UK Critical Minerals
Intelligence Centre

# Methodological advances in UK criticality assessment

Decarbonisation and Resource Management Programme

Open Report OR/26/011

Department for Business & Trade

British Geological Survey

*This report does not constitute Government policy.*

*BRITISH GEOLOGICAL SURVEY*

*DECARBONISATION AND RESOURCE MANAGEMENT PROGRAMME*

*OPEN REPORT OR/26/011*

# Methodological advances in UK criticality assessment

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# Foreword

This report is the published product of a study by the UK Critical Minerals Intelligence Centre (CMIC), hosted at the British Geological Survey (BGS), which was commissioned by the Department for Business and Trade (DBT) as part of the 2025 to 2026 work programme for CMIC.

This report explores methodological development to further the accuracy and representativity of criticality assessments applied to the UK economy.

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# Executive summary

Critical minerals (CMs) underpin the UK's economy, technology, energy transition and industrial resilience. As global markets become more volatile and supply chains more complex, the UK must continually refine how it identifies and manages material supply risk. This report evaluates a series of methodological enhancements designed to better tailor future UK Critically Assessments (UK CA) (Mudd et al., 2024) to the structure of the UK economy, its trade profile and strategic industrial sectors. This report explores methodological advances in seven key areas:

- Market sentiment
- Economic importance
- Trade restrictions
- Material flow characterisation
- Environmental, social, and governance standards
- Corporate concentration
- Future mineral production

These updates provide a more UK-specific analysis, with stronger representation of the manufacturing sector and more accurate integration of material use across the UK's predominantly service-based economy. For import-reliant nations, like the UK. with limited upstream production, accurate tracking of intermediate and manufactured product flows is essential to understanding true supply dependencies and points of intervention. A key development is the explicit mapping of interconnections between industrial sectors, identification of provider–consumer relationships and more robust quantification of supply chain vulnerabilities, including cascading impacts and competition for constrained resources. Incorporating market sentiment and trade interventions indicators introduce a new geopolitical and financial dimension to supply risk assessment.

Together, these enhancements deliver a more comprehensive and policy-relevant understanding of criticality, particularly by improving visibility of mid-stream supply chain risks. While the new indicators reduce the relative weighting of those used in the 2024 UK CA, their impact will be rigorously tested through sensitivity analysis in the next assessment cycle, including retrospective evaluation against 2024 results.

In line with previous recommendations, the next UK Criticality Assessment should be delivered in 2027/28.

## KEY ACHIEVEMENTS

### New indicators

'**Market sentiment'** (MS) developed two new indicators, 'market turbulence' (MT) and 'market disorder' (MD), to assess market performance and liquidity through price time-series analysis of dominant traded forms.

- Market Turbulence (MT) captures short-term volatility and price instability through peak volatility, historic-to-peak volatility ratio, volatility concentration, and breakout intensity.
- Market Disorder (MD) assesses long term signal coherence and reliability through consideration of regime change frequency, false break ratio, break intensity, and dominance of high-turbulence over persistent volatility.

These highlight potential market manipulation or opaque practices, revealing whether markets are liquid and transparent or thin and vulnerable to disruption.

In ‘**economic importance’**, new input/output tables from the Office for National Statistics (ONS) have enabled comprehensive mapping of inter-sector dependencies, moving beyond the previous manufacturing-focused ‘gross value added’ approach. Eight new metrics (including the ‘forward linkage index’ (FLI), a methodological advance over international assessments) combine into three indicators:

- direct economic importance (DEI)
- supply-chain centrality (SCC)
- economic multiplier effects

This provides unprecedented insight into how materials support interconnected industrial ecosystems, where strategic dependencies emerge, and how disruptions propagate through the economy.

## New weighting factors

Global protectionism trends have accelerated trade restrictions and interventions affecting mineral supply chains. A new **‘trade intervention factor**’ (TIF) captures the frequency, scale and range of liberalising and harmful trade practices by nations. This adds a geopolitical dimension to supply risk assessments.

## Expanded datasets

Harmonized System (HS) code coverage has been expanded to more than 600 codes across 41 commodities to improve **material flow characterisation**, tripling the UK’s ability to track midstream (semi-manufactured goods; chemical precursors) and end-of-life (waste and scrap) products. This delivers a robust global material flow quantification that strengthens UK assessment of import reliance and provenance, and supports wider needs such as customs intelligence, trade negotiations and circular economy initiatives. Future work is required to cover the remaining commodities of interest and continue progressing characterisation of downstream supply codes.

| Substance updated | | | |
|---|---|---|---|
| Antimony | Fluorspar | Nickel | Tantalum |
| Beryllium | Gadolinium | Niobium | Terbium |
| Borates | Holmium | Phosphorus | Tin |
| Cerium | Lanthanum | Praseodymium | Titanium |
| Chromium | Lead | REEs | Tungsten |
| Cobalt | Lithium | Rhenium | Vermiculite |
| Copper | Lutetium | Samarium | Yttrium |
| Diatomite | Magnesium | Scandium | Zinc |
| Dysprosium | Manganese | Silica sand | |
| Erbium | Molybdenum | Silicon | |
| Europium | Neodymium | Silver | |

A critical gap in previous environmental, social and governance (ESG) monitoring, climate vulnerability, has been addressed through the incorporation of the Notre Dame Global Adaptation Initiative (ND-GAIN) country index. ND-GAIN combines climate vulnerability (exposure to water scarcity, extreme heat and flooding across six systems) with readiness (adaptive capacity) providing transparent, globally comprehensive, forward-looking measures.

## EXPLORATORY ADVANCEMENTS

**Corporate concentration**: Explored single point-of-failure (SPoF) analysis, market diversity and production concentration metrics identified supply-chain pinch points at corporate level (complementing national-level concentration). Data coverage remains limited, but the approach is valuable for targeted commodities.

**Future mineral production projections:** Hubbert peak models were used to forecast production trajectories, offering useful strategic scenarios for mature commodities with stable data (for example, mined copper; nickel; rare earths) but showing high sensitivity to parameterisation when historical datasets are short, volatile or influenced by co- or by-product dynamics. The models are not suitable currently as systematic criticality indicators but are useful for exploratory strategic scenarios (more than 10-year horizons). It is recommended these are complemented with autoregressive time-series models for near-term dynamics for their comparison with growth consumption projections to assess gap or match between potential future supply and demand.

## STRATEGIC RECOMMENDATIONS

### Immediate implementation

Four methodological enhancements are ready for immediate integration into the next UK criticality assessment.

- Market sentiment indicators should be applied whenever price data reveals whether markets are liquid and transparent or thin and vulnerable to disruption
- Economic importance indicators: Direct Economic Importance, Supply Chain Centrality, and Economic Multiplier Effects should be implemented using ONS input/output tables weighted 0.25, 0.45 and 0.30 to reflect supply-chain significance.
- The Trade Intervention Factor should adjust trade concentration indicators (TCIs), distinguishing between reliable trading partners and those demonstrating interventionist tendencies given current geopolitical volatility
- Expanded HS code coverage (more than 600 additional codes) should be incorporated into UK import reliance and global trade concentration (GTC) calculations, providing more accurate representation of midstream and downstream supply chains
- Climate vulnerability should be added to the ESG indicator by integrating the ND-GAIN country index to the existing three factors (environmental performance index (EPI); human development index (HDI); world governance indicators (WGI)).

### Selective and targeted application

Two methodological areas should be applied selectively in future dedicated analysis, not systematically in criticality assessments, due to data limitations.

- Corporate SPoF analysis remains valuable for known chokepoint commodities; however, accessible datasets cover only publicly listed companies and lack adequate coverage of co-products, by-products and downstream materials, making systematic application across all 82 candidate materials inappropriate.
- Hubbert-based production forecasting models provide useful long-term scenario framing for mature commodities with long, stable datasets, but require at least 50 years of historical data, model fit quality of $R^2 \geq 0.93$, and agreement between alternative parameterisations within ±20 years on peak timing. The approach is unsuitable for materials with major secondary supply chains or those produced as co-products, where output depends on primary commodity economics rather than own-resource constraints. Further work is recommended to explore more sophisticated models that could better

account for market forces, evolving production trends and the recent increase in global exploratory activities.

## BEYOND THE CRITICALITY ASSESSMENT

Several outputs have strategic value beyond criticality scoring and merit sustained cross-government investment. The enhanced ONS input/output analysis enables comprehensive UK supply-chain dependency mapping, revealing sector-specific bottlenecks, regional vulnerabilities, trade priorities and industrial strategy opportunities relevant to industrial policy and resilience planning. Ideally, further work by the ONS is required to continue improving the resolution of the input/output datasets, which currently have varying degrees of resolution and aggregation of the Standard Industrial Classification (SIC) codes.

The expanded HS code database strengthens customs intelligence, trade negotiations and circular economy initiatives by improving visibility into material flows through global trade channels. Trade intervention monitoring informs bilateral relationship management and supply diversification strategies by distinguishing reliable partners from intervention-prone suppliers. These datasets represent significant analytical infrastructure with applications well beyond criticality assessment (CA).

### Data infrastructure investments

Sustained improvement of criticality assessment methodologies depends on strengthening the CMIC's underlying data infrastructure. The growing scale and complexity of HS codes, trade statistics and price datasets require automated systems for data acquisition, validation and transformation into decision-ready indicators.

Over the coming year, CMIC will prioritise the development of these capabilities to enable faster detection of changes in critical mineral markets and provide more timely intelligence to policymakers and industry. This includes establishing robust databases, automated data collection pipelines from online sources, quality assurance and quality control (QA/QC) tools, and standardised processing workflows to deliver consistent outputs.

Investment in these systems will support a more responsive and scalable approach to criticality assessment, positioning the UK to deliver increasingly automated and up-to-date analyses by 2027.

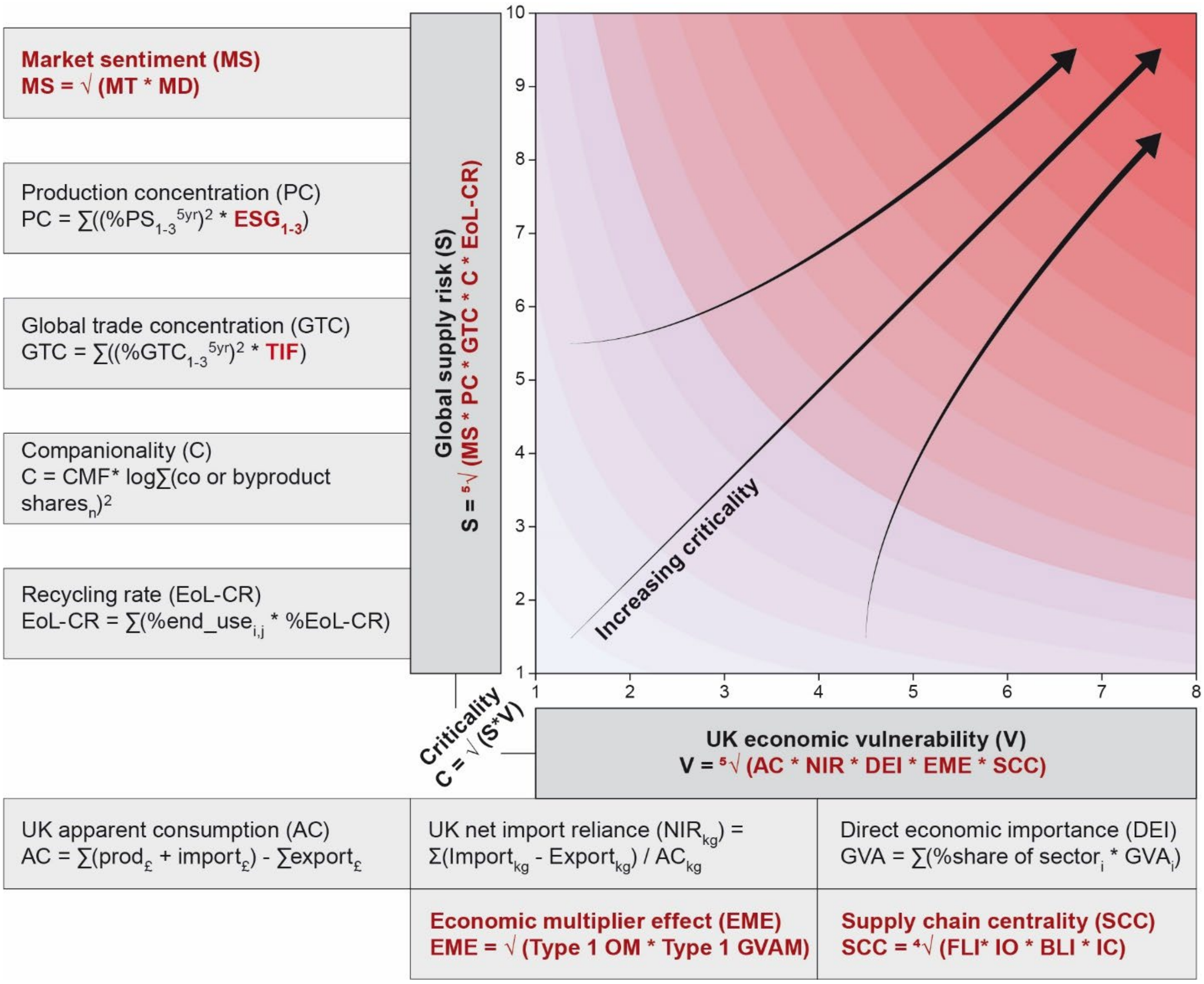
## CONCLUSION

This methodology strengthens the UK's CA by integrating market dynamics, supply-chain interdependencies, geopolitical risks and climate vulnerabilities through multiple complementary indicators. Three areas provide immediate, high-confidence enhancements:

- market sentiment (MS) indicators
- economic importance analysis using input/output tables
- trade restrictions weighting

Material flow characterisation through expanded HS codes strengthens trade-based indicators, while ESG climate vulnerability integration addresses a critical gap with minimal methodological disruption. Corporate concentration (CC) and production forecasting offer value for targeted deep-dive analyses and potential stress-testing of industry supply chains but data limitations prevent systematic application. Using each method where it is most robust ensures analytical quality and strengthens the overall framework.

The result is a more granular, evidence-based understanding of how different materials exhibit criticality, whether through market opacity, supply-chain centrality, geopolitical concentration, or climate exposure, enabling tailored intervention strategies matched to specific material risk profiles rather than one-size-fits-all approaches.



Updated summary of the UK criticality assessment matrix highlighting how the new methodological developments presented in this study (in red) would integrate within the framework of the 2024 criticality assessment. Note the presence of new indicators which will therefore influence the balancing of the global supply risk and UK economic vulnerability dimensions, as well as new and improved (TIF, ESG) weighing factors. All trade-related indicators (global trade concentration, UK apparent consumption, UK net import reliance) will benefit from the expanded coverage and characterisation of HS code bringing more mid-stream details relevant to the UK economy.

# Introduction

The publication of the UK's new Critical Minerals Strategy, Vision 2035 (Department for Business and Trade, 2025), alongside its industrial, and upcoming steel and circular economy strategies, reflects growing recognition that critical metals underpin modern technological society and defence and energy systems. As major economic powers, including the USA, China and the European Union (EU), intensify legislation to secure their own supply chains of metals essential for energy, artificial intelligence, defence, aerospace, mobility and electronics, it is more prevalent than ever for the UK to define its strategic priorities and strengthen resilience.

Criticality assessments (CAs) are widely used to identify commodities with the highest risk of supply disruption and associated economic impacts. The resulting CM lists increasingly guide national and regional strategies for investment, industrial development and supply-chain resilience. CAs integrate diverse datasets and methodologies to evaluate both the supply of raw, processed and manufactured materials and their economic importance to a company, industrial sector or nation.

In 2024, the UK published its updated critical raw material (CRM) list (Mudd et al., 2024), supported by improved and transparent methodology (Josso et al., 2023). This assessment utilised available data covering the last five to ten years and was complemented by foresight studies on UK demand for CRMs to 2050 for key decarbonisation technologies (Jackson et al., 2024a, Jackson et al., 2024b, Petavratzi et al., 2024a, Petavratzi et al., 2024b, Petavratzi et al., 2024c, Petavratzi et al., 2024d, Petavratzi et al., 2024e, Zils, 2024a, Zils, 2024b, Zils, 2024c). As global CRM markets evolve rapidly, further refinement and expansion of the metrics used in CAs is required.

The 2024 UK Critically Assessment (2024 UK CA) (Mudd et al., 2024) methodology relied on seven indicators covering the full material life cycle, from mining and refining to end-of-life recovery, assessing variable trade concentration and economic importance of the upstream stages of materials in the UK economy (Figure 1). This report evaluates a series of methodological enhancements designed to better tailor future UK CAs to the structure of the UK economy, its trade profile and strategic industrial sectors. These improvements reflect stakeholder feedback and areas identified by CMIC during the previous assessment cycles where deeper analysis would add value.

The main areas considered are:

- market sensitivity (MS) and volatility
- environmental, social and governance (ESG) metrics
- Harmonized System (HS) code monitoring
- company ownership and market concentration
- economic importance and commodity linkage in UK industrial sectors
- global trade restrictions
- future of CM production

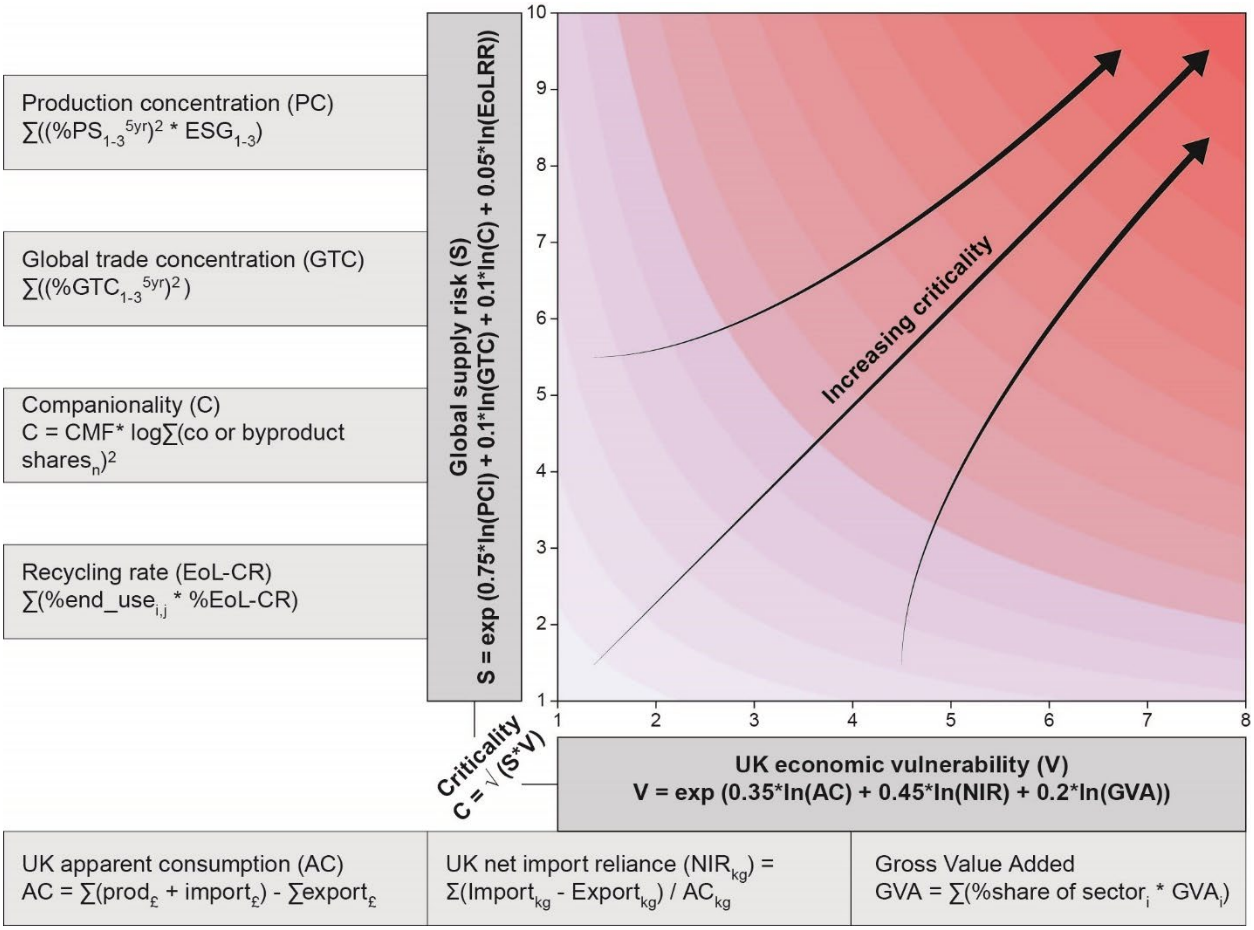


**Figure 1** Summary of the UK CA matrix, showing the four indicators used to calculate the global supply risk (S) and the three indicators to calculate UK economic vulnerability (V). The criticality score (C) is the geometric mean of the product of both axis values. From Mudd et al. (2024). BGS © UKRI 2024.

This report presents a high-level summary of the approach and key findings for each area. Detailed analyses and supporting discussion are provided in the appendices.

# 1 Market sentiment

Market behaviour provides crucial signals about supply-chain health. Opaque pricing, thin markets and excessive volatility indicate structural vulnerabilities that can compound physical supply risks. Traditional CAs focus on production concentration and trade flows but often overlook market dynamics that can amplify or mask underlying fragilities. For the UK, which is heavily reliant on imports across diverse commodities, understanding market liquidity, stability and transparency is essential to identifying where strategic interventions may be needed.

## 1.1 METHODOLOGY OVERVIEW

Two complementary indicators were developed to assess different dimensions of market risk using commodity price time-series data:

- Market Turbulence (MT) captures short-term volatility and price instability
- Market Disorder (MD) assesses signal coherence and reliability of long-term pricing information

Together, these indicators reveal whether markets are liquid, transparent and resilient, or thin, manipulated and vulnerable to disruption.

## 1.2 MARKET TURBULENCE

MT quantifies price volatility through four metrics derived from rolling-window analysis of price data (Argus Metals, 2025)

- peak volatility: maximum short-term price fluctuation
- historic-to-peak volatility ratio: comparison of recent vs. long-term volatility
- volatility concentration: proportion of time spent in high-volatility regimes
- breakout intensity: frequency and magnitude of sharp price spikes

High MT scores indicate markets are prone to rapid, destabilising price movements, often reflecting supply shocks, speculative activity or strategic stockpiling or dumping behaviour.

## 1.3 MARKET DISORDER

The MD indicator measures how reliable and stable price signals are in a mineral market. It focuses on whether price reflect real supply-demand conditions or whether they behave unpredictably. It looks at four aspects:

- How often the market suddenly changes direction: frequent “regime changes” suggest instability.
- How many apparent trends turn out to be false alarm: a high “false break ratio” means prices start to move but then reverse quickly.
- How big the reversals are when they happen: larger “break intensity” signals stronger disorder.
- Whether short, chaotic price swings dominate over steady, long-term trends.

High MD suggests unstable market expectations where price signals are unreliable, potentially indicating thin markets, bilateral contracts dominating open trading, or strategic price manipulation.

## 1.4 KEY FINDINGS

Analysis across 16 commodities, representative of a broad range of market sizes, liquidity levels and reporting practices reveals significant variation. Copper and aluminium (traded on the London Metal Exchange (LME)) show relatively high turbulence but better market order, reflecting liquid but volatile markets. Minor metals like germanium and cerium exhibit low scores on both indicators, not signalling stability but instead highlighting thin markets with limited price discovery. Lithium shows moderate turbulence with low disorder, reflecting rapid demand growth with developing market structures.

## 1.5 CRITICAL INSIGHT

Commodities lacking transparent, continuous pricing should be treated as inherently higher risk. Absence of price data masks structural fragility rather than indicating market resilience.

