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Technical documentation for an official statistic estimating the global environmental impacts of consumption: 2025 Version

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Update March 2026:

Please note that Version 2 of this report was published on 27 March 2026, to correct an error that was identified in the underlying methods for the water footprint and water scarcity metrics. Figures 9 to 13, and the relevant descriptions and accompanying datasets have been updated to reflect this. All other content is unaffected.

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Evidence Quality Assurance:

This document is compliant with JNCC's Evidence Quality Assurance Policy.

Summary

The Global Environmental Impacts of Consumption (GEIC) indicator provides estimates of environmental impacts and risks driven by international consumption and production. The full global dataset can be downloaded from an interactive dashboard, where you can also explore the data from the perspective of different consumption and production countries/territories. A subset of results estimating the global biodiversity impacts of UK consumption are published as a UK Biodiversity Indicator: an official statistic. These data also feed into the UK Government's 25 Year Environment Plan Outcome Indicator Reporting as indicator K1.

This report describes the methods behind the GEIC indicator, including:

- An overview of the modelling framework, which is based on hybrid multi-regional input-output modelling using data from the Food and Agriculture Organisation (FAO) of the United Nations and GLORIA, combined within the Stockholm Environment Institute's IOTA (Input-Output Trade Analysis) framework (Croft *et al.*, 2018) (Section 2).
- An explanation of the treatment of commodities that differ in methods and data from the other commodities analysed, namely cattle and timber (Section 2.5).
- An explanation of the data sources used for each impact metric type, how they are integrated into the modelling, and any known data update plans. In brief:
  - Cropland area harvested is based on FAO data on land areas harvested (Section 3).
  - Deforestation and associated carbon emissions are based on methods originally developed in Pendrill *et al.* (2019a, b) which have subsequently been updated with methodological enhancements to improve spatialised crop-specific attribution and forest-loss coverage and to include in non-tropical regions (Singh & Persson, 2023 & 2024) (Section 4).
  - Water footprint metrics are based on annualised Water Footprint Network data, with a water scarcity metric combining this data with AWARE factors (relative Available WAter REmaining per area in a watershed, Boulay *et al.,* 2018) (Section 5).
  - Three separate methods are used for estimating biodiversity loss:
    - Characterisation factors provided by Chaudhary and Kastner (2016) are used to predict regional species loss (Section 6).
    - MapSPAM data is used alongside species richness information from the International Union for the Conservation of Nature (IUCN) and BirdLife International to estimate species richness-weighted extent of crop production (section 7).
    - The LIFE (Land-cover change Impacts on Future Extinctions) metric provides estimates of changes in the expected number of global extinctions summed across species. This approach integrates information on species richness, rarity, and past habitat loss. A score of one is equivalent to an average of one species pressurised to global extinction (Section 8).

Supplementary results to the main indicator release are included in Appendix 1. A discussion of alignment with related metrics is given in Appendix 2. Methodological updates since GEIC was first published in 2021 are summarised in Appendix 3. Detailed concordances between data sources used are provided in Appendix 4.

Contents

1. Introduction

This report constitutes the technical and methodological documentation for the Global Environmental Impacts of Consumption (GEIC) indicator, available as:

- An interactive dashboard with global coverage, providing estimates of environmental impacts associated with consumption in countries, territories and regions around the world, and
- A UK official statistic: the UK Biodiversity Indicator providing these estimates from a UK consumption perspective i.e. estimates of global biodiversity impacts of UK economic activity.

Since its original publication in 2021, GEIC has been updated annually. While based on the same core methods, each update has incorporated developments (e.g. the addition of new impact metrics) and an extension to the time series. Results are recalculated for each publication, so that methodological improvements and any updates to the underlying data (e.g. the physical production and trade data, detailed in section 2.2, are updated periodically) are applied across the full time series. Users should note that for this reason, results for any given year in the time series may differ from results for the same year in previous releases. Table 3 in Appendix 3 provides a summary of the main methodological changes since the indicator's release in 2021. Full details of the methods used for each previous release can be found on The National Archives website.

