JNCC Report 806

Methods and initial results for a metals and minerals footprint estimate for the UK

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October 2025

ISSN 0963 8091

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This report was produced by JNCC in collaboration with the Stockholm Environment Institute, University of York, under contract to Defra.

This document should be cited as:
Croft, S.[1], Harris, M.[2], Wood, E.[1], Titley, M.[1] & West, C.[1] 2025. Methods and initial results for the UK's metals and minerals footprint. *JNCC Report 806*. JNCC, Peterborough, ISSN 0963-8091.
https://hub.jncc.gov.uk/assets/bb5a5bcf-6297-4570-bbc3-83fc85a13467

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Acknowledgements:
We would like to thank Stefan Giljum, Stefan Lutter (WU Vienna) and Jim West (CSIRO) for data provision linked to the International Resource Panel, and for the important guidance and support provided in the formulation of the methods summarised in this report. We also thank Defra for funding the work.

Summary

Understanding the global environmental impacts of commodity consumption is necessary to inform evidence-based action. The Global Environmental Impacts of Consumption (GEIC) indicator is a key data source to support this, but data from mined commodities are currently out of its scope. Their inclusion would broaden its applicability and meet the needs of a number of additional stakeholders. This report therefore aims to begin filling this data gap, presenting a proposed method for including mined commodities within the GEIC dataset, and an initial, prototype dataset of material footprint (tonnes of consumption) using the Input-Output Trade Analysis (IOTA) framework that underpins GEIC, which can act as the basis for further potential methodological improvement and could eventually be extended to provide information on environmental impacts.

The method proposed follows broadly the same modelling framework currently used within GEIC for agricultural commodities, with some additional steps and processes specific to mined commodities, such as the use of conversion factors to 'translate' between extracted ores and final products. It uses data sources provided by WU Vienna, UN Comtrade and EXIOBASE.

Prototype results, which should be treated with caution due to their experimental nature, are provided for metal and mineral commodities consumed by the UK between 2005 and 2018 (with partial data also available for 2019 and 2020 on request). These can be broken down by the country of origin and by the specific metal or mineral of interest. For example, in 2018, the mined commodities with the largest mass linked to UK consumption were 'sand, gravel and crushed rock for construction', 'stone', and 'crude oil'.

Next steps to develop and improve the method further are outlined, including efforts to use more granular commodity-specific information to make fuller use of ore and concentrates and alloy physical trade data, ways to improve the allocation of materials downstream in the model, and addressing the issue of missing conversion factors. Work to build on and improve this initial dataset and further scope the addition of associated environmental datasets is provisionally planned for the financial year 2026–2027.

An appendix also provides details of some scoping work investigating the potential to integrate deforestation data, for potential eventual provision of a deforestation footprint rather than just a material footprint.

Contents

1. Introduction

1.1. Background and context

Commodity consumption is a major driver of natural habitat loss and degradation of ecosystem services, such as biodiversity, resilience to hazards, and climate change mitigation and adaptation. Understanding how consumption links to these impacts is crucial to be able to address them. The issue has been highlighted in multiple high-profile reports and policies, such as the National Food Strategy, the Dasgupta Review, the Government's 25 Year Environment Plan and its first revision (the Environmental Improvement Plan), and the Convention on Biological Diversity's Kunming-Montreal Global Biodiversity Framework.

The Global Environmental Impacts of Consumption (GEIC) indicator is a key data source estimating the biodiversity loss, deforestation, water use and a range of other impact types associated with the consumption of countries and territories around the world, which can be broken down to give commodity-specific results. However, its scope is currently restricted to agricultural crop commodities, and in some cases cattle-related products and timber. This leaves an evidence gap relating to mined commodities, such as metals and minerals.

Mined commodities are a particularly pertinent evidence gap to fill given the high proportion of total material footprint that they represent, their unique and significant impacts (e.g. acid pollution), and the increasing demand that there is for them, especially in the case of rare earth metals to support the transition to Net Zero. The importance of their inclusion was highlighted in the initial stakeholder group that was convened to input into the GEIC indicator before its original publication in 2021, but they were not possible to include at the time due to time and data constraints. More recently, the Environmental Audit Committee included a recommendation that "UK consumption monitoring be developed to incorporate the monitoring of mined products, so as to support the Government's programmes addressing the impact of mining-related deforestation" (House of Commons 2024).

1.2. Aims and scope

This report therefore aims to begin filling this data gap, presenting a proposed method for including mined commodities within the GEIC dataset, and an initial, prototype dataset. At this stage, only the material footprint of metals and minerals is covered. However, it is calculated in a way that will allow for country- and commodity-specific estimates of environmental impacts to be obtained in future if relevant environmental data can be identified (see Appendix 1 for initial scoping work on linking it to deforestation).

1.3. Disclaimer

The inclusion of mining data is a novel attempt to expand the commodity coverage of the GEIC indicator. Due to difficulties in the data landscape for metals and minerals and the early nature of this work, results presented should be considered a prototype dataset. Further work is planned to address some of the limitations identified in an iterative process – including via discussion with data providers, for example from WU Vienna - but it is likely to have lower certainty than the main GEIC dataset (agricultural commodities) for the foreseeable future. Users should therefore treat results with caution and consider them to be of a preliminary and interim nature and should not at this stage make direct comparisons with the main GEIC dataset.

2. Methods

The implementation of mining products within the GEIC/IOTA modelling framework largely follows the existing logic of agricultural commodities, albeit with some important differences. For further information on GEIC's methods, please refer to Croft *et al*. (2024). This report details how the methods used for metals and minerals differ to those described in Croft *et al*. (2024). In the following sections we provide a high-level summary of the key differences, then lay out the data available, the exploratory process involved to determine the scope of the integration of mining data, the methods utilised for implementation, and finally a discussion of existing limitations and areas for potential future improvement.

2.1. Summary of key methodological differences compared to Croft *et al*. (2024)

For agricultural products within GEIC, "production" refers to the growing of primary commodities (e.g. soybeans, wheat, maize). Trade data integration is limited to that of the same primary forms (note: cattle and timber products are treated slightly differently, due to their fundamentally different commodity properties). Given the nature of mining and the products originating from mining, "production" is fundamentally different; extraction often consists of bulk ores of varying material quality and content which can then be processed and refined and traded at myriad levels of "purity" (i.e. focal material concentration). As such, for integration into the GEIC/IOTA modelling framework, trade data for various commodity forms is converted into primary equivalents, with this primary equivalent referring to the extracted material within countries of origin.

Such conversions rely on having available data, but the information available to us (sourced from researchers at WU Vienna) is often patchy and incomplete given the complexity and opacity of mining production statistics. We therefore adopt a hierarchical approach to best match trade information to available conversion factors, as follows:

- If a direct match (country, commodity and year) is available, adopt this value.
- If no direct match is available, but available factors for a given commodity (across geographies and time) take one unique value across all available data, use this value.
- If, for a given country and commodity (across time), a unique conversion factor is provided, adopt this value.
- If different factors are available for a given country/commodity, but not the specific year, adopt the value for the nearest available year.
- If for a given country/commodity no value has been assigned, look within the provided factors for the commodity for other countries to see if they are estimated from global averages; if there exists such a value adopt this value for the nearest available year.

This approach successfully provides trade for all country/commodity/year combinations with an appropriate conversion factor and allows the reported exports to be converted to raw primary equivalents.

At this point, the production (extraction) data and converted trade data can be run through the re-export algorithm within the IOTA codebase to balance and resolve trade flows to represent country of origin to country of final import.