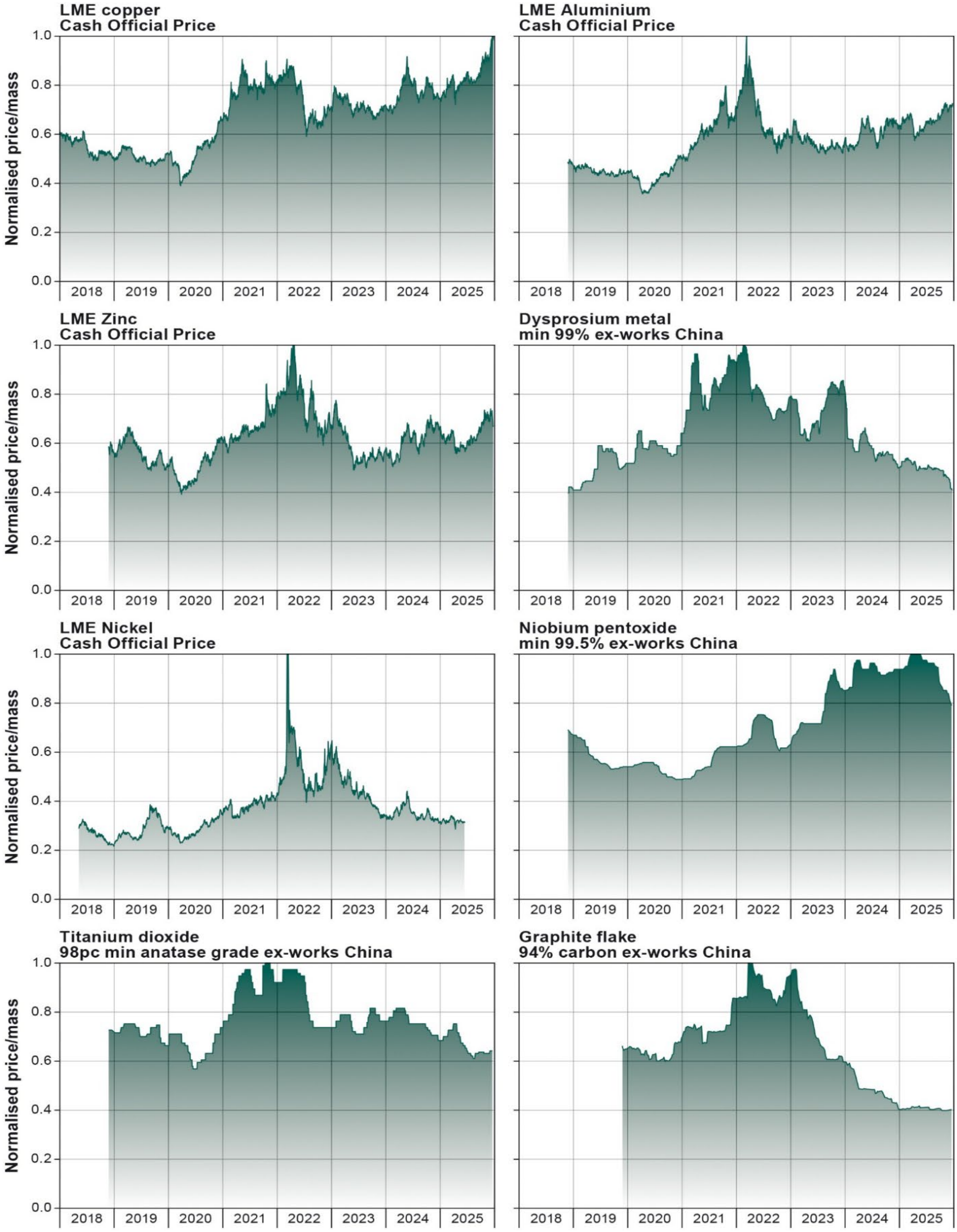


**Figure 2** Price-normalised time-series data (Argus Metals, 2025). BGS © UKRI 2026.

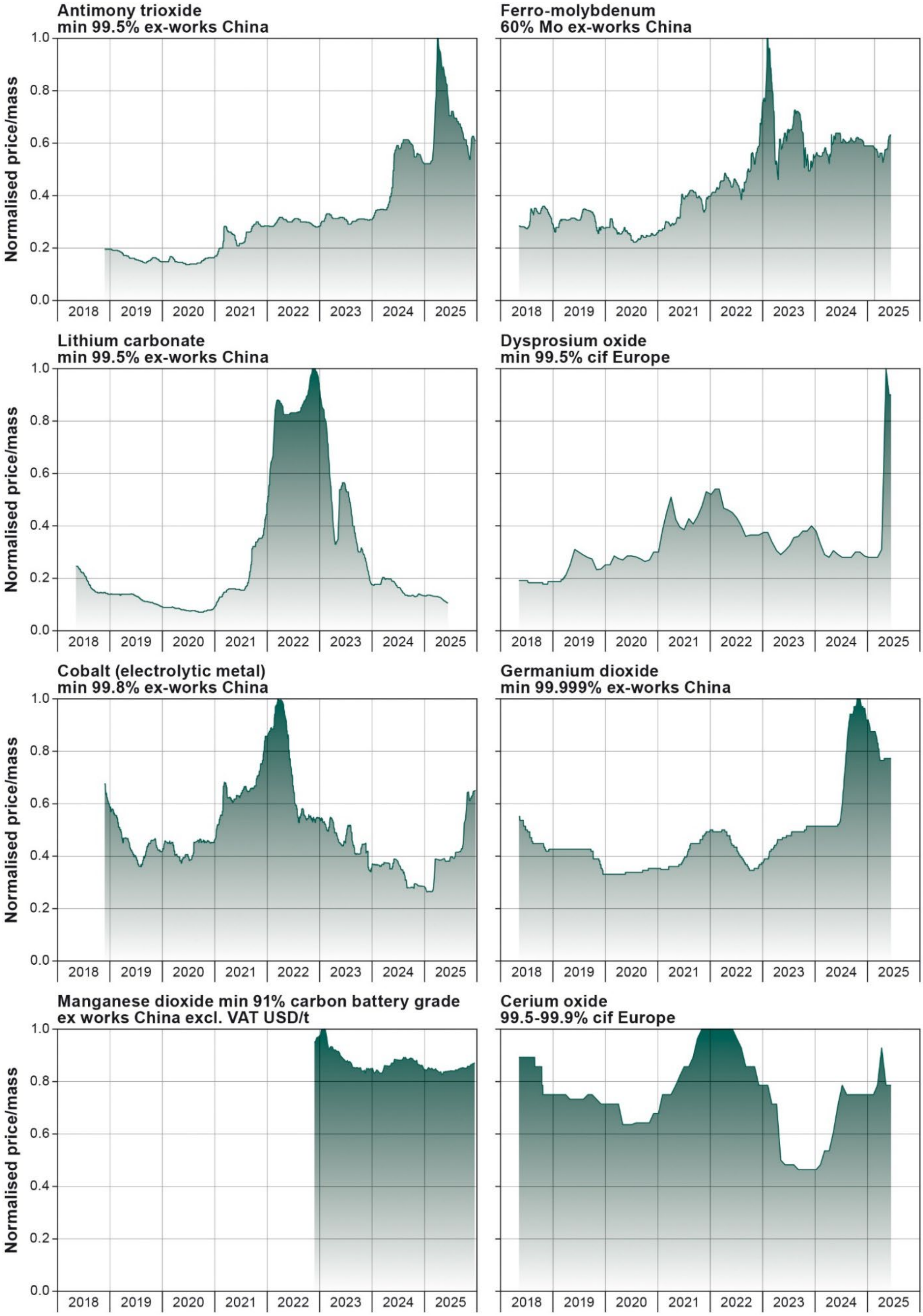


**Figure 3** Price-normalised time-series data (Argus Metals, 2025). BGS © UKRI 2026.

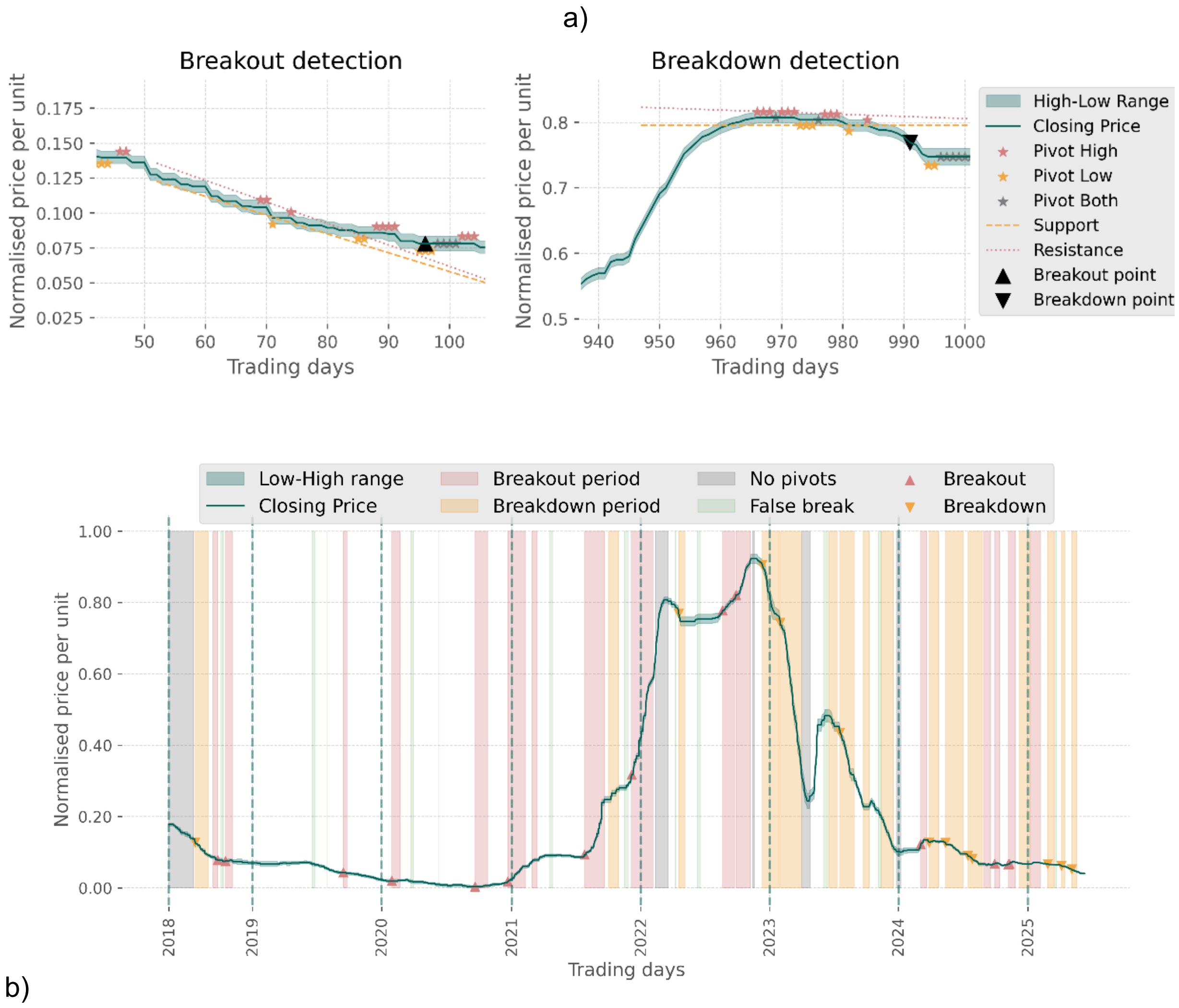


**Figure 4** Breakout and breakdown detection procedure for lithium carbonate. For each new price, pivot points in the preceding reference period of 44 days are used to draw the support and resistance lines. If the closing price is above the resistance level, it is a breakout point. If it is lower than the support level, it is a breakdown point. a) Pivot points determined with a 13-point rolling window. b) Breakouts through resistance and support levels determined by pivot points in the sliding window of 44 trading days. Only breaks longer than 10 trading days are included; any period below 10 days is considered a false break. Periods for which no information can be recovered due to the lack of pivot points are highlighted separately. Price-normalised time-series data (Argus Metals, 2025). BGS © UKRI 2026.

**Table 1** Summary of commodities, price time-series analysed and derived metric covered.

| Element | Argus data (Argus Metals, 2025) | MT metric | MD metric | MS indicator |
|---|---|---|---|---|
| Copper | LME Copper Cash Official Price USD/kg | 6.8 | 8.2 | 7.5 |
| Aluminium | LME Aluminium Cash Official Price USD/mt | 5.5 | 6.9 | 6.2 |
| Zinc | LME Zinc Cash Official Price USD/mt | 5.4 | 7.1 | 6.2 |
| Dysprosium | Dysprosium metal min 99% ex-works China CNY/kg | 5.6 | 6.4 | 6.0 |
| Nickel | LME Nickel Cash Official Price USD/mt | 4.4 | 6.1 | 5.1 |
| Niobium | Niobium pentoxide min 99.5% ex-works China CNY/kg | 6.0 | 4.2 | 5.0 |
| Titanium | Titanium dioxide 98% min anatase grade ex-works China CNY/mt | 4.8 | 5.1 | 5.0 |
| Graphite | Graphite lake 94% carbon ex-works China excl. VAT USD/mt | 5.2 | 3.8 | 4.5 |
| Antimony | Antimony trioxide min 99.5% ex-works China CNY/mt | 3.5 | 4.1 | 3.8 |
| Molybdenum | Ferro-molybdenum 60% Mo ex-works China CNY/mt | 2.4 | 5.0 | 3.4 |
| Lithium | Lithium carbonate min 99.5% ex-works China CNY/mt | 3.4 | 3.3 | 3.3 |
| Dysprosium | Dysprosium oxide min 99.5% cif Europe USD/kg | 5.6 | 1.5 | 2.9 |
| Cobalt | Cobalt (electrolytic metal) min 99.8% ex-works China USD/mt | 3.3 | 2.7 | 3.0 |
| Germanium | Germanium dioxide min 99.999% ex-works China CNY/kg | 1.9 | 3.6 | 2.6 |
| Manganese | Manganese dioxide min 91% carbon battery grade ex-works China excl. VAT USD/mt | 2.8 | 2.0 | 2.4 |
| Cerium | Cerium oxide 99.5-99.9% cif Europe USD/kg | 1.9 | 3.0 | 2.4 |

## 1.6 IMPLEMENTATION RECOMMENDATIONS

- Multiple price series per commodity, representatives of different processing stages and regional markets, should be considered where possible
    - analysis of dysprosium (metal vs. oxide) data (Figure 2, Figure 3, Table 1) demonstrates that indicator scores vary significantly by supply-chain stage
- Commodity-level scores should be derived through volume-weighted aggregation when high-resolution trade and price data is available, otherwise adopt the highest-risk score value
- Commodities with extremely limited price data should be treated as high-risk cases, requiring expert assessment
- Price series analysis should be updated regularly, supported by automated data processing, allowing MS indicators to evolve as new data accumulates and relative scores shift

# 2 Economic importance indicators

Previous CAs characterised economic importance primarily through gross value added (GVA) in manufacturing sectors. This approach captures direct economic contribution but overlooks wider interdependencies, such as:

- how materials support interconnected industrial ecosystems
- how disruption in one sector propagates through supply chains
- where strategic vulnerabilities concentrate

For example, a steel shortage doesn't just impact steelmakers; it cascades through the construction, automotive, machinery and infrastructure sectors. Understanding these interdependencies is essential for prioritising interventions and building resilience in a highly integrated modern economy.

## 2.1 METHODOLOGY OVERVIEW

The 2025 release of ONS input/output tables (product-by-product and industry-by-industry) (Office for National Statistics, 2025b, Office for National Statistics, 2025a) enabled comprehensive mapping of economic sector interdependencies. Combining these with Standard Industrial Classification (SIC) material usage mappings produced in the 2024 UK CA allows derivation of new metrics capturing both direct economic contribution and systemic positioning of a commodity within the broader UK economy. These metrics consolidate into three indicators, reflecting different dimensions of economic risk.

## 2.2 CORE METRICS

### 2.2.1 Direct economic contribution

The sector's direct economic contribution (wages; profits; taxes generated) and closely related to gross domestic product (GDP), GVA shows the intrinsic importance of a sector to the global UK economy. High GVA indicates substantial economic activity at risk from material disruption, though by itself doesn't reveal supply-chain dependencies.

### 2.2.2 Supply-chain position

#### 2.2.2.1 INTERMEDIATE OUTPUT

This represents production sold to other sectors rather than final consumers, commonly referred to as the ‘forward linkage’. This shows how many downstream industries depend on this sector as a supplier. High intermediate output indicates the sector is deeply embedded as a supplier, meaning its disruption cascades to customer sectors.

#### 2.2.2.2 INTERMEDIATE CONSUMPTION

This is the total inputs purchased from other industries to produce a sector’s output, also known as ‘backward linkage exposure’. It reflects how dependent the sector is on upstream suppliers. High intermediate consumption indicates vulnerability to input supply shocks.

#### 2.2.2.3 BACKWARD LINKAGE INDEX

The backward linkage index (BLI) is a normalised measure of supplier dependence calculated from the Leontief inverse matrix in input/output tables (Office for National Statistics, 2025a, Office for National Statistics, 2025b). This metric captures the structural position of a sector or how strongly sector expansion pulls activity through upstream supply chains. Values greater than one indicate above-average supplier dependence; below one is below-average supplier dependence. Unlike intermediate consumption (absolute GB pound (£) values), this index provides a scale-independent measure of structural positioning, enabling cross-sector comparison regardless of scale.

#### 2.2.2.4 FORWARD LINKAGE INDEX

The forward linkage index (FLI) is a normalised measure of downstream dependence calculated from the Leontief inverse matrix (row sums). This metric shows how strongly other sectors depend on this sector as an input supplier. Values above one indicate above-average criticality as supplier; values below one represent below-average supplier position. This metric complements intermediate output by providing a scale-independent measure of SCC. A sector can have a moderate intermediate output (£ value) but a high forward linkage index if small volume supplies are essential inputs to many diverse sectors.

### 2.2.1 Economic propagation

#### 2.2.1.1 TYPE 1 OUTPUT MULTIPLIER

This represents the total output change across the entire economy per £1 increase in final demand for this sector's output. This coefficient captures direct production plus indirect supply-chain activation and is calculated as the column sum of the Leontief inverse matrix. High multipliers (for example, 2.5) indicate that each £1 of final demand generates £2.50 of total economic activity through cascading supplier effects.

#### 2.2.1.2 TYPE 1 GVA MULTIPLIER

This represents the total GVA change across the entire UK economy per £1 increase in final demand. It is calculated by weighting Leontief inverse by sectoral GVA coefficients and shows economy-wide effects in terms of income, employment and tax generation rather than gross output.

Higher multipliers, whether output or GVA, indicate stronger propagation of shocks across the economy.

## 2.3 COMPOSITE INDICATORS

These eight metrics combine into three strategic indicators reflecting distinct aspects of economic vulnerability to material disruption:

### 2.3.1 Direct economic importance

Direct economic importance (DEI) = GVA.

#### 2.3.1.1 RATIONALE

DEI measures intrinsic sector size and economic contribution, independent of supply-chain position, or how much economic activity (income; employment; taxes) occurs directly in sectors using this material. A high DEI indicates material disruption would directly affect substantial economic value creation. This indicator was already included in the 2024 UK CA.

#### 2.3.1.2 POLICY RELEVANCE

DEI identifies materials supporting major employers or high-value industries. However, DEI alone is insufficient for criticality; a large but isolated sector may be less critical than a smaller one occupying a strategic network position.

### 2.3.2 Supply-chain centrality

SCC =
$$\sqrt[4]{\text{Forward Linkage Index} \ * \ \text{Intermediate Output} \ * \ \text{Backward Linkage Index} \ * \ \text{Intermediate Consumption}}$$

#### 2.3.2.1 RATIONALE

SCC measures how embedded the sector is within the UK industrial network, capturing both supplier (forward) and customer (backward) roles using absolute values and structural indices. The four components provide complementary perspectives.

- Together, FLI and intermediate output characterise supplier importance
    - FLI shows structural importance (how essential sector is as an input to diverse industries)
    - intermediate output represents scale (£ volume supplied)
    - a sector critical to a few large customers has high intermediate output but moderate FLI
    - a sector supplying small but essential inputs to many diverse sectors has high FLI but moderate intermediate output
- BLI and intermediate consumption together characterise supply vulnerability
    - BLI shows structural dependence (how tightly a sector is coupled to its suppliers)
    - intermediate consumption shows exposure magnitude (£ at risk)
    - a sector purchasing large volumes from few suppliers has high intermediate consumption but moderate BLI
    - a sector dependent on complex multi-tier supply chains has high BLI even with moderate spend

#### 2.3.2.2 POLICY RELEVANCE

A high SCC identifies sectors and possibly materials that act as systemic chokepoints, where disruption propagates broadly. These are even if DEI is moderate. SCC reveals hidden criticality invisible in GVA-only analyses.

### 2.3.3 Economic multiplier effects

Economic multiplier effects (EMEs) = $\sqrt{\text{Type 1 Output Multiplier} * \ \text{Type 1 GVA Multiplier}}$

#### 2.3.3.1 RATIONALE

This indicator quantifies how sector shocks amplify through the economy via inter-industry transactions. The output multiplier captures the total cascading activity whilst the GVA multiplier captures the value-added (income/employment) cascade. Together, they measure economic propagation intensity.

#### 2.3.3.2 POLICY RELEVANCE

A high EME indicates a material disruption that can trigger disproportionate, economy-wide effects. Sectors with high multipliers warrant strategic intervention even if direct scale (DEI) or network position (SCC) are moderate, because knock-on effects would dominate total impact.

## 2.4 COMBINING INDICATORS INTO AN OVERALL ECONOMIC IMPORTANCE DIMENSION

In the calculation of the economic importance dimension of a CA, the two new indicators (SCC and EME) are added to the existing list of indicators considered (GVA; net import reliance;

apparent consumption). A differentiated weighting structure is recommended if weighting is to be applied to combine these indicators. SCC should receive the highest weighting because criticality fundamentally concerns interconnection and dependency. Materials may have a modest direct economic footprint but occupy strategic network positions where disruption generates wide-ranging impacts.

SCC captures this criticality dimension most directly. The EME indicator should receive a lower but still substantial weighting, reflecting that knock-on effects often exceed direct effects during disruptions. Multipliers quantify cascade risks essential to CA, but they are partially correlated with SCC (highly central sectors often have high multipliers).

GVA should have the lowest weighting factor of the three reviewed indicators. GVA alone is a poor predictor of criticality: large sectors can be isolated, while small sectors can be critical. However, direct contribution cannot be ignored. Sectors with extremely high economic activity are strategically important regardless of network structure. Weighting must therefore ensure that large, material-dependent sectors are not under-represented while avoiding situations where GVA dominates more nuanced supply-chain measures.

## 2.5 DATA QUALITY CONSIDERATIONS

The ONS input/output tables are currently reported with variable aggregation; most SIC codes are represented at two-digit resolution with uneven three- or four-digit breakdown. Finer resolution would strengthen the analysis, particularly for sectors with diverse material dependencies that behave differently at subsector level. Notably, the FLI calculation requires full input/output accounting tables. The 2025 ONS release includes these components, enabling robust calculation that represents a significant methodological advance.

A symmetrical treatment of upstream (backward) and downstream (forward) dependencies provides a more complete picture of supply-chain position within the UK economy than the backward-only analyses typical of many international CAs.

## 2.6 IMPLEMENTATION RECOMMENDATIONS

The DEI, SCC and EME indicators should be incorporated into the next UK CA using the suggested weighting order and a sensitivity analysis should be conducted to ensure the weighting and scaling are applied appropriately. This represents a substantial methodological advance over the previous GVA-only approach, integrating a wider UK supply-chain perspective.

The ONS should be supported in improving the resolution of its input/output tables, particularly for material-intensive sectors (chemicals; metals processing; advanced manufacturing). Greater disaggregation would enhance the accuracy of both structural indices and opportunities to track materials’ pathways in the UK economy.

The SIC-material usage mappings developed for the 2024 UK CA should be expanded and updated as a foundational dataset, enabling future assessments and broader supply-chain analysis.

A deeper exploration of the ONS input/output dataset beyond its use in CAs would provide valuable UK supply-chain dependency mapping. This would enable identification of sector-specific bottlenecks, regional vulnerabilities, trade priorities and industrial strategy opportunities, extending the value of the methodology to industrial policy, regional development and economic resilience planning. An example mapping of the SIC network connectivity and dependencies is provided in Figure 5 and Figure **6**.

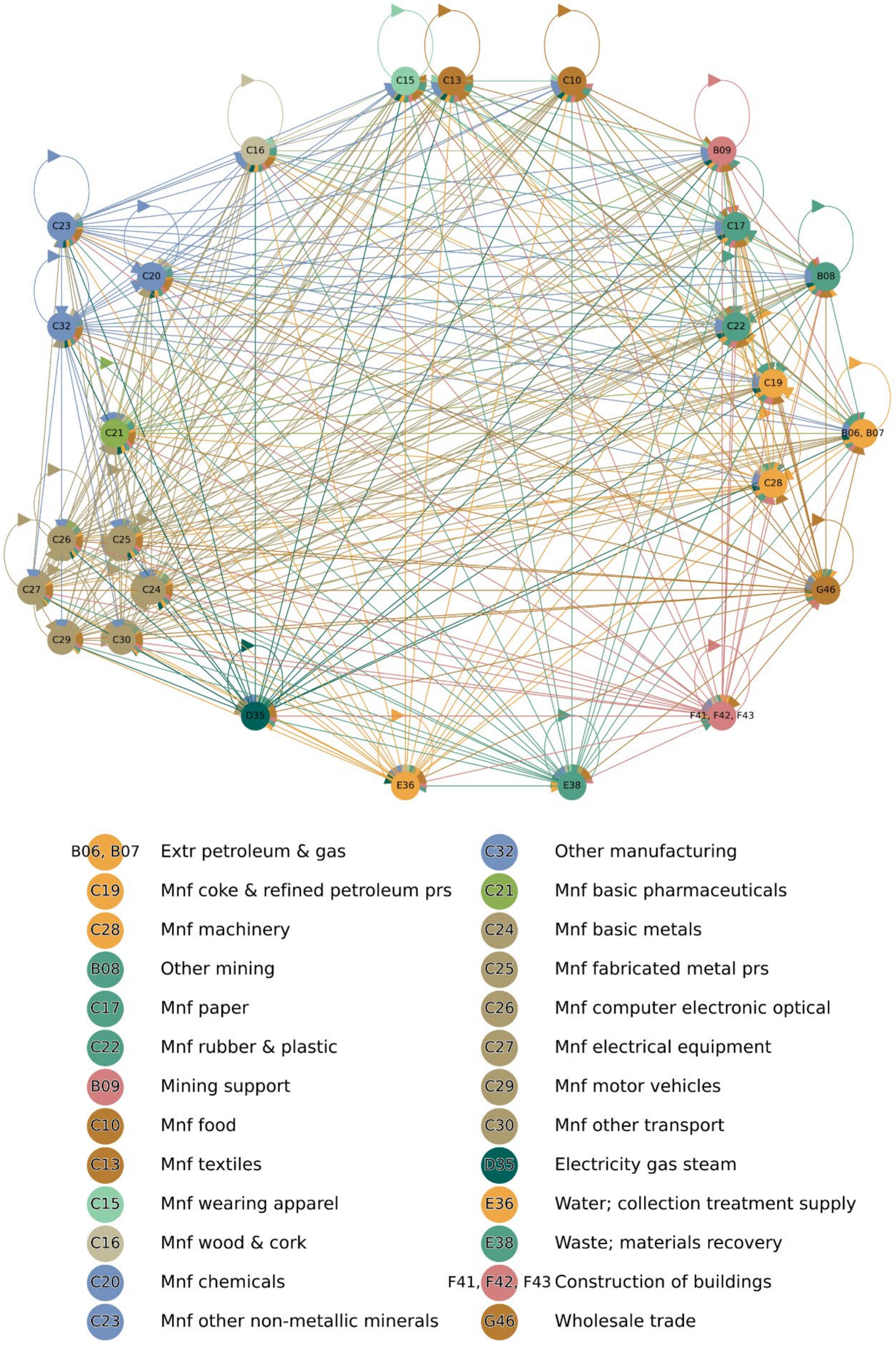


**Figure 5** Network of economic sectors that depend on mineral use in the UK. The links are colour-coded to match the colour of the input sector. Majority of the links are bi-directional (Office for National Statistics, 2025a, Office for National Statistics, 2025b). BGS © UKRI 2026.

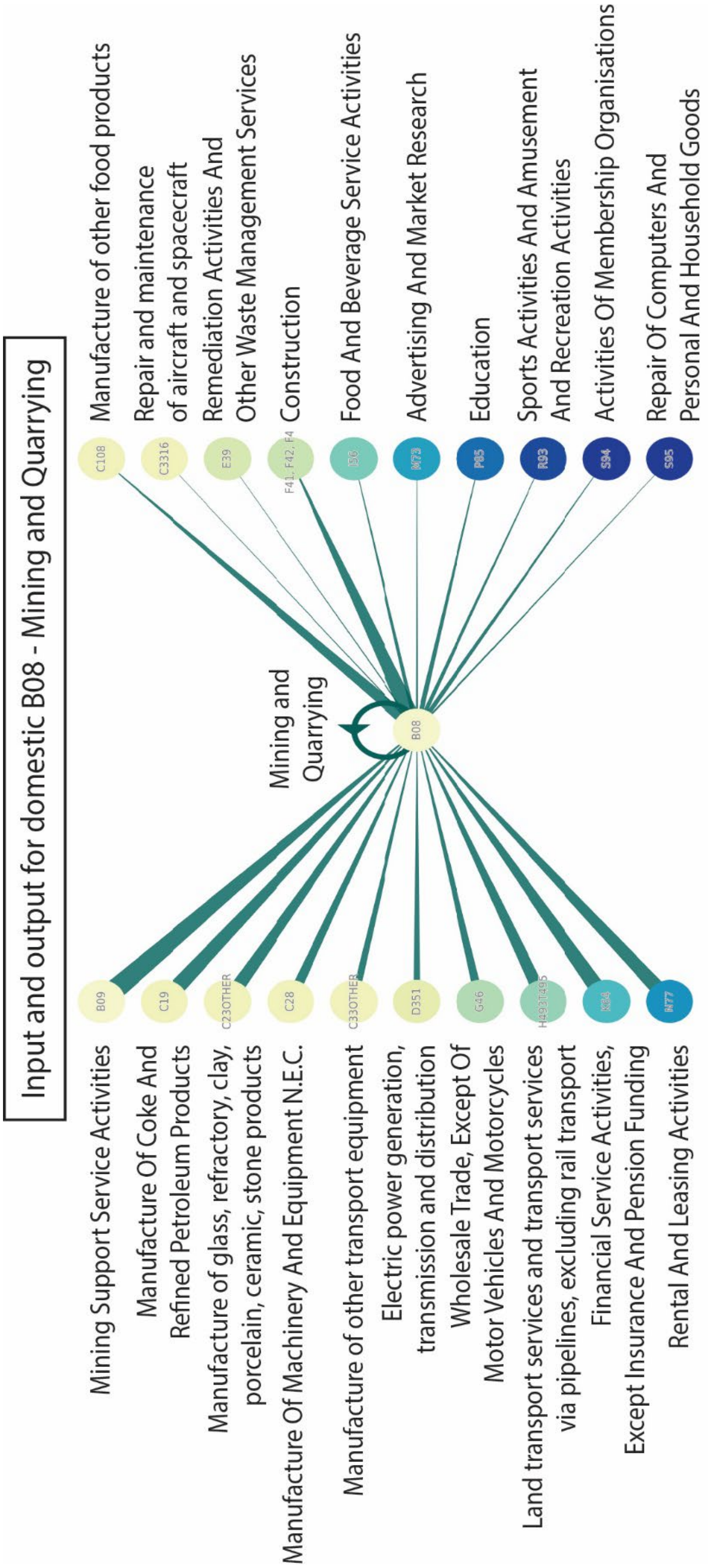


**Figure 6** Examples of top 10 input/output contributions for of the industry sector B08 Mining and Quarrying (Office for National Statistics, 2025b). BGS © UKRI 2026.

This complex network can be broken down into its individual nodes, making it possible to visualise the respective contribution of forward and backward links proportionated to their size, which could be further broken down between domestic and import/export contributions.

# 3 Trade restrictions weighting factor

Global trends in protectionism are accelerating. Sanctions associated with the Russia–Ukraine conflict, USA–China trade tensions and strategic mineral export controls demonstrate how rapidly trade interventions can disrupt supply chains. For import-reliant nations such as the UK, understanding partners' propensity to impose restrictions is as important as understanding production concentration. Static trade concentration metrics overlook this geopolitical dimension, failing to distinguish between reliable partners and those likely to weaponise access to resources.

## 3.1 METHODOLOGY OVERVIEW

Using the Global Trade Alert (GTA) database, the most comprehensive source for unilateral trade interventions since 2009, this work analyses the frequency, scale, and range of both harmful and liberalising interventions. The focus is put on export-relevant measures, as inward interventions occurring solely within other jurisdictions do not directly affect the UK. Analysis of the GTA datasets allows the creation of a trade intervention factor (TIF) to be applied as a weighting on the national-level trade concentration indicator (TCI) previously used in the 2024 UK CA, to reflect partners' intervention history and inherent interventionism risk profiles.

### 3.1.1 Data processing

The following filters from the GTA database were applied on interventions announced since 2008:

- retained only those interventions currently in force (expired or revoked ones were removed)
- kept interventions affecting the UK or with ambiguous jurisdiction listings
- filtered using those HS codes relevant to CA candidate commodities
- counted affected HS codes by commodity and by country separately for harmful and liberalising interventions

### 3.1.2 Trade intervention factor

The TIF combines the number of commodity-specific interventions with their directional impact, subtracting liberalising interventions from harmful ones. Countries with extensive harmful interventions receive higher risk weightings for a given commodity (**Figure 7** and **Figure 8**). This factor is then applied as a weighing factor on the TCI (Josso et al., 2023, Mudd et al., 2024) to distinguish between concentrated supply from stable partners vs. concentrated supply from interventionist ones.

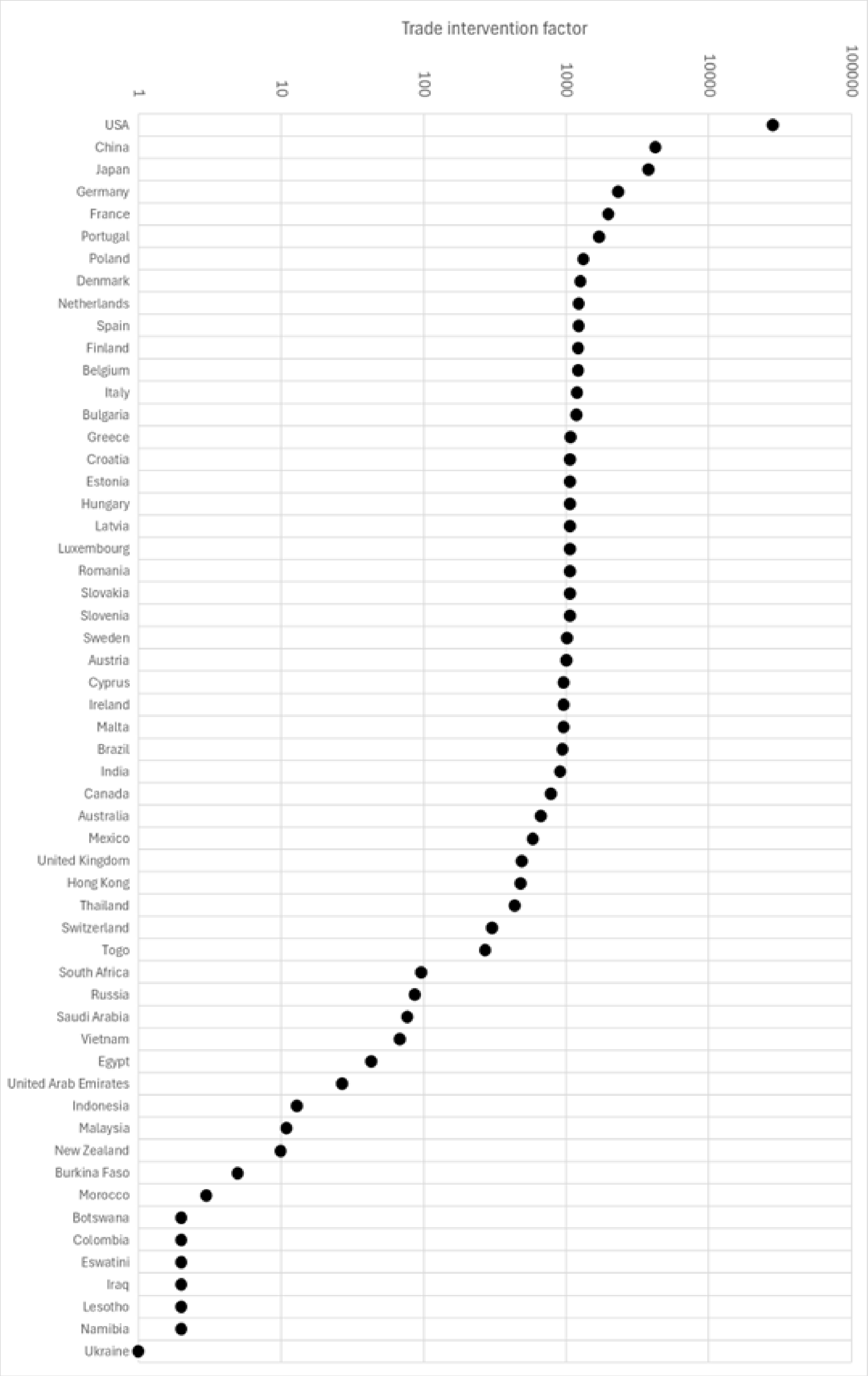


**Figure 7** TIFs for all countries with a value calculated above zero. Any country not included in this figure had a factor of zero or a negative value, where **zero** represents a country that either has no trade interventions or has the same number of harmful and liberalising trade interventions, indicating that they are relatively neutral within global trade, and n**egative** represents a country that has more liberalising

trade interventions than harmful, indicating that they are more open to global trade. Underlying data from Global Trade Alert (2026). BGS © UKRI 2026.