This document outlines the methods behind the 2025 indicator release and the resulting data for 2005–2023. The subsequent sections of the report cover:

- Policy context for GEIC (sections 1.1 and 1.2), previous work underpinning the methods outlined in this document (section 1.3), an explanation of the datasheets containing the 2025 results (section 1.4), notes on related work published separately from the main indicator release, and ongoing GEIC development (section 1.5);
- Details of the methods behind GEIC, including an overview of the modelling framework (section 2), and an explanation of how each impact metric (environmental extension) is incorporated into the model (section 3 onwards);
- References and weblinks (at the end of the main report);
- Supplementary information provided as four appendices: supplementary graphs (Appendix 1), consideration of alignment and consistency with the UK Carbon Footprint and UK Material Footprint (Appendix 2), summary of methodological updates since GEIC was first published in 2023 (Appendix 3), and concordances used in the modelling (Appendix 4).

1.1. Global policy relevance

Commodity consumption underpins the global environmental crises, driving natural habitat loss and degradation of ecosystem services, such as biodiversity, resilience to hazards, and climate change mitigation and adaptation (IPBES 2019). For example, 9–14% of global annual greenhouse gas (GHG) emissions come from the gases emitted and sequestration potential lost when land is converted for food and fibre commodity production (reviewed in Harris *et al.*, 2020).

The Convention on Biological Diversity (CBD)'s Kunming-Montreal Global Biodiversity Framework Target 16 therefore aims to enable sustainable consumption choices to reduce waste and overconsumption, while Goal 12 in the Sustainable Development Goals is to ensure sustainable consumption and production patterns. In order to respond to such international commitments, Parties need tools that can help them understand the impacts of their consumption and production.

Grounded in internationally recognised impact assessment methods combining peer-reviewed modelling with global production and trade statistics, the GEIC indicator is one such tool. GEIC enables users to quantify and track environmental impacts – such as biodiversity loss, deforestation and water stress – driven by consumption and trade. Governments can use GEIC to understand the global environmental impacts driven by their domestic consumption, as well as the domestic impacts driven by consumption in other countries/territories. In this way, GEIC can support informed national strategies and stronger international cooperation to halt and reverse nature loss driven by consumption and trade.

1.2. Using GEIC at a national level: UK policy relevance

While it is a tool with global coverage, GEIC provides data on environmental impacts of consumption at a national level and can be used to inform policies and strategies at this scale. The IOTA framework underlying GEIC has been successfully applied to assess supply chain impacts for governments such as Germany and Belgium. Further, GEIC is already being used as an official statistic in the UK.

Understanding the environmental impacts of UK consumption is a complex problem. An estimated 43% of direct UK food supply (based on the farm-gate value of unprocessed food) is met from production in other countries/territories (Defra, 2024). The UK is also heavily reliant on imports for other commodities such as minerals and fuels. Therefore understanding the impacts UK consumption has on environments overseas, via the commodities imported, is at least as important as understanding domestic impacts of UK commodity production. Further, commodities embedded within products (directly as an ingredient such as palm oil in cosmetics, or indirectly such as soy used as feed in the production of meat) are more difficult to trace, but also make up a substantial proportion of UK consumption. These issues have been highlighted in high-profile reports such as the Dasgupta Review.

The UK Government's 25 Year Environment Plan (25YEP) and its first revision, the Environmental Improvement Plan 2023, recognise the need to better understand the environmental impacts of UK consumption. GEIC meets this need: providing estimates of consumption impacts across several environmental metrics, while accounting for the complexities of consumption described above (including products being re-exported through multiple countries, and commodities embedded within other products). As an official statistic, GEIC is the basis for the UK Biodiversity Indicator on "Global biodiversity impacts of UK economic activity / sustainable consumption." It is also used to track progress against the associated Outcome Indicator Framework by providing measures of the "overseas environmental impacts of UK consumption of key commodities" under indicator K1, and has provided data for publications such as the UK Food Security Report, and a House of Commons Committee report on the UK's contribution to tackling global deforestation.