The resulting data are then hybridised with the financial MRIO component of the modelling framework. Here, another difference occurs from the standard agricultural commodity implementation. Typically, each agricultural product is associated with a single producing sector, and when it comes to combining the production and trade data within the MRIO it is sales/purchases by/from this sector that are used to allocate imports across purchasing sectors within the importing country's economy. Because production and trade data for mining products cover a broader range of commodity types (i.e. many types of products), sectors associated with production (extraction) and sales/purchases (of processed commodities) can differ. The hybridised allocation process accounts for this by differentiating between the different appropriate sectors for different materials and splits the allocation accordingly. The split typically consists of one sector for production (extraction) and another for traded goods. Where this is the case, the split allocation is handled quite simply by differentiating between domestic supply of domestically sourced products and those that have been traded, separating the two, handling the allocations in two stages and then recombining. In some instances, the traded commodities are associated with more than one sector of origin. In such cases, a global average (relative global trade of the different commodity types across the time series) is utilised to weight the splitting of imported goods across the different sectors accordingly.

From this point, the remainder of the calculations of subsequent supply chains, and ultimately material footprints, follow the same process as within the traditional GEIC/IOTA framework (i.e. application of standard MRIO methods on a hybridised Leontief inverse).

2.2. Data sources

The following datasets are utilised in the construction of a material footprint for metal and mineral products within the GEIC/IOTA framework:

- **Metal and mineral production timeseries:** We were supplied by WU Vienna with a global metal and mineral production dataset produced for the UN International Resource Panel by an international consortium (www.resourcepanel.org/global-material-flows-database), covering the years 1970 to 2020 (although commodity coverage for 2019 and 2020 is incomplete). This provides a breakdown of the mined products and associated masses of material extraction per country of production. Note that in the case of coupled production, as often occurs in the mining of metal ores (e.g. combined copper and gold mining), price allocation is used to allocate the 'auxiliary material' (i.e. the part of the crude metal ore that does not contain the metals) to the different metal commodities produced from the same crude ore. Two classification schemes are provided, a more detailed scheme with 129 material categories, and a more aggregated 'Common Compilation Category' scheme which contains 39 categories.

- **Metal-to-ore conversion factors:** Based on the same UN IRP dataset, we were also supplied by WU Vienna with factors that allow conversion between (some) metal products (and a handful of relevant non-metal products) and raw material equivalents. These allow, for example, traded downstream products (e.g. refined metals) to be converted back into the mass of their constituent crude ore extraction. Thirty-six conversion factor classifications were supplied, but individual conversion factors are specific to country and year of production.

- **UN Comtrade:** Using a combination of HS-code and keyword searches, we identified potentially relevant traded products from the UN Comtrade database. Where this information can be linked explicitly to produced commodities with limited assumptions (see details below) it is used to map commodity trade.

- **EXIOBASE MRIO:** Raw material production and/or trade is mapped into appropriate sectors in the EXIOBASE MRIO to ensure production is distributed through to final consumption.

2.3. Method applied

The description below outlines the methods applied to link the UN IRP metal and mineral production data through to final consumption via the use of the EXIOBASE MRIO and (where possible) UN Comtrade data. It should be noted that, whilst steps have been taken to ensure a robust application within the constraints of the data and time availability, several limitations exist which could be a target for further work. Additionally, where assumptions have been made to connect datasets, further validation of the methods would be beneficial (e.g. in consultation with WU Vienna).

Starting from the metal and mining production data, production is associated, where possible, with physical estimates of trade in materials that can be directly linked back (without complex assumptions) to raw material extraction (Figure 1). Once the physical-trade step is complete, we are left with an estimate of the traded material quantities, per origin, and (subtracting trade from production) a remaining amount of production that was not distributed using physical trade data. This remaining quantity is allocated to the relevant production sector within the MRIO in the country of origin. Traded quantities are allocated to the relevant producing sector and distributed according to relative sectoral expenditure in the destination country (e.g. UK purchases of copper from Chile are based on sector-specific economic shares of purchases from Chilean ‘copper production’ sectors). Standard MRIO methods are then utilised to ensure production is mapped in its entirety to final demand.

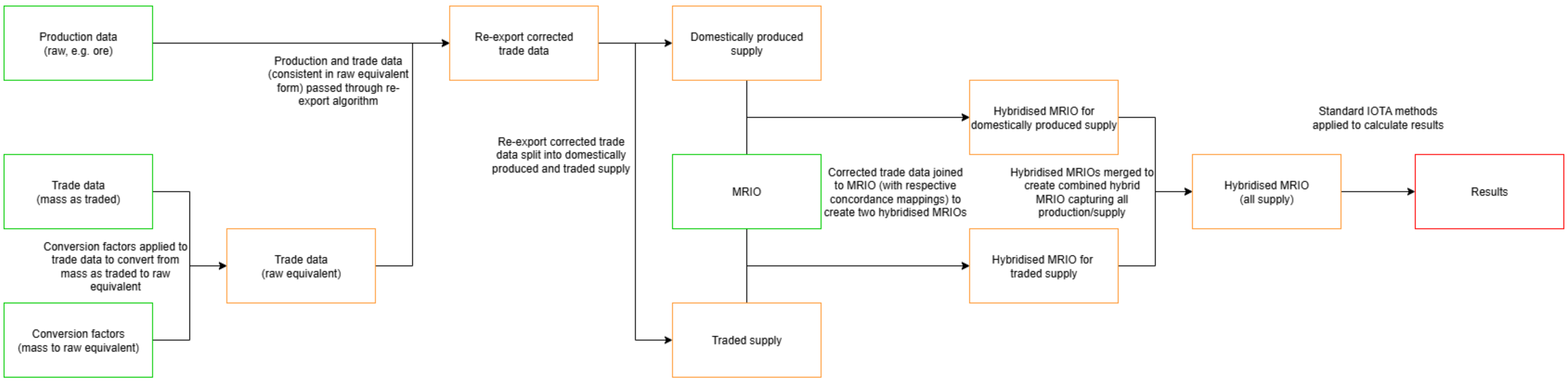

Figure 1. A flow chart illustration of the data pipeline used to produce initial results for a metals and minerals footprint estimate for the UK. The green boxes (production data, trade data mass, conversion factors and MRIO) show inputs, the orange boxes (trade data raw equivalent, re-export corrected trade data, domestically produced supply, traded supply, and hybridised MRIO data) show intermediate data, and the red box (results) represents final outputs from the modelling process.

2.3.1. Mapping production data to trade

An initial step was to develop an IOTA-specific classification system based on the material classifications provided by UN IRP. In most cases a 1:1 mapping was made between materials in the production dataset and those used in IOTA. However, there were exceptions. The IOTA classifications adopted seek to balance the specificity available across multiple datasets. For example, UN IRP provides five ore products associated with titanium. However, the trade data are non-specific about the sources of titanium, and therefore combining into one category was deemed to reflect the most communicable classification. 98 individual commodities (or commodity groups) result from this classification exercise.

Search terms were then developed to identify potentially relevant materials in the UN Comtrade dataset. Given that materials relevant to mining may be spread across multiple HS sub-classifications, a search-term-based method was believed to offer the most comprehensive option for initial screening (as opposed to searching within codes known to contain metal products alone, for example). The Comtrade API was queried and all resulting HS classifications downloaded. Resulting products identified in the trade records were then coded for relevance according to the criteria detailed in Table 1.

Table 1. Categories that UN Comtrade were grouped into, and their treatment in the modelling framework.