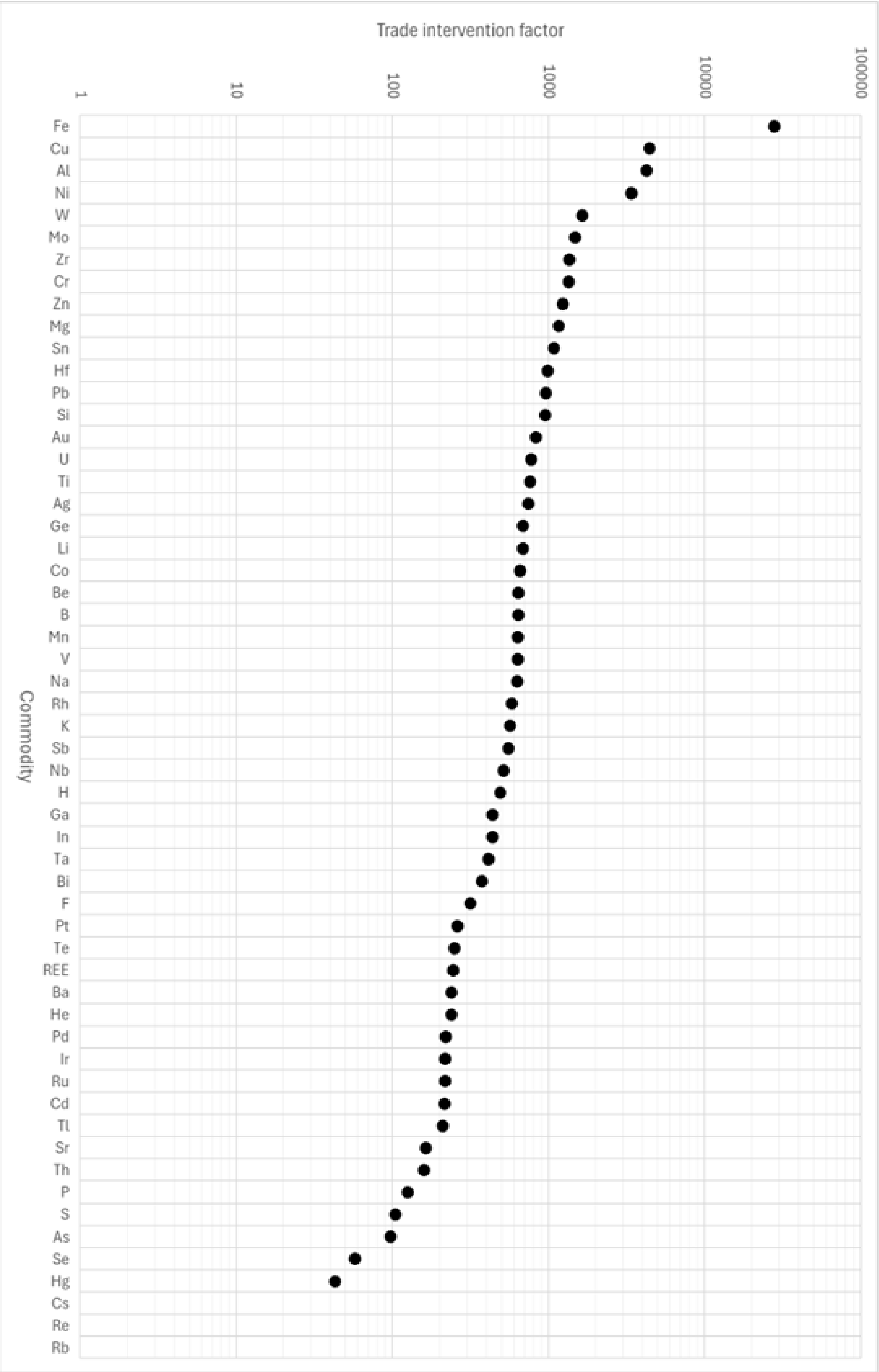


**Figure 8** TIFs for all commodities considered as a candidate during the 2024 UK CA, except industrial minerals. These interventions will be proportioned to the number of HS codes tracked for each commodity. Underlying data from Global Trade Alert (2026). BGS © UKRI 2026.

## 3.2 KEY FINDINGS

Analysis reveals significant variation in intervention behaviour. The USA, China, Russia, and several developing nations show high frequencies of commodity-targeted restrictions. Some bilateral relationships (for example, USA–China) exhibit mutual escalation. Rare earth elements (REE), lithium, and graphite face particularly heavy intervention exposure and are commodities where China dominates processing.

The challenge from the highly dynamic nature of trade interventions is critical, implying the TIF will need to be updated regularly. However, applying it as a weighing factor on the TCI reduces sensitivity to intervention events.

## 3.3 IMPLEMENTATION RECOMMENDATIONS

- The TIF should be incorporated as weighting factor in TCIs for the next UK CA
- The TIF database should be updated regularly using GTA data, with automation introduced to ensure efficient quarterly updates (given geopolitical volatility)
- An alert system for rapid identification of interventionist changes affecting high-priority commodities could be developed, also relying on an automated process
- The current methodology only considers unilateral interventions: bilateral or multilateral agreements in future iterations should be considered and a method developed to incorporate them

# 4 Material flow characterisation

Supply risk perception has evolved from a narrow focus on mining and refining concentration to a more holistic value-chain analysis. Materials flow through complex transformation stages, evolving from ores to concentrates, refined metals to chemical precursors, semi-manufactured to manufactured goods. Each stage presents distinct chokepoints. For the UK, with a predominantly downstream industry but limited upstream capacity, accurate tracking of intermediate and manufactured product flows is essential to understanding true supply dependencies and identifying intervention opportunities.

## 4.1 METHODOLOGY OVERVIEW

Owing to the large range of candidate materials and the rapid turnaround of the 2024 UK CA, only 204 HS codes across 84 materials were considered, focusing on the upstream segments of the value chain (ores; concentrates; refined forms; simple compounds). The present work expands coverage, with more than 1400 additional HS codes across 41 key commodities, extending into midstream (transformed products; intermediate manufactured goods) and end-of-life (waste and scrap). This expansion required careful estimation of material content, which is particularly challenging for aggregated trade codes.

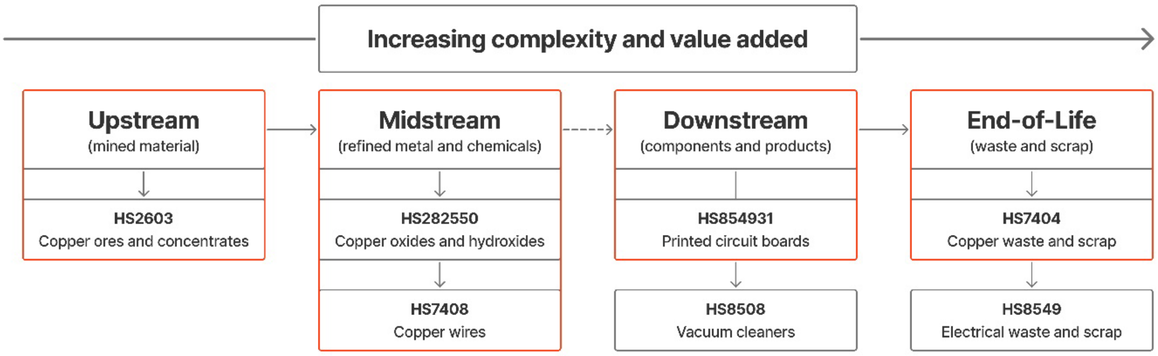


**Figure 9** Idealised value chain with non-exhaustive example HS codes for copper ores, chemicals, refined metal, components, products, and waste and scrap. Areas bounded in red have been considered in the expansion of the HS code list; complex products, such as electricals and vehicles, have not been included due to their inherent complexity. The dashed line between mid- and downstream highlights the diffuse boundary that exists between these two transformation stages. BGS © UKRI 2026.

### 4.1.1 Expanded coverage

The focus was placed on HS codes characterising:

- chemical precursors and intermediate compounds
- semi-manufactured products (for example, battery components; sheets; pipes; steel; magnetic alloys, etc.)
- waste and scrap (old and new), critical for circular economy analysis
- element-specific REE codes plus agglomerated REE codes

This enables robust quantification of the UK's position in global value chains, showing where the nation adds value and where dependencies concentrate.

**Table 2** Substances for which the HS code list has been expanded towards the midstream.

| Substance updated | | | |
|---|---|---|---|
| Antimony | Fluorspar | Nickel | Tantalum |
| Beryllium | Gadolinium | Niobium | Terbium |
| Borates | Holmium | Phosphorus | Tin |
| Cerium | Lanthanum | Praseodymium | Titanium |
| Chromium | Lead | REEs | Tungsten |
| Cobalt | Lithium | Rhenium | Vermiculite |
| Copper | Lutetium | Samarium | Yttrium |
| Diatomite | Magnesium | Scandium | Zinc |
| Dysprosium | Manganese | Silica sand | |
| Erbium | Molybdenum | Silicon | |
| Europium | Neodymium | Silver | |

### 4.1.2 Methodological challenges

Estimating the material content of an HS code becomes increasingly difficult downstream. Key issues include:

- aggregated descriptions: for example, HS 850690 'Cells and batteries; primary, parts thereof' is too broad to reliably estimate phosphorus and other element content given diverse battery chemistries
- definition ambiguity: the same code may represent an end-product in one context and a precursor in another (for example, sulfuric acid for ore leaching vs. chemical synthesis), with different composition ranges depending on use
- component vs. product classification: for instance, ‘battery packs’ may be a vehicle component or a consumer end-product depending on application, widely affecting mass and metal content

These challenges require expert judgement and conservative estimation. Transparency about uncertainty is maintained throughout the data compilation, with reference to industry sources or published literature whenever possible. Where ambiguous content ranges exist, a conservative estimate (lower bound) is used to avoid over-estimating content.

## 4.2 KEY FINDINGS

The number of HS codes compiled by CMIC has more than quadrupled and now covers segments of the supply chains particularly critical for the UK economy, which relies heavily on importing semi-manufactured and intermediate goods rather than raw materials. This aligns with advanced economy positioning, creating exposure to midstream bottlenecks in refining and processing, particularly for commodities where China or other single players dominate (REEs; lithium chemicals; refined cobalt; magnesium).

Waste and scrap flows show significant re-export activity, indicating opportunities for enhanced circular economy integration, as highlighted in Mudd et al. (2024).

## 4.3 IMPLEMENTATION RECOMMENDATIONS

- Continue expanding coverage across commodities, prioritising remaining candidate commodities and complex downstream codes where feasible
- Integrate the expanded HS codes compilation into all relevant indicators for the next CA. The increased data volume will require automation to support data manipulation and analysis
- Develop standardised protocols for material content estimation for aggregated codes, documenting assumptions and uncertainty ranges
- Maintain a living database with regular updates as new codes emerge and product definitions evolve based on stakeholders’ feedback to the World Customs Organization (WCO)

# 5 Environmental, social and governance standards

Supply chains cannot be considered secure or resilient unless they are sustainable and responsible. ESG risks characterise, amongst others:

- geopolitical tensions
- human rights violations
- corruption
- emissions
- water stress
- biodiversity loss

These can all directly disrupt production, constrain market access and increase operational costs. Poor ESG management triggers community opposition, litigation, investment withdrawal and regulatory barriers. The 2024 UK CA is among the most comprehensive in ESG integration, but gaps remain, particularly around climate vulnerability, which threatens supply chains but isn't explicitly captured in current indicators.

## 5.1 CURRENT METHODOLOGY

The 2024 UK CA applied an ESG weighting to the production concentration indicator (PCI). The ESG coefficient was calculated as the geometric mean of three global indices:

- Environmental Performance Index (EPI (Block et al., 2024)
- Human Development Index (HDI (United Nations Development Programme, 2024)
- World Governance Index (WGI (World Bank, 2022)

This country-level approach penalises concentration in jurisdictions with poor governance, civil unrest or elevated pollution risks.

## 5.2 DATASET REVIEW FINDINGS

Additional datasets were reviewed for potential addition to the ESG coefficient. Extensive review of commercially available ESG ratings, voluntary standards (for example, Initiative for Responsible Mining Assurance (IRMA); Copper Mark), and open global datasets reveals:

- commercial datasets offer depth and credibility but are constrained by limited coverage (publicly listed companies only; 40 to 60 per cent of world production across most commodities), licensing costs, inconsistent transparency and poor alignment with country-level CA needs
- company or commodity-level data is insufficiently mature, standardised or comprehensive for consistent integration, while coverage gaps and methodological heterogeneity preclude robust systematic application
- open datasets are the best fit for public, reproducible assessments; many overlap with current methodology, but new sources were identified for strengthening the specific existing ESG coefficient

Country-level data remains the most practical approach despite limitations in capturing subnational and site-specific risks, which may vary strongly between geographical areas, climate and commodities within a single country.

## 5.3 CRITICAL GAP: CLIMATE VULNERABILITY

Climate-related physical risks (water scarcity for processing or hydropower; extreme heat; flooding) and transition risks (policy shifts; carbon pricing; stranded assets) are already disrupting CM supply chains and are likely to intensify in the near future. Current ESG indicators used in the 2024 UK CA do not explicitly capture this dimension, creating a significant gap in capturing disruption risk.

### 5.3.1 Recommended solution: ND-GAIN index

Incorporate the Notre Dame Global Adaptation Initiative (ND-GAIN) country index as fourth ESG factor. ND-GAIN combines:

- vulnerability: exposure to climate impacts across food, water, health, ecosystem, human habitat and infrastructure systems
- readiness**:** capacity to leverage investments and adapt, considering ESG dimensions

This provides a transparent, globally comprehensive, forward-looking measure of climate risk. The dataset is fully compatible with the existing methodology and can be incorporated with minimal disruption.

## 5.4 IMPLEMENTATION RECOMMENDATIONS

- Add the ND-GAIN composite score as the climate change vulnerability (CCV) dimension in the ESG indicator and recalculate the ESG factor as a geometric mean of four indices (EPI; HDI; WGI; ND-GAIN)
- Continue monitoring company- and commodity-level ESG data and revisit the ESG rating as standardisation and coverage improve in future iterations
- Document the limitations of the country-level approach in future methodology reports, flagging where subnational variation may be significant and adapting with bespoke variation at regional or commodity level where data is available

# 6 Corporate concentration analysis

CAs typically consider production concentration at national level but overlook corporate concentration (CC) or control. A few companies dominating supply creates distinct vulnerabilities, including operational disruptions, corporate decisions, financial distress and strategic behaviour, which can constrain access regardless of national-level diversification. Identifying SPoFs and measuring CC complements geographical risk analysis.

## 6.1 APPROACHES TESTED

Several datasets were assessed for suitability (company ownership structures and time-series production data for each producing company for each candidate material). The following datasets were considered:

- Argus
- Digbee
- Jasansky et al. (2023)
- Market Atlas
- Mining Data Online (MDO)
- S&P Capital IQ Pro
- Statista
- Wood Mackenzie

All platforms suffer from one or more limitations and cannot fully satisfy all requirements due to:

- restricted access in the form of expensive user licenses
- poor coverage for minor and by-product metals such as antimony, cadmium, gallium, germanium, REEs and tellurium
- limited data coverage (for example, only publicly listed companies are included)
- limited temporal coverage
- missing or unclear information (for example, gaps in time-series production data)

Nonetheless, three methodologies were tested using the MDO database, which is the most complete, freely available dataset.

### 6.1.1 Single point of failure

The SPoF represents a qualitative identification of companies controlling disproportionate market share with no viable substitutes. This approach is simple to implement in a qualitative way to flag critical chokepoints, but is difficult to incorporate numerically in a CA as data completeness is uneven. The SPoF is likely better suited for specific industry sector considerations. For example, Companhia Brasileira de Metalurgia e Mineração (CBMM)'s control of niobium production or Nornickel's dominance over rhodium and palladium production were identified through BGS expertise but are not visible in the MDO alone.

### 6.1.2 Production concentration

A production-weighted Herfindahl-Hirschman index (HHI) calculated at the corporate level for top supplying countries would directly link concentration to material volumes. This company HHI would be a preferred quantitative metric where production data is available and could be used as a weighting factor on the PCI to reflect cases where corporate control amplifies geographical concentration risks.

### 6.1.3 Diversity factor

This factor assesses market diversity by quantifying the number of assets (mines) associated with each CM and the number of individual companies who own those assets. As project-level production data is commonly unknown across most commodities, this approach treats all mines equally and therefore over-weights small operations and under-weights large ones. It is useful as a secondary indicator but can misrepresent supply risk where production is highly concentrated in few large mines.

## 6.2 DATA LIMITATIONS

The MDO database proves insufficient for comprehensive CC analysis due to:

- incomplete commodity coverage, especially for co- or by-products
- sparse reporting by state-owned and private firms (for example, CBMM and other state-owned companies are absent)
- there is no smelting or refining data for facilities not co-located with mines
    - the midstream is completely missing
- complex ownership structures (minority stakes; joint ventures) are not captured
- hidden commercial arrangements (offtake agreements; financing) are invisible

Coverage is adequate for Chilean copper (highly diversified supply) but calculations perform poorly for most other commodities and key producing nations (China; Russia).

## 6.3 IMPLEMENTATION RECOMMENDATIONS

- Do not implement CC as a systematic indicator across all 82 candidate materials because of insufficient data coverage
- Use SPoF identification for targeted commodities where BGS expertise and external sources identify clear chokepoints
    - add a SPoF metric on a case-by-case basis when data is available and judgement is robust
- Apply production concentration (HHI) selectively where robust data is available (this is a limited set of commodities and countries)
- Reserve CC analysis for deep-dive, sector-specific studies rather than systematic use
- Explore alternative commercial databases (for example, S&P Capital IQ Pro) recognising that multiple sources are needed to achieve adequate coverage across commodities but would not prevent lack of data reporting across all datasets on state-owned assets

# 7 Future mineral production projections

Understanding whether future supply can meet projected demand is fundamental to CA. Production forecasting helps identify looming shortfalls, peak production timing and whether current expansion rates are sustainable. For strategic planning around technology deployment (electric vehicles; renewables; defence), knowing production trajectory constraints is essential.

## 7.1 METHODOLOGY OVERVIEW

Hubbert peak models, originally developed for oil production forecasting, were applied to CM production time series. The Hubbert approach assumes logistic growth curve: production rises, peaks, then declines as a finite resource depletes. Whilst imperfect by design, the approach allows exploration of the range of future timing for potential ‘peak’ production stress. Two model parameterisations were tested to explore scenario ranges rather than single-point forecasts.

### 7.1.1 Hubbert peak model

The model captures three key parameters:

- ultimate recoverable resource (URR) (cumulative production capacity)
- peak production timing
- growth/decline rate

Fitting historical data yields plausible scenario ranges constrained by observed production trajectories. A conservative approach is applied considering only scenarios with a peak year occurring prior to 2100, avoiding unrealistic far-future extrapolations.

## 7.2 KEY FINDINGS

Model performance varies by commodity. Strong fits for mined copper, nickel and REEs ($R^2$ >0.95) suggest production patterns approaching mature logistic curves, whilst poor fits for pig iron and refined copper ($R^2$ <0.90) indicate structural breaks, regime shifts or insufficient data maturity for meaningful Hubbert analysis.

### 7.2.1 Critical limitations

Models are highly sensitive to parameterisation when historical data is limited in time or production hasn't exhibited mature growth curve. Observations are equally weighted, so recent trends responding to major changes are not prioritised over older data, which is problematic during rapid, demand-driven expansions or structural shifts. The models assume finite resource depletion dynamics, partially inappropriate for materials with significant secondary sources (recycling) or those produced as co- or by-products where output depends on primary commodity economics rather than own-resource constraints.

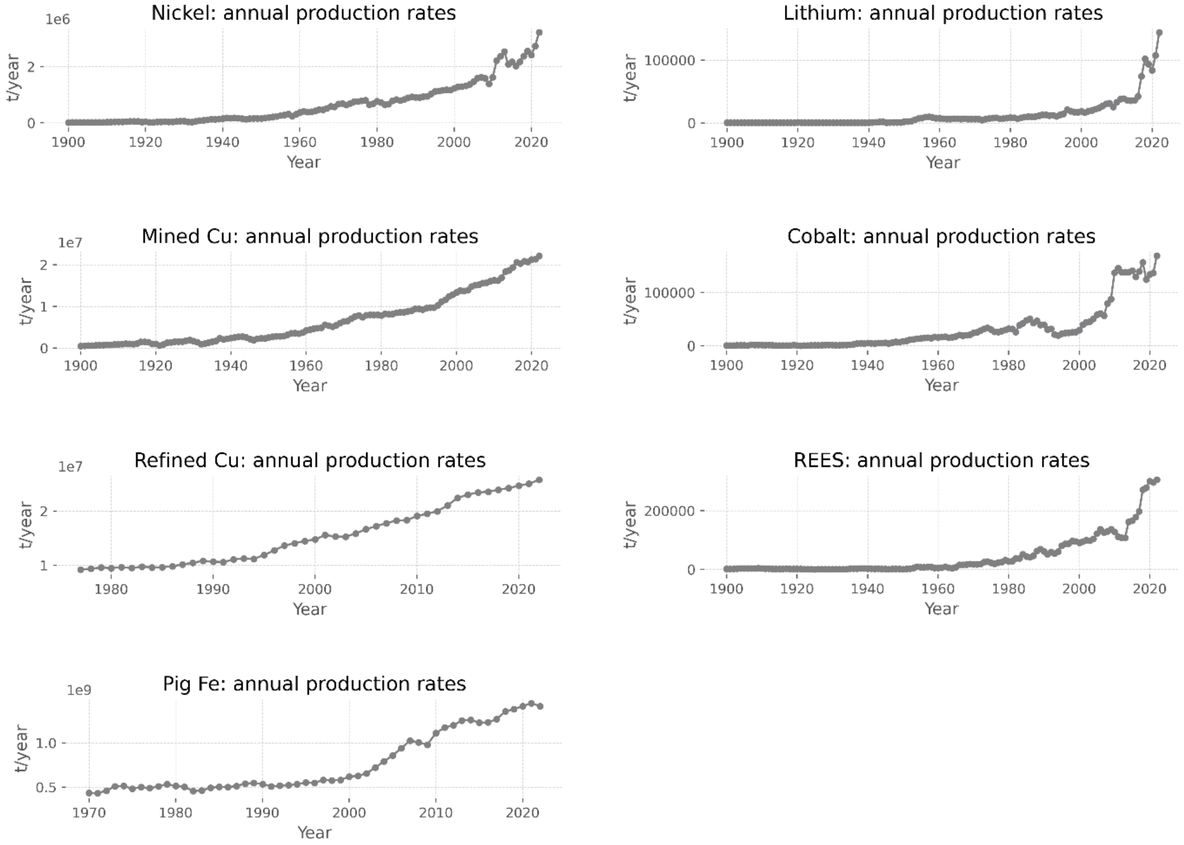


**Figure 10** Example time series of annual production in tons per year (Idoine et al., 2025). BGS © UKRI 2026.

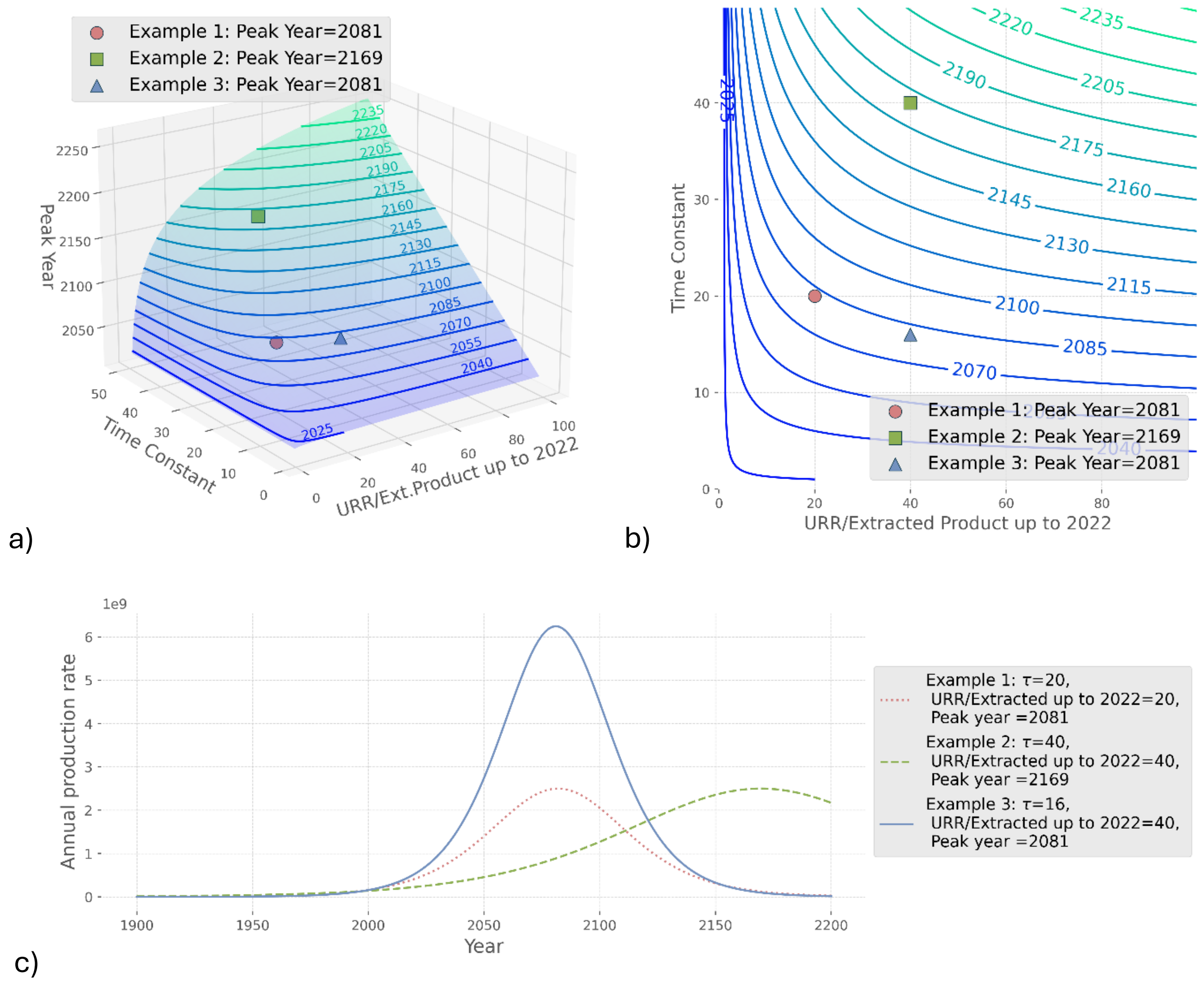
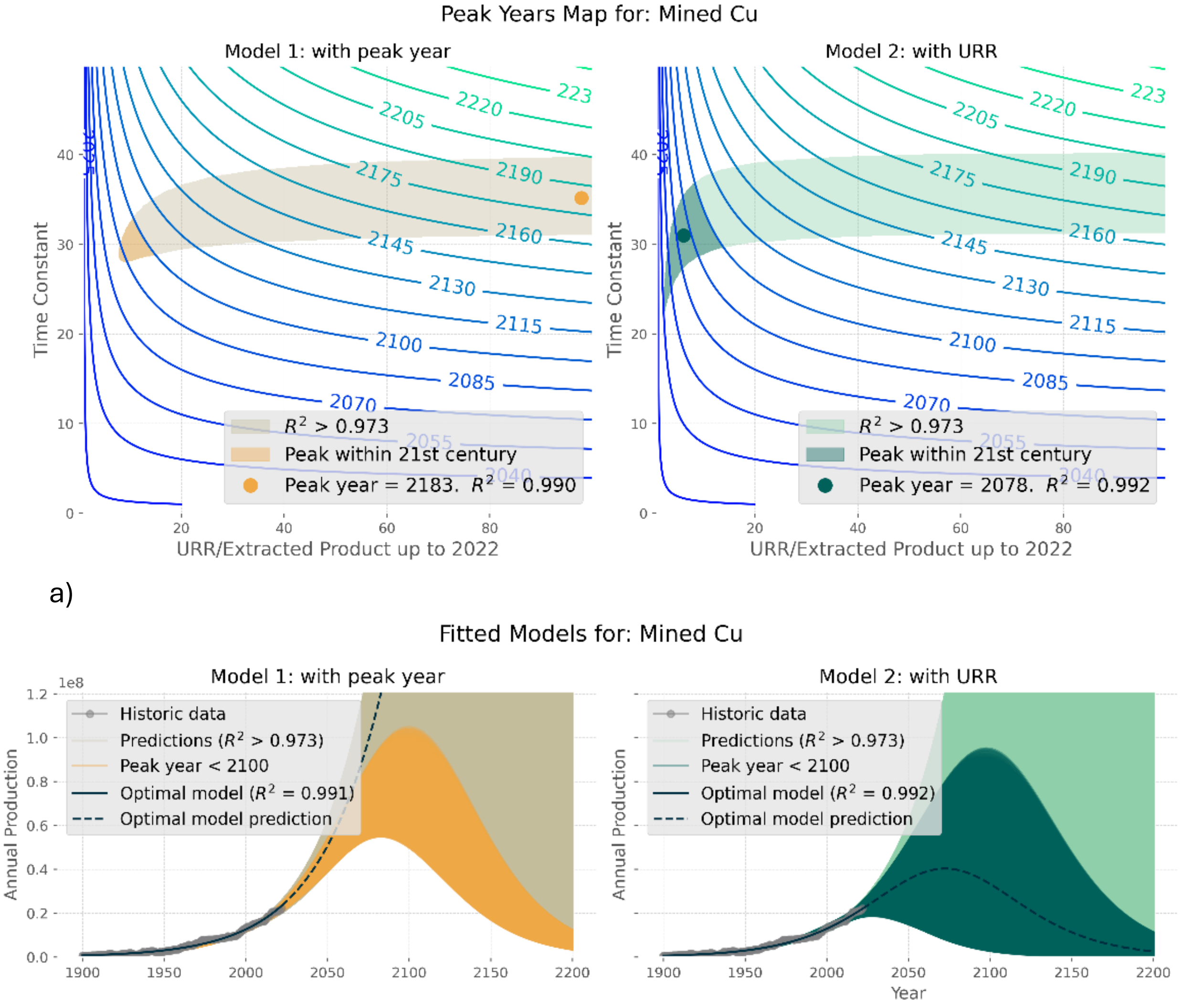


**Figure 11** Representations of invariant relationship between Hubbert model parameters as a map. a) Three model parameters — time constant, URR ratio to production to date, and the peak year — are linked by a deterministic relationship that can be represented by a 3D surface. The surface is marked by the temporal isolines that correspond to all combinations of time constant and URR that result in the same peak year. b) The isolines from the time peak surface form a 2D map onto which possible production scenarios can be assessed. c) Example scenarios of mineral production that are represented by single points in a Hubbert map correspond to different temporal profiles. BGS © UKRI 2026.



a)

b)

**Figure 12** Example of scenario modelling for mined copper data. a) The region of possible scenario productions if found in the parameter space. b) The models from the equivalent set are simulated up to year 2200 to visualise the range of future production rates. Fitting model (1) results in more optimistic estimates of future production than model (2). BGS © UKRI 2026.