1.3. Previous publications

The methods outlined in this document build on previous work contracted and conducted by JNCC and/or SEI on behalf of Defra, including:

- An investigation of best practices in the field of measuring consumption impacts (Route2 and Carbon Smart, 2019);

- An investigation of the feasibility of an indicator originally proposed to act as K1 (Harris *et al*., 2019);
- A research output detailing interim methods for a draft version of the statistic (Croft *et al*., 2021);
- The first version of this technical and methodological documentation, published in 2021, and subsequent annual updates describing further methodological developments (summarised in Table 3 in Appendix 3). Full details of the methods used for each previous release can be found on The National Archives website.

1.4. Explanation of datasheets published

The datasheets detailing the underlying data behind the indicator are published on the JNCC Resource Hub and include:

- results-total-annual: aggregated results showing the total estimate for each impact type associated with all UK consumption (of all commodities and from all countries/territories combined) for each year;
- producing-country-results: results showing the total estimate for each impact type associated with UK consumption, broken down by the producing country/territory in which the impact took place (but aggregated across all commodities produced within that country/territory) for each year;
- commodity-results: results showing the total estimate for each impact type associated with UK consumption, broken down by the commodity responsible for the impact (but aggregated across producing countries/territories from which the commodities came) for each year;
- uk-results-disaggregated: results showing the estimate for each impact type associated with UK consumption for each commodity in each country/territory of production for each year;
- Additional datasheets, including those relevant to other consuming countries/territories assessed, can be downloaded from the associated interactive dashboard.

Descriptions of column headings in these datasheets can be found in Section 2.4.6 of this report (Table 1).

1.5. Ongoing indicator development

There are many further improvements to the underlying methods and increases to the scope of the indicator that could be made. Work has already been undertaken on several developments that are related to this official statistic release but, due to their more experimental nature, have been (or plan to be) published separately. This includes an initial dataset on the material footprint of metal and mineral commodities (which could, at a later date, be extended to include environmental impact metrics).

Additional development work is currently underway, and users can therefore expect the methods to continue to change and improve going forwards. In the coming months we are working on further improving the LIFE score metric in GEIC, and generating an initial dataset integrating finer resolution trade data for certain commodities. Future development may also include work to improve our understanding of uncertainty in GEIC, scoping the addition of social metrics, and estimating the impact of consumption patterns on resource security. Comments on potential data updates for specific indicator metrics are given in the relevant section (see subsections entitled ‘Data update plans’, in sections 3–8).

Users should contact ukglobalimpacts@jncc.gov.uk with any enquiries or ideas related to future indicator development.

2. Overview of modelling framework

2.1. Background

The results are produced from a version of SEI's Input-Output Trade Analysis (IOTA) modelling framework (Croft *et al*., 2018).

Traditional production and bilateral trade statistics detail production quantities of commodities and their flows between countries and territories. However, this 'point of import' viewpoint is often quite different from that obtained from 'final consumption' profiles that aim to understand the dependencies of products associated with the final purchases and consumption of materials and services. This is especially true for commodities with long and complex supply chains, where consumption of the commodity is indirect and embedded within other consumption activities (for example most soy is "consumed" as feed within meat products).

Multi-regional input-output modelling (MRIO) approaches overcome this limitation by offering a representation of the entire global economy, which captures the full breadth (all sectors) and depth (all tiers of the supply chain from point of production to point of consumption) of global supply chains. MRIOs detail financial transactions between different sectors of the economy, and final purchases from the economy for consumption. Standard MRIO methods allow for consumption activities to be linked not just to outputs associated with direct purchases, but also all up-stream outputs throughout the entire supply chain. This means that footprints of consumption can be linked to points of origin of raw commodity production, regardless of how many trade, processing or utilisation steps there are between these points of origin and the final consumption.

However, traditional MRIOs offer this breadth and depth at the sacrifice of resolution. This applies to both geographic and commodity fidelity; whilst physical data will often detail commodity-specific production and country-to-country trade, typical MRIO representations will cover purchases between (often broad) economic sectors and a mix of countries/ territories and geographic regions (MRIOs contain some countries/territories, while other countries/territories are aggregated together into 'rest of world' regions). Not only does this limit the resolution of results, but it can be especially problematic when looking at impacts which can be highly heterogeneous within sectors and regions.