Criterion	Description	Treatment
O	Ores or concentrates of an identifiable metal	Not modelled in physical units (but may be possible in future versions; see ‘Limitations’ section)
M	Metal product that can be converted readily into ore-equivalents using conversion factors	Modelled in physical units, subject to associated conversion factor availability
A	Specific metal alloy	Not modelled in physical units (but may be possible in future versions; see ‘Limitations’ section)
NM	Non-metal product that can be used directly (or if relevant with a conversion factor) to link to raw material equivalents	Modelled in physical units, with associated conversion factor applied where relevant (otherwise no conversion factor needed)
U	Uncertain metal/mineral content, a complex mixed product or compound, or otherwise difficult to link back to relevant ore/raw material without complex assumptions	Not modelled in physical units

Criterion	Description	Treatment
X	Irrelevant code (i.e. product not linked to metal/mineral product in question)	Not relevant for inclusion
W	Metal/mineral derived from waste or scrap (and therefore not associated with material extraction)	Not relevant for inclusion for a material footprint covering raw material extraction

Trade records typically group together (O) ores and concentrates (e.g. HS261000 “Chromium ores and concentrates“). This is problematic as the metal content of these products can vary drastically and within the classification scheme there is no direct mechanism to tell at what concentration the metal exists. Consultation with Jim West (CSIRO) revealed that whilst there may be case-by-case approaches to deal with this issue in future iterations (see ‘Limitations’ section), it could not be generally assumed that materials would be traded as ores or concentrates and therefore it would not be possible to apply general conversion factors. In this release, therefore, the decision was taken to exclude physical trade of ore and concentrate products. Instead, untraded material production is allocated to the relevant production sector in the country of origin.

A similar issue exists for alloys (A). Certain alloys are specified in the trade data (e.g. HS 740322 “Copper; copper-tin base alloys (bronze) unwrought”) but without information about the respective base metal composition. Without information, or the application of assumptions, to estimate the base-metal content of alloys, in this release it was deemed necessary to also exclude physical-trade treatment of alloy products.

A number of traded materials are for products which include the commodity of interest in more downstream processed states or within other complex products/compounds (U) that makes it impossible to define target-material content (e.g. HS 741021 “Copper; foil, backed with paper, paperboard, plastics or similar backing material, of a thickness (excluding any backing) not exceeding 0.15 mm, of refined copper”). Again, these are excluded from the physical-trade treatment within IOTA.

Waste or scrap (W) materials are not directly associated with new raw material extraction. In some cases, virgin materials may be used alongside waste products to form recycled materials, but the trade data does not contain such specificity, and therefore the decision was taken to exclude waste products from the physical-trade treatment. An exception to this is where HS codes do not provide equivalent non-waste linked data (i.e. where virgin metals appear to be classified in a category which may also include waste – for example HS810600 “Bismuth; articles thereof, including waste and scrap”). Information on the trade of waste or scrap-derived products is potentially of interest in the context of a circular economy and therefore these data might be of interest in alternative applications within IOTA in future.

2.3.2. MRIO mapping

The process above identifies the products that can be modelled within IOTA in physical units, with any remaining unallocated production then dependent on insertion into the primary producing sector in the country of origin. Both insertion points require the product or commodity to be mapped to corresponding EXIOBASE sectors. To facilitate this, a mapping exercise was undertaken using UN IRP material names, relevant HS code, NACE classification information and EXIOBASE sector descriptions.

For primary production, fifteen EXIOBASE sectors are relevant and can be easily identified. In some cases, there is a 1:1 mapping against the raw material production data (e.g. EXIOBASE ‘Mining of nickel ores and concentrates’ matches UN IRP ‘Nickel - associated ore’). In many cases, however, several raw material products are mapped to a single MRIO sector.

For traded products, the mapping is more complex and careful screening against NACE documentation (which provides more detail than, but can be concorded against, EXIOBASE classifications) was used to identify the relevant sectors that should be associated with traded materials. Since the relevant traded products are typically associated with base metals, there is often just a single relevant downstream sector that applies. For example, 30 traded copper products were identified in the trade-screening exercise to be taken forward in the physical-trade analysis. These are all, however, associated with the single ‘Copper production’ sector in EXIOBASE. In other cases, more than one relevant EXIOBASE sector exists. For stone products, for example, NACE descriptions reveal that basic processing of stone can be associated with the ‘Quarrying of stone’ EXIOBASE sector, but that further shaping/cutting (e.g. for construction should be associated with the ‘Manufacture of other non-metallic mineral products n.e.c.’ sector).

The steps above result in a finalised mapping list whereby an IOTA-specific commodity code and name is mapped to:

- The UN IRP code and material name.
- The CCC code and material name.
- Data to be treated as a primary or physically traded component of the modelling; process.
- The respective sector (or sectors) for insertion of production or trade information into the MRIO model.

2.3.3. Conversion factors and determining final product-treatment with the IOTA framework

The process described above determines the theoretical treatment of identified products within the IOTA framework. However, to avoid underestimating the material extraction requirements of traded metals (and some other minerals) conversion factors must be used. Conversion factors for 36 materials were supplied by WU Vienna based on the UN IRP database, of which 34 map onto the materials used in the production dataset. For the most part, non-metal products do not have conversion factors (as raw material extraction is equivalent to that present in the traded commodity, for example anthracite, limestone). Exceptions where conversion factors are provided include ‘oil shale and oil sands’, ‘nepheline syenite’, ‘potash’, ‘diamond ore, gems’, ‘diamond ore, industrial’ and ‘sulphur ore’. Conversion factors are provided for most major traded metals, with the exception being aluminium/bauxite. Where conversion factors are not available for metals (in addition to aluminium this includes commodities such as cadmium, magnesium or selenium) we take the decision not to model these in physical units due to the likelihood of significantly underestimating associated raw material extraction. Where conversion factors are not available for non-metals, these are modelled in physical units (as in most cases it is reasonable to assume material equivalence).

Conversion factors are available per-year and per-country of origin. In some cases, production data exist in a particular year and/or country without an equivalent conversion factor being supplied. In instances where a value is missing for a given country and year, but factors exist for alternative years for this country, the closest year's value is used as a substitute (using nearby year(s) if only one date is missing). In cases where a country has no conversion factor for any year, a global-average conversion factor is utilised (for the nearest possible year if a corresponding year is unavailable).

In some instances, IOTA commodity classifications are coarser than the availability of material production and conversion factor data from UN IRP. In these instances, we have initially selected the conversion factors which result in the lowest 'material equivalent' values. There is a risk that, in actuality, the commodity is composed of material which has higher material extraction requirements, but erring on the lower side allows the MRIO in theory to "correct" for this discrepancy, whereas erring on the higher side is more prone to "locking in" incorrect flows. It is likely that this simplifying assumption could be improved in future via case-by-case data interrogation (see 'Limitations' section) but in the immediate term the effect of this assumption may be that a greater volume of recorded material is processed via insertion into the primary production sector rather than via bilateral trade. Within IOTA, total consumption and trade is capped at total production, so at the system level the reported production quantities are preserved.

Following application of conversion factors, we obtain the traded production quantities in raw material equivalents. These are then inserted into the IOTA framework in terms of production (of the raw material) and trade (of raw equivalent materials). These get processed through the re-export algorithm of the framework to link points of final import to points of origin and then get incorporated into the financial MRIO component of the framework to complete the modelling of the supply chains. The modelling is conducted at appropriate levels of commodity resolution to ensure that equivalent sector-level information is preserved (i.e. the trade and application to the MRIO will be done in similar commodity groupings), before being aggregated at the end to give unified raw-equivalence values.

3. Results

Files providing the data produced are available through the JNCC Resource Hub. Below, a summary of some key results are presented. As the methods remain experimental and require further improvement, results should be used with caution at this stage. As preparation of the data differs from the main agricultural GEIC dataset in terms of the methodology applied and levels of uncertainty involved, users should also avoid comparing or aggregating with the main GEIC results at this stage.

The mined commodities linked to UK consumption in 2018 with the highest mass were ‘sand, gravel and crushed rock for construction’, ‘stone’, and ‘crude oil’ (Table 1). Time series for several selected commodities (‘sand, gravel and crushed rock for construction’, ‘bituminous and sub-bituminous coal’, ‘copper’, and ‘lithium’) are shown in Figures 2 to 5, including a breakdown of the data by country of origin. For example, it can be seen that ‘sand, gravel and crushed rock for construction’ mass consumed by the UK has fluctuated over the years, with peaks in 2007 and 2015, and low points in 2010 and 2017, but has remained between 250,000 tonnes and 350,000 tonnes throughout the time series. Most ‘sand, gravel and crushed rock for construction’ comes from the UK itself, with most of that imported coming from China. Lithium is notable for its significant increase in mass consumed within the last two years of the time series (2016–2018), with most UK supply originating in Australia.