## 7.3 IMPLEMENTATION RECOMMENDATIONS

- Do not incorporate Hubbert forecasts as systematic criticality indicators due to excessive uncertainty and sensitivity.
- Use Hubbert maps for exploratory scenario analysis in long-term strategic planning (> 10-year horizons), not near-term supply risk assessment
- Complement Hubbert analyses with autoregressive time-series models better suited to short-term dynamics and recent trend dynamics
- Develop commodity-specific diagnostic criteria to identify suitable materials for Hubbert analysis (data maturity; production system stability; presence of structural breaks; reliance on secondary sources or co-production)
- Explore alternative process-based models (for example, fundamental equations of mineral production) to capture wider range of production behaviours and multi-driver dynamics

# 8 Conclusions and strategic priorities

This exploratory research significantly expands the methodological toolkit for UK CAs. Three areas deliver immediate, high-confidence enhancements ready for implementation:

- market sentiment indicators
- economic importance analysis using input/output tables
- trade restrictions weighting

Material flow characterisation through expanded HS codes strengthens trade-based indicators, expanding the characterisation of supply chains into the midstream. The integration of climate vulnerability (ND-GAIN) into the ESG area addresses a critical gap with minimal methodological disruption.

Two areas, corporate concentration and production forecasting, prove valuable for targeted analyses but are unsuitable as systematic indicators due to data limitations and methodological sensitivities. These remain important tools for deep-dive studies in specific sectors or commodities but should not be applied uniformly across all candidate materials.

## 8.1 PRIORITY ACTIONS FOR NEXT ASSESSMENT

### 8.1.1 Immediate implementation

- Market sentiment indicators (MD; MS; MT) for all commodities with adequate price data
- Economic importance indicators using ONS input/output tables
- Trade restrictions weighting factor (TIF) applied to trade concentration
- Expanded HS codes in trade-based indicators (UK import reliance, trade concentration)
- Climate vulnerability (ND-GAIN) as fourth ESG dimension

### 8.1.2 Selective or targeted application

- Corporate SPoF identification for known chokepoint commodities
- Production forecasting for long-term scenario planning (not near-term supply risk)

### 8.1.3 Further methodological development required

- Continuous monitoring of data completeness of ESG and company ownership related datasets for evaluation and possible incorporation into CA
- Exploration of autoregressive time-series models for better-suited projections of future mineral production to be coupled with demand projections

## 8.2 DATA INFRASTRUCTURE INVESTMENTS

Sustained methodology improvement requires ongoing data infrastructure development.

- Partner with ONS to improve input/output table resolution (critical multiplier)
- Establish GTA database update protocol for trade intervention monitoring
- Continue HS code expansion, documenting material content estimation protocols
- Maintain price series database for MS indicators
- Monitor corporate- and commodity-level ESG data evolution for future integration.

## 8.3 BEYOND CRITICALITY ASSESSMENT

Several outputs have strategic value beyond criticality scoring:

- ONS input/output analyses enable comprehensive UK supply-chain dependency mapping that is critical for industrial policy
- expanded HS code database supports customs intelligence, trade negotiations and circular economy initiatives
- trade intervention monitoring informs bilateral relationship management and diversification strategies

These datasets represent significant analytical infrastructure, meriting sustained investment and cross-government utilisation.

This methodological advancement (**Figure 13**) positions the UK CA among the most sophisticated globally, providing policymakers with granular, evidence-based insights to guide strategic interventions in an increasingly complex and contested CMs landscape.

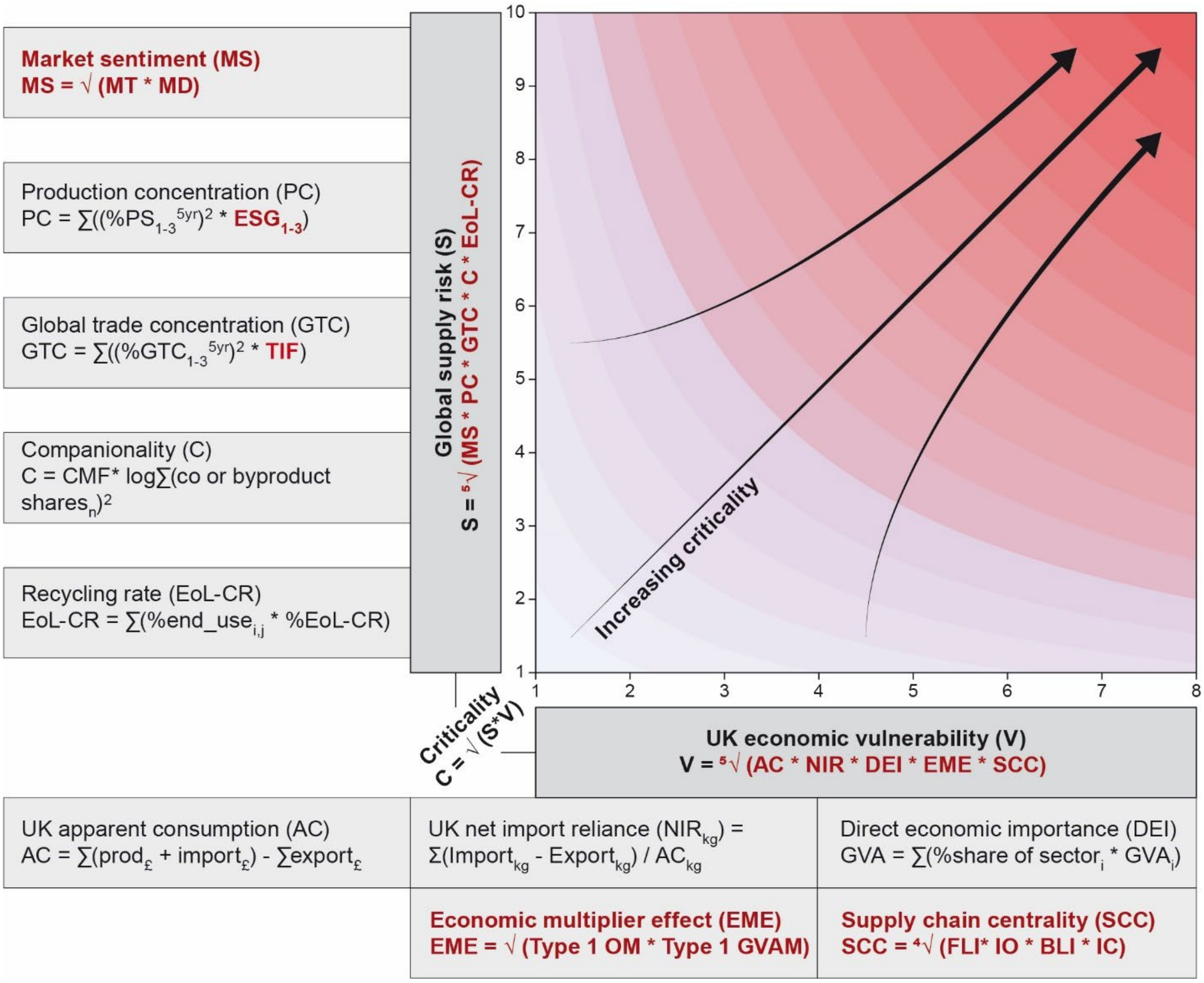


**Figure 13** Updated summary of the UK criticality assessment matrix highlighting how the new methodological developments (in red) integrate in the UK 2024 CA. New indicators will influence the balancing of the global supply risk and UK economic vulnerability dimensions, All trade-related indicators (global trade concentration, UK apparent consumption, UK net import reliance) will benefit from the expanded coverage and characterisation of HS code bringing more mid-stream details relevant to the UK economy. BGS © UKRI 2026.

# Appendix 1 Market sentiment

The 2023 methodology review (Josso et al., 2023) concluded that historic price volatility alone was insufficient to serve as an indicator for market vulnerability. However, recent research demonstrates that price uncertainties of CMs can have a macroeconomic effect (Considine et al., 2023), highlighting the need for a more comprehensive indicator of market behaviour. This work develops additional metrics to distinguish between structural market shifts and short-term noise, producing a robust price time-series analysis that assesses whether markets behave in a stable and transparent manner or show signs of instability, illiquidity or inconsistent price signals.

## DATA AND COMMODITY SELECTION

Retrospective daily pricing data from Argus Metals (Argus Metals, 2025) were used to explore potential metrics for a MS indicator. The sample dataset includes 16 price series covering 15 commodities, with five to thirteen years of historical pricing data. Commodities were selected to represent a broad range of market sizes, liquidity levels and reporting practices. Two time-series datasets for dysprosium (metal and oxide) were investigated to explore how market behaviour can differ between different traded forms of the same element.

The selected price series were:

- antimony trioxide minimum 99.5 per cent ex-works China (CNY/mt)
- cerium oxide 99.5 to 99.9 per cent cif Europe (USD/kg)
- cobalt (electrolytic metal) minimum 99.8 per cent ex-works China (USD/mt)
- dysprosium metal minimum 99 per cent ex-works China (CNY/kg)
- dysprosium oxide minimum 99.5 per cent cif Europe (USD/kg)
- ferro-molybdenum 60 per cent molybdenum ex-works China (CNY/mt)
- germanium dioxide minimum 99.999 per cent ex-works China (CNY/kg)
- graphite flake 94 per cent carbon ex-works China excl. VAT (USD/mt)
- lithium carbonate: minimum 99.5 per cent ex-works China (CNY/mt)
- LME aluminium cash official price (USD/mt)
- LME copper cash official price (USD/kg)
- LME nickel cash official price(USD/mt)
- LME zinc cash official price (USD/mt)
- manganese dioxide: minimum 91 per cent carbon battery grade ex-works China excl. VAT (USD/mt)
- niobium pentoxide minimum 99.5 per cent ex-works China (CNY/kg)
- titanium dioxide 98 per cent minimum anatase grade ex-works China (CNY/mt)

Reporting frequency varies greatly between commodities. Some price series are reported daily, while others are available weekly, twice weekly or monthly. A few include high and low prices in addition to closing prices. This inconsistency in reporting intervals prevents reliable application of data-driven anomaly detection methods (Blázquez-García et al., 2021, Schmidl et al., 2022) or autoregressive models (Bollerslev, 1986, Kriechbaumer et al., 2014), which assume consistent, fixed time increments.

In classical volatility analysis, it is possible to estimate historic variance by assuming average daily returns for longer reporting increments. However, averaging leads to information loss and produces artificially low volatility in long reporting gaps, making classical volatility approaches insufficient for the given market data.

Technical analysis methods (Murphy, 1999) were therefore employed as a complementary approach as they incorporate all available price data and quantify structural shifts rather than random fluctuations. Among these methods, breakout analysis is particularly appealing because it provides economically interpretable assessments of abrupt price changes that reflect shifts in MS and supply and demand dynamics.

## VOLATILITY MODELS

Previously, only close-to-close historic volatility of commodities — defined as the inter-day variance of closing prices over a defined reference period — was considered. The reference window is a fixed-length period that ends on the day when the volatility estimate is calculated. When the reference period is small, volatility is underestimated as variance estimation is highly dependent on the number of samples (in this case, days in the reference period). To address this, an improved model introducing  bias-correcting scaling (Hodges and Tompkins, 2002) was evaluated and is referred to as the Hodges-Tompkins volatility model. This correction is particularly important when the number of observations is limited, as is common with weekly or irregular reporting frequencies.

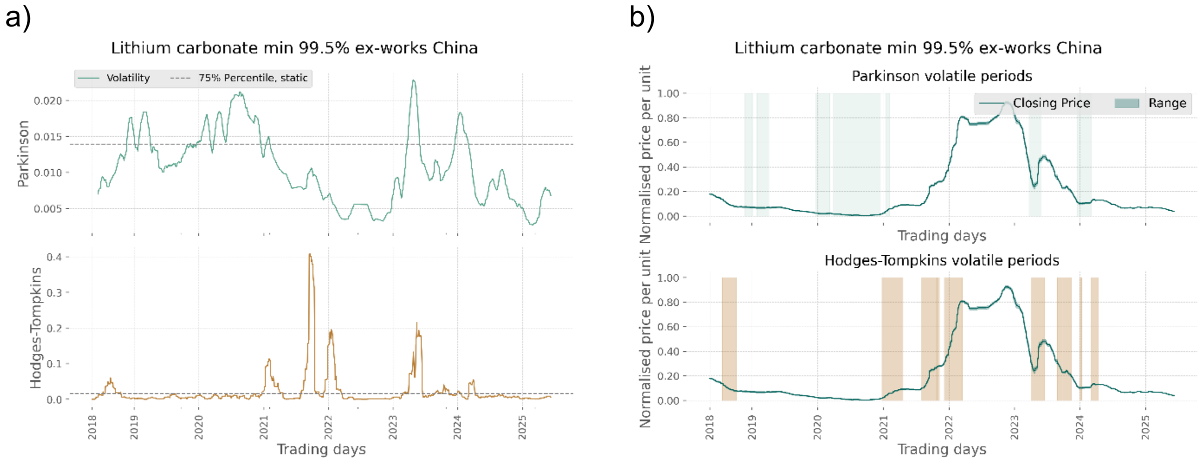


**Figure 14** Intra-day and inter-day volatility of the lithium carbonate prices calculated over the reference period of 22 trading days. a) Parkinson volatility incorporates differences between high prices. Hodges-Tompkins volatility incorporates closing prices via daily returns. Constant threshold equal to the 75th percentile of the volatility over the entire period was used to determine volatile periods. b) Volatile periods determined with the 75th percentile threshold. Price-normalised time-series data (Argus Metals, 2025). BGS © UKRI 2026.

In addition to closing prices, the variability between reported high and low prices can be incorporated into the assessment via the Parkinson historic volatility model, which characterises intra-day variance (Parkinson, 1980). The Parkinson estimator is more statistically efficient than close-to-close estimators when high-low range data is available, as it uses additional information about price movements within the trading period.

Combining information from both models improves overall characterisation of market variation. The intra-day resolution captured by the Parkinson model is particularly valuable for retrospective analysis spanning multiple years, as it reveals price dynamics that close-to-close analysis would miss.

For both inter-day and intra-day models, the market is considered volatile when its variance is outside the level defined by the previous reference period. Since the analysis is performed on historical data, the threshold can be set to a constant or defined across the entire time series. In this study, the threshold was set at the 75th percentile of all calculated volatility values, with volatile periods shorter than five trading days discarded as noise. This five-day minimum filter reduces false positives arising from single-day spikes or brief anomalies that do not reflect sustained market stress.

It is important to note that, under this definition, a volatile market is not inherently negative. The frequency, duration and recovery time of volatile episodes must be assessed to judge whether volatility is disruptive or represents natural market movement responding to genuine supply and demand shifts. Sustained high volatility may indicate chronic market stress, while brief volatile episodes followed by rapid stabilisation may reflect efficient price discovery.

## BREAKOUT DETECTION

In addition to volatility-based measures, pricing time-series data can reveal structural elements such as support and resistance levels. These levels are derived from the high-low price range over a set reference period. The support level is defined as the price point where the price tends to start growing again, signifying increased demand at that price. Resistance represents the opposite: falling demand at a certain price point leading to a decrease in price. If the price breaches either of these levels for a significant period or with significant traded volume, it is considered to have undergone a breakout (sometimes referred to as a breakdown when the support is breached). Thus, breakouts characterise structural changes in the market due to participant sentiment, complementing volatility as a measure of random fluctuations.

Support and resistance levels were obtained as linear regressions through pivot points in the historical low and high daily prices. A pivot high is defined as a price peak that exceeds highs immediately before and after within a defined sliding window. A pivot low is the lowest point within its surrounding window. For this analysis, a 13 reporting-day window was used to identify pivot points, although this window may span more actual trading days depending on reporting frequency. This 13-day window was selected because it provides sufficient context to identify meaningful local extrema while remaining responsive to recent price movements.

To determine rolling support and resistance levels, several reference window lengths were considered: 22, 44 and 130 trading days, corresponding approximately to one month, two months and six months of trading activity. On each day, the reported closing price was assessed against the support and resistance levels calculated from pivot points in the preceding reference window.

Periods where the closing price broke above the resistance level were labelled as breakout periods. Periods where price fell below support were labelled as breakdown periods. Short-term breaches lasting fewer than ten trading days were classified as false breaks, which is a phenomenon where the price breaks through previous levels but fails to establish a new trend and quickly reverts to previously established patterns. False breaks may indicate testing behaviour by market participants, unsuccessful attempts to establish new price levels or potential market manipulation tactics such as stop-loss hunting (Noertjahyana et al., 2020). Including this classification helps distinguish meaningful structural shifts from temporary or misleading market noise.

Lithium carbonate provides a useful example of these dynamics due to the variable pattern in its pricing data and clear dominance of structural changes over random fluctuations. The analysis clearly demonstrates the pitfalls of any approach that depends on a sliding window of short length. For example, shorter windows may fail to capture significant movements as meaningful structural changes, risking miss classification as ordinary price variations.

During periods of constant pricing or very low reporting frequency, there may be fewer than three pivot points in the preceding reference window, making it impossible to construct meaningful support or resistance lines. These periods are labelled as ‘no pivots’ to distinguish them from periods where support and resistance are calculable, but no breakouts occur. This label serves as a data quality indicator: if pricing data remains constant over extended periods, all other metrics will indicate market stability, but this apparent stability may not represent real trading patterns. The market could be illiquid, thinly traded or subject to price-fixing arrangements that suppress natural price discovery.

It must be noted that the initial reference window of the time-series data (equal to the length of the reference period) will always be marked as no pivot since all metrics are calculated in relation to preceding periods. This initial window is excluded from final reporting to avoid artificial inflation of no pivot statistics.

Breakouts can be analysed alongside volatility to provide a clearer picture of MS and trend shifts related to fundamental changes in policy or supply conditions. Long breakout periods with low volatility characterise a stable, confident market controlled by buyers establishing a new, higher price equilibrium. Multiple short breakouts with high volatility may indicate low liquidity (Vayanos and Wang, 2013) and uncertain participants reluctant to commit after initial price movements. Long breakdowns indicate fundamental deterioration of investor confidence with sellers controlling the market, potentially signalling sustained oversupply or weakening demand. Multiple short-term breakdowns may reflect seller reactions to temporary shocks and could indicate speculative trading or tactical dumping.

To ensure this level of interpretability, it is essential to incorporate both the length of breakouts and the volatile periods with the frequency of occurrence. Such interpretation relies on data being of high quality with high-frequency reporting. Unfortunately, some emerging mineral commodity markets do not benefit from the same transparency and established market practices as major commodities such as copper or aluminium traded on the LME, which can limit confidence in interpreting market behaviour.

All assessment metrics discussed so far focus on the temporal aspects of time series, quantifying how long or how often the market spends in any regime. In the absence of traded volume data (which would provide direct evidence of market depth and participant conviction), the only way to assess the nature of regime changes is to analyse the price movements themselves. Two additional values are therefore compared: the total amplitude of closing prices (the difference between maximum and minimum prices observed) and the maximum absolute change in closing price over the sliding reference period. The former quantifies the global breadth of market regimes over the entire time series, while the latter indicates short horizon swings in pricing that may reflect sudden shocks or liquidity constraints, helping differentiate structural shifts from short term variability.

## REPORTED METRICS

To develop a comprehensive estimate of market uncertainty from retrospective data, a combination of metrics quantifying both the length and frequency of unstable periods was extracted from all datasets. The following metrics were calculated across the entire time series, using sliding reference windows of 22, 44 and 130 trading days:

Intra-day volatility was calculated using the Parkinson method, which measures variance based on the difference between the high–low range within the reference window.

The Parkinson volatility (PV) estimator is defined as:

$$PV = \sqrt{(1/(4n \ln(2)) \times \Sigma(\ln(H_i/L_i))^2)}$$

Where $H_i$ and $L_i$ are the high and low prices on day $i$ and $n$ is the number of observations in the reference window. Periods where variance exceeded the global 75th percentile for at least five trading days were marked as volatile.

Inter-day volatility was estimated using the Hodges-Tompkins method, which corrects for bias when daily closing price observations are limited. The Hodges-Tompkins estimator scales the standard close-to-close volatility by a bias correction factor:

$$HTV = \sqrt{((n/(n-1)) \times (1/(n-1) \times \Sigma(r_i - \bar{r})^2))}$$

Where $r_i$ is the logarithmic return on day $i$, $\bar{r}$ is the mean return over the reference window, and $n$ is the number of observations. The correction factor $n/(n-1)$ becomes more important for smaller reference windows. As with intra-day measures, periods above the 75th percentile for a minimum of five trading days were marked as volatile.

Breakouts were identified when the closing price exceeded the resistance level calculated from pivot points in the preceding reference window. The following metrics are associated with breakouts:

- breakout periods: sustained breaches of the resistance level lasting more than ten trading days
- breakout points: the first day of each breakout period
- false breaks: short-lived breaches lasting fewer than ten trading days

Breakdowns are the parallel set of measures calculated for periods when prices fell below the support level:

- breakdown periods: closing price remained below the support level for more than ten trading days
- breakdown points: the initial day of each breakdown period
- false breaks: closing price remained below the support level for fewer than ten trading days

No-pivot periods are the time periods for which the preceding reference window did not contain enough pivot points (minimum of three) to draw support or resistance lines.

Absolute level change is the difference between maximum and minimum values within the sliding reference window. The reference window with the highest level change is labelled as the max-change period; this maximum change value is stored as a metric representing the largest single-window price swing observed.

Intra-day and inter-day volatility are valuable for monitoring random price variations, while breakout and breakdown periods are optimal for capturing structural regime changes. All metrics were computed for reference windows of the same length to enable direct comparison. For each reference window length (22, 44 and 130 trading days), the total duration of volatile, breakout, breakdown, false break and no-pivot periods was calculated, along with the longest continuous episode of each type. These metrics collectively allow identification of markets that are stable, disorderly, or structurally fragile.

The choice of multiple reference window lengths addresses an inherent challenge in time-series analysis: short windows are more responsive to recent changes but may overfit to noise, while long windows are more stable but may miss important short-term dynamics. By calculating metrics across three window lengths spanning one to six months of trading activity, the analysis captures both tactical (short-term) and strategic (medium-term) market behaviour. Any reference window length below one month (22 trading days) was deemed uninformative due to high variance in emerging CM markets and substantial variability between commodities with different reporting frequencies.

## FUTURE CONSIDERATIONS

The most obvious immediate improvement to these metrics would be the incorporation of opening daily prices. This data would enable the use of more comprehensive volatility models such as the Garman-Klass estimator, which incorporates opening, closing, high and low prices to provide more efficient variance estimates. Additionally, opening prices would enable more comprehensive analysis of bullish and bearish trends through candlestick pattern analysis, describing structural pressures in the market with greater nuance.

Improving the resolution of pricing data would be of great benefit and enable the use of autoregressive models that have been successfully employed in short-term forecasting and retrospective analysis (Kriechbaumer et al., 2014). Models such as generalised autoregressive conditional heteroscedasticity (GARCH) explicitly model time-varying volatility and volatility clustering, which are common features of commodity markets. However, these models require consistent time intervals between observations and sufficient data density to estimate parameters reliably.

Most critically, traded volume data at similar resolution or at longer regular intervals would enable breakout validation and aid interpretation of the underlying sentiment that caused the breakout. Volume confirms whether price movements reflect genuine market participation (high volume) or thin trading conditions where small transactions can move prices significantly (low volume). Volume divergence, where prices break out on declining volume, often signals weak breakouts that are likely to reverse, while breakouts on increasing volume suggest strong underlying demand or supply pressure. Without volume data, the analysis relies entirely on price patterns, which can be ambiguous to interpret.

## MARKET SENTIMENT INDICATOR CONSTRUCTION

The range of metrics calculated for each commodity (volatility measures; breakout statistics; amplitude changes) captures multiple facets of market behaviour. Because commodities differ greatly in terms of liquidity, reporting frequency, traded volume, transparency and market structure, combining these metrics meaningfully is essential to ensure consistent interpretation. Although many of the metrics are correlated, they are not interchangeable and all are needed to distinguish volatility magnitude from persistence, whether price variations are coherent, and whether price signals are reliable.

There is no canonical econometric method to merge all or some of these metrics into a single indicator; however, they can be broadly grouped into conceptual categories. Volatility measures and their related estimators provide robust historical estimates of price variation and underlying uncertainty using reported price ranges (Parkinson, 1980). Persistence and regime shifts are common econometric indicators considered in Markov-switching models of commodity markets (Fong and See, 2002), while structural breaks and volatility clustering support the use of longest periods or total volatility duration as indicators of persistent stress (Hamilton, 1989).

Two distinct composite metrics are proposed to capture how turbulent and how reliable price information is for each commodity.

Market Turbulence (MT) captures the intensity and persistence of price movements regardless of whether they are orderly or chaotic. MT is calculated from:

- peak volatility (maximum observed volatility across all reference windows)
- ratio of historic-to-peak volatility (indicating whether high volatility is chronic or episodic)
- proportion of time spent in high-volatility regimes (volatility concentration)
- intensity of breakout movements (maximum level change)

Higher MT indicates exposure to supply and demand imbalances, logistical stress and structurally tight markets. Low MT represents a stable, well-supplied, demand-balanced market. It is important to note that this indicator does not reflect the direction of price evolution: high MT is possible for markets moving towards both high and low prices over time. A market experiencing sustained price increases due to supply constraints and a market experiencing sustained price decreases due to demand collapse can both exhibit high MT. For details on these metrics see Appendix 1.

Market Disorder (MD) MD focuses on signal coherence and the quality of long-term pricing information rather than volatility magnitude. MD is calculated using:

- total number of regime change periods (breakouts plus breakdowns)
- ratio of false breaks to successful regime changes
- intensity of breaks (how sharply prices deviate from established support/resistance)
- relative dominance of HTV over PV

Combined, these metrics assess weather frequent regime changes imply unstable market expectations, with apparent price signals failing to materialise into sustained market reality and indicating vulnerability to manipulation or tactical investment and dumping behaviour. A high MD score represents prices that are unreliable and unrepresentative of real commodity market fundamentals, suggesting hoarding, strategic pricing or market manipulation. Conversely, low MD represents a transparent and liquid market where price signals reliably reflect supply and demand conditions and where regime changes, when they occur, are sustained and meaningful.

Together, the MT and MD indicators capture different dimensions of complex market behaviour by incorporating multiple underlying metrics. Considering them jointly reduces the risk of over-interpreting any single indicator or becoming overly dependent on the choice of sliding window length. The indicators may be used independently to assess different aspects of market risk or combined into a single MS indicator for overall market quality assessment.

Because the indicators are normalised on a one to ten scale and interpreted comparatively across commodities, scores are distributed across the range of metric values observed in the selected time series. As additional time series are incorporated into future analyses, these relative scores will evolve. A commodity scoring 7.5 on MT is more turbulent than one scoring 3.3 within the observed dataset, but the absolute threshold values should not be interpreted as having universal meaning across all possible commodities or time periods.

While this work demonstrates that meaningful MS indicators can be derived from price data alone, providing insight into market solvability, transparency and potential manipulation, the choice of price series remains critically important. As illustrated by neodymium prices for 99.5 per cent oxide and 99 per cent metal, MS scores can vary substantially (from 6.0 to 2.9 in this case), reflecting differences between stages of value-chain transformation. This variation highlights how bottlenecks and risks may concentrate at specific processing stages even when the commodity as a whole is considered critical. A material may have stable pricing at the ore concentrate stage but highly volatile pricing at the refined metal or chemical compound stage, indicating that risks concentrate in refining capacity or chemical processing rather than mining.