IOTA is an environmentally extended hybridised MRIO model. IOTA's hybridised approach attempts to overcome the limitations of both approaches by adopting a modelling framework comprising a hybrid of commodity- and country/territory-specific physical production and trade data with the sector- and regional- level representation of the global economy offered by MRIOs. The result is a model that links individual commodity production, resolved to country/territory level, via commodity-specific country/territory-level trade flows and the sector/regional financial flows, to final consumption behaviour at the MRIO regional-level. That is, it retains the production-end resolution of commodity and country/territory specificity but allows for full length supply chain modelling through to final consumption activities, and thus a better understanding of specific production footprints driven by final demand. Environmental extensions allow for any production-linked impacts to be likewise linked through to consumption.

Results are generated for the years 2005 to 2023 inclusive, in line with the current availability of underlying data (based on Singh & Persson, 2024, with data supplied directly by the authors for this indicator release) for the primary indicator of deforestation.

2.2. Physical production and trade data

Most of the country/territory-level commodity-specific data are taken from FAOSTAT – a database of global food and agriculture statistics provided by the Food and Agriculture Organisation (FAO) of the United Nations. The main source of FAOSTAT trade data is official country/territory statistics compiled by UNSD (the United Nations Statistics Division) and Eurostat.

For crop and cattle products, production data are sourced from the FAOSTAT “Production - Crop and livestock products” dataset, and bilateral trade data from the “Trade - Detailed trade matrix” dataset.

For forestry products, production data are sourced from the FAOSTAT “Forestry - Forestry Production and Trade” dataset, and bilateral trade data come from UN Comtrade (in the 2021 and 2022 indicator release, FAOSTAT trade data were used, but data from this source have not been updated in recent years, with no data available for 2019 onwards, necessitating the adoption of an alternative dataset from the 2023 release onwards).

2.3. MRIO data

There are multiple MRIO models available for use, each with relative strengths and weaknesses. This includes geographic and sectoral resolution, temporal coverage and lag, as well as licensing constraints and considerations around future availability. There is no clear “correct” or “best” option that can be adopted when selecting an MRIO for consumption-based accounting.

In previous indicator releases, EXIOBASE 3.8.1 MRIO was the underlying data model. However, currently EXIOBASE’s time series only runs to 2022. Therefore, in order to provide an updated time series for the indicator, in the 2025 release we have for the first time utilised GLORIA as the underlying data model, which provides results to 2028 (later years being projections). Further, GLORIA has higher geographic resolution than EXIOBASE; it contains more individual countries, which not only allows more individual countries to explore their consumption-based impacts, but also improves the resolution with which country-to-country supply chain paths are represented in the modelling framework. The GLORIA dataset has an annual timeseries allowing year-to-year changes in consumption and impacts to be estimated.

In the 2023 and 2024 release, results from a Global Trade Analysis Project (GTAP) version of the model were accessible via the associated interactive dashboard, primarily in order to allow results for more consuming countries to be included than were represented within EXIOBASE. Given GLORIA’s significantly greater geographic coverage compared to EXIOBASE, we have not included the GTAP version of the model on the 2025 dashboard release as it would offer very little additional data coverage. The data results for GTAP and EXIOBASE are still available to download from the dashboard website for those interested.

The GLORIA consumption model is used under the terms of a creative commons licence for non-commercial use (https://creativecommons.org/licenses/by-nc/3.0/au/). We used Release 059a of the GLORIA global environmentally-extended MRIO database (Lenzen *et al*. 2021), constructed in the Global MRIO Lab (Lenzen *et al*. 2017).

2.4. Implementation

2.4.1. Re-exports and trade balancing

Challenge: trade data often do not actually represent origin-to-destination flows. MRIO modelling is therefore required to resolve origin to destination flows.