Table 2. Top ten mined commodities linked to 2018 UK consumption, with masses (tonnes).

Commodity Name	Tonnes
Sand, gravel and crushed rock for construction	313,495,003
Stone	133,861,118
Crude oil	81,862,638
Bituminous and sub-bituminous coal	54,804,587
Natural gas	50,509,942
Gold - associated ore	48,728,031
Other clays	30,121,536
Iron ores	22,999,752
Copper - associated ore	21,254,072

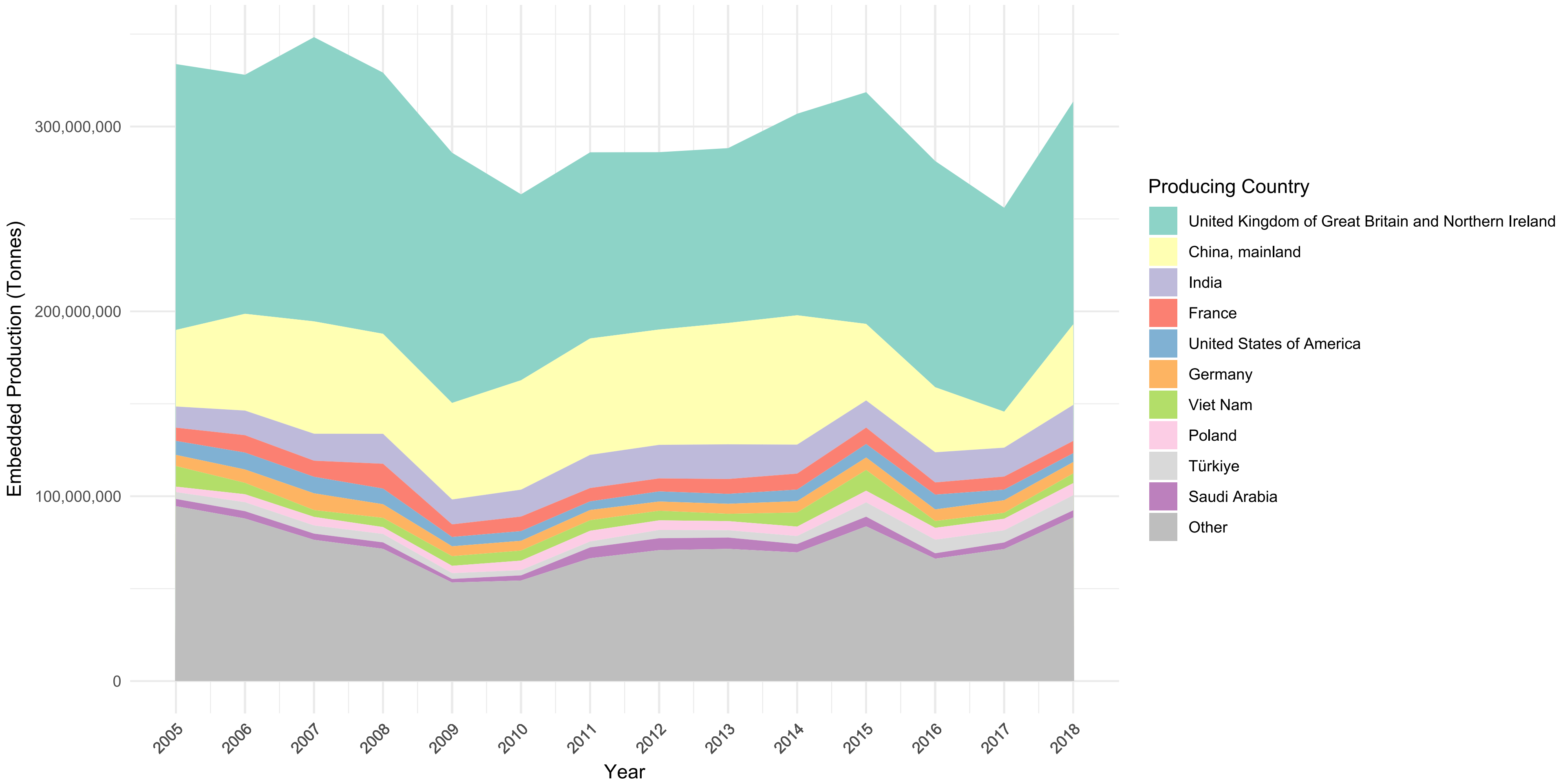

Figure 2. Timeseries of UK consumption linked to 'Sand gravel and crushed rock for construction' production, with top-ten countries of origin; tonnes. The order in which the countries appear in the graph match the order in the legend (e.g. UK is the top bar, 'other' is the bottom bar).