Furthermore, minor commodities with limited or absent price series should be treated as inherently higher risk rather than dismissed as data-poor exceptions. A lack of transparent, continuous pricing typically reflects thin markets, low liquidity and a reliance on bilateral, long-term offtake agreements rather than open market trading. In such settings, observed price stability does not necessarily indicate market resilience. Instead, it can mask structural fragility, limited price discovery mechanisms and heightened exposure to supply disruptions or strategic behaviour by dominant actors. Small market size means that marginal changes in supply or demand can have disproportionate impacts, while contract-dominated trading structures increase rigidity and counterparty risk. The absence of price volatility may simply mean that market transactions are too infrequent or too opaque to generate observable price series, not that the market is inherently stable.

# Appendix 2 Economic importance

Previous CAs characterised economic importance primarily through GVA in manufacturing sectors. This approach captured direct economic contribution but missed crucial interdependencies:

- how materials support interconnected industrial ecosystems
- how disruption in one sector propagates through supply chains
- where strategic vulnerabilities concentrate

A steel shortage doesn't just affect steelmakers: it cascades through the construction, automotive, machinery and infrastructure sectors. Understanding these interdependencies is essential for prioritising interventions and building resilience in a highly integrated modern economy, where disruptions spread far beyond the originating sector.

## METHODOLOGY OVERVIEW

The 2025 release of ONS input/output tables (product-by-product and industry-by-industry) has enabled comprehensive mapping of sector interdependencies through established input/output economics methods (Office for National Statistics, 2025a, Office for National Statistics, 2025b). Combined with SIC material usage mappings from the 2024 UK CA, this allows derivation of eight core metrics that capture three distinct dimensions of economic risk that together provide a more complete and systemic view of material importance:

- the sector's direct contribution
- its structural position within supply networks
- how shocks propagate through the broader economy

## SEVEN CORE METRICS

### Direct economic contribution

**Gross Value Added (GVA):** GVA is the sector's direct economic contribution measured as wages, profits and taxes generated. Closely related to GDP, GVA shows intrinsic importance to the UK economy. High GVA indicates substantial economic activity at risk from material disruption, although by itself it does not reveal supply-chain dependencies or propagation effects. This metric was used in the 2024 UK CA as the primary economic importance indicator.

### Supply-chain position

**Intermediate Output (Forward Sales):** production sold to other sectors, rather than final consumers, representing forward linkage or how much downstream industries depend on this sector as supplier. It is calculated as the total value of a sector's products consumed as inputs across all UK industries. High intermediate output indicates the sector is deeply embedded as a supplier and its disruption cascades to customer sectors relying on these inputs.

**Intermediate consumption (Backward Purchases)** is the total inputs purchased from other industries to produce the sector's output, representing backward linkage exposure, that is, the sector's dependence on upstream suppliers. This metric reveals vulnerability to disruption, shocks or input shortages. High intermediate consumption indicates substantial exposure to upstream supply risks, as the sector's own activities depend on the continued availability and affordability of these inputs.

**Backward Linkage Index** (BLI) is a normalised measure of supplier dependence calculated from the Leontief inverse matrix column sums. It captures structural position: how strongly sector expansion pulls activity through upstream supply chains. Values greater than one indicate above-average supplier dependence; values less than one indicate below-average dependence. Unlike intermediate consumption (absolute £ values), this index shows scale-independent structural positioning, enabling cross-sector comparison regardless of size. A sector with a BLI of more than one creates above-average ripple effects through its supply chain when it expands or contracts.

**Forward Linkage Index (FLI):** FLI is a normalised measure of downstream dependence calculated from the Leontief inverse (row sums). It shows how strongly other sectors depend on this sector as the input supplier. Values greater than one indicate above-average supplier importance; values less than one indicate below-average supplier position. This index complements intermediate output by providing a scale-independent measure of supply-chain criticality. A sector can have moderate intermediate output (£ value) but high FLI (structural criticality) if small volume supplies are essential inputs to many diverse sectors. The FLI calculation represents a methodological advance: most international CAs examine only backward linkage, thereby missing the downstream dependency dimension.

## Economic propagation

The **type 1 output multiplier** is the total output change across entire economy per £1 increase in final demand for that sector's output. It captures direct production plus indirect supply-chain activation, calculated as column sum of the Leontief inverse matrix. High multipliers (for example, 2.5) mean each £1 of final demand generates £2.50 total economic activity through cascading supplier effects. This coefficient quantifies economy-wide amplification: how sector growth or contraction propagates through inter-industry transactions.

The multiplier is calculated as:

Output multiplier = (direct effect + indirect effect) / change in final demand

Where *direct effect* is the sector's own output change and *indirect effect* is the sum of all supplier sectors' output changes triggered by the initial demand shock.

The **type 1 GVA multiplier** is the total GVA change across entire economy per £1 increase in final demand and is calculated by weighting the Leontief inverse by sectoral GVA coefficients. It is typically lower than the output multiplier because intermediate transactions include cost pass-through, not just value creation. It shows economic impact in terms of income, employment and tax generation rather than gross activity. A high GVA multiplier indicates that demand shocks in this sector create substantial economy-wide employment and income effects.

Note: type 2 multipliers, which additionally incorporate induced effects from household spending changes linked to employment shifts, are not currently produced by ONS. Future availability of type 2 data would enhance impact assessment by capturing full income-expenditure cycles.

## Three composite indicators

These eight metrics combine into three strategic indicators reflecting distinct aspects of economic vulnerability to material disruption.

### DIRECT ECONOMIC IMPORTANCE

DEI = GVA

***Rationale***

This is a measure of intrinsic sector size and economic contribution independent of supply-chain position. It answers the question ‘How much economic activity (income; employment; taxes) occurs directly in sectors using this material?’ High DEI indicates material disruption would directly affect substantial economic value creation. This indicator maintains continuity with the 2024 UK CA methodology.

### *Policy relevance*

DEI identifies materials supporting major employers or high-value industries. However, DEI alone is insufficient for CA: a large isolated sector may be less critical than a smaller one occupying a strategic network position. Direct scale must be assessed alongside supply chain structure and propagation dynamics.

### SUPPLY-CHAIN CENTRALITY

$$\text{SCC} = \sqrt[4]{(\text{FLI} \times \text{intermediate output} \times \text{BLI} \times \text{intermediate consumption})}$$

### *Rationale*

This measures how embedded the sector is within the industrial network, capturing both supplier role (forward) and customer role (backward) using absolute values and structural indices. The four components provide complementary perspectives.

Together, FLI and intermediate output characterise supplier criticality. FLI shows structural importance, or how essential the sector is as an input to diverse industries, while intermediate output shows scale (£ volume supplied). A sector critical to only a few, large customers has high intermediate output but moderate FLI; a sector supplying small but essential inputs to many diverse sectors has high FLI but moderate intermediate output. Both dimensions capture distinct aspects of supply side criticality.

Together, BLI and intermediate consumption characterise supply vulnerability. BLI shows structural dependence, or how tightly the sector is coupled to suppliers, while intermediate consumption shows exposure magnitude (£ at risk). A sector purchasing large volumes from only a few suppliers has high intermediate consumption but moderate BLI; a sector dependent on complex, multi-tier supply chains has high BLI even with moderate spending. Both dimensions capture different aspects of upstream vulnerability.

The geometric mean formulation (fourth root of the product) ensures all four components contribute equally to the final score while maintaining scale appropriateness. High SCC scores require reasonable performance across all four dimensions: a sector cannot achieve high centrality through one dimension alone.

### *Policy relevance*

High SCC identifies materials occupying strategic network positions where disruption propagates broadly. These are systemic chokepoints even if DEI is moderate. SCC reveals hidden criticality invisible in GVA-only analyses, particularly for materials used in small quantities but essential to many interconnected sectors.

### ECONOMIC MULTIPLIER EFFECTS

$$\text{EME} = \sqrt{(\text{type 1 output multiplier} \times \text{type 1 GVA multiplier})}$$

### *Rationale*

EME quantifies how sector shocks amplify through the economy via inter-industry transactions. The output multiplier captures total activity cascade and the GVA multiplier captures the value-added (income/employment) cascade. Together, they measure economic propagation intensity. The geometric mean ensures balanced contribution from both dimensions: sectors must demonstrate propagation through both gross activity and value-added channels to achieve high EME scores.

#### *Policy relevance*

High EME indicates material disruption triggers disproportionate economy-wide effects. Sectors with high multipliers warrant strategic intervention even if their direct scale (DEI) or network positions (SCC) are moderate, because knock-on effects dominate total impact. Construction and automotive sectors typically exhibit very high multipliers, meaning material shortages affecting these sectors rapidly spread across the wider economy.

### COMBINING INDICATORS INTO OVERALL ECONOMIC IMPORTANCE

For CA, these three indicators should be combined to produce an overall ‘economic importance’ dimension. While exact weighting requires sensitivity analysis and calibration against historical disruption impacts, the following weight distribution reflects the relative importance of each dimension to criticality.

#### *Recommended weights*

- Supply Chain Centrality (SCC): 45 per cent
- Economic Multiplier Effects (EME): 30 per cent
- Direct Economic Importance (DEI): 25 per cent

#### *Weighting rationale*

SCC receives the highest weight (45 per cent) because criticality fundamentally concerns interconnection and dependency. Materials may have a modest direct economic footprint but occupy strategic network positions, creating systemic vulnerability. SCC captures this criticality dimension most directly through its measurement of both forward (supplier criticality) and backward (supply vulnerability) linkages.

EME receives a substantial weight (30 per cent) reflecting that knock-on effects often exceed direct impacts during disruptions. Multipliers quantify cascade risks, but their correlation with SCC warrants a slightly lower weight.

DEI receives the lowest weight (25 per cent) because GVA alone is an unreliable predictor of criticality: large sectors can be isolated while small sectors can be strategically critical. However, direct economic contribution remains essential and must not be underweighted.

#### *Sensitivity analysis*

Alternative weighting schemes should be tested during implementation, including equal weights (33.3/33.3/33.3 per cent), centrality-dominant (20/55/25 per cent) and multiplier-focused (20/35/45 per cent) configurations. If material rankings remain stable across weighting schemes (Spearman correlation over 0.80), the recommended weights are defensible. Large ranking shifts would indicate materials requiring additional expert judgment.

### DATA QUALITY CONSIDERATIONS

ONS input/output tables currently exhibit variable aggregation. Most SIC codes are available at two-digit resolution with uneven three- or four-digit breakdown. Some three- and four-digit subsectors are aggregated together, likely reflecting data availability, economic size and distinguishability considerations within each sector. This aggregation obscures important subsector heterogeneity in material dependencies; different manufacturing activities within broadly defined sectors may have radically different material intensities and vulnerability profiles, which can affect the accuracy of sector level risk metrics.

Finer resolution would strengthen analyses, particularly for sectors with diverse material dependencies that behave differently at the subsector level. Priority sectors for disaggregation include those that are highly material intensive with diverse subsectors, thus warranting separate treatment:

- SIC 24: basic metals
- SIC 25: fabricated metal products
- SIC 26: computer and electronic products
- SIC 27: electrical equipment
- SIC 28: machinery and equipment

Forward Linkage Index calculation requires full input/output accounting tables, including both intermediate use matrices and final demand vectors. The 2025 ONS release includes these components, enabling robust FLI calculation. This represents a significant methodological advancement over international CAs that typically examine only backward linkage. Symmetrical treatment of upstream (backward) and downstream (forward) dependencies provides a more complete picture of supply-chain position. For CAs addressing supply disruption scenarios, forward linkage (identifying which sectors are at risk if a material supply is disrupted) is equally or more relevant than backward linkage (identifying which inputs are needed if a sector expands).

### SIC material usage mapping

The metrics require mapping materials to relevant SIC codes. The SIC-material usage mappings developed during the 2024 UK CA link each candidate material to sectors with significant usage, based on industry surveys, trade association data, technical literature and BGS expertise. Each linkage includes a usage intensity classification.

Current implementation weights all using sectors equally per material. Alternative weighting approaches merit investigation:

- usage intensity, prioritising sectors with high material dependence
- sector scale, prioritising large economic contributors
- material quantity consumed, prioritising high-volume users

However, equal weighting is defensible as an initial approach. Even low-intensity uses in critical sectors (for example, REEs in fighter jet components) can constitute material criticality.

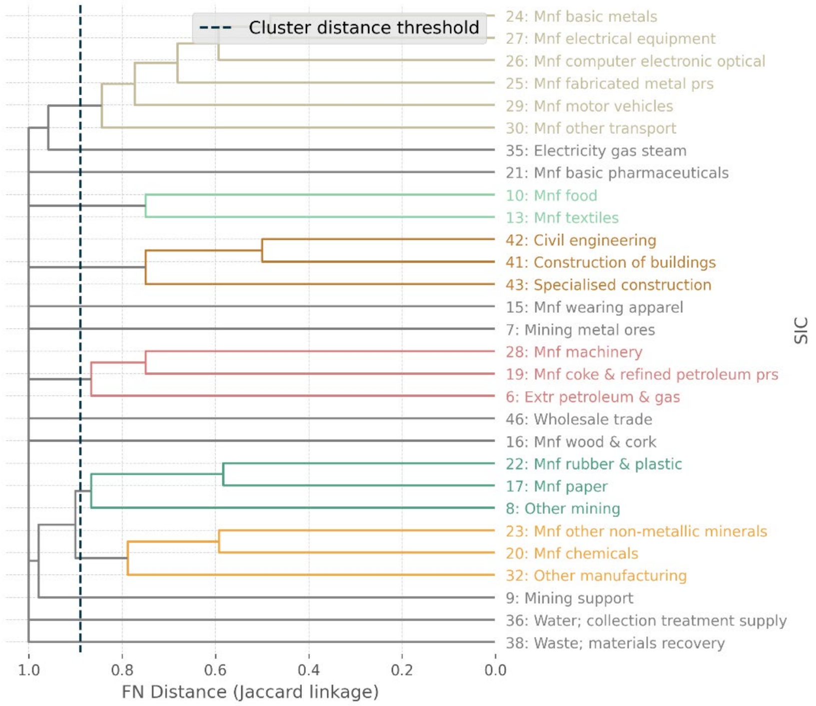
For materials used across multiple SIC codes, composite indicator scores are calculated by aggregating across using sectors. The aggregation method affects interpretation:

- usage-weighted average: weights each sector by its material usage intensity, reflecting that higher-intensity users contribute more to overall material criticality
- maximum risk: takes the highest score across using sectors, representing a conservative assumption that vulnerability at any stage affects overall criticality
- consumption-weighted: weights sectors by material quantity consumed (where data is available), prioritising commercially significant applications

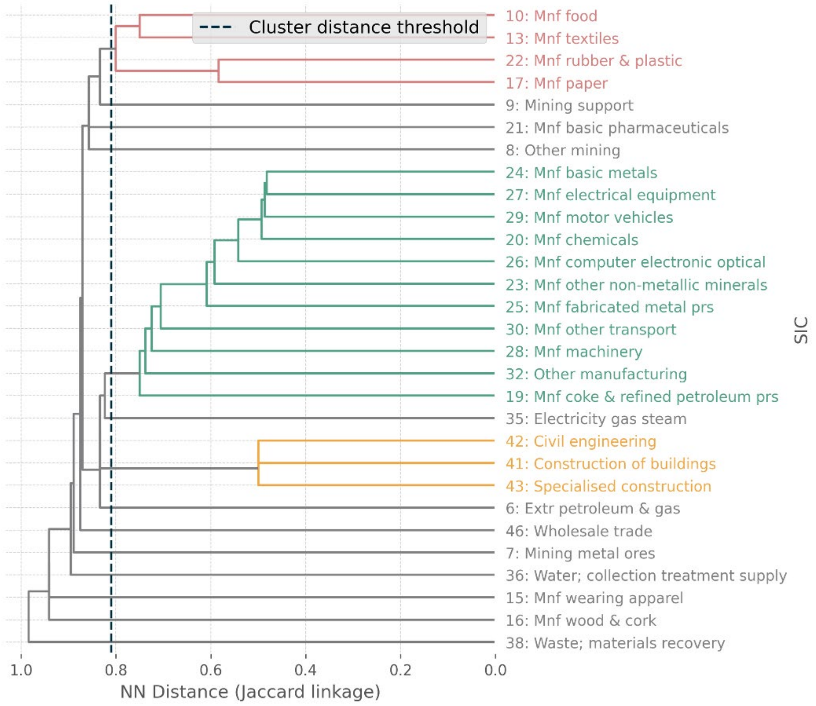
The appropriate aggregation method depends on the criticality question being addressed. Usage-weighted averaging suits assessment of overall economic exposure, while maximum risk is appropriate for identifying worst-case vulnerabilities. The choice of aggregation should therefore be explicitly aligned with the assessment objective.

### CASE STUDY: ECONOMIC SECTOR CONNECTIVITY ANALYSIS

The ONS input/output tables can be combined with material usage data to construct networked representations of mineral-dependent economic sectors. This framework elucidates how changes in mineral supply or demand propagate through the economy.



a)



b)

**Figure 15** Clustering of industry two-digit codes base on mineral use. Mnf: manufacturing; Extr: extraction; prs: products. a) Clustering using farthest method (furthest neighbour) results in a set of compact clusters. b) Clustering using nearest neighbour method results in one large cluster (Office for National Statistics, 2025a, Office for National Statistics, 2025b). BGS © UKRI 2026.

Mineral usage data was hierarchically clustered to identify groups of economically interconnected sectors. Each mineral was treated as a binary variable (1 if used by a sector; 0 otherwise), enabling use of the Jaccard distance to measure similarity between sectors' mineral usage patterns. Jaccard distance ranges from 0 (identical mineral usage) to 1 (no shared minerals), emphasising shared presence rather than shared absence.

Complete linkage clustering was applied, merging clusters based on most dissimilar element pairs. This method produces compact clusters with high internal similarity. The ONS industry-by-industry input/output table provided adjacency relationships between sectors, revealing a highly connected network. At the two-digit SIC aggregation level, the UK economy appears tightly interlinked, indicating disruptions to commodity and component value chains likely propagate widely, amplifying knock-on effects across multiple sectors.

Network analysis can be decomposed to individual nodes, visualising forward and backward linkages scaled by sectoral economic size, further broken down between domestic and import/export contributions. This reveals which sectors are hub suppliers (high forward linkage) vs. hub consumers (high backward linkage), and where international trade concentrations create vulnerabilities.

Similar clustering can be performed on commodities rather than sectors, revealing which minerals show correlated usage patterns across the economy. A more refined analysis based on detailed commodity-to-end-use sector mapping could highlight sectors with shared exposure to specific minerals, their potential competition for the same raw or manufactured materials, and correlated vulnerabilities to supply disruptions or price shocks.

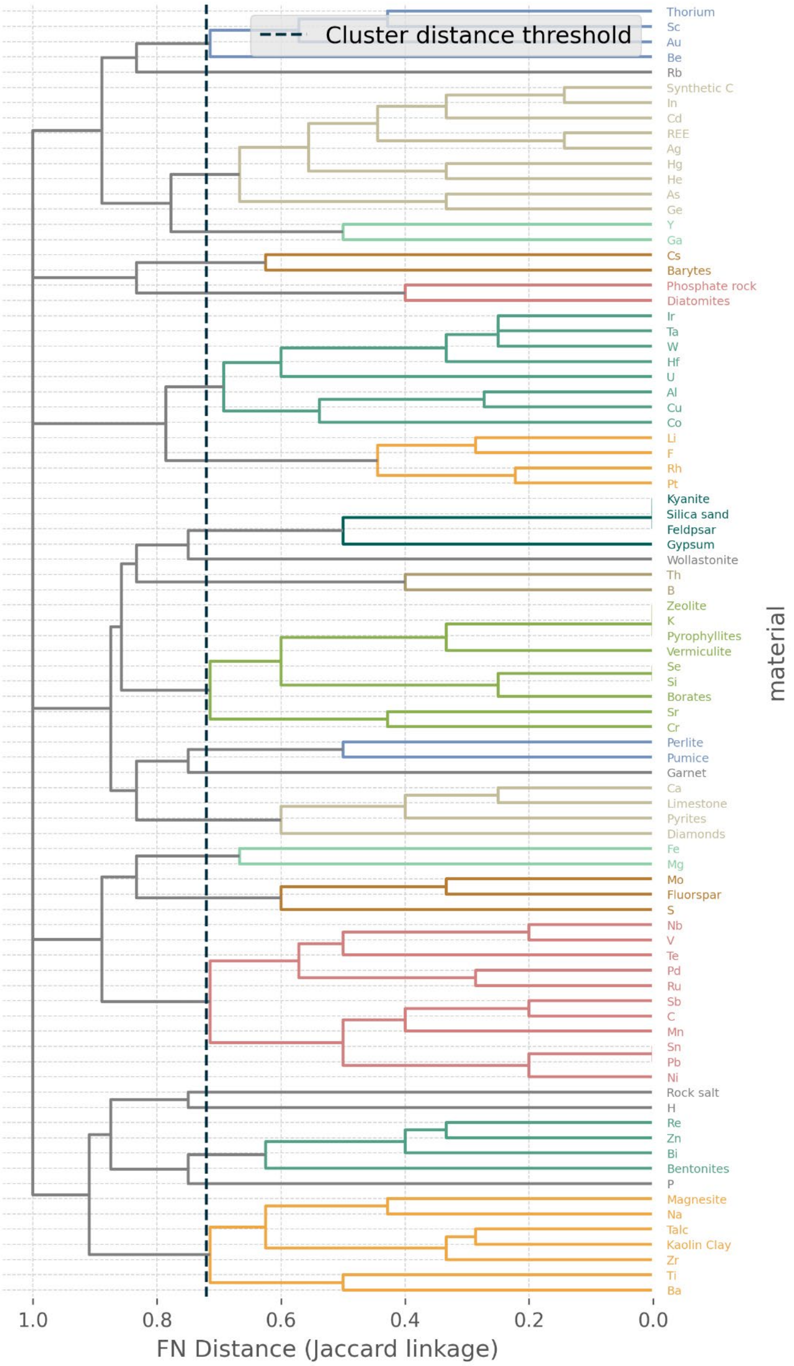


**Figure 16** Clusters of minerals based on their utilisation in economy sectors. Clustering is performed using the complete linkage method with Jaccard distances (Office for National Statistics, 2025a, Office for National Statistics, 2025b). BGS © UKRI 2026.

Such analysis reveals which minerals underpin multiple otherwise unrelated sectors, enabling targeted policy interventions to safeguard multiple economic areas simultaneously. It also highlights ‘quietly critical’ minerals: elements that don't dominate any single high-visibility sector but are ubiquitous across clusters, reinforcing the importance of specialty metals, additives and alloying elements that lack high GVA in manufacturing but enable essential technologies. These minerals often have low direct GVA but are indispensable for enabling key technologies.

Systemic risk assessment could move beyond single-sector stress tests to economy-wide exposure mapping. If several high-output or high-GVA sectors fall within the same mineral-use cluster, supply shocks to one mineral propagate horizontally across sectors, not just vertically through value chains, amplifying economic disruption beyond sector-by-sector predictions.

# Appendix 3 Trade interventions

Trade interventions are the actions and instruments of policies that governments implement to influence international trade by restricting imports or promoting exports (Cadot et al., 2011, Evenett and Fritz, 2020, Acharyya, 2023). These interventions range from traditional tariffs to regulations, subsidies, quotas and export restrictions with the potential to affect both global trade relationships and supply chains. Understanding trade intervention patterns is increasingly critical for CA given accelerating global protectionism trends and the growing weaponisation of resource access in geopolitical conflicts.

Trade interventions can be classified by their implementation mechanism and their effect on trade flows. Border measures such as tariffs, quotas, taxes and bans are implemented at the point where goods enter a country. Behind-the-border interventions are non-tariff barriers operating inside a country, including subsidies, domestic content requirements and discriminatory technical standards (Quak, 2025). Interventions are categorised as either liberalising (removing or reducing barriers) or harmful (imposing barriers).

Trade interventions can be implemented at multiple scales. Unilateral interventions are one-sided measures, typically adjusting trade barriers to benefit the implementing country. Bilateral agreements are negotiated between two countries, while multilateral agreements involve more than two countries and are typically harder to negotiate and implement (Race, 2022). The World Trade Organization (WTO), established in 1995, governs global trade rules negotiated among most of the world's trading nations, promoting trade liberalisation principles.

### Historical context and recent developments

Since the Second World War, international trade has expanded substantially due to declining transportation and communication costs and reduced tariffs resulting from the General Agreement on Tariffs and Trade (World Trade Organisation, 1947) and WTO creation (Greenaway, 1998, Santos-Paulino, 2005). Tariffs have decreased significantly over recent decades, representing a shift toward liberalising interventions. However, non-tariff trade barriers have simultaneously increased substantially (Zongo and Oyelami, 2021), indicating protectionism has evolved rather than disappeared.

Recent global events highlight the critical importance of trade interventions to supply-chain security and materials criticality. The Russia–Ukraine conflict escalation in 2022 affected global supply chains through both reduced Ukrainian production capacity and sanctions on Russian exports by Canada, the USA and the EU (Bargujar et al., 2025). Russia is a key exporter of antimony, palladium, phosphate and tungsten, while Ukraine is a major producer of hafnium, titanium and zirconium (SCRREEN, 2023, Idoine et al., 2025), creating current and potential future supply reductions.

The USA–China trade war, initiated in March 2018 with US tariffs on aluminium, steel and Chinese products, has escalated through multiple waves of retaliatory tariffs (Kapustina et al., 2020, Caliendo and Parro, 2023, York and Durante, 2026). This conflict has significantly affected global supply chains, leading to higher consumer prices (Caliendo and Parro, 2023), reduced export volumes (Benguria, 2023, Yang et al., 2025) and negative impacts on technological innovation (Chen et al., 2023). Many interventions have specifically targeted CM supply chains, including graphite (Risse et al., 2025), lithium and REEs (Risse et al., 2025, Woods, 2025). China's dominance in production, processing and smelting of materials critical to defence, renewable energy, electric vehicles, telecommunications and information technologies, combined with trade intervention escalation, creates substantial supply risks exposure and trade vulnerabilities.

## Methodological considerations

Trade interventions have not previously been incorporated into UK CA factors due to the complexity of analysing both their implementation and impact. Other assessments, such as the EU methodology (European Commission, 2023), have used frequency of embargoes, tariffs and quotas to calculate trade barrier scores, but these approaches often lack the commodity-specific detail needed for material level assessment.

A high-level assessment of total trade interventions imposed by each nation provides an indication of general willingness to trade but does not indicate whether this impacts the supply of specific commodities. For example, if a country has 100 trade interventions spread across diverse commodities, there is a lower supply risk impact than if the same 100 interventions were concentrated on one or a few commodities. Similarly, assessing the main suppliers of each commodity imported into the UK provides an overview of supply-chain concentration risks but does not indicate whether these suppliers are implementing trade barriers on that specific commodity.

Assessing both the implementing nation and the number of trade interventions imposed on each commodity therefore provides more detailed insight into current and potential future supply-chain risks. This commodity-specific, country-specific approach allows recent geopolitical developments to be incorporated into more robust CAs, differentiating between concentrated supply from reliable partners vs. concentrated supply from intervention-prone jurisdictions.

## Data source: Global Trade Alert database

The GTA database is an initiative of the St Gallen Endowment for Prosperity Through Trade, a non-profit organisation providing stakeholders with data and analysis to increase transparency of policies and interventions affecting the global economy, trade and investment. The organisation has produced a comprehensive database of unilateral government interventions and policies potentially impacting trade in goods and services, investment and labour migration since 2009 (Global Trade Alert, 2026). This is the most complete, robust and up-to-date dataset currently available for this purpose.

The GTA database does not cover bilateral or multilateral agreements or negotiations (Evenett and Fritz, 2020). The data is open access and free to download, requiring only free user registration to access larger database proportions. Each intervention record includes:

- implementing jurisdiction
- affected jurisdictions
- intervention type
- affected products (identified by six-digit HS codes)
- announcement date
- implementation date
- removal date (if applicable)
- classification (liberalising or harmful)

## Data processing methodology

To determine the feasibility of incorporating trade interventions into CA, a subset of the GTA database was downloaded covering interventions announced from the beginning of 2008 until 29 July 2025. Both harmful and liberalising interventions were included. Only interventions applicable to outward trade (exports) were selected, as interventions applicable to inward trade in other jurisdictions would not directly impact UK import access.

Data processing involved four filtering steps.

1. Temporal filtering: interventions not currently in force were removed. Only active interventions (announced and implemented but not yet removed) were retained, ensuring the dataset reflects current trade policy landscape rather than historical interventions no longer affecting markets.

2. Jurisdictional filtering: all interventions including the UK as an affected jurisdiction were retained. Additionally, interventions with ambiguous or blank affected jurisdiction fields were conservatively retained, as these may indicate interventions with global applicability. This conservative approach ensures potentially relevant interventions are not excluded through data quality issues.

3. Commodity filtering: products affected by trade interventions are indicated as six-digit HS codes in the GTA database. A compilation of all HS trade codes relating to UK CA candidate commodities (developed through the HS code expansion work described in Section 3) was used to identify impacted commodities and filter out interventions not relevant to this assessment. This linkage requires careful interpretation, as some materials are traded in both elemental and industrial mineral forms (for example, barium and barytes; phosphorus and phosphate), necessitating precise HS code matching to avoid double-counting.

4. Aggregation: for each country/commodity pair, the number of HS codes impacted by harmful trade interventions and liberalising trade interventions were counted separately, providing a quantitative indication of trade policy stance.

Data processing revealed practical challenges requiring careful handling. GTA records contain complex data structures with multiple affected jurisdictions or products listed in data fields, requiring data normalisation before analysis. Some records lack affected jurisdiction or information entirely (Evenett and Fritz, 2020). These were conservatively treated as globally applicable to avoid underrepresenting risk.

Search logic also required refinement. For example, element symbols such as Ga (gallium) may incorrectly match unrelated terms such as garnet; P (phosphorus) may match Pt (platinum) or Pd (palladium). This was mitigated by using comma-bounded search strings, to ensure only exact element matches were captured.