Bilateral trade data often contain records pertaining to the *re-export* of goods i.e. the report of exporting a good that has previously been imported. This is problematic since such records do not provide a direct link between point of origin and destination, and instead contain records e.g. A -> B and B -> C, when the information that is desired is the *resolved flow* A -> C. This issue is resolved by running the production and trade data through an algorithm which takes countries'/territories' supply (production + imports) into account and reassigns exports accordingly to estimate their true origin.

For this re-export algorithm to operate within the framework, it is important that reported exports from a given country/territory do not exceed the available supply in that country/territory (i.e. production plus imports). This constraint is sometimes not satisfied by the *reported* production and trade data. Thus, a balancing step is required. The idea is to find an adjusted set of trade data that are 'as close as possible' to the reported data, among all possible sets that satisfy the constraint that exports do not exceed production plus imports in any country/territory. Here, 'close' is measured as the statistical 'divergence' between the resolved dataset and the original reported dataset, specifically, the Kullback-Liebler divergence (Kullback & Leibler, 1951; Többen & Schröder, 2018; Golan & Vogel, 2010) – whereby less divergence indicates a 'closer' relationship. By definition, this results in the creation of no new trade relationships, and rather only adjusts reported trade flows. Reported trade can be split into disjoint trading groups (countries/territories whereby there is trade *within* each group, but there is no trade *between* these groups), which can be solved in isolation. Where possible, an additional constraint is imposed that the total resolved trade within each group is equal to the total reported trade in that group.

Outcome: a trade dataset corrected for intermediate flows to give origin-to-destination flows.

2.4.2. Concordance of FAO countries/territories and commodities to GLORIA countries/territories/regions and sectors, respectively

Challenge: the physical and monetary datasets use different geographic and commodity classification schemes.

The re-export algorithm provides a best estimate of where (at the country/territory level) a country's production of a commodity has been distributed to after all trade activity associated with the raw commodity has been conducted. To align this with the MRIO database, all of the countries/territories in the FAOSTAT data need to be concorded to GLORIA's countries/territories and regions. This is typically a one-to-one mapping for countries/territories within the MRIO, and an aggregation of countries/territories for the ROW regions. This allows the country/territory of origin to country/territory of destination results from the re-export algorithm to be transformed into a country/territory of origin to MRIO country/territory/region of destination array.

Likewise, to understand which sectors within the MRIO database the production of a given commodity is associated with (which is important for allocation within the MRIO; see below), the FAOSTAT commodities need to be concorded to appropriate producing sectors within the MRIO database (Appendix 4, Table 7). In some cases, this is a one-to-one mapping (e.g.

"Rice, paddy" within the FAOSTAT database maps to the "Growing rice" sector within GLORIA), but typically it is an aggregating process (e.g. "Barley", "Rye", "Oats" etc. all map to the " Growing cereals n.e.c" sector).

Outcome: the different datasets have a "mapping" to join them together, allowing one to be aligned with the other.

2.4.3. Hybridisation of FAO-derived re-exports data and GLORIA MRIO database

Challenge: merging the two datasets still requires action on how to apportion disaggregated values from one to the other.

The concorded results of the re-export algorithm provide the MRIO countries/territories/ regions to which each country's traded production of a given commodity needs to be allocated. However, each country/territory/region within the MRIO comprises multiple sectors across which this needs to be further allocated. This is done by taking the relative expenditure by sectors within an importing country/territory/region on outputs of the concorded sector responsible for the production. Below is an example of this allocation process (note "Country/territory *B_c*" in the example below could be a country/territory or region within the MRIO database).

Example:

From re-exports results:

Country/territory *A* exports *X* tonnes of Commodity *Y* to Country/territory *B*

Concordance relationships:

Country/territory *A* concords to Country/territory *A_c*

Country/territory *B* concords to Country/territory *B_c*

Commodity *Y* concords to Sector *Y_c*

(i.e. Sector *Y_c* is the sector associated with production of Commodity *Y*)

Concorded results:

X tonnes of Country/territory *A*'s production of Commodity *Y* allocated to Country/territory *B_c*

Disaggregation of Country/territory *B_c*'s allocation to sectors:

Take relative expenditure by all sectors within Country/territory *B_c* on outputs from Sector *Y_c*, and distribute concorded results proportionally

After this process, the production of a given commodity within a given country/territory has been allocated to the importing countries/territories/region and sectors within the MRIO.