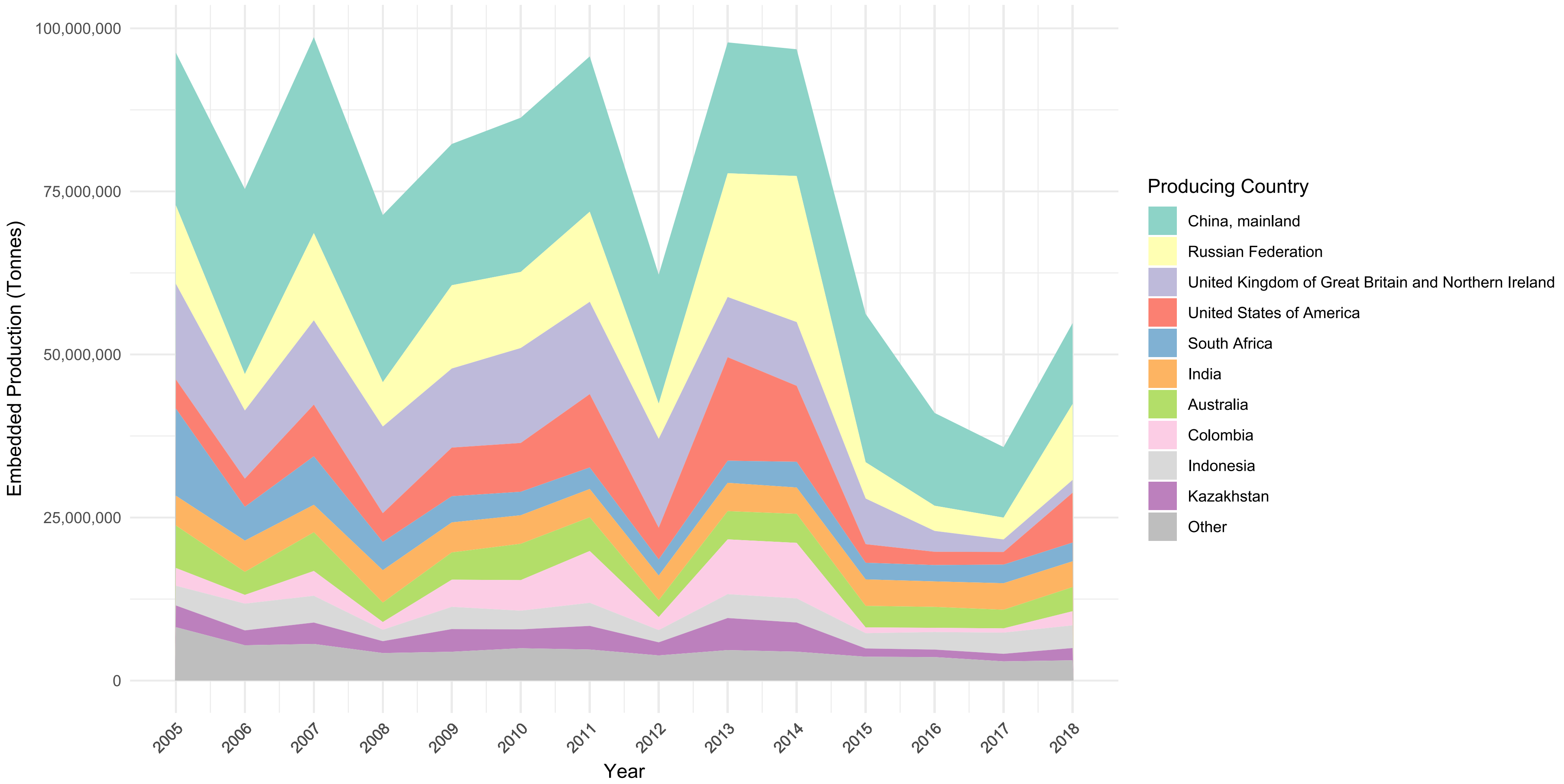

Figure 3. Timeseries of UK consumption linked to 'Bituminous and sub-bituminous coal' production, with top-ten countries of origin; tonnes. The order in which the countries appear in the graph match the order in the legend (e.g. China is the top bar, 'other' is the bottom bar).

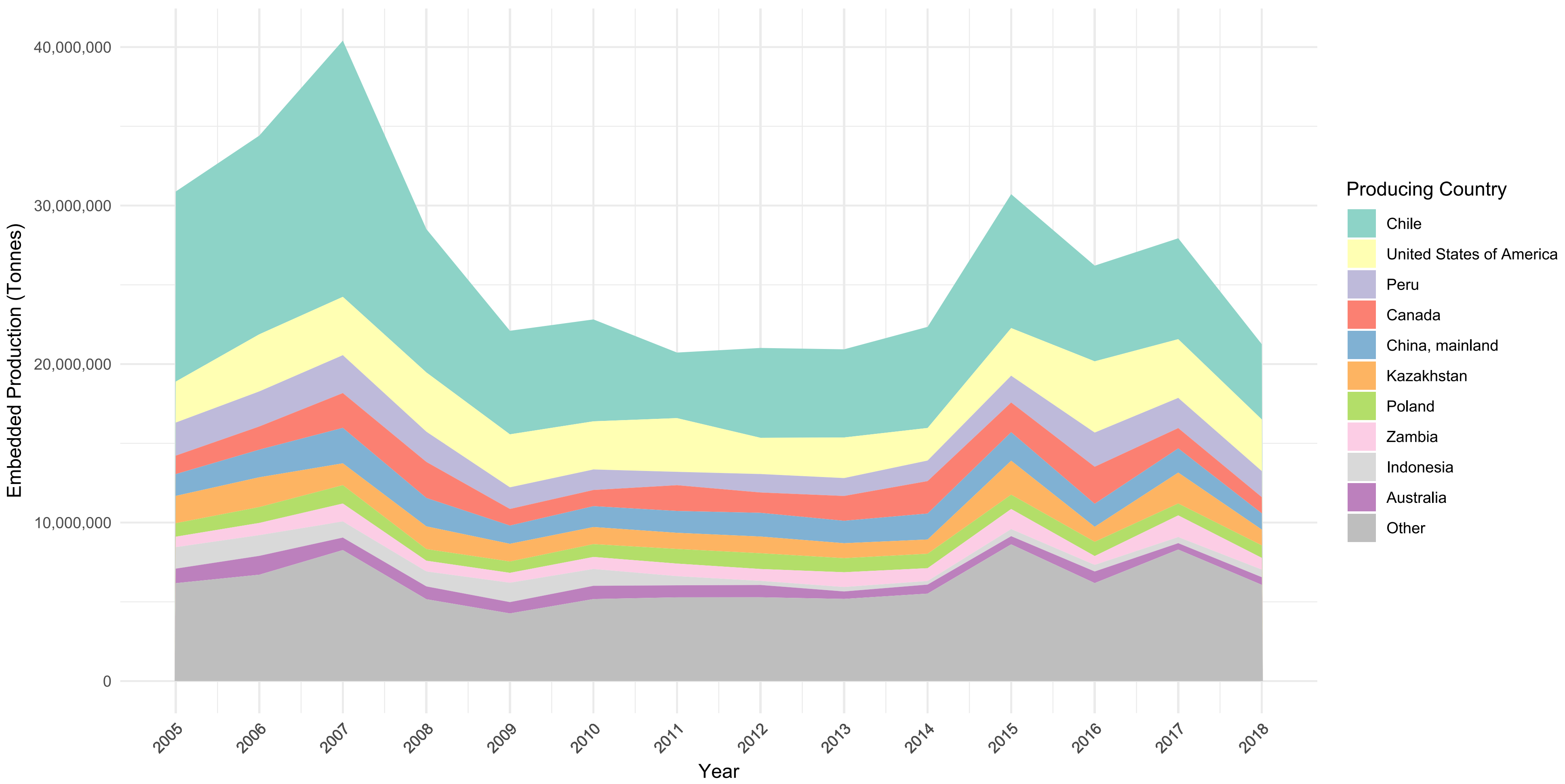

Figure 4. Timeseries of UK consumption linked to 'Copper - associated ore' production, with top-ten countries of origin; tonnes. The order in which the countries appear in the graph match the order in the legend (e.g. Chile is the top bar, 'other' is the bottom bar).