## TRADE INTERVENTION FACTOR CALCULATION

The TIF for each country/commodity pair was calculated as:

> TIF = (Number of HS codes affected by harmful interventions) - (number of HS codes affected by liberalising interventions)

This provides an indication of a country's net trade restrictiveness for a given commodity. Positive TIF values indicate harmful interventions outweigh liberalising ones (net protectionist stance), while negative values indicate liberalising interventions dominate (net trade-facilitating stance). Zero indicates either balanced intervention types or absence of interventions.

The TIF reflects commodity-specific trade policy rather than general trade orientation. A country may have a high TIF for strategic materials while maintaining a low TIF for other commodities, revealing targeted protectionism. Conversely, a country with generally high intervention counts may show a low commodity-specific TIF if interventions are broadly distributed rather than concentrated on CMs.

## Important note on interpretation

The TIF counts affected HS codes rather than individual interventions, as single interventions often affect multiple product codes. This approach better captures intervention scope: a single broad intervention affecting 100 HS codes has greater potential supply impact than 10 narrow interventions each affecting one code. However, the TIF should be normalised by the total number of HS codes tracked for each commodity to avoid bias toward commodities traded in more diverse forms (for example, iron has many HS codes covering different grades, forms and processing stages, potentially inflating raw TIF values).

## Results

### COUNTRY-LEVEL ANALYSIS

Country-level TIF analysis reveals substantial variation in trade intervention behaviour. The USA exhibits the highest TIF at 28 309, indicating extensive use of trade restrictions. China shows the second-highest TIF at 4223, substantially lower than the USA but still representing significant intervention activity.

Countries not shown in **Figure 8** have zero or negative TIF values. Negative TIF indicates that liberalising interventions affect more trade codes than harmful interventions, suggesting overall greater willingness to trade.

The dominance of the USA and China in TIF rankings reflects both their economic scale and their use of trade policy as geopolitical tool. Japan and Germany also emerge as substantial contributors to commodity-specific intervention factors, particularly for metals and alloys. This pattern suggests that major industrial economies, not just emerging markets or resource-dependent nations, actively employ trade interventions to protect or promote strategic industries.

### COMMODITY-LEVEL ANALYSIS

Commodity-level TIF analysis reveals that metals and elements have substantially higher intervention factors than industrial minerals. Iron exhibits the highest TIF at 27 973, followed by copper at 4410, which is a much lower magnitude despite copper's criticality. Among industrial minerals, diamond has the highest factor at 491, while salt has the lowest at -20 (indicating net liberalisation).

Many commodities with the highest TIFs are related to steel and other alloys, including chromium (1338), molybdenum (1478) and tungsten (1648). This pattern reflects the strategic importance of the steel industry to national defence and industrial capacity, making it a frequent target of protectionist measures. The concentration of interventions on alloy elements suggests countries are protecting integrated metal supply chains rather than isolated commodity flows.

Figure 9 and Figure 10 display the TIF for all candidate materials from the 2024 UK CA, separated into metals/elements and industrial minerals, respectively. These figures illustrate that intervention intensity varies dramatically across commodity types, with strategic metals facing substantially more trade policy attention than bulk industrial minerals.

### COUNTRY/COMMODITY INTERSECTION ANALYSIS

Analysing which countries contribute to each commodity's TIF is essential for determining trade intervention impacts on global supply and UK import security. A country producing a small proportion of global supply but with a large TIF has a lower impact on global supply risk than a country producing a high proportion of global supply with a large TIF. This intersection of production concentration and trade interventionism identifies critical vulnerabilities.

For example, the USA was the tenth-largest global iron producer in 2023 (Idoine et al., 2025) but accounts for approximately 77 per cent of total TIF attributed to iron. Although China was the top global REE producer in 2023 (Idoine et al., 2025), it accounts for only approximately 18 per cent of total REE TIF. This suggests that, for iron, trade intervention risk concentrates in a secondary producer with high protectionist tendencies, while for REE, the dominant producer shows relatively restrained intervention behaviour (though this may change as geopolitical pressures evolve and China continues the use of REEs as geopolitical leverage).

### Relationship to criticality scores

Commodities ranked with the highest criticality scores in the 2024 UK CA do not necessarily have the highest TIF values. Niobium has the highest criticality score (6.6) but a TIF of only 519 (ranking 30th). Cobalt and REEs have the next-highest criticality scores but TIF values of only 659 and 248, respectively (21st and 39th). This divergence suggests that global supply risks for the most critical commodities are already highly concentrated geographically, meaning even small numbers of trade interventions by top producers could have large impacts on global supply.

This finding underscores why the TIF must be considered at both country and commodity level, weighted by production share. A low absolute TIF may be highly consequential if concentrated among dominant producers, while a high absolute TIF may be less dramatic if distributed among minor producers. TIF should thus be applied as a modifier to existing TCIs, increasing risk where interventions coincide with production concentration.

### Implementation in criticality assessment

The recommended method for incorporating trade interventions into CA is to apply TIF as a weighting factor to the GTC indicator, which measures concentration of import sources. For each country supplying a commodity to the UK, its TIF value (normalised and scaled appropriately) would modify its contribution to the GTC score.

The weighting formula would take the form:

$$\text{Weighted GTC} = \Sigma(\text{market share\_i}^2 \times \text{TIF\_weight\_i})$$

Where *market share_i* is country *i*'s proportion of global exports and *TIF_weight_i* is a scaling function of that country's TIF value for the commodity. This approach increases the concentration penalty when supply comes from interventionist jurisdictions and reduces it when supply comes from liberalising partners, more accurately reflecting supply security risks.

The TIF weighting should be normalised relative to the observed distribution across commodities to maintain comparability. One approach is to convert TIF to a 1 to 10 scale based on percentile ranking within the commodity portfolio, then apply this as a multiplicative factor to each country's concentration contribution. Countries with very high TIF (top decile) would receive a weighting of over 1.5, amplifying their contribution to concentration risk, while countries with negative TIF (net liberalising) would receive a weighting of less than 1.0, reducing their contribution.

### Normalisation consideration

As mentioned earlier, the TIF should be divided by the total number of HS codes tracked for each commodity before comparison across commodities, as commodities traded in more diverse forms have more opportunities for intervention. Iron's high TIF partly reflects that it is traded under numerous HS codes (various grades, forms and processing stages), while REEs have fewer distinct trade codes.

The normalised metric would be:

Normalised TIF = raw TIF / (total HS codes tracked for commodity)

This normalisation enables fair comparison across commodities with different trade product diversity and ensures that differences in TIF values reflect policy intensity rather than coding complexity

### Future considerations and data quality

The dynamic nature of trade intervention data presents both challenges and opportunities. The data becomes historical as soon as it is downloaded, similar to other datasets used in CA. Interventions may be announced at any time and historical patterns are not necessarily reliable predictors of future interventions. However, historical data does provide an indication of which countries are most likely to impose interventions and against which commodities, enabling risk-adjusted assessment even if specific future interventions cannot be predicted.

For example, the extensive harmful trade interventions imposed by the USA affecting iron-related trade codes indicate future potential for escalation. The USA was the tenth-largest global iron producer in 2023 (Idoine et al., 2025), so these interventions have implications for future supply security. Conversely, Australia was the top global lithium producer in 2023 (Idoine et al., 2025) but has imposed harmful trade interventions against only 20 lithium-related trade codes, suggesting lower near-term intervention risk for this critical material from this major supplier.

### Update protocol requirements

Given the dynamic nature of both trade interventions and HS code classifications, regular updates are essential.

- Quarterly GTA downloads: trade policy can shift rapidly in response to geopolitical developments: quarterly downloads ensure assessment reflects the current intervention landscape, particularly during periods of heightened trade tensions
- HS code list maintenance: the WCO regularly creates new HS codes to respond to global tracking requirements and new product or technology emergence, so the commodity-to-HS code mapping must be reviewed and updated before each CA cycle to ensure all relevant product forms are captured
- Alert system: an automated flagging system should trigger timely expert review and potential updates, as well as identify:
    - significant changes
    - new interventions on high-priority commodities
    - removal of longstanding interventions
    - major TIF shifts for key supplier countries
- Integration with HS code expansion: the trade intervention analysis can be integrated with the ongoing HS code expansion effort (Section 3), avoiding duplication of effort. As new HS codes are identified and classified for material flow analysis, they can simultaneously be added to the trade intervention filtering criteria

### Data quality considerations

GTA database quality issues require careful handling. Some interventions lack clear affected jurisdiction data; some HS code classifications may be ambiguous, and some interventions are announced but never fully implemented or enforced. Enforcement stringency varies substantially across jurisdictions; some countries rigorously implement announced interventions while others maintain interventions on paper but apply them inconsistently. These factors introduce uncertainty that cannot be fully resolved through data analysis alone, requiring expert judgement for high-stakes commodities.

Additionally, the GTA database captures unilateral interventions but not bilateral or multilateral agreements, which can substantially offset or compound unilateral intervention effects. For example, free trade agreements may nullify harmful interventions for specific partners, while coordinated multilateral sanctions may amplify individual country interventions. Future refinements should explore integrating bilateral and multilateral agreement data where relevant to UK trade relationships.

# Appendix 4 Material flow

The 2024 UK CA tracked material flows across global markets and in and out of the UK using HS codes, a globally standardised numerical classification system used by customs authorities to classify traded products. Developed by the WCO, HS codes follow a hierarchical structure in which the first six digits are internationally consistent, with some countries extending classifications to eight- or ten-digit levels for finer product differentiation. This standardised system enables quantitative analysis of international trade flows, providing a robust empirical foundation for measuring UK import reliance, apparent consumption and global trade concentration.

## HS CODE APPLICATION IN CRITICALITY ASSESSMENT

HS codes were previously used to calculate three indicators in the 2024 UK CA:

- UK apparent consumption
- UK net import reliance
- global trade concentration

For each candidate material, a set of HS codes representing the upstream segment of the commodity's life cycle was selected and the element content in the traded form evaluated. The focus on upstream product forms, ores and concentrates, refined metals, simple chemical compounds and basic products was driven by limited assessment timeframes and by the greater accuracy achievable when estimating material content in these relatively pure forms.

Estimating the share of a material embedded in more advanced manufactured products becomes increasingly challenging in midstream and downstream value chain stages. Aggregated trade code descriptions introduce additional uncertainty, limiting the ability to assign meaningful proportions of target materials. The level of uncertainty and the methods employed to manage it depend on the nature of the aggregation and the availability of supporting market data.

### Challenges in material content estimation

Two examples illustrate the spectrum of difficulty in material content estimation.

#### MANAGEABLE AGGREGATION

HS code 850760 'Electric accumulators; lithium-ion, including separators, whether or not rectangular (including square)' encompasses multiple lithium battery chemistries (lithium-iron-phosphate (LFP); nickel-manganese-cobalt (NMC); lithium-nickel-cobalt-aluminium oxide, and lithium-ion manganese oxide). Phosphorus content can be estimated by applying the market share of LFP batteries within this code. Industry data and International Energy Agency battery deployment statistics provide reasonable market share estimates (about 30 per cent of lithium-ion batteries by capacity in 2022 to 2023), enabling proportional allocation of phosphorus content. The key enabler is that battery chemistry distributions are relatively well-documented through market research and energy transition tracking.

#### PROBLEMATIC AGGREGATION

HS code 850690 'Cells and batteries; primary, parts thereof' is too broad to permit meaningful material content estimation for many elements. This code encompasses diverse primary cell chemistries (zinc-carbon; alkaline; lithium primary; silver oxide, etc.) and unspecified battery components. For phosphorus estimation, the proportion attributable to LFP cathodes, $LiPF_6$ electrolyte salts used in various lithium batteries, or entirely phosphorus-free chemistries cannot be determined. The code aggregates complete batteries, cells and component parts, and spans both consumer products and industrial applications, making reliable estimation impossible without detailed data segmentation.

These examples demonstrate that successful midstream and downstream material content estimation requires:

- sufficient granularity in HS code descriptions to distinguish material-relevant product categories
- availability of market share or composition data for material-containing variants within aggregated codes
- reasonable stability in market structures over the time periods being analysed

Where these conditions are not met, conservative exclusion is preferable to speculative estimation that introduces substantial uncertainty into trade flow calculations.

### HS code expansion scope and scale

In total, 204 HS codes were initially assessed across the 84 candidate materials considered in the 2024 UK CA (Mudd et al., 2024). During the current review, a further 600+ HS codes were processed across 31 key commodities, expanding coverage into the midstream segment of value chains. This expansion more than triples the tracking capability, extending monitoring from predominantly upstream forms to include transformed products, intermediate manufactured goods and end-of-life material streams (both old scrap from post-consumer waste and new scrap from manufacturing processes).

The expanded HS code coverage better reflects the structure of UK supply chains and the position of candidate materials in global supply networks. It recognises the added value embedded in products and acknowledges that the UK economy is characterised by dominant downstream industries compared to limited upstream and midstream capacity globally. Understanding where materials enter UK value chains and in what form is essential for identifying where risks and dependencies concentrate.

REEs’ trade monitoring has been substantially expanded with the addition of both agglomerated REE codes (covering mixed REE products like didymium, mischmetal and REE alloys) and element-specific HS codes where individual lanthanides are separately classified in trade (particularly for high-value elements like dysprosium, europium and terbium, used in phosphors and magnets). This granularity provides a clearer understanding of REE supply-chain structure, revealing that some elements are predominantly traded in separated forms, while others circulate mainly as mixed compounds or alloys.

Table 3 lists the 31 elements for which HS code coverage has been expanded toward midstream stages. These were selected based on:

- strategic importance in the 2024 UK CA
- availability of sufficient market data to support material content estimation
- diversity of traded forms warranting expanded tracking
- UK industry reliance on midstream and downstream product imports rather than raw material imports

#### DEFINITIONAL AMBIGUITY IN VALUE CHAIN CLASSIFICATION

The application of standard value chain definitions (precursor; intermediate; component; end-product) to trade codes reveals that these categories are not always clearly delineated in chemical and metal supply chains. Product classification depends on application context rather than inherent product characteristics. The following two examples illustrate how this ambiguity affects interpretation in CA.

Sulphuric acid (HS 280700 'Sulphuric acid; oleum') can be classified as an end-product when used directly in industrial processes such as paper bleaching, ore leaching or wastewater treatment. However, it also serves as a chemical feedstock for further transformation in the production of fertilisers (phosphates; ammonium sulfate), detergents or other chemicals, in which contexts it functions as a precursor. The same HS code encompasses both applications and trade data does not distinguish between them. For material flow analysis, this means sulfuric acid imports could represent either final UK consumption (end-product use) or inputs to further UK chemical manufacturing (precursor use). Without supplementary data on sector specific consumption, precise classification becomes challenging.

The reported trade of nickel-metal hydride (NiMH) batteries under codeHS 850750 ('Electric accumulators; nickel-metal hydride, including separators, whether or not rectangular (including square)') can represent battery packs used as components in hybrid electric vehicles (automotive component) or rechargeable AA or AAA batteries sold directly to consumers (end-product). Vehicle manufacturers importing NiMH packs are acquiring components for further assembly, while retailers importing consumer NiMH batteries are acquiring finished products. The HS code does not differentiate between these distinct supply-chain positions. This matters for the CA of nickel because component-level imports are exposed to automotive sector-specific supply shocks, while consumer battery imports face different market dynamics.

This definitional ambiguity has implications for how HS code data is interpreted in CA. When a single code encompasses multiple value chain stages, analysts must choose from:

- using supplementary data to disaggregate imports by end-use sector
- making conservative assumptions about the value chain stage represented
- accepting classification ambiguity and focus on total material flow regardless of application

The appropriate approach depends on the specific analytical question being addressed and the availability of supplementary information.

### IMPLICATIONS FOR UK SUPPLY-CHAIN UNDERSTANDING

The expanded HS code dataset enables far more robust tracking of material flows within the advanced UK economy. By capturing midstream and downstream product imports, the dataset reveals where UK manufacturing obtains material inputs, as opposed to where raw materials are initially extracted or refined globally. This distinction is crucial for understanding UK-specific exposure and vulnerabilities.

For example, the UK may import minimal copper ore or concentrate (upstream) but substantial volumes of copper wire rod, copper sheet and copper tubes (midstream), plus manufactured components containing copper (downstream). Assessing the security of UK copper supply solely through upstream HS codes would dramatically underestimate actual copper flow volumes and misidentify the true geographical sources of the UK's copper supply. The expanded dataset corrects this by tracking the actual forms in which materials enter the UK economy.

The inclusion of waste and scrap codes (both old scrap from end-of-life products and new scrap from manufacturing processes) provides visibility in circular economy flows. For many materials, substantial quantities flow through international scrap markets, with scrap being exported for reprocessing, imported for recycling operations, or re-imported after being embodied in manufactured goods. Understanding these circular flows is essential for evaluating whether enhanced UK recycling infrastructure could substitute for primary material imports and for identifying where scrap export restrictions by other nations could affect the UK's access to secondary material sources.

IMPLEMENTATION AND MAINTENANCE REQUIREMENTS

The continuously expanding HS code dataset requires systematic maintenance to remain accurate and comprehensive. Several implementation challenges must be addressed.

### *HS code revision cycles*

The WCO updates HS nomenclature approximately every five years (major revisions in 2007, 2012, 2017 and 2022) with the next major revision expected in 2027. These revisions restructure code hierarchies, introduce new product categories, eliminate obsolete codes and re-assign products between codes. Material flow analysis must maintain concordance tables that map old codes to new codes to enable time-series analysis across revision cycles. When codes are restructured, historical trade data must be retroactively reclassified to current nomenclature to avoid artificial breaks in trend analysis.

### *New product emergence*

Technological change and market evolution create new product categories requiring new HS codes. Battery technology evolution provides clear examples: early HS codes did not distinguish between lithium-ion chemistries, but as LFP, NMC and other variants gained market share, more granular codes became necessary for trade policy purposes. Similarly, emerging technologies such as solid-state batteries, hydrogen fuel cells and advanced photovoltaic materials will require new codes as they achieve commercial scale. The HS code database must be reviewed regularly to identify newly created codes that are relevant to candidate materials, so that emerging supply-chain pathways are not overlooked.

### *Market share evolution*

Even when HS codes remain stable, the material content estimation models depend on market share assumptions that evolve over time. The 30 per cent LFP market share used for phosphorus estimation in lithium-ion battery codes reflects 2022 to 2023 market conditions; by 2025 to 2030, LFP may represent 40 to 50 per cent of the market as sodium-ion and other alternatives emerge. Material content estimation protocols must incorporate regular market share updates from industry sources, with transparent documentation of assumptions, data sources and uncertainty ranges.

### *Coordination with trade intervention monitoring*

The expanded HS code database serves dual purposes: material flow quantification for CA and trade intervention tracking (Section 4). Maintaining a unified commodity-to-HS-code mapping that serves both purposes avoids duplication of effort and ensures consistency. When new codes are added for material flow tracking, they should simultaneously be incorporated into trade intervention filtering criteria (and vice versa) ensuring that both analytical streams remain aligned.

### *Material content estimation protocol documentation*

Each HS code in the database should be accompanied by documentation specifying:

- material content estimation method used:
    - stoichiometric calculation
    - market share allocation
    - engineering specification
    - industry survey
    - expert estimate
- data sources supporting the estimate:
    - academic literature
    - industry reports
    - manufacturer specifications
    - trade association data
- uncertainty range or confidence level
- date of last review

This documentation enables future analysts to understand estimation basis, identify where updates are needed, and evaluate whether uncertainty levels are acceptable for specific analytical purposes. Clear documentation is essential for reproducibility and long-term methodological integrity.

#### ***Quality assurance through multiple estimation methods***

Where feasible, material content estimates should be cross-validated using independent methods. For example, lithium content in battery codes can be estimated through:

- battery chemistry market share allocation
- energy density specifications and lithium requirements per kWh
- vehicle production data and average battery size
- manufacturer-reported battery composition data

When multiple methods yield consistent estimates, confidence increases; when methods diverge significantly, this flags the need for more detailed investigation or conservative uncertainty bounds. This multi-method approach strengthens the reliability of material flow calculations.

Figure 7 displays the total trade code record count for commodities investigated in this project, illustrating the variable density of HS code coverage across materials. Some commodities (iron; copper; aluminium) have extensive HS code lists covering numerous product forms, grades and applications, while others (REEs; minor metals) have relatively few codes reflecting limited product diversity or market aggregation in trade classifications. This variation in code density has implications for trade intervention analysis (Section 4), where TIF normalisation by code count is necessary to ensure fair comparison across commodities.

### STRATEGIC VALUE BEYOND CRITICALITY ASSESSMENT

The expanded HS code database constitutes significant analytical infrastructure with applications extending well beyond criticality scoring.

#### ***Customs intelligence***

Detailed material content estimates enable customs authorities to improve tariff classification guidance, detect potential misdeclaration or smuggling (where declared values deviate substantially from expected material content values) and identify circumvention attempts where traders shift products between similar HS codes to avoid tariffs or restrictions. This enhances compliance, enforcement and risk profiling.

### *Trade negotiations*

Understanding which HS codes carry significant CRM content enables targeted discussions in bilateral and multilateral trade negotiations. Rather than generic materials access provisions, negotiators can identify specific product codes where tariff reductions, rules of origin relaxation, or non-tariff barrier elimination would most directly impact CRM security.

### *Circular economy policy*

Waste and scrap code expansion provides an empirical foundation for circular economy initiatives. The data reveals:

- where the UK exports scrap for reprocessing abroad, indicating potential for domestic recycling infrastructure investment
- where the UK imports processed scrap, identifying foreign dependencies in circular supply chains
- which materials show high recovery rates vs. losses to landfill or irretrievable dispersion

This supports evidence-based design of recycling and secondary material strategies.

### *Industrial strategy*

Midstream product import patterns reveal where UK manufacturing relies on foreign intermediate goods rather than domestic processing capacity. This informs industrial strategy decisions about whether to incentivise domestic processing capacity development, whether certain midstream activities are economically viable in the UK, and where UK manufacturing occupies competitive positions in global value chains.

### *Supply-chain resilience mapping*

Combined with the ONS input/output analysis (Section 2), HS code data enables identification of which imported product forms supply which UK industrial sectors. This reveals sector-specific supply vulnerabilities; for example, the automotive sector relies heavily on specific battery component codes supplied predominantly from single countries, which highlights a targeted resilience-building opportunity.

# Appendix 5 Environmental, social and governance

ESG factors are increasingly central to global trade and supply-chain resilience (Runyon, 2024), making them a growing focus for CAs (Josso et al., 2023) given their potential to significantly affect supply security and sustainability. However, ESG factors are rarely assessed comprehensively or systematically in criticality methodologies. Most assessments incorporate ESG in a basic and limited manner, typically applying governance indices such as WGI as weighting factors for supply risk indicators like production or trade concentration (Josso et al., 2023).

The 2024 UK CA is among the most comprehensive in terms of ESG integration for calculating supply risk (Mudd et al., 2024). This work reviews how ESG factors are currently incorporated into CA methodologies and examines alternative datasets and methods that could strengthen and refine the ESG indicator. A central focus is the feasibility of integrating company-level or commodity-level ESG data, as well as the broader challenges associated with embedding ESG factors into criticality methodologies.

## ESG AND SUPPLY-CHAIN RESILIENCE

Mines, processing facilities and refineries are all subject to ESG risks. If these risks are not effectively managed, they can adversely disrupt CM supply. CM supply chains therefore cannot be considered secure, reliable or resilient unless they are also sustainable, socially responsible and well governed (International Energy Agency, 2024, International Energy Agency, 2025).

ESG risks include

- armed conflict
- biodiversity loss
- bribery and corruption
- emissions ($CO_2$ and others)
- geopolitical tensions
- human rights violations
- water stress

If poorly managed, these risks may (International Energy Agency, 2025):

- create legal barriers
- damage reputations
- discourage investment
- drive operational disruptions and costs
- increase community opposition
- restrict market access
- spur litigation

By contrast, effective ESG implementation reduces these risks and strengthens operational performance and long-term supply stability (Royer, 2024, Horn et al., 2025).

Integrating ESG into the supply risk dimension of CA is essential, as ESG risks can directly disrupt production, constrain market access and amplify geopolitical and operational risks. Including ESG factors provides a more realistic and comprehensive reflection of real-world vulnerabilities.

## CURRENT METHODOLOGY: 2024 UK CRITICALITY ASSESSMENT

For the 2024 UK CA, ESG was incorporated within the Production Concentration Indicator (PCI. Each country's market share was squared and multiplied by a scaled (1 to 10) ESG factor that incorporated risk in countries with lower standards, such as poor governance, civil unrest or elevated pollution.

The ESG indicator is based on the geometric mean of three global indices (Mudd et al., 2024):

- EPI: from Yale University (Block et al., 2024)
- HDI: from United Nations Development Programme (Conceição et al., 2022)
- WGI: from the World Bank (World Bank, 2024)

This three-factor geometric mean provides a balanced and multidimensional representation across ESG pillars. Lower ESG scores amplify the supply risk contribution of countries with poor ESG performance.

## REVIEW OF INTERNATIONAL METHODOLOGIES

An increasing number of national CAs are being undertaken with evolving methodologies. This section examines the extent and method of ESG integration in published assessments (Deberdt et al., 2025).

Across published national CAs, approaches to ESG integration cluster into three patterns. Some systems do not include ESG as a dedicated input; South Africa is one example that does not incorporate explicit ESG aspects (Department of Mineral and Petroleum Resources, 2025). Many others incorporate ESG considerations indirectly rather than through standalone indicators. This includes Australia, where ESG-type issues appear within general vulnerability-to-disruption constructs; Canada, which follows the EU approach embedding governance while emphasising sustainable supply in strategy language, and the USA, where earlier work captured governance via the Fraser Institute's policy perception index within the Alternate Supply Indicator rather than as full ESG dimension (Nassar and Fortier, 2021a, Government of Canada, 2022, Natural Resources Canada, 2024, Geoscience Australia, 2025, Nassar et al., 2025a).

A smaller group directly embeds governance or broader ESG within supply risk calculations: the EU incorporates governance by using WGIs within ‘supply risk’ and Germany applies governance-weighted concentration measures (‘weighted country risk’) across mining output, refinery output and net exports (Blengini et al., 2017, DERA, 2023, DG GROW, 2023).

The World Materials Forum (WMF) CA methodology ((BRGM et al., 2021) incorporates eight key performance indicators (KPIs), including an environmental performance KPI, with a social acceptance KPI added in 2024 (Poinssot, 2024). The environmental performance KPI consists of six components combining quantitative and qualitative indicators primarily drawn from the 2021 OekoRess II programme. Equal weight is assigned to each indicator, with the final environmental score calculated by averaging components. The social acceptance KPI rates countries on human rights and environmental protection using the Yale Environmental Performance Index as a proxy.

**Table 3** Summary of the indicators used in the World Materials Forum, environmental performance KPI. Adapted from (BRGM et al., 2021).

| | KPI | Assessment type | Criteria | Score |
|---|---|---|---|---|
| 1 | Pre-conditions for acid mine drainage (AMD) | Qualitative | Geochemical preconditions for AMD do not exist | 1 |
| | | | Geochemical preconditions for AMD exist in part | 2 |
| | | | Geochemical preconditions for AMD exist | 3 |
| 2 | Mining method | Qualitative | Mostly extracted in underground mines or low-energy intensity | 1 |
| | | | Mostly extracted from open pit mines or medium-energy intensity | 2 |
| | | | Mostly extracted from alluvial or unconsolidated sediments; high energy | 3 |
| 3 | Use of auxiliary substances | Qualitative | Extraction and processing methods with low use of auxiliary chemicals | 1 |
| | | | Extraction and processing methods using auxiliary chemicals | 2 |
| | | | Extraction and processing methods using toxic reagents | 3 |
| 4 | Environmental governance | Quantitative | < 25% quantile of EPI for 180 countries | 1 |
| | | | 25% and 75% quantile of EPI for 180 countries | 2 |
| | | | > 75% quantile of EPI for 180 countries | 3 |
| 5 | Size of energy flow | Quantitative | < 25% quantile of 52 raw materials with available data | 1 |
| | | | 25% and 75% quantile of 52 raw materials with available data | 2 |
| | | | > 75% quantile of 52 raw materials with available data | 3 |
| 6 | Water stress index | Quantitative | < 25% quantile of 42 raw materials with available data | 1 |
| | | | 25% and 75% quantile of 42 raw materials with available data | 2 |
| | | | > 75% quantile of 42 raw materials with available data | 3 |

The WMF method remains one of the most comprehensive uses of ESG found in CA, though from a different perspective (non-national vs. national) and with environmental and social assessment applied as standalone indicators rather than weightings applied to supply indicators.

Current CA methodologies vary in ESG incorporation. In most cases, ESG is not included as direct or comprehensive component; instead, it is often captured indirectly through governance-focused proxies such as the WGI, providing only a partial view of ESG risks. This highlights the need for more multi-dimensional indicators that capture environmental and social dimensions alongside governance.

## Dataset reviews

### EVALUATION CRITERIA

The following criteria were considered when evaluating potential datasets and methods for future UK CA:

- accessibility: usable formats with clear licensing and reasonable fees; methods must be transparent and replicable as public-science body requirement
- compatibility: new methods or datasets must be compatible with wider CA methodology and feasible within available resources
- ESG coverage: metrics relevant to CM mining and supply chains
- geographical scope: coverage of all relevant producer countries and regions
- resolution: data at the appropriate level (commodity, company or country)
- source credibility: reliable and transparent sources
- temporal resolution: frequent updates reflecting current conditions

If new data is incorporated or methods are changed, it is essential that the changes add value. A simpler and more transparent approach may be preferable, reducing the risk of inherited errors and uncertainty. Any changes should deliver meaningful improvement to the ESG indicator, sufficient to justify the additional effort required.

### COMMERCIAL ESG DATASETS

Commercial ESG datasets generally score highly on credibility and geographical scope, with many offering regular updates. They include well-established corporate or sectoral providers (MSCI; Sustainalytics; LSEG; S&P Global) as well as country and commodity risk services (Maplecroft) and cross-sector risk tools (Sedex). Most products are designed for corporate- or sector-level benchmarking rather than country- or commodity-level analysis. Mining-focused datasets can provide project- or asset-level insights better aligned with CMs (Digbee), but coverage remains limited.