Outcome: a simple but robust approach is in place to handle splitting national-level values across sub-sectors of its economy.

2.4.4. Calculation of "physical L matrix"

Challenge: we want to understand the total upstream material requirements associated with economic outputs.

In traditional MRIO methods, the *L* matrix (or Leontief inverse/"total requirements" matrix) allows the calculation of all financial outputs required across the entire economy (all sectors in all countries/territories/regions) for the purposes of enabling a given sector within a given country/territory/region to produce a unit of output. By allocating the physical quantities of traded commodities to the appropriate sectors of import (see above), a "physical *L* matrix" can be constructed which allows the estimation of the amount of these physical flows embedded in the final consumption from different sectors within different countries/territories or regions. This means that final consumption within a given country/territory can be linked back to the country/territory within which its component commodities were produced.

This is achieved by normalising the sector allocations by total sector monetary outputs (i.e. converting the total allocations into intensities, e.g. unit mass of commodity per unit value of output) and multiplying the monetary *L* matrix. A unique matrix is constructed for each individual commodity.

Outcome: we produce a matrix of values for each commodity which captures the upstream material requirements for economic activity across each and all countries/territories and sectors.

2.4.5. Compiling results for final demand

Challenge: we want to calculate total material requirements associated with consumption.

Multiplying the "physical *L* matrix" for a given commodity by the final demand vectors for a consuming country/territory/region (the UK in this case), calculates the physical quantities of that commodity embedded within this final demand. This process works by taking the value of purchases from a given sector in a given country/territory/region, and accounting for all required outputs from all other sectors for the given sector to meet this demand. By way of the "physical *L* matrix", these "outputs" take the form of physical flows of the commodity associated with each possible point (i.e. country/territory) of production.

Outcome: a list of total material requirements, including country/territory of origin, associated with localised consumption activities.

2.4.6. Applying indicator metrics

Challenge: we want to know the values of different metrics associated with these material requirements.

The indicator metrics (Table 1, with methodological details in sections that follow) are transformed into per-unit-mass intensities. This is done by taking the annual total for each metric per country/territory e.g. total deforestation linked to a country/territory's production of a given commodity in a given year, and dividing this by total mass produced of that commodity in that country/territory/year. This is then simply applied as a scaling factor to the embedded production (mass) results to convert these mass-flow results into results for the different indicator metrics in their appropriate units.

Table 1. Summary of indicators used in this study that are applied within the IOTA framework.

Indicator (commodities applied to)	Units	Brief description	Report section providing further detail
production_embedded_in_consumption__tonnes (all commodities)	tonnes	Tonnes of commodity production embedded within consumption activities	2
cropland_area_harvested_embedded_in_consumption_ha (crops)	hectares (ha)	Area of cropland used to produce materials embedded in consumption. If the same crop is sown and harvested more than once per year in the same area, the area is counted as many times as harvested.	3
def_risk_embedded_in_consumption_amoritized_ha (all commodities)	hectares (ha)	Area of deforestation associated with the production of materials embedded in consumption	4
def_emis_excl_peat_drainage_embedded_in_cons_tCO2 (all commodities)	tonnes of CO_2 (tCO_2)	Net tonnes of CO_2 emissions associated with the area deforested, excluding due to the drainage of peatlands	4
def_emis_incl_peat_drainage_embedded_in_cons_tCO2 (all commodities)	tonnes of CO_2 (tCO_2)	Net tonnes of CO_2 emissions (above-, below-ground and change in soil organic C stocks) associated with the area deforested to produce materials embedded in consumption, including due to the drainage of peatlands	4
blue_water_use_embedded_in_consumption_m3 (crops)	metres cubed (m^3)	Ground and surface (blue) water used to produce materials embedded in consumption	5
green_water_use_embedded_in_consumption_m3 (crops)	metres cubed (m^3)	Rain (green) water used to produce materials embedded in consumption	5