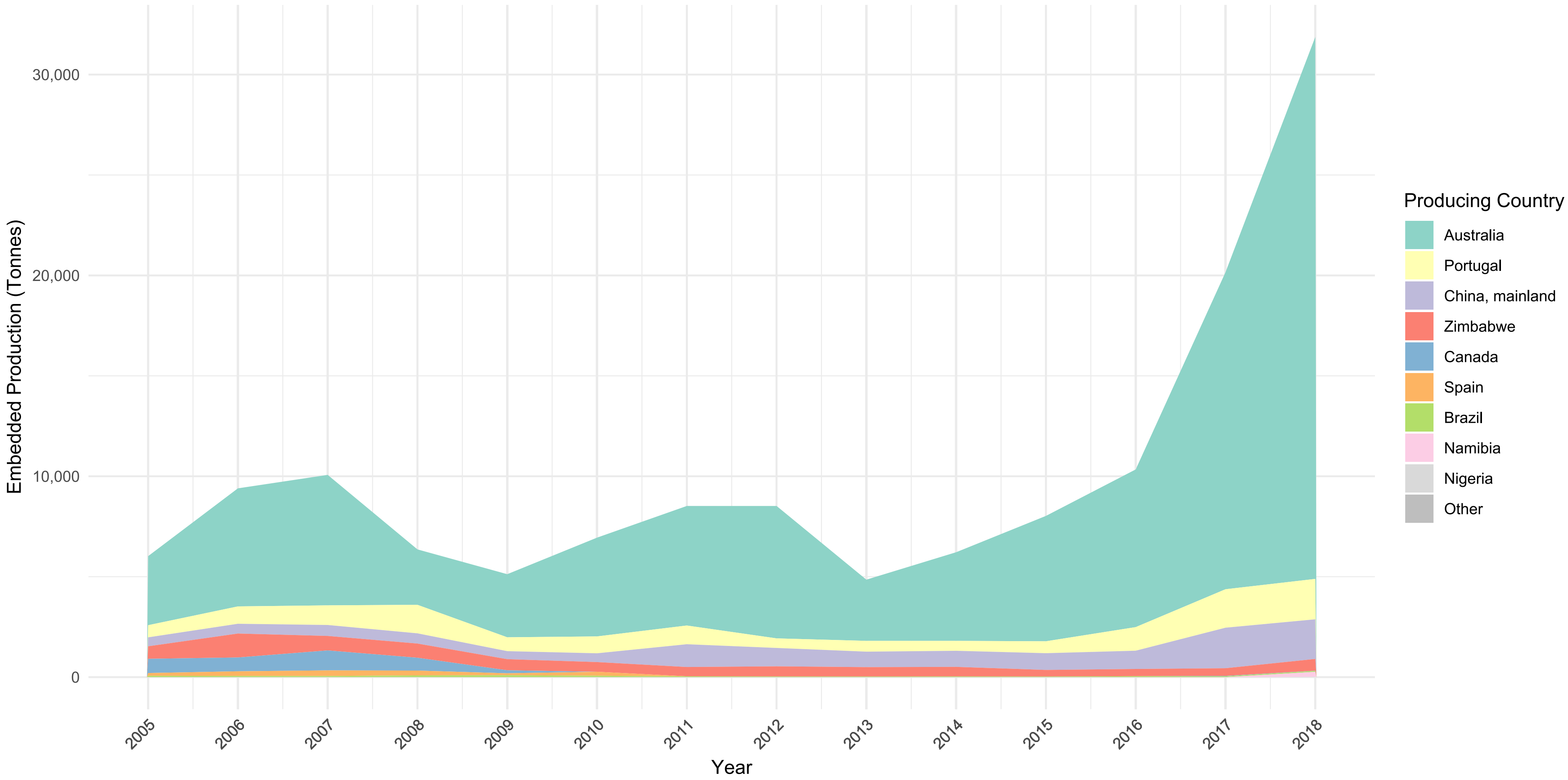

Figure 5. Timeseries of UK consumption linked to 'Lithium ore' production, with top-ten countries of origin; tonnes. The order in which the countries appear in the graph match the order in the legend (e.g. Australia is the top bar, Portugal is in the second from top bar).

4. Next steps

4.1. Limitations and areas for potential improvement

The following areas of potential improvement have been identified in the course of this initial development work.

4.1.1. Use of ore and concentrates physical trade data

It is potentially possible to utilise a combination of the monetary value of trade information and commodity-price statistics to estimate whether trade is taking place in terms of ores or commodities. Equally, commodity-specific information could help to make assumptions (e.g. iron ore traded in ore, copper as concentrates). Aspects such as regional electricity prices could also be used to inform assumptions (e.g. we have received anecdotal evidence that Australia has started to ship bauxite to China for processing as local electricity costs have made it less profitable to produce aluminium concentrates locally). Identifying a handful of priority metals to undertake such an analysis for would likely be necessary to develop a proof of concept.

4.1.2. Use of alloy physical trade data

Comtrade reports alloy trade meaning that should data be available on typical metal content (e.g. from industry sources) it could be used to approximate the metal content associated with certain materials. Again, focusing on a handful of metals to test out potential options would be helpful to developing a proof of concept.

4.1.3. Improving methods to allocate materials downstream in the MRIO

Currently, MRIO expenditure data are used to distribute materials after they are inserted into the MRIO. Interrogation of the expenditure data for the UK, however, reveals that this general approach is likely to bias dissimilar materials towards certain sectors. For example, the UK 'Processing of Food products nec' sector of EXIOBASE appears to have high levels of expenditure on the 'Mining of chemical and fertilizer minerals, production of salt, other mining and quarrying n.e.c.' sector, yet some materials inserted into this sector are unlikely to have direct food use. It may be possibly therefore selectively to include/exclude downstream sectors for each commodity to refine allocations further. A more thorough review of expenditure profiles, and commodity-by-commodity mapping to downstream-utilisation, would be necessary.

4.1.4. Missing conversion factors

Some conversion factors are not available within the dataset provided by WU Vienna based on the UN IRP database. The most notable is for bauxite/aluminium. For other materials we could explore whether appropriate factors could be obtained from WU Vienna (who are working to further improve their database on ore grades and the environmental impacts of mining on a site-specific level, through the EU project RAWCLIC) or other sources.

4.2. Potential future work

Work to build on and improve this initial dataset and further scope the addition of associated environmental datasets is provisionally planned in the coming years.

References

Alvarez-Berríos, N.L. & Aide, T.M. 2015. Global demand for gold is another threat for tropical forests. *Environmental Research Letters,* **10**(1). http://dx.doi.org/10.1088/1748-9326/10/1/014006

Asner, G.P., Llactayo, W., Tupayachi, R. & Luna, E.R. 2013. Elevated rates of gold mining in the Amazon revealed through high-resolution monitoring. *PNAS,* **110**(46), 18454-18459. https://doi.org/10.1073/pnas.1318271110

Asner, G.P. & Tupayachi, R. 2016. Accelerated losses of protected forests from gold mining in the Peruvian Amazon. *Environmental Research Letters,* **12**(9). https://doi.org/10.1088/1748-9326/aa7dab

Croft, S., West, C., Harris, M., Green, J., Molotoks, A., Harris, V., Egan, C., Wood, E., Ball, T. & Way, L. 2024. Technical documentation for an official statistic estimating the global environmental impacts of consumption: 2024 version. JNCC Report 786, JNCC, Peterborough, ISSN 0963 8091. https://jncc.gov.uk/resources/7a4063c9-a221-4ca1-ab6a-3b2fae544b32

Curtis, P.G., Slay, C.M., Harris, N.L., Tyukavina, A. & Hansen, M.C. 2018. Classifying drivers of global forest loss. *Science,* **361**(6407), 1108-1111. https://doi.org/10.1126/science.aau3445

Espejo, J.C., Messinger, M., Román-Dañobeytia, F., Ascorra, C, Fernandez, L.E. & Silman, M. 2018. Deforestation and Forest Degradation Due to Gold Mining in the Peruvian Amazon: A 34-Year Perspective. *Remote Sensing,* **10**(12), 1903. https://doi.org/10.3390/rs10121903

Hoang, N.T. & Kanemoto, K. 2021. Mapping the deforestation footprint of nations reveals growing threat to tropical forests. *Nature Ecology & Evolution,* **5**, 845-853. https://doi.org/10.1038/s41559-021-01417-z

House of Commons Environmental Audit Committee. 2024. The UK's contribution to tackling global deforestation. Available from: https://committees.parliament.uk/publications/42709/documents/212302/default/ [Accessed 8 April 2025].

Jasansky, S., Lieber, M., Giljum, S. & Maus, V. 2023. An open database on global coal and metal mine production. *Scientific Data,* **10**(52). https://doi.org/10.1038/s41597-023-01965-y

Kalamandeen, M., Gloor, E., Johnson, I., Agard, S., Katow, M., Vanbrooke, A., Ashley, D., Batterman, S.A., Ziv, G, Holder-Collins, K., Phillips, O.L., Brondizio, E.S., Vieira, I. & Galbraith, D. 2020. Limited biomass recovery from gold mining in Amazonian forests. *Journal of Applied Ecology,* **57**(9), 1631-1871. https://doi.org/10.1111/1365-2664.13669

Kramer, M., Kind-Rieper, T., Munayer, R., Giljum, S., Masselink, R., van Ackern, P., Maus, V., Luckeneder, S., Kuschnig, N., Costa, F. & Rüttinger, L. 2023. Extracted Forests. Available from: https://www.wwf.de/fileadmin/fm-wwf/Publikationen-PDF/Wald/WWF-Studie-Extracted-Forests.pdf [Accessed 8 April 2025].