Commercial datasets require paid licenses and platform access, with redistribution often restricted. While cost is not prohibitive in principle, these were not pursued for detailed investigation or integration due to:

- availability of open datasets providing sufficient country-level coverage and timeliness
- greater methodological transparency and replicability achievable with open sources
- licensing costs and usage constraints

### VOLUNTARY STANDARDS

Voluntary and industry standards were considered for potential integration, including:

- Towards Sustainable Mining (TSM)
- International Council on Mining and Metals (ICMM)
- Mining Principles
- IRMA
- Extractive Industries Transparency Initiative (EITI)

TSM is an industry programme focusing on responsible mining practices across environmental stewardship, community engagement and safety. It offers detailed protocols and third-party verification, providing strong ESG coverage for operational practices. However, geographical scope is limited to member jurisdictions and companies, with performance data not consistently public, which reduces replicability.

ICMM's principles set global benchmarks for responsible mining, covering governance, environmental performance and social responsibility. They align well with ESG coverage and source credibility, with international recognition. However, coverage is limited to ICMM member companies representing a fraction of global operations, with site-level performance data often proprietary.

IRMA provides a comprehensive, multi-stakeholder standard with independent audits, addressing ESG issues in detail. It strongly meets ESG coverage and credibility requirements, with audit processes offering higher assurance than self-reporting schemes. However, geographical scope and granularity are limited because only small numbers of mines have achieved certification, with framework complexity challenging the ease of integration.

EITI focuses on governance and transparency in revenue flows and contracts, contributing to social and governance coverage while meeting source credibility requirements. It has broad geographical scope (over 50 countries), but coverage is narrow compared to the full range of ESG factors, with accessibility of country-level reports being good.

Overall, these standards are credible and valuable but lack scale and uniformity for primary use as an ESG indicator. They are more suitable as secondary modifiers or qualitative flags.

### OPEN GLOBAL DATASETS

Several global indices and analytical tools were evaluated, providing country-level or thematic data relevant to ESG factors. While none are specific to mining or CMs or offer asset-level resolution, they provide credible metrics.

Environmental datasets reviewed include:

- WRI Aqueduct Global Water Risk Atlas (World Resources Institute, 2025), providing global water risk assessments including:
  - baseline water stress
  - flood risk
  - scarcity
  - water quality
- WULCA AWARE, offering characterisation factors quantifying regional freshwater scarcity for life cycle assessment

- Climate Change Performance Index (CCPI), measuring country climate-mitigation performance across:
    - climate policy
    - emissions
    - energy use
    - renewables

Social datasets include:

- Social Progress Index, measuring health, education, safety, opportunity, and rights reflecting societal well-being beyond economic metrics (Social Progress Imperative, 2025)
- Fragile States Index, evaluating state fragility across cohesion, economic, political and social indicators

Governance datasets include:

- World Justice Project Rule of Law Index (World Justice Project, 2025), benchmarking constraints on:
    - civil justice
    - corruption
    - government powers
    - open government
    - order and security
    - regulatory enforcement
    - rights
- Resource Governance Index (NRGI, 2025), assessing in resource sectors:
    - accountability
    - governance effectiveness
    - transparency

Collectively, these datasets offer strong ESG coverage at the country level, with high credibility, broad geographical scope and generally good accessibility and update cadence. Inclusion could enhance assessment of systemic climate, water, social and governance risks in producing countries, though many ESG factors overlap with current indicators (WGI; EPI; HDI).

## CHALLENGES WITH ESG DATA

Few studies examine ESG ratings within the mining industry (Jin, 2023, Fikru et al., 2024, Fu et al., 2024), with existing studies tending to focus on financial or market performance. Overall, ESG research in mining and extractive industries remains limited compared to other manufacturing sectors. Variation in ESG methodologies and inconsistency in underlying data creates uncertainty for stakeholders, highlighting the need for more comprehensive and harmonised approaches (Fikru et al., 2024).

Climate change impacts on supply chains are often overlooked. Increasing frequency of natural hazards and extreme weather events introduces significant risk affecting extraction, processing and transportation. For instance, the 2022 drought in China's Yunnan Province severely reduced hydropower availability, forcing a 90 per cent reduction in metallurgical silicon production for several months (Deberdt et al., 2025).

Most datasets focus on large-scale mining, excluding artisanal and small-scale mining. There is heavy reliance on self-reported information, raising greenwashing risks. Recycling-source supply chains are underreported. ESG ratings often suffer from temporal lag, missing real-time events or rapid policy changes, which limits value for dynamic supply-chain risk assessment.

One aim of this study was to evaluate the incorporation of commodity- or company-level data in the ESG indicator. Commodity-level data highlights specific ESG risks associated with individual commodities (cobalt; lithium; nickel), enabling differentiation by mining methods and sourcing risks. This granularity allows tailored ESG assessments. However, ESG data at the commodity level is still emerging, lacks standardisation and is often sparse, particularly for minor metals. Aggregating data across supply chains is difficult when its origin is unclear or material from multiple sources is mixed.

Company-level ESG data typically covers emissions, labour practices, governance and community engagement. While granular, producer-level tracking is attractive, practical challenges remain: high variability in disclosure quality, incident-driven score volatility and aggregation at company level may obscure mineral- or region-specific performance. Units, methodologies and scope often vary even within the same report (International Energy Agency, 2024).

Country-level ESG data evaluates broader governance, environmental policy and social conditions of mineral-producing nations. Advantages include overview of risk context, near-global coverage and alignment with the scale at which the supply risk indicator is assessed. Using regional datasets would require detailed information on production shares within each region of a country. Limitations include lack of specificity and potential over-generalisation, given intra-country variations across commodities and companies.

## ALTERNATIVE METHODOLOGIES TO CONSIDER

Several methodological approaches were reviewed but are not proposed for near-term incorporation as they do not sufficiently meet combined requirements. They remain of interest for future research.

WMF-style KPI assessment provides comprehensive ESG assessments via multi-component KPIs across environmental and social dimensions. However, it functions as a standalone indicator rather than an ESG modifier integrated into supply-risk concentration. Adopting this approach would require substantial restructuring and added scoring complexity.

A standards adoption modifier would assign scores to countries related to standards (TSM; EITI, etc.) as an additional or modifying metric to the ESG indicator. While standards and assurance schemes can signal improved practices, coverage is uneven, adoption is partial, and site-level data is not consistently available. Certification alone does not guarantee improved performance and incorporating multiple schemes adds complexity without significant methodology benefit.

GIS integration for subnational assessment involves intersecting mine and refinery locations with subnational ESG-related datasets (basin-level water stress) to calculate asset-level exposure scores, then aggregating by production weights to country or commodity level. However, comprehensive, replicable asset-location datasets and subnational production weights are not available at scale and adding multiple spatial layers would increase complexity. Spatial overlays are better suited to pilot studies rather than broad incorporation into the next UK CA.

The World Bank Sovereign ESG dataset composite ESG pillars indicator, constructed from the World Bank Sovereign ESG data portal, was explored as an evolution of the current ESG modifier. Several underlying datasets were insufficiently comprehensive with issues including outdated, uneven geographical coverage. As a result, this approach is not proposed for further development at this stage but it remains documented due to future potential, should data coverage and timeliness improve.

## INCORPORATING CLIMATE CHANGE VULNERABILITY

Climate change is an increasingly important driver of disruption and responsibility risk in CM supply chains. Acute and chronic hazards (such as droughts, floods, storms, heat and sea-level rise) curtail mine and plant uptime, constrain water and power availability, interrupt logistics and translate into capacity losses, delays and market tightness (Ramdoo, 2022, United Nations Environment Programme, 2024).

Real-world effects are visible across supply chains. In 2023, drought severely reduced the Panama Canal’s capacity, resulting in multi-week queues (Tandon, 2024). In producing regions, extreme rainfall in Minas Gerais, Brazil, prompted temporary mine and rail shutdowns across major iron-ore operations (Kirch and Yep, 2022). Chronic water stress in arid copper districts has forced costly adaptations (desalination; long-distance pumping) and sharpened community-water conflicts (United Nations Environment Programme, 2024).

Because climate hazards directly affect both availability (uptime; throughput; logistics) and responsibility (water governance; safety; community impacts), a transparent, forward-looking, climate vulnerability dimension should be incorporated into CAs. This would complement existing indicators and better reflect real-world supply risk.

We propose incorporating climate risk using the ND-GAIN country index composite score, which is a free, open-source, country-level index designed to assess how climate change affects a national system’s ability to deliver economic and social functions (University of Notre Dame, 2025). ND-GAIN conceptualises climate risk as interaction between vulnerability and readiness.

- Vulnerability reflects a country's exposure and sensitivity to climate hazards and its adaptive capacity. Several exposure indicators incorporate mid-century climate projections, providing an embedded, forward-looking dimension. This factor spans six sectors:
  - ecosystem services
  - food
  - health
  - human habitat
  - infrastructure
  - water
- Readiness captures ESG conditions that enable countries to mobilise investment and translate adaptive capacity into action

ND-GAIN combines vulnerability and readiness into a composite score ranging from 0 to 100 (higher is better), offering a policy-relevant measure of climate risk reflecting both future hazard pressure and present adaptive capacity. This is conceptually distinct from EPI, HDI, and WGI:

- EPI measures environmental outcomes
- HDI summarises development status
- WGI captures institutional quality
- ND-GAIN uniquely focuses on climate-driven system stress and adaptive readiness, making it complementary rather than duplicative

## Implementation method

We retain the existing structure and add a fourth CCV indicator to the ESG indicator calculation, derived from the ND-GAIN composite score.

1. Data ingestion: use the latest ND-GAIN composite scores for all producing countries (series currently available through 2023).

2. Direction and scaling: ND-GAIN composite ranges from 0 to 100, with higher values indicating lower vulnerability and higher readiness. No inversion is required: re-scale across producer-country and set to the 1 to 10 range used in the CA.

3. Composite ESG with climate: replace the three-factor geometric mean with a four-factor geometric mean, incorporating the CCV indicator:

$$\text{ESG-C}i = \sqrt[4]{(\text{EPI}(i) \times \text{HDI}(i) \times \text{WGI}(i) \times \text{CCV}(i))}$$

4. Application to PCI: apply ESG-Ci within PCI.

Incorporating climate-change vulnerability via the ND-GAIN composite as a fourth factor in the ESG modifier is recommended. It explicitly links climate risk to supply reliability and responsibility, is open and globally comprehensive, and is fully compatible with our existing CA methodology.

# Appendix 6 Corporate concentration

CAs have historically relied on country-level mineral production statistics to quantify global production concentration as a key aspect of supply risk (European Commission, 2023, Mudd et al., 2024, Nassar et al., 2025b). However, country-level statistics can mask the influence that individual companies exert on CRM supply at various value-chain stages (Ericsson et al., 2024a, Andrieu et al., 2025). Corporate concentration (CC) is explored here to refine how market diversity in the mining sector is assessed and to understand how it impacts supply risk beyond country-level measures. Two case studies illustrate the distinction CC provides.

Niobium is geographically concentrated, with over 80 per cent of global supply from Brazil (Mudd et al., 2024). It faces extreme CC, with a single company (CBMM) responsible for extraction. Conversely, cobalt is similarly geographically concentrated in the Democratic Republic of the Congo (DRC) but exhibits much lower CC, as multiple mining companies are responsible for extraction (Ericsson et al., 2024a). This reduces disruption risk related to company structure.

Where mineral production occurs in emerging economies, ownership often remains concentrated in higher-income nations (Ericsson et al., 2024b, Andrieu et al., 2025). Complex corporate ownership structures involving cross-border ownership, joint ventures and offtake agreements can concentrate upstream supply control and market power. Several Chinese lithium refiners (for example, Ganfeng) and battery makers (for example, CATL) have invested in lithium mines globally to ensure secure feedstock (Prina Cerai, 2024), demonstrating how corporate strategy shapes supply access.

## DATA SOURCES AND LIMITATIONS

Several datasets were assessed for suitability:

- Argus
- Digbee
- Jasansky et al. (2023)
- Market Atlas
- MDO
- S&P Capital IQ Pro
- Statista
- Wood Mackenzie

All platforms exhibit limitations, including:

- high costs
- limited coverage (often only publicly listed companies)
- limited temporal coverage
- missing or unclear production information
- poor coverage of minor and by-product metals (antimony; cadmium; gallium; germanium; REEs; tellurium)
- restricted access

Two recurring constraints were identified:

- incomplete mine- or company-level production time-series
- poor coverage of minor and by-product metals

As of January 2024, S&P Capital IQ Pro reportedly includes production information for 7750 operating mines (Andrieu et al., 2026) compared with 1456 in MDO, though these figures are not directly comparable due to differences in definitions and scope. A satellite-based comparison (Maus and Werner, 2024) suggests approximately 56 per cent of mines identifiable from imagery lack production information in S&P Capital IQ Pro, highlighting that even comprehensive platforms capture only a fraction of global mining activities. Within a fixed license budget, MDO represented the best value-for-purpose option for this study.

MDO dataset coverage was evaluated for 61 of the 82 candidate materials from the 2024 UK CA. Country-level production coverage was quantified by comparing MDO mine or company production against BGS World Mineral Statistics' country totals for a subset of materials:

- aluminium
- antimony
- beryllium
- bismuth
- borate
- boron
- cadmium
- caesium
- cobalt
- copper
- gallium
- gold
- iron
- lead
- lithium
- molybdenum
- nickel
- silver
- zinc
- zirconium

This cross-validation revealed coverage averaging only 36 per cent of BGS country-level data. Major discrepancies appear driven by lack of data for Chinese companies and omission of companies in Japan, Myanmar, North Korea and Russia. Coverage for by-product metals is particularly poor, with no data for bismuth, cadmium, caesium, gallium or indium. Despite these shortcomings, MDO was used to test several options for calculating CC factors and evaluate validity for future prospects.

## THREE APPROACHES TO CORPORATE CONCENTRATION

### Single point of failure

The SPoF concept, used by the USGS (Nassar and Fortier, 2021b), identifies commodities for which a single domestic supplier dominates production or processing such that disruption could endanger national supply. The approach is simple and qualitative, capturing corporate-level failures (insolvency; sanctions; strategic withdrawal) with immediate supply impact even where country-level capacity is sufficient.

For the UK with its limited upstream mineral production (Mudd et al., 2024), genuine domestic single producers are largely absent. However, this could change, with the Hemerdon tungsten mine in Devon operated by Tungsten West as one example (AMC Consultants, 2025).

The SPoF approach can be adapted to identify international single-company chokepoints, such as CBMM supplying significant proportions of global niobium (Gómez et al., 2024) or Molymet producing about 70 per cent of global rhenium (Molymet, 2023). The approach could extend further down supply chains to evaluate failure points at various transformation stages, though no dataset captures such detail holistically.

Limitations for international application include:

- applicability to only a small number of candidate materials internationally
- challenge of assessing the control of private- or state-owned companies on supply due to lack of production information
- qualitative nature making numerical incorporation into CA difficult

## Production concentration

The most direct approach is to capture CC using the Herfindahl-Hirschman Index (HHI) based on production-weighted shares of individual companies. This measures mine production concentration across corporate owners and has been successfully applied in previous studies including for cobalt (Ericsson et al., 2024a). The advantage is integration of both ownership structure and production volumes of each asset, which complements country-level concentration by providing higher-resolution insight, since companies ultimately control mining output and supply decisions (Ericsson et al., 2024a). The main limitation is the requirement for detailed production statistics for each asset, which is challenging to access for private- or state-owned assets.

HHI approaching zero indicates a market occupied by many equally small companies; a maximum of 10 000 indicates a monopoly controlled by a single company. Current guidelines indicate HHI values over 1500 as ‘moderately concentrated’ and over 2500 as ‘highly concentrated’ (Competition & Markets Authority, 2024).

Conventional HHI uses company market share; we use production output of assets (mines) owned by each company. Mine production is attributed to indirect owners meeting a majority ownership threshold of at least 50.1 per cent. Where assets are jointly owned with no majority shareholder, production is divided equally among owners.

As proof of concept, production-weighted HHI was determined for copper in Peru during 2018 to 2022. Comparison of MDO and BGS World Mineral Statistics indicates that MDO captures approximately 94 per cent of Peruvian copper output (Idoine et al., 2025). The calculated production-weighted HHI for Peruvian copper is 1086, indicating an unconcentrated and relatively diverse corporate structure.

The production-weighted approach is limited by data availability, as reliable asset-level production statistics are often missing for private- or state-owned companies. While production-weighted HHI is the preferred measure, another proxy is required to address data availability issues.

## Diversity factor

This factor assesses market diversity by quantifying both the number of assets (mines) associated with each candidate material and the number of companies owning those assets. Using HHI on an ownership-by-asset basis, where each asset is weighted equally, provides a simple and quantitative measure of diversity. This approach does not require asset-level production data, which is often unavailable. The main limitation is weighting each mine equally, ignoring production volume, meaning a corporation controlling a few, very large mines can appear less important than a firm controlling many very small mines.

Two HHI variants were calculated:

- direct-ownership HHI assigns each mine to its direct owner (the operating entity in MDO)
- indirect-ownership HHI assigns each mine to its ultimate controlling parent (the company holding 50.1 per cent or more shares in the direct owner)

Where no shareholder owns 50.1 per cent or more of the direct company, the asset is excluded from the HHI calculation. All direct owners hold majority shares, resulting in no data loss for direct-ownership HHI; however, an indirect-ownership approach results in a 3 to 10 per cent dataset reduction depending on commodity (copper: 3 per cent; cobalt: 5 per cent; zinc: 6 per cent; lithium: 10 per cent).

**Table 4** Calculated diversity factor using HHI. Data acquired from MDO database in September 2025.

| Scale | Ownership | Cobalt | Copper | Lithium | Zinc |
|---|---|---:|---:|---:|---:|
| Global | Direct owners | 664 | 52 | 242 | 97 |
| | Indirect owners | 1111 | 167 | 567 | 257 |

As proof of concept, the HHI was determined for cobalt, copper, lithium and zinc under both direct and indirect ownership.

**Table 4** shows copper is most diverse with the lowest HHI values, while cobalt is least diverse with the highest HHI values. Generally, HHI values are higher with indirect ownership, indicating a small number of large diversified companies (Glencore; Rio Tinto) investing in assets vs. larger numbers of smaller- or medium-sized companies operating assets.

| Scale | Ownership | Cobalt | Copper | Lithium | Zinc |
|---|---|---|---|---|---|
| Global | Direct owners | 664 | 52 | 242 | 97 |
| | Indirect owners | 1111 | 167 | 567 | 257 |

Because HHI values were not calculated for all commodities, it remains unclear whether an HHI of 1111 (cobalt, indirect owners) reflects low or high diversity relative to the full range of commodities. However, these calculations demonstrate HHI can be applied to asset ownership and used to calculate a diversity factor.

Applying this factor to future UK CA would require calculating diversity metrics for the top three producing countries per commodity, rather than globally. Country-level production concentration could then be adjusted by multiplying by country-specific diversity factors. High diversity (low HHI) would reduce production concentration impact; low diversity (high HHI) would increase it. Normalisation and scaling would facilitate incorporation.

## CRITICAL CHALLENGES

### Coverage issues

The MDO database provides generally good coverage for 61 of the 82 candidate materials but data coverage is typically poor (averaging 36 per cent). For example, MDO silver production data for China represents only 10 per cent of BGS country totals. Given China's, Russia's and Japan's dominant roles in global mineral supply chains, the absence of data for these countries represents a major limitation.

Coverage of co- or by-products (antimony; bismuth; cadmium; caesium; gallium; indium; niobium; vanadium) is virtually absent. These commodities are valorised at later supply-chain stages by different industrial actors independently of mining decisions, resulting in poor capture by MDO. For antimony, only two assets are listed (Costerfield in Australia and Vares in Bosnia and Herzegovina), with only one providing production data. China and Russia, two of the top three antimony producers, are absent from MDO for this metal.

Coverage for industrial minerals and bulk commodities of lower economic value typically traded domestically (barytes; bentonite; silica; limestone) is also poor due to low interest from international monitoring platforms.

### Terminology ambiguity

The terminology used in MDO to describe production statistics can be ambiguous, increasing uncertainty in calculations. A key issue is that MDO sometimes reports refined output (copper cathode) rather than mined ore or concentrates, the standard basis for mine-production statistics. This reduces comparability with mine-level datasets (Idoine et al., 2024).

El Abra, Chile, an open-pit mine with an on-site solvent-extraction electrowinning plant (Freeport-McMoRan, 2023), reports copper cathode production, but mined copper is not separately captured. Similarly, copper production at El Teniente, also in Chile, is reported as 'metal' without disclosing whether this refers to concentrate, smelted metal or refined metal. These inconsistencies likely explain MDO's reduced coverage for Chile, which accounts for approximately 53 per cent of world mine-production statistics (Idoine et al., 2024).

## Private and state enterprises

Public companies are legally required to make ongoing disclosures under Financial Conduct Authority rules (or equivalent frameworks), including audited reports, market announcements and major shareholder notifications. Data availability for listed companies is generally greater than for private or state-owned firms. Private companies have fewer disclosure requirements, only filing accounts at Companies House (or similar), and are not required to publish production volumes.

In the USA, the majority of businesses are privately owned (Hodge et al., 2022) and are not required to report to FCA equivalents, making data access highly challenging. State-owned enterprises are typically not required to disclose production statistics.

Approximately 27 per cent of global mineral and metal production is from state-owned enterprises, with Chinese state-owned companies accounting for an estimated 17 per cent of global output (Hodge et al., 2022). Private or state-owned companies can be dominant suppliers. CBMM, a privately owned mining and refining company in Brazil, supplies over 80 per cent of global niobium yet it does not publish production figures and is absent from MDO (Gómez et al., 2024). Private and state-owned companies affect production dataset completeness, likely being the leading cause of lack of coverage for countries such as China and key players such as CBMM.

## Corporate ownership complexity

Corporate ownership structures add complexity to production concentration analysis. While companies fall into three basic categories — public; private; state-owned — structures may mix public and state-owned or private and state-owned. Parent/subsidiary relationships can obscure true control.

- DeBeers Group appears as the indirect owner of South Africa's Venetia mine on MDO but is itself a subsidiary of Anglo American, meaning Anglo American ultimately influences governance, budget and strategic alignment (Anglo American, 2024)
- At Broken Hill, Australia, operator Perilya Broken Hill Ltd is owned by China's Shenzhen Zhongjin Lingnan Nonfemet Co. (Perilya, 2013), which is almost 40 per cent state-owned by the People's Republic of China (Mining Data Online, 2025). Such partial ownership raises methodological questions for concentration metrics

Ownership and financing arrangements directly shape trade flows and availability. Hemerdon mine, owned by Tungsten West, may receive up to US$95 million over 15 years from the US Export-Import Bank tied to offtake arrangements with US buyers, potentially under the China & Transformational Exports Program that aims to reduce Chinese influence in critical sectors (Fieldhouse, 2025). Such conditional finance can direct product away from domestic markets, reducing availability to domestic consumers.

In 2011, CBMM sold 30 per cent of its shares to a Japanese/South Korean consortium (15 per cent) and Chinese companies (15 per cent) (CBMM (2025), leading to long-term niobium supply agreements (AIST, 2011) and limiting resource availability to other consumers.

Multiple mine ownership complicates determining controlling entities. For example, the Kamoa-Kakula copper mine in the DRC is jointly owned by (Ivanhoe Mines (2025):

- Ivanhoe Mines Ltd: 39.6 per cent
- Zijin Mining Group: 39.6 per cent
- DRC government: 20 per cent
- Crystal River Global: 0.8 per cent

With no majority shareholder, attributing production becomes arbitrary.

### Country-specific data omissions

Russia, a top-three producer of aluminium, cobalt, gallium, gold and nickel (Idoine et al., 2025), is not represented. This is despite the availability of public production data from companies like Norilsk, which is a leading global mining company and publishes annual reports detailing production statistics. In 2024, the company accounted for approximately (Nornickel, 2024):

- 40 per cent of global palladium supply
- 16 per cent of nickel
- 11 per cent of platinum
- 2 per cent of copper

Japan is a top-three producer of bismuth, cadmium and indium (Idoine et al., 2025) yet is also absent from MDO. The platform also omits data from North Korea and Myanmar, which are known metal-producing countries (Idoine et al., 2025).

### Companion metals

Companion metals (by-products or co-products) are recovered during the processing of primary ore. Antimony, bismuth, cadmium, caesium, cobalt, gallium, indium, niobium and vanadium are typically companion metals. For example, cadmium and indium are recovered during zinc ore processing (Nassar et al., 2015, Werner et al., 2017, Mudd et al., 2024).

Understanding metal associations can help infer companion-metal production where direct data is missing. However, companion-based inference depends on understanding the deposit geology and the primary commodity; for example, zinc occurs in diverse deposit types (skarn; sediment-hosted; porphyry; magmatic; epithermal) and indium content varies between these types (Werner et al., 2017).

Crucially, companion-based estimation requires good coverage of primary commodities. For the top-three zinc producers (2018 to 2022), available zinc production data coverage averages only 31 per cent. Australia's zinc coverage is good at about 83 per cent, but this is of limited use if coverage is poor for dominant producers such as China (Idoine et al., 2025).

### Smelting and refining

Mine production represents only the upstream stage of the supply chain. Downstream refining and smelting are equally important for supply-risk analysis (Mudd et al., 2024). MDO primarily reports mined output, with limited refined production data. Copper is an exception: MDO provides data for both mined forms (metal in concentrate) and refined cathode, but only when the mine produces cathode. The dataset does not report output from dedicated smelters or refining-plant production volumes.

Occasionally, MDO includes intermediate products (matte; doré), which can support limited midstream concentration analyses. However, for most commodities, refined-production data is sparse or absent, limiting the ability to assess risks at the smelting or refining stage.

## IMPLEMENTATION PATHWAYS

The three CC approaches tested face interconnected challenges including:

- complex ownership structures where companies hold minority but influential stakes
- hidden commercial arrangements (such as financing or offtake agreements) that effectively shape supply
- incomplete commodity coverage (especially co- and by-products)
- lack of smelting and refining data

- sparse reporting by state-owned and private firms resulting in poor data coverage

No single data source can completely satisfy these issues. Any corporate-concentration metric in future UK CAs must be supplemented by expert judgment and data collection from other sources.

### Single point of failure

The SPoF approach is simplest to implement, providing straightforward, qualitative flagging of international chokepoints. Although qualitative, it considers dominant corporate actors. Limited commodities and poor MDO coverage meant we did not detect clear SPoFs from data alone. In practice, SPoFs must be identified through expert knowledge and external evidence, such as corporate reports, trade intelligence and long-term agreements. Current BGS expertise identifies CBMM, Norilsk and Nornickel as SPoFs for niobium, rhodium and palladium respectively (Gómez et al., 2024, Nornickel, 2024).

SPoFs could be incorporated into future UK CAs based on BGS expertise and research outside MDO, which cannot identify SPoFs within commodities tested. Incorporation would likely apply to a small number of candidate materials.

### Production concentration

The production-weighted HHI remains the preferred quantitative metric because it directly links CC to material volume supplied. Implemented at country level for top-supplying countries and included as a weighting factor in the PCI, it has the clearest relationship to supply risk: higher production concentration results in higher effective supply risk.

### Diversity factor

The diversity factor is useful when production volumes are missing but mine ownership is well known. As a simple mine-count based measure, it can be introduced into the PCI as a weighting term: a higher diversity factor would reduce a commodity's criticality score and vice versa. However, this method treats every mine equally, over-weighting small mines and under-weighting large ones. Comparison with production-weighted concentration highlights this issue: a few large mines can dominate supply while many small mines contribute little. Consequently, diversity factor can misrepresent actual supply risk for commodities where production is highly concentrated in a small number of large operations. The diversity factor could be used as a secondary indicator where production data is missing.

# Appendix 7 Future projections

Previously, the influence of production evolution on mineral criticality was assessed by retrospectively analysing the compound annual growth rate (CAGR) for global production data between 2010 and 2018. Forecasting future global production is challenging, as production rates depend on multiple interconnected and uncertain factors, including mining technology change, variable demand and evolving resource availability. Predictive models of future mineral production are underpinned by multiple simplifying assumptions and varying parametric complexity (Rodríguez, 2020, Saadat et al., 2021).

Hubbert's peak model was considered for this analysis due to its simple structure, straightforward parameter interpretation and existing applications to CM production data. For example, REE production was previously shown to conform with Hubbert theory (Gann, 2018). Hubbert's model describes production as a symmetrical process that accelerates until peak production is reached and then slows down at the same rate. The key parameter is the timing of peak production, complemented by a production rate constant. These parameters are intuitive and easily applied in foresight analyses (Riondet et al., 2023).

The predictive capacity of Hubbert’s model is often subject to criticism (Jones and Willms, 2018) because, in all its forms, it relies on parameters that cannot be inferred from historical production data, such as peak time or volume of ultimate recoverable resource (URR). A recent approach addresses this by generating all possible parameter combinations, expanding the model from temporal-only prediction to a plane of possible scenarios for foresight analysis (Riondet et al., 2023).

The general idea is that Hubbert's model represents production that is neither disrupted nor accelerated by external events. Calibrating the model against data results in a range of business-as-usual scenarios, each associated with its own peak. Quantifying the dispersion of these scenarios for individual commodities can be instrumental for CA in providing a range of potential timescales in which production will continue to grow before declining based on historic data.

## MODEL LIMITATIONS AND ASSUMPTIONS

Hubbert's models are best interpreted as constraint-based scenario frameworks, rather than predictive tools. This distinction is important because mineral production is dominated by demand, economics, technology and geopolitics rather than geology alone (availability of resource in the ground). While such assumptions work well for oil and gas production predictions, minerals are more sensitive to price movement influencing cut-off grade at mine sites and therefore recoverable resource volumes, technology improvement influencing recovery efficiency, and geopolitics opening or closing access to resources. Under these considerations, the concept of URR is a scenario assumption, not a model parameter.

Furthermore, metals are not consumed in the same way as hydrocarbons, as most materials are ultimately recoverable when not used in dispersive applications. For commodities with high recyclability, secondary supply decouples cumulative extraction from primary depletion, leading to Hubbert’s models overstating scarcity. Mineral production is also typically demand constrained rather than depletion constrained. Production may peak because demand collapses or substitutes emerge due to technological evolution or changes in environmental regulation. The production of lead, arsenic and mercury are good examples of demand change linked to end-use change that is in turn linked to the goal of decreasing the overall use of toxic metals.