Indicator (commodities applied to)	**Units**	**Brief description**	**Report section providing further detail**
scarcity_weighted_blue_water_use_embedded_in_cons_m3 (crops)	metres cubed (m^3)	Ground and surface (blue) water used, adjusted for water scarcity in the country/territory of production, to produce materials embedded in consumption	5
predicted_species_loss_embedded_in_cons_species_lost (crops)	species lost	Number of species predicted to become extinct within an ecoregion due to conversion of land for the production of commodities embedded in consumption	6
species_richness_area_embedded_in_cons_species_ha (crops)	species-hectares (species_ha)	An estimate of biodiversity loss in terms of a species richness-weighted extent of crop production embedded in consumption	7
LIFE_score__change_in_probability_of_extinction	species extinctions within 100 years	An estimate of change in the expected number of global extinctions within 100 years, summed across species.	8

Outcome: a measure of impact/risk for each indicator is assigned to each point of material use.

2.5. Further details on inclusion of different commodity types

For crops, the treatment is consistent throughout the framework, with production and trade data from FAOSTAT used for the individual commodities, and the individual commodity identity preserved through to final results. However, for cattle and forestry products bespoke approaches were adopted.

2.5.1. Cattle (and buffalo) meat and leather

To align with the deforestation datasets (see below), for which cattle (specifically meat and leather) is a key component of impact, the appropriate FAOSTAT commodities associated with cattle need to be handled slightly differently to FAOSTAT crop data.

Whilst the production of crops can be easily represented within the IOTA framework by the harvest of the raw primary commodity due to simple seasonal cycles, cattle "production" is a more complex matter. Herd sizes do not provide an appropriate analogy for annual output given cattle live for multiple years and also are used for e.g. dairy production, so instead the mass of production of derived products from slaughter, from FAOSTAT, are used as the measure of material production. As a result, it is not just one single commodity which is considered at the point of production (as with a crop), but rather four commodities linked to the production of cattle (meat, offal, fats and hides). Such data are also available for buffalo, which are included alongside cattle for alignment with the deforestation datasets.

These individual cattle/buffalo-linked commodities are initially run through the IOTA framework following the same logic as the crop commodities, with the flows of the individual commodities modelled independently through the trade stages and the MRIO within the indicator framework. In the preparation of results, they are then aggregated together under a title of "Cattle and buffalo meat, plus associated co-products", ready for the application of indicator extensions. Since this is no longer aligned with the FAOSTAT classification scheme, it is assigned a commodity code of "-1".

2.5.2. Forestry

Production and trade of forestry products, in physical terms within the IOTA framework, is limited to the treatment (i.e. production and trade of) "industrial roundwood". For forestry, production data come from FAOSTAT while trade data come from UN Comtrade.

Within the FAOSTAT production datasets, relevant commodities (and FAO commodity codes) are:

1601 Sawlogs and veneer logs, coniferous
1604 Sawlogs and veneer logs, non-coniferous
1602 Pulpwood, round and split, coniferous (production)
1603 Pulpwood, round and split, non-coniferous (production)
1623 Other industrial roundwood, coniferous (production)
1626 Other industrial roundwood, non-coniferous (production)

Within the Comtrade trade datasets, the associated commodities (and HS6, Harmonised System, codes) are:

44032X: Industrial roundwood, coniferous (export/import)

44034X, 44039X: Industrial roundwood, non-coniferous (export/import)

Note: the latter two HS codes are mapped as aggregate pairs (i.e. all non-coniferous timber) since the HS code 440399 is an unspecified mix of tropical and non-tropical non-coniferous goods, and thus it is not possible to disentangle the reporting to tropical and non-tropical type. Hence, forest commodities are classified as either “Industrial roundwood, coniferous” or “Industrial roundwood, non-coniferous” throughout the modelling process.

FAOSTAT report their timber data in volume units of m^3, whilst Comtrade provide volume and mass. Therefore, while the Comtrade mass values are used for the trade data, the conversion of production values to mass is required. Conversions (based on FAO’s own literature) are applied such that coniferous products are converted at 1.43 m^3/tonne, with non-coniferous from fully tropical countries/territories at 1.37 m^3/tonne, from non-tropical countries/territories at 1.25 m^3/tonnes, and partially tropical countries/territories at the average of 1.31 m^3/tonne (with tropical status based on World Population Review classifications).