Maus, V., da Silva, D.M., Gutschlhofer, J., da Rosa, R., Giljum, S., Gass, S.L.B., Lueckeneder, S., Lieber M. & McCallum, I. 2022. Global-scale mining polygons (Version 2) [dataset]. *PANGAEA*, https://doi.org/10.1594/PANGAEA.942325

Pendrill, F., Persson, U.M., Kastner, T. & Wood, R. 2022. Deforestation risk embodied in production and consumption of agricultural and forestry commodities 2005-2018 (Version 1.1) [Dataset]. *Zenodo*. https://doi.org/10.5281/zenodo.5886600

Schueler, V., Kuemmerle, T. & Schröder, H. 2011. Impacts of Surface Gold Mining on Land Use Systems in Western Ghana. *Springer Nature Link,* **40**, 528-539. https://doi.org/10.1007/s13280-011-0141-9

Singh, C & Persson, M. 2024. Global patterns of commodity-driven deforestation and associated carbon emissions. EarthArXiv pre-print. Available from: https://eartharxiv.org/repository/view/7000/ [Accessed 8 April 2025].

Weblinks

Table 3. Full URLs for weblinks used in the text.

Weblink text	Full URL
Dasgupta Review	https://www.gov.uk/government/publications/final-report-the-economics-of-biodiversity-the-dasgupta-review
Environmental Improvement Plan	https://www.gov.uk/government/publications/environmental-improvement-plan
EU RAWCLIC project	https://www.rawclic.eu/home
Example bauxite facility	https://www.fineprint.global/visualisations/global-coal-and-metal-mining-viewer/?_inputs_&facility_id=%22COM00861.00%22
Fineprint Data Visualisation	https://www.fineprint.global/visualisations/viewer/
FinePrint project	https://www.fineprint.global/
Global Environmental Impacts of Consumption (GEIC) indicator	https://commodityfootprints.earth/
Hansen/GFW forest change	https://glad.earthengine.app/view/global-forest-change
International Resource Panel	https://www.resourcepanel.org/
Kunming-Montreal Global Biodiversity Framework	https://www.cbd.int/gbf/
National Food Strategy	https://www.nationalfoodstrategy.org/
SNL Metals and Mining data	https://www.marketplace.spglobal.com/en/datasets/snl-metals-mining-(19)
Statista	https://www.statista.com/statistics/267998/countries-with-the-largest-gold-reserves/
25 Year Environment Plan	https://www.gov.uk/government/publications/25-year-environment-plan

Appendix 1: Scoping a deforestation extension for mining

Estimating the deforestation associated with the trade and consumption of mined products depends on a suitable data layer, or layers, to connect tree cover loss through to mining activity. Additionally, in the context of the GEIC indicator, which seeks to maintain the commodity-specificity of impacts where possible, data which allow associated mine-production output to be obtained per unit of deforestation would be beneficial.

There have been prior attempts to compile mining-linked deforestation footprints. For example, Hoang and Kanemoto (2021) utilised Curtis *et al.* (2018) 'deforestation driver' information to allocate tree cover loss associated with an 'agricultural, mining and energy infrastructure' category through the MRIO sectors based on country-wise economic outputs. Whilst this kind of approach represents a potentially viable mechanism for integration of mining linked deforestation data within the GEIC dataset, implementation of this kind within the IOTA framework would depend wholly on the economic structure of the MRIO to determine the final-demand drivers of forest loss. In other words, aggregated deforestation across multiple production drivers (agricultural and non-agricultural) would have to be apportioned not via granular commodity-specific information but rather according to relative levels of economic activity. An approach of this kind would depart from a main 'value add' of the hybrid MRIO structure that IOTA allows; that of retaining commodity-specificity linked to production impacts. Furthermore, the aggregate nature of the deforestation-driver information provided via utilisation of the Curtis *et al.* (2018) dataset alone sits in contrast with the specific crop-information provided by the deforestation data currently used within GEIC (Singh & Persson 2024) whilst also overlapping with the drivers (agriculture) that Chalmers' data model. Whilst measures could be taken to 'remove' deforestation calculated from one dataset from another estimate, this represents an inelegant solution.

A recent WWF report (contributed to by WU Vienna authors, among others) indicates that the majority of mining related deforestation can be attributed to gold and coal (Kramer *et al.* 2023). Their study estimates both direct and indirect deforestation from mining. For the former, geospatial records of mine location are utilised (see below for further details on the geospatial polygons utilised) which are overlaid with Hansen/GFW forest change information to estimate deforestation linked to mines occurring since the year 2000. Data from the SNL Metals and Mining data was then cross-referenced to 'clusters' of mining polygons to relate the forest cover loss within each mining area to reported commodity production. In cases where several commodities were mined within a single cluster of mined polygons, price allocation was applied to distribute responsibility for deforestation impacts between different commodities (note that this has the effect of biasing deforestation attribution towards high-value commodities such as gold). Tentative indirect deforestation effects are determined by adding buffer-zones around the polygons. Deforestation per commodity is then attributed to the GLORIA MRIO model (which includes ten mining sectors). Results are not annualised (see below for discussion); rather the consumption footprint represents the total deforestation impact estimated over the 2000–2021 period covered.

In the context of GEIC, a potentially appropriate approach exists in the exploration of a similar direct integration of geospatial mining information into the existing deforestation data layer utilised by GEIC. The existing deforestation dataset within the GEIC indicator depends on deforestation estimates compiled, on a per-commodity basis, by the Chalmers University of Technology. Previous versions of the dataset (Pendrill *et al*. 2022) were dependent on statistical 'land balance' allocations of tree cover loss through to land-use classifications and then to crop-types. This utilised consistent (FAO) records of land utilisation (which do not contain estimates for mining). However, more recently, advances have been made to allow spatially- and crop-specific remote-sensing data to be utilised in the first instance with land-balance assumptions being used only where spatial data do not exist (Singh & Persson

2024). An option exists, therefore, for geospatial information on mine extent - such as that from Maus *et al*. (2022; as used in the WWF study) to be associated, in a spatially explicit manner, with tree cover loss data utilised by Chalmers (in an equivalent manner to, for example, soy-linked land occupation being used). In a basic case, this could result in a general 'mining' attribution to deforestation. To provide a year-on-year assessment (as is conducted for the existing deforestation layer) sensible assumptions about the time-period over which initial forest loss can be attributed to mining products would need to be adopted (as opposed to a total deforestation sum as published in the WWF study). If the use of mine-specific production data was deemed to be too complex, a further basic assumption could be made that this general 'mining activity' assessment constitutes the measurable deforestation footprint of mining associated with a country, which could be linked to all (appropriate) aggregated national mining production estimates in that country before linkage to the hybrid-MRIO framework. Whilst limiting, this assumption would likely improve, for example, upon the Hoang and Kanemoto (2021) approach but would lack the specificity of the WWF (Kramer *et al.* 2023) approach.

A more powerful option would be, as per the WWF work, to attempt to link geospatial mining activities to commodity-specific outputs where possible (at either the individual polygon or polygon-cluster level). Jasansky *et al.* (2023) provide an open database on global coal and metal mine production which has the potential to facilitate this, which ongoing work through the EU RAWCLIC project is aiming to update. They provide an open database of mining production at the level of 1171 individual mines (artisanal and small-scale mining is not included), reporting for 80 different materials in the period 2000–2021. Data were gathered manually from public records (mainly sustainability reports from mining companies). Within the accounting framework used for the dataset, annual data on the extraction and production of coal, metal order, metal concentrates and non-metallic minerals are collected. These data may also be valuable in refining estimates of ore/concentrate levels in international trade statistics - see section above. This database is not comprehensive - it misses information which is not placed in the public domain. A comparison was made by the authors with the International Resource Panel global production dataset, revealing that (including China where coverage within the open database is poor) coverage for copper is reasonably good (60–70% over the time period analysed) but for gold is around 30–40%, with potential for high year-on-year variability. As such, it will only provide a partial picture of production within a country (some countries' estimates are much better than others), and an uncertain picture over time. Nonetheless, where records can be cross referenced to geospatial land-occupation (e.g. Maus *et al.* 2022) and material outputs derived, it would theoretically be possible to attribute deforestation to some, specific, mined commodities. Further assumptions would likely be needed on co-products/poly-metallic outputs from mines which may not be fully reported by companies, or instances where multiple mines are clustered into 'areas' in the disclosed records.

Both the Jasansky *et al.* (2023) and Maus *et al.* (2022) datasets are available via the FinePrint project website. This example, shows a bauxite facility in Brazil which is associated with a geospatial mining polygon appropriate for overlaying with tree cover information. (Note that this has not been conducted here; the mine sits within the Amazon biome and would therefore be associated with deforestation but was established in 1979 and therefore tree cover loss would likely have been historic, prior to the GEIC timeseries). Polygons may, however, not align perfectly (or at all) with the open database's geospatial information. Therefore, careful alignment will be necessary between data resources to link any tree cover loss through to production and trade. We understand that WU Vienna are in the process of trying to consolidate these datasets themselves, which would reduce potential workloads in any preparation for GEIC.

Ultimately, it appears that - with recent, and short-term future, data releases - there may be sufficient data in the public domain to provide reasonable - if still partial - allocations of deforestation through to mined-commodity production. However, third-party resources remain at a stage where there is no 'off-the-shelf' data availability to do so and therefore further development work would be needed to integrate information into a deforestation-linked dataset. A potential approach to progressing work within the context of the GEIC indicator and/or more broadly via collaboration with the Chalmers University of Technology, therefore, is to focus initially on commodities which are both of high-interest and have reasonable data-quality. For the former, the EAC recently called for gold mining to be investigated in more detail as a source of deforestation risk (House of Commons 2024). For the latter, Jasansky *et al.* (2023)'s dataset indicates that whilst coverage of global gold mines is in the region of 30–40%, it does benefit from being a specific metal product covered individually in the dataset. Thus, we now turn to gold mining information in more detail.

Gold mining as a source of deforestation and potential data availability

There are a handful of studies that show links between gold mining and deforestation, including the WWF study noted above (Kramer *et al.* 2023), which (from an economic-allocation standpoint) determines gold to be the leading mining-driver of deforestation. Illegal gold mining is also an issue, having increased in recent years, particularly in South America around the Amazon (Asner *et al*. 2013; Alvarez-Berríos & Aide 2015; Asner & Tupayachi 2016) driven by increases in gold prices in international markets and in some countries such as Brazil, encouraged by political support. Where forests are not cleared, they are significantly degraded by gold mining activities (Espejo *et al.* 2018), severely limiting the potential for ecosystem recovery (Kalamandeen *et al.* 2020) with mines often abandoned once their reserves have been exhausted.

Research has also been conducted in West Africa (e.g. Ghana; Schueler *et al.* 2011) on the impacts of gold mining on the environment. However, there appear to have been fewer studies in recent years. Small scale gold mining is difficult to detect and has received little attention compared to agricultural activities due to the comparatively small geographical extent it covers (Alvarez-Berríos & Aide 2015). As above, satellite imagery has recently been utilised to detect gold mines and create datasets on where these activities are occurring. As things stand, however, these still mainly cover large scale mining. Furthermore, gold is often mined in combination with other metals, which makes it challenging to attribute deforestation directly to a single commodity.

Australia and Russia are the two countries with the highest gold reserves, followed by South Africa, USA and China (Statista). However most gold-related deforestation comes from four countries: Peru, Suriname, Russia and Brazil (Kramer *et al.* 2023). In order to examine whether available data can be used to explore gold mining as a source of deforestation, we have undertaken work to screen the previously mentioned datasets (via the Fineprint Data Visualisation tool) in order to understand the level of alignment between the two. The share of production covered by spatially explicit data for gold mining operations lies roughly between 30–40%, which is calculated by comparing production data from the open mining database (Jasansky *et al.* 2023) on global coal and metal mine production, to national production data. These data were cross referenced with the spatial data on the extent of the gold mines provided by Maus *et al.* 2022.

Although the share of gold production globally covered by the data is relatively low, there is reasonable coverage in terms of spatial data for the gold mines with production data provided by Jasansky *et al.* (2023). For example, for 2018, there are 183 listed mines in the open database on global coal and metal mine production which include gold as a commodity. When cross referenced with the Maus *et al*. (2022) dataset, only 5% of data points are not directly aligned with spatial information on the extent of mining activities. Of these mines, the vast majority show polygons nearby the mining data points which could be assumed to be those matching the production dataset. In a handful of examples, a greater mismatch exists. As an example, facility COM01256.00 located in Australia shows the spatial location of the mine as approximately 40km from where the data point coordinates are listed. Satellite imagery confirms there is a mine in the location of the spatial polygon (Figure 6). However, it also shows mining activity where the data point is located which is not covered in the spatial data.

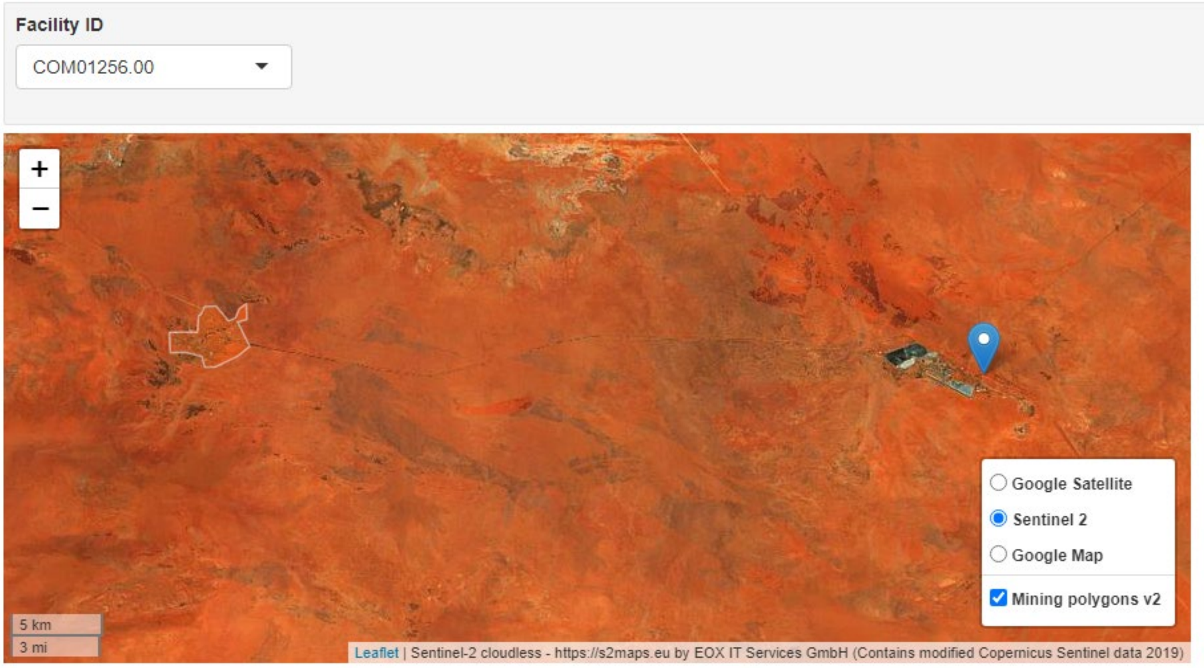

Figure 6. Facility COM01256.00 located in Australia, showing the spatial location of the mine as approximately 40km from where the data point coordinates are listed. Image reproduced from Fineprint Geovisualisations under CC BY-NC-SA 4.0 license.

In conclusion, our explorations show a reasonably high degree of alignment between the two datasets, however in a small percentage of cases the full extent of mining activities is not covered by the spatial data. Overall, this indicates that whilst the global coverage of gold production is not high, there is potential to use spatial data on gold mining to explore associated deforestation from this (and other mined) commodities.