Despite these limitations, application of Hubbert's models at the global scale lessens their impact, smoothing local discontinuity in mine production while physical limitations in ore grade, energy intensity and waste volume remain essential in assessing accessibility and valorisation of deposits.

The output of these models in the form of an envelope of possible production trajectories allows identification of unreasonable targets to be reached outside the bounds of geological, financial and logistical plausibility. Handling uncertainties as an envelope or surface of peak time possibilities effectively reframes the discussion from when the peak could occur to what parameters or assumptions make the peak move forward or further away in time. Further derivatives of these models beyond peak time are also useful and closely align with mining reality, such as rates of depletion or production increase. Incorporating multiple cycles of Hubbert models could provide an approximation of metal production evolution incorporating changes driven by technology or access changes.

## DATA AVAILABILITY

Annual production time series for seven example minerals were used to investigate forecasting potential of Hubbert model variants:

- cobalt
- lithium
- mined copper
- nickel
- REEs
- refined copper
- pig iron

For five minerals, historic data is available from 1900 onwards. For refined copper and iron, production rates are reported from the 1970s. For all minerals, data is available until 2022 in this analysis.

### Hubbert model variants

In its classical form, the Hubbert model (Cavallo, 2004) provides an idealised representation of production trend, from increase to reaching a maintained plateau, followed by decline. It can define either a cumulative production or an annual production rate. The mode of annual production rates was used to match the nature of available production data:

$$r(t) = \frac{r_{max} \exp\left(-\frac{t - t_{peak}}{\tau}\right)}{1 + \left(\exp\left(-\frac{t - t_{peak}}{\tau}\right)\right)^2}\ , \qquad 1$$

Where:

- r(t): current annual production rate for time t given in years; this time-varying variable is fit to data to find model parameters
- *r_max*: maximal annual production rate that can be achieved; estimated in the model fitting process
- *t_peak*: year when peak production is reached; estimated in the model fitting process
- *τ*: time constant quantifying how quickly production grows and declines; large time constants signify slow rates of change, small time constants signify rapid rates of change; estimated in the model fitting process

Rise and decline trends are symmetrical, leading to simplistic representation that peak production is reached when half of the URR is produced (Riondet et al., 2023).

Another variant of Hubbert's model depends explicitly on ultimate recoverable resource:

$$r(t) = \frac{Q_{URR}}{\tau} \frac{\left(\frac{Q_{URR}}{Q(t_0)} - 1\right) \exp\left(-\frac{t - t_0}{\tau}\right)}{1 + \left(\left(\frac{Q_{URR}}{Q(t_0)} - 1\right) \exp\left(-\frac{t - t_0}{\tau}\right)\right)^2}, \qquad 2$$

Where:

- $t_0$: reference time given in years; can be set arbitrarily, in this case chosen as final year of reporting in data
- $Q(t_0)$: cumulative production volume at reference time, calculated directly from historic data
- $r(t)$: current production rate for time $t$ given in years; the time variable is fitted to data to optimise parameters
- *Q_URR*: volume of URR, representing all resources that will be extracted to infinity; by definition can be known exactly only at end of production curve. URR in this model is assumed constant and thus cannot be directly aligned with mining notion of resource or reserve but can be used as an idealised representation of total resource possible to recover; estimated in the model fitting process
- $\tau$: time constant; same interpretation as in first model variant

Models (1) and (2) are mathematically equivalent. The structure of model (1) arises directly from model (2) when the reference time is set to peak year ($t_0$ = t_peak). The three parameters on which Hubbert models depend are:

$$t_{peak} = t_0 + \tau \log \frac{Q_{URR}}{Q(t_0)} \qquad 3$$

This relationship can be represented by parameter-invariant maps for any given $t_0$ (Riondet et al., 2023). The dependency is visualised as a 3D surface characterised by temporal isolines representing sets of all pairs of time constant and URR corresponding to the same peak year. The isolines form the Hubbert map for the selected reference year (in this case 2022). To simplify the scale of the map, the ratio of URR to total extracted product up to the reference point is used as a parameter.

This map demonstrates the proportional effect of time constant on peak time: as the time constant grows (meaning slower production acceleration), the peak year moves further into future. The effect of URR is log proportional and weakens as the value increases. This trend is well observed where, for smaller values of URR-to-extracted ratio, the effect of the time constant on peak year is minimal, leading to isolines almost parallel to the time constant axis. As URR-to-extracted ratio increases, the time constant starts to dominate influence on peak year and isolines tend to run parallel to the URR axis.

Outcomes of fitting Hubbert models to historic data for all minerals of interest can be plotted on this map as long as they all incorporate the same reference time $t_0$. A scenario is represented by a point in the coordinate space. For example, if the time constant and ratio of URR to total extracted product for 2022 are set to 20, this corresponds to one peak year; if both are set to 40, this corresponds to a different peak year. The production scenario for each point can be modelled on the temporal scale using either parameterisation shown in equations (1) or (2), resulting in traditional Hubbert curves. Peak year on its own is not a sufficient characteristic of production, as it does not characterise the volume of production in any way.

The benefit of Hubbert maps is that they provide compact representation of a temporal scenario attached to a single reference year without any loss of information, so it is irrelevant when recording of production data has started. Such unified representation can facilitate comprehensive comparative analysis of various minerals.

## INFERRING POSSIBLE PRODUCTION SCENARIOS

Estimation of future production scenarios relies on fitting mathematical models (1) and (2) to historic production data. This statistical procedure aims to minimise the discrepancy between observed production rates and those generated by models. The residual sum of squares (RSS) is a commonly used metric of model performance; parameter values that minimise RSS are considered optimal among all admissible combinations. However, Hubbert model parameters obtained this way are characterised by high levels of uncertainty arising from:

- the true underlying processes generating historical production profiles are unknown and subject to non-random and structural changes, resulting in noisy production data
- Hubbert models incorporate parameters relating to future production that cannot be inferred from historic data
- the inference process may be sensitive to model parameterisation; fitting model (1) and model (2) may result in different optimal parameters despite parameterisations being deterministically linked

Consequently, interpreting individual points on the Hubbert map corresponding to isolated temporal profiles obtained from optimal fits to data is insufficient for inclusion in CA. A meaningful indicator of potential future production levels should reflect this inherent uncertainty.

Classic uncertainty quantification approaches based on confidence intervals around estimated parameters are not suitable in this context. Parameters relating to future production dynamics are not inferable from historical data, leading to confidence intervals for URR or a time of peak that would be extremely wide and not discriminate sufficiently between candidate materials.

Instead, the methodology proposed by Riondet et al. (2023) adopts the concept of ‘equifinality’, whereby multiple combinations of model parameters can describe the same data equally well (Beven and Freer, 2001, Beven, 2019). This approach allows identification and visualisation of regions of equally possible production scenarios on the Hubbert map. The present analysis extends this approach by combining the two model parameterisations described previously. Combining admissible regions derived from models (1) and (2) yields more conservative estimates of possible production scenarios.

For each mineral, the following procedure was applied to infer the region of possible production scenarios:

1. Model parameters were optimised to minimise RSS between historic data and model output. Initial parameter guesses were chosen based on a grid search of the smallest residual cost, followed by a gradient-based optimisation procedure to refine optimal estimates. For model (1), three parameters were optimised: peak year, rate constant (inverse of time constant) and maximal rate. For model (2), rate constant and ratio of URR to cumulative production up to 2022 were optimised.

2. Estimated model parameters were converted to time constant and ratio of URR to cumulative production up to 2022, to match the grid used in Hubbert maps.

3. For both parameterisations, the coefficient of determination ($R^2$) was computed from residuals. $R^2$ quantifies the proportion of variance in observed data explained by the model. The global maximum $R^2$ value across both parameterisations was selected to represent the best possible fit of Hubbert's model to the data and termed $R^2\_opt$.

4. Surfaces of $R^2$ and RSS were produced for all parameter combinations defined on the Hubbert map grid. The resulting surfaces for mined copper clearly demonstrate one source of model uncertainty. Weak influence of URR ratio on cost function and goodness of fit results in surfaces having a very small gradient along the URR axis, appearing almost flat.

5. The level set equal to 98 per cent of $R^2\_opt$ value was identified within the parameter grid. The relative level of $R^2\_opt$ is selected because model fits vary significantly across different minerals. The value of 98 per cent is selected to generate a wide enough range of potential scenarios that is compact enough to emphasise the difference in shape across minerals. This level set defines the region containing all parameter combinations that produce a fit at least as good as $0.98 \times R^2\_opt$. All points on the Hubbert map within this specified level set constitute the region of possible production scenarios; each explaining at least 98 per cent of $R^2\_opt$ in historic production data of the mineral considered.

6. Scenarios within the possible region can be viewed on the Hubbert map or simulated in time up to any year in the future to assess the range of possible production rates.

## RESULTS

### Model sensitivity

Examples of possible production regions and their corresponding temporal trajectories are shown for copper and cobalt. For both models, URR and peak year are poorly identifiable from historic data, as evidenced by the width of possible production regions along the URR axis.

Although mathematically equivalent, the two Hubbert models do not have the same optimum. This is explained by the fact that model (1) treats maximal production rate as a separate, inferable parameter, whereas in model (2) it is implicitly incorporated as the combination $r\_max = Q\_URR/\tau$. The additional degree of freedom in model (1) leads to discrepancy in RSS functions for two models and thus to different shapes of possible production region.

Mined copper was selected to illustrate the sensitivity of inferred production scenarios to model parameterisation. Fitting of model (1) to data produces a narrow set of optimistic future scenarios characterised by high time constants and varied URR ratios. Interestingly, best-case scenarios (highest rate of production and highest peak year value) for model (2) are consistent with model (1), though its region of possible production also includes scenarios with very low time constants that result in extremely close peak years. Model (1) was also found to produce more optimistic future scenarios for refined copper and pig iron.

For cobalt, optimal fit obtained with model (2) is more optimistic than that obtained with model (1), although the difference between admissible production regions is less pronounced than in the copper example. Similar outcomes were obtained for fitting models to lithium historical production. In contrast, for nickel and REEs, admissible production regions were very similar for the two model parameterisations. It is not yet clear which properties of historic time series drive differing sensitivities of two model parameterisations across minerals. Exploring this is an avenue for future work.

### Proposed metrics

Poor identifiability of peak time from historic production data leads to substantial variability in model predictions across minerals with broadly similar production profiles. It is thus inappropriate to incorporate predicted production volume directly into assessment criteria. Instead, Hubbert maps and an ensemble of admissible modelling scenarios can be used to derive a set of more robust metrics.

### OPTIMAL PARAMETER COMBINATIONS

The best-fitting solution to data may be retained into the final indicator. The corresponding optimal peak year represents the expected peak production under business-as-usual conditions. The optimal time constant characterises the rate at which production would accelerate or decelerate in this scenario. The range of future peak production rates across the admissible set can be computed as:

Range = (r_max^high − r_max^low) / r_max^low

Where *r_max^high* and *r_max^low* are the highest and lowest annual production at peak year, respectively. This is the only metric that explicitly characterises uncertainty in future production volumes.

### AREA OF POSSIBLE PRODUCTION REGION

The area on a Hubbert map provides a measure of uncertainty in inferred production trajectories. It is computed in Hubbert map coordinates defined by time constant and URR-to-extracted ratio. For CA, modelling far into the future is not feasible nor reliable due to model limitations discussed previously. This provides further motivation to use a Hubbert map, where admissible scenario regions can be constrained by an isoline corresponding to a particular year of interest (for example, 2070 or 2100), resulting in a bounded set of scenarios. Constrained regions represent all possible scenarios where production reaches peak within 21st century. The larger the area, the more potential scenarios of business-as-usual production will reach peak before 2100.

### AREA OF UNION OF ADMISSIBLE PRODUCTION REGIONS

Regions obtained from Hubbert's model parameterisations (1) and (2) can be used as a robust estimate of model uncertainty by combining information from the two model variants. The union is meant to represent a more conservative insight into the future. If one parameterisation systematically yields more optimistic outcomes than the other, it is important not to exclude the more pessimistic scenarios, as they are most relevant for potential criticality. The benefit of using the joint region is demonstrated for mined copper and cobalt. For copper, model (1) is more optimistic than model (2), producing no admissible peak years earlier than 2075. For cobalt, model (2) is more optimistic, with its earliest admissible peak year occurring in 2043. For consistent assessment across all minerals, a combined region is more robust as it retains worst-case scenarios, regardless of which model parameterisation produced them.

### CLOSEST PEAK YEAR TO PRESENT DAY

This provides explicit representation of the worst-case scenario of future production within the admissible set. This value is expected to be quite pessimistic for most minerals and should therefore be down-weighted in any criticality calculation to avoid disproportionate influence of worst-case, but still admissible, scenarios. Note that these scenarios are produced on the set of assumptions listed at the beginning of this section and have significant caveats attached to them.

### GOODNESS OF FIT

The goodness of fit of the Hubbert model to historical data, quantified by $R^2$, is in itself a powerful indicator of how predictable a current production profile is. For mined copper, 97 per cent of variability observed in production data can be explained by the model. This high score can be expected for longstanding and steady historic production not marked by any major shocks or disruptions. For cobalt, only 90 per cent of historic data variability is explained by the model, reflecting major production volume changes around 2000s. For refined copper and pig iron, model fits explain around 80 per cent of historic data.

It is important to note that $R^2$ largely characterises the model's ability to reproduce historical data rather than representing the underlying production process. Nevertheless, it can be incorporated as a confidence metric of the model-derived regions. For example, comparing areas of possible production regions for refined and mined copper might indicate a positive outlook for refined copper, as few admissible areas result in peak year within the 21st century. However, the $R^2$ value used to create this region is only 0.860, meaning scenarios in the region only explain 98×0.86 = 84 per cent of historic data variability, compared to 98×0.97 = 95 per cent for mined copper. Including $R^2$ provides more balanced assessment and reduces reliance of criticality indicator on model structure alone.

## Summary

**Table 5** presents parameters resulting in best fit of the Hubbert model to historic production data for seven minerals. Peak years range from 2036 (refined copper, model 2) to 2183 (mined copper, model 1). Time constants range from 9.6 years (lithium, model 1) to 35 years (mined copper, model 1). Model fit quality ($R^2$_opt for union) ranges from 0.860 (refined copper) to 0.992 (mined copper).

| Mineral | t_peak (years) M1 | t_peak M2 | Time constant (τ) M1 | τ M2 | Model fit ($R^2$_opt) union |
|---|---|---|---:|---:|---:|
| Cobalt | 2088 | 2124 | 21.0 | 22.0 | 0.900 |
| Lithium | 2039 | 2084 | 9.6 | 14.0 | 0.906 |
| Mined copper | 2183 | 2078 | 35.0 | 31.0 | 0.992 |
| Nickel | 2151 | 2152 | 28.0 | 28.0 | 0.975 |
| REEs | 2105 | 2106 | 18.0 | 18.0 | 0.961 |
| Refined copper | 2138 | 2036 | 26.0 | 17.0 | 0.860 |
| Pig iron | 2141 | 2056 | 26.0 | 22.0 | 0.872 |

**Table 5** Parameters resulting in best fit of Hubbert model to historic production data.

| Mineral | t_peak (years) M1 | t_peak M2 | Time constant (τ) M1 | τ M2 | Model fit ($R^2$_opt) union |
|---|---|---|---:|---:|---:|
| Cobalt | 2088 | 2124 | 21.0 | 22.0 | 0.900 |
| Lithium | 2039 | 2084 | 9.6 | 14.0 | 0.906 |
| Mined copper | 2183 | 2078 | 35.0 | 31.0 | 0.992 |
| Nickel | 2151 | 2152 | 28.0 | 28.0 | 0.975 |
| REEs | 2105 | 2106 | 18.0 | 18.0 | 0.961 |
| Refined copper | 2138 | 2036 | 26.0 | 17.0 | 0.860 |
| Pig iron | 2141 | 2056 | 26.0 | 22.0 | 0.872 |

**Table 6** presents metrics of future production scenarios where possible production region is constrained by peak year 2100. Peak production rate amplitude, area, and closest peak year are calculated for this constrained region.

**Table 6** Metrics of future production scenarios.

| Mineral | Peak prod. rate amplitude M1 | Amp. M2 | Amp. union | Closest t_peak M1 | t_peak M2 | t_peak union | Area M1 | Area M2 | Area union |
|---|---|---|---|---|---|---|---|---|---|
| Cobalt | 12.6 | 13.5 | 15.1 | 2040 | 2045 | 2040 | 217.6 | 188.6 | 245.9 |
| Lithium | 23.6 | 2.5 | 23.6 | 2027 | 2066 | 2027 | 275.1 | 107.2 | 275.1 |
| Mined copper | 0.9 | 4.1 | 4.6 | 2080 | 2040 | 2040 | 19.1 | 65.3 | 70.3 |
| Nickel | 3.3 | 7.3 | 8.3 | 2061 | 2042 | 2042 | 80.7 | 105 | 125.9 |
| REEs | 17.4 | 24.9 | 25.3 | 2042 | 2041 | 2039 | 378.7 | 367.3 | 415.9 |
| Refined copper | - | 0.4 | 0.4 | - | 2032 | 2032 | - | 2.2 | 2.2 |
| Pig Fe | - | 0.5 | 0.5 | - | 2051 | 2051 | - | 1.7 | 1.7 |

Key observations from tables 8 and 9:

- lithium shows the earliest closest peak year (2027; model 1 constrained to 2100) and largest peak production rate amplitude (23.6; union), reflecting rapid recent growth and high uncertainty in future trajectories
- mined copper shows highest model fit ($R^2 = 0.992$) and latest optimal peak year (2183; model 1), indicating a stable long-term production profile
- refined copper and pig iron show poorest model fits ($R^2 = 0.860$ and $0.872$), indicating production profiles less consistent with logistic depletion dynamics
- REEs show a large area of possible production region (415.9; union) despite moderate model fit ($R^2 = 0.961$), indicating high scenario uncertainty
- model 1 often produces more optimistic scenarios (later peaks) than model 2 for copper and iron, but the reverse is true for cobalt and lithium

## FUTURE CONSIDERATIONS

Hubbert's models are extremely sensitive to parameterisation when historic data is short or when the production system has not yet exhibited a mature logistic curve. By its nature, Hubbert's model is a global representation of the entire time series and all observations contribute equally to parameter estimation; therefore, more recent data is not prioritised over older observations. This is problematic when data contains structural breaks, rapid demand-driven expansions or regime shifts, or when the commodity has not yet entered a stage where production dynamics resemble the rising and stabilising phase of a logistic curve. As illustrated by the results for pig iron and refined copper, such cases lead to poor model performance and high sensitivity of inferred scenarios to model parameterisation.

A more comprehensive analysis would benefit from considering autoregressive models of production in addition to process-based ones, better suited to short-term dynamics. These models represent production at each new time point as a function of immediately preceding production (Saadat et al., 2021). Although these models lack interpretable parameters related to resource depletion or URRs since they are usually based on regression structure, they can be useful for short-term forecasts and may better capture influence of recent trends. Such predictions from autoregressive models should be considered alongside long-term trends from Hubbert maps.

The Hubbert peak model is traditionally applied to materials produced from finite natural resources. The present analysis has not considered how this model would need to be adjusted for minerals produced from alternative sources such as secondary sources (recycling), or accounting for dependencies on commodities such as co- or by-products that are coupled to extraction and production of another commodity. In such cases, production trajectories may be controlled less by depletion dynamics and more by the demand for and the processing capacity and economics of the major commodity. Future work should therefore explore alternative model structures that explicitly represent these mechanisms and allow multi-driver production dynamics. Autoregressive model structures allow incorporation of external outputs as contributing factors and present a potential avenue for future research.

Another promising alternative model to consider is the use of more general process-based formulations, such as systems of fundamental equations of mineral production (Rodríguez, 2020). These models retain interpretability while allowing a wider range of production behaviours than the classical logistic form, including asymmetrical growth and decline, multi-stage development and more complex responses to market and technological drivers. Such models could provide a useful intermediate level of complexity between purely statistical time-series forecasting and the highly constrained Hubbert framework.

Given the demonstrated sensitivity of inferred scenario regions to model parameterisation, future research should also focus on identifying which properties of historical production time-series (volatility; presence of structural breaks; length of record; maturity of production system) systematically influence the divergence between alternative Hubbert parameterisations. Establishing such diagnostic criteria would support more consistent model selection and improve the robustness of criticality indicators derived from Hubbert maps.

## IMPLEMENTATION RECOMMENDATIONS

Based on this exploratory analysis, the following recommendations are made for potential incorporation of production forecasting into future CAs.

### Not suitable as systematic indicator across all materials

Production forecasting using Hubbert models should not be implemented as a systematic indicator applied uniformly across all 82 candidate materials. Data requirements (minimum 50 years historical production; mature logistic production profile), model sensitivity to parameterisation and fundamental assumption violations (recyclability; co-product dependencies; demand-driven rather than depletion-driven production) make systematic application unfeasible and potentially misleading.

### Diagnostic criteria for selective application

Production forecasting should only be applied to commodities meeting specific diagnostic criteria:

- agreement between model (1) and model (2) optimal peak years within ±20 years
- agreement between model (1) and model (2) URR estimates within ±30 per cent
- historical production data spanning at least 50 years
- less than 30 per cent of current production from secondary sources (recycling)
- model fit quality $R^2\_opt \geq 0.93$ for at least one parameterisation
- not a co-product or by-product where output is determined by primary commodity economics
- production profile exhibits a clear logistic rise phase and is not dominated by recent rapid expansion

### Long-term scenario framing only

Where applied, Hubbert models should only be used for long-term scenario framing (beyond ten-year horizons) to understand he  production constraints under business-as-usual assumptions, not for near-term supply risk assessment (five to ten year horizons relevant to criticality). The scenarios provide boundary conditions: policy ambitions requiring production levels exceeding the upper bounds of plausible Hubbert scenarios signal that demand projections may be unrealistic, major technological or geological breakthroughs are necessary, or substitution and efficiency improvements must compensate for supply constraints.

### Conservative union of model parameterisations

If production forecasting is applied, always use the union of admissible regions from both model (1) and model (2) parameterisations rather than relying on a single model formulation. This conservative approach retains worst-case scenarios regardless of which parameterisation produced them, avoiding systematic bias toward optimistic or pessimistic outcomes.

### Explicit uncertainty quantification

Any production forecasting results incorporated into a CA must include explicit uncertainty quantification through:

- area of possible production region constrained by relevant time horizon (for example, 2100)
- closest peak year to present as worst-case scenario indicator (down-weighted appropriately)
- $R^2$ goodness of fit as confidence metric
- range of peak production rates within admissible set

### Complement with autoregressive models

For commodities where short-term dynamics are of interest, complement Hubbert long-term scenarios with autoregressive time-series models (for example, ARIMA) that are better suited to capturing recent trends and near-term forecasting. These models lack physical interpretability but can better represent demand-driven dynamics, market responses and regime shifts.

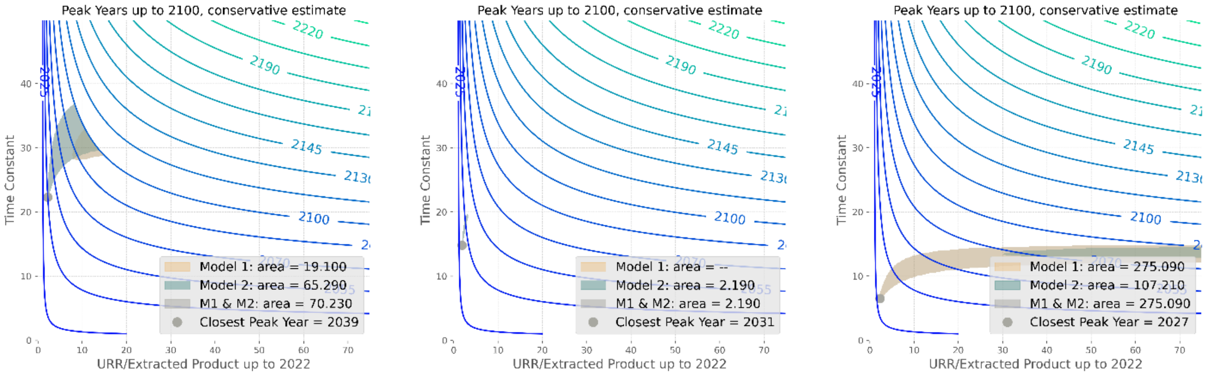
### Transparent communication of assumptions

Any use of production forecasting in CA must be accompanied by transparent communication of underlying assumptions (finite resource depletion; symmetrical production profile; business-as-usual conditions; no major technological or policy disruptions) and limitations (does not account for recycling; co-product dependencies; demand shifts; substitution; geopolitical access changes). Users must understand that scenarios represent constraint-based boundary conditions, not predictions of likely outcomes.

Based on the exploratory results and diagnostic criteria, only mined copper, nickel and REEs from the seven commodities tested would meet thresholds for potential inclusion ($R^2 \geq 0.93$, reasonable model agreement). Lithium would be excluded due to its short production record dominated by recent rapid expansion. Cobalt would be excluded due to structural breaks in its production profile and moderate model fit. Refined copper and pig iron would be excluded due to poor model fits indicating production dynamics that are inconsistent with logistic depletion assumptions.

Even for commodities meeting diagnostic criteria, the use of production forecasting should be clearly labelled as exploratory and supplementary rather than core to criticality scoring. The primary value is in identifying commodities where business-as-usual production trajectories may not support long-term demand scenarios, flagging the need for enhanced exploration, technology development, substitution strategies or demand management rather than providing definitive supply risk scores.

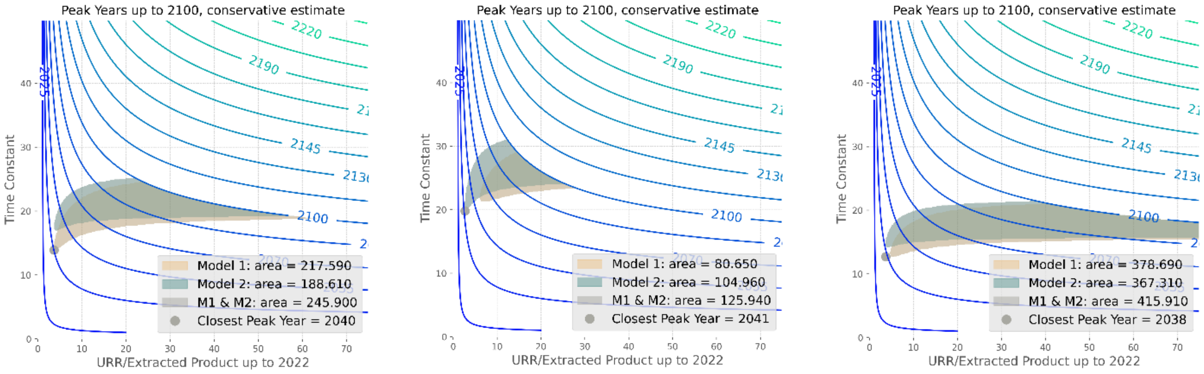
The regions of possible production scenarios for all example minerals are shown in **Figure 17**.



a) Mined copper

b) Refined copper

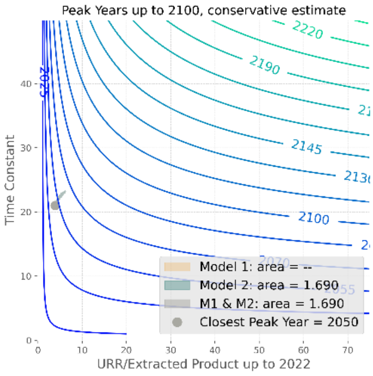
c) Lithium



d) Cobalt

e) Nickel

f) REEs



g) Pig iron

**Figure 17** Regions of possible production scenarios with peaks within the 21st century. The areas are shown for all considered minerals to visually aid comparative analysis. BGS © UKRI 2026.

# Abbreviations

| | |
|---|---|
| 2024 UK CA | 2024 UK Critically Assessment (Mudd et al., 2024) |
| BGS | British Geological Survey |
| BLI | Backward linkage index |
| CA | Criticality assessment |
| CBMM | Companhia Brasileira de Metalurgia e Mineração |
| CC | Corporate concentration |
| CCV | Climate change vulnerability |
| CM | Critical mineral |
| CMIC | Critical Minerals Intelligence Centre |
| CRM | Critical raw material |
| DEI | Direct economic importance |
| DRC | The Democratic Republic of the Congo |
| EITI | Extractive Industries Transparency Initiative |
| EME | Economic multiplier effects |
| EPI | Environmental performance index |
| ESG | Environmental, social and governance |
| EU | European Union |
| FLI | Forward linkage index |
| GATT | General Agreement on Tariffs and Trade |
| GDP | Gross domestic product |
| GTA | Global Trade Alert (database) |
| GTC | Global trade concentration |
| GVC | Gross value added |
| HDI | Human development index |
| HHI | Herfindahl-Hirschman index |
| HS | Harmonized System |

| | |
|---|---|
| HTV | Hodges-Tompkins volatility |
| ICMM | International Council on Mining and Metals |
| IRMA | Initiative for Responsible Mining Assurance |
| KPI | Key performance indicator |
| LFP | Lithium-iron-phosphate (battery) |
| LME | London Metal Exchange |
| MD | Market disturbance |
| MDO | Mining Data Online (database) |
| MS | Market sentiment |
| MT | Market turbulence |
| ND-GAIN | Notre Dame Global Adaptation Initiative |
| NiMH | Nickel-metal hydride (battery) |
| NMC | Nickel-manganese-cobalt (battery) |
| ONS | Office for National Statistics |
| PCI | Production concentration indicator |
| PV | Parkinson volatility |
| REE | Rare earth element |
| RSS | Residual sum of squares |
| SCC | Supply-chain centrality |
| SIC | Standard Industrial Classification |
| SPoF | Single point of failure |
| TCI | Trade concentration indicator |
| TIF | Trade intervention factor |
| TSM | Towards Sustainable Mining |
| URR | Ultimate recoverable resource |
| WCO | World Customs Organization |
| WGI | World governance index |
| WMF | World Materials Forum |
| WTO | World Trade Organization |

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