Following this conversion, the commodities are aggregated to form an “Industrial roundwood” commodity, in mass units, before being run through the framework and having indicators applied. Since this is no longer aligned with the FAOSTAT classification scheme, it is assigned a commodity code of “-4” (-2 and –3 are used for coniferous and non-coniferous, respectively, during the modelling process before being aggregated).

3. Cropland area harvested metric

3.1. Overview

This indicator provides an estimate of the land area harvested in order to produce the commodities embedded in UK consumption. The data are sourced from the same FAOSTAT "Production – Crop and livestock products" datasets as the crop production data.

3.2. Methodological summary

Along with production masses, the FAOSTAT "Production – Crop and livestock products" dataset provides associated land use (ha) and yield (hectograms/hectare) values. We create land use intensities (ha/tonne) from this data, which can equivalently be done by either taking the area harvested values and dividing by associated production mass, or multiplying the inverse of the yield value by 10,000.

3.3. Data update plans

The relevant FAOSTAT datasets are updated annually and often revised and improved in between (e.g. updated reporting, replacing inferred data with official data, improved methodologies applied etc.). For entries where no land use/yield data are available, we could look to fill these data gaps by e.g. utilising global average values, checking other reference years, and looking at nearest neighbour yields, but this has not been attempted in this release

3.4. Source(s)

FAOSTAT "Production – Crop and livestock products" dataset

3.5. Application in the IOTA framework

The country/territory-commodity specific land use intensities (ha/tonne) are multiplied by the associated calculated mass flows to provide the estimates of cropland use embedded within these flows. Where no data are available, entries are left as zero.

This indicator is applied to all crop commodities in the dataset.

4. Deforestation and associated carbon emissions metrics

4.1. Overview

The deforestation (and associated deforestation-linked emissions) metrics are based on a series of datasets provided by the Chalmers University of Technology. These datasets contain estimates of deforestation embodied in the production, exports, imports and consumption of agricultural and forestry commodities by country/territory, year, and commodity. In the most up-to-date approach, the authors used spatialised land use and commodity datasets, in combination with land-balance approaches where geospatial land use data is unavailable, to generate these estimates of global deforestation, as well as associated emissions (Singh & Persson, 2024).

For the 2025 indicator release, deforestation and associated emissions data were supplied to the indicator team directly by the authors (therefore note that the dataset detailed in Singh & Persson, 2024, is marginally different to the dataset supplied for GEIC e.g. it does not contain data for the year 2023). See commentary on and references for previous versions of this dataset in Appendix 3 (Table 3).

4.2. Methodological summary

A detailed description of the current methods for these metrics can be found in Singh & Persson (2024). In brief, the process of allocating forest loss (and associated emissions) to agricultural production happens in three steps. Firstly, forest loss is categorised according to drivers, incorporating certain spatially explicit crop and forest plantation datasets, as well as spatially explicit land use information where available. Further information on specific drivers of forest loss (in addition to the three broad categories of cropland expansion, pasture expansion, and forest plantation expansion) is also included. Secondly, attribution of cropland expansion to specific commodities takes place. Thirdly, in addition to the deforestation estimates, associated emissions from land use change are estimated.

4.2.1. Forest loss categorisation

Classifying forest loss according to its proximate drivers allows later sub-classification to commodity-level (in the case of agriculture-driven forest loss). Tree cover loss data (from Hansen *et al.,* 2013) is overlaid with a number of datasets including the MapBiomas (MapBiomas, 2022) collection (covering various Latin American countries, plus Indonesia), individual spatial commodity-expansion data (for soy (Song *et al.,* 2021) and plantations (Du *et al.,* 2022)), plus other spatialised classifications of forest-loss drivers (fire (Tyukavina *et al.,* 2022) and other drivers (Curtis *et al.,* 2018)). These different datasets provide varying levels of detail regarding the deforestation drivers for each pixel globally. Therefore, for each pