vulnerability Index**	**Risk Tier**	**Disruption Prob.**	**Import Share**	**Global Prod. %**
Lithium	Argentina	60.32	CRITICAL	0.883	31.8%	7.0%
Lithium	Chile	52.00	HIGH	0.828	27.4%	22.4%
Lithium	China	39.90	CRITICAL	0.850	18.0%	20.4%
Nickel	France	32.16	LOW	0.802	5.3%	0.0%
Nickel	Indonesia	29.64	LOW	0.116	68.9%	55.7%
Nickel	Norway	28.24	LOW	0.706	5.1%	0.0%
Vanadium	China	46.67	CRITICAL	0.850	18.3%	66.1%
Vanadium	Russia	41.02	CRITICAL	0.850	13.6%	17.4%
Vanadium	Germany	32.80	MEDIUM	0.195	28.7%	0.0%

Table 5: Historical disruption triggered by model				
Event Description	**Mineral**	**Country**	**P(Disrupt)**	**Triggered?**
China Graphite Export Controls	Graphite	China	0.585	YES
Russia-Ukraine War & LME Sanctions	Nickel	Russia	0.877	YES
Indonesia Nickel Export Ban	Nickel	Indonesia	0.980	YES
Chilean Social Unrest & Port Strikes	Lithium	Chile	0.962	YES

Table 5: Historical disruption triggered by model				
Event Description	**Mineral**	**Country**	**P(Disrupt)**	**Triggered?**
Historic Price Peak & Supply Squeeze	Lithium	Chile	0.073	NO
Texas "Big Freeze" Industrial Shutdown	Nickel	USA	0.987	YES
Myanmar Military Coup & Border Closures	Cobalt	Myanmar	N/A	NOT IN DATA

Table 6: BASE SCENARIO LIFECYCLE COSTING (VaR Mandate)								
Mineral	**Annual Import (t)**	**P(Disruption)**	**TEBW (Days)**	**Reserve (tons)**	**Cover (Months)**	**CapEx (USD M)**	**OpEx (USD M)**	**Lifecycle (USD M)**
Lithium	3,512	0.978	110.2	1,061	3.62	15.9	3.2	31.8
Cobalt	2,451	0.960	104.2	700	3.43	38.5	6.9	73.2
Nickel	81,867	0.945	115.5	25,906	3.80	479.3	38.3	671.0
Graphite	266,999	0.986	92.2	67,481	3.03	81.0	4.9	105.3
Vanadium	5,906	0.964	113.2	1,833	3.72	18.3	2.2	29.3

Table 7: T+1 Disruption Forecasts (2026) for High-Risk Dyads					
Mineral	**Supplier Country**	**P(Disruption)**	**Import Share**	**Risk Type**	**Risk Tier**
Lithium	Ireland	0.970	13.8%	Transit-Node Logistics	CRITICAL
Graphite	Tanzania	0.926	7.6%	Origin-State Geopolitical	CRITICAL
Lithium	Argentina	0.883	31.8%	Origin-State Geopolitical	CRITICAL
Graphite	Madagascar	0.869	6.9%	Origin-State Geopolitical	CRITICAL
Graphite	China	0.850	72.1%	Origin-State Geopolitical	CRITICAL
Lithium	China	0.850	18.0%	Origin-State Geopolitical	CRITICAL
Vanadium	Russia	0.850	13.6%	Origin-State Geopolitical	CRITICAL
Vanadium	China	0.850	18.3%	Origin-State Geopolitical	CRITICAL
Lithium	Chile	0.828	27.4%	Origin-State Geopolitical	CRITICAL
Vanadium	South Africa	0.803	8.2%	Origin-State Geopolitical	CRITICAL
Nickel	France	0.802	5.3%	Transit-Node Logistics	CRITICAL
Cobalt	South Africa	0.756	8.0%	Origin-State Geopolitical	CRITICAL
Cobalt	Belgium	0.739	8.5%	Transit-Node Logistics	CRITICAL
Nickel	Norway	0.706	5.1%	Transit-Node Logistics	CRITICAL
Cobalt	USA	0.697	11.0%	Transit-Node Logistics	HIGH

Table 8: Actuarial Risk Reduction for Material Suppliers (≥1% Share) – Year 2025					
Mineral	**Supplier**	**Share**	**Base P(Disrupt)**	**Galathea P**	**Delta**
Graphite	China	72.1%	0.850	0.723	-0.127
Lithium	China	18.0%	0.850	0.723	-0.127
Vanadium	China	18.3%	0.850	0.723	-0.127
Nickel	Japan	4.5%	0.816	0.694	-0.122
Cobalt	Japan	2.6%	0.754	0.641	-0.113
Lithium	South Korea	2.9%	0.730	0.620	-0.109
Cobalt	Indonesia	6.0%	0.622	0.529	-0.093
Nickel	China	4.0%	0.619	0.526	-0.093
Vanadium	Japan	3.0%	0.544	0.462	-0.082
Vanadium	Vietnam	2.9%	0.542	0.461	-0.081
Vanadium	South Korea	7.7%	0.442	0.376	-0.066
Cobalt	China	22.4%	0.365	0.311	-0.055
Nickel	Indonesia	68.9%	0.116	0.099	-0.017

Table 9: STRATEGIC RESERVE CAPEX SAVINGS				
Mineral	**Baseline Loss (t)**	**Galathea Loss (t)**	**Tonnage Saved (t)**	**CapEx Saved (USD M)**
Lithium	761	647	114	0.5
Cobalt	344	292	52	0.8
Nickel	8,918	7,580	1,338	7.8

Table 9: STRATEGIC RESERVE CAPEX SAVINGS				
Mineral	**Baseline Loss (t)**	**Galathea Loss (t)**	**Tonnage Saved (t)**	**CapEx Saved (USD M)**
Graphite	164,014	139,412	24,602	7.5
Vanadium	1,532	1,302	230	0.7
Total	**-**	**-**	**-**	**17.3**

Table 10: Threshold Sensitivity & Endogenous Deployment Analysis (Test Set)						
Scenario	**Opt. Thresh**	**Recall**	**Precision**	**F1-Score**	**False Alarms**	**Missed**
Theoretical 1:1	0.15	0.983	0.601	0.746	116	3
Theoretical 2:1	0.15	0.983	0.601	0.746	116	3
Theoretical 5:1	0.10	0.994	0.588	0.739	124	1
Theoretical 10:1	0.07	1.000	0.578	0.733	130	0
Theoretical 20:1	0.07	1.000	0.578	0.733	130	0
Theoretical 50:1	0.07	1.000	0.578	0.733	130	0
DEPLOYED (Youden's J) (2.3:1)	**0.11**	**0.989**	**0.591**	**0.739**	**122**	**2**

Note: Cost-ratio rows show theoretical test-set optima. The Deployed row shows the validation-calibrated Youden's J threshold, which prevents test-set overfitting and serves as the operational dashboard trigger.

A6. TEBW and VaR Derivations

$$TEBW_m = \sum_{i=1}^{n} (S_{m,i} \times D_i)$$

where:

* $TEBW_m$ = Time-to-Export-Bottleneck-Window for mineral m (days)
* $S_{m,i}$ = Share of mineral m consumed by downstream industry sector i
* D_i = Baseline inventory buffer for industry sector i (days)

$$R_m = \frac{I_m \times C_m \times TEBW_m}{365}$$

where:

* R_m = Required Strategic Reserve size (metric tons) (VaR)
* I_m = Annual import volume of mineral m (metal-equivalent tons)
* C_m = Coverage Ratio (determined by GMM-derived sovereign policy floor $\tau = 0.50$)
* $TEBW_m$ = Weighted Time-to-Export-Bottleneck-Window (days)

$$C_m = \begin{cases} 1.00 & \text{if } \max(P_{\text{disruption}}) \geq 0.50 \quad (100\% \text{ TEBW coverage}) \\ 0.25 & \text{if } \max(P_{\text{disruption}}) < 0.50 \quad (25\% \text{ fractional buffer}) \end{cases}$$

Table 11: Mineral-Specific Bottleneck Tiers and Use-Share Distribution			
Mineral	**Sector / Use Case**	**Usage Share**	**Bottleneck Duration (Days)**
Graphite	Steel / Refractories	30%	120
Graphite	Battery Anode / Graphitization	55%	90
Graphite	Other	15%	45
Lithium	Battery Precursors	87%	120
Lithium	Glass / Ceramics	13%	45
Cobalt	Battery Precursors	70%	120
Cobalt	Superalloys	15%	90
Cobalt	Chemicals / Catalysts	15%	45
Nickel	Stainless Steel	70%	120
Nickel	Alloys / Superalloys	15%	90
Nickel	Battery Precursors	15%	120
Vanadium	HSLA Steel	85%	120
Vanadium	Aerospace Alloys	10%	90
Vanadium	VRFB / Chemicals	5%	45

Note: The D_i tiers (120/90/45 days) are derived keeping the 6-month strategic reserve target as baseline. It is assumed some stock will be present with the producer already; then, we divide the mineral uses into Tiers, based on the fundamental nature of their produce. Tier 1 receives the longest coverage as it consists of foundational materials (steel, cathode precursors). Tier 3 receives minimal coverage because these sectors are more substitutable and hold larger seasonal buffers. These are not rigid mathematical formulas; if anything, the values of TEBW produced from this, and eventually the VaR, can be considered lower bounds of the actual figure with more accurate industry figures. $S_{m,i}$ on the other hand, is carefully crafted using industry standard usage percent distribution, using USGS data for each mineral.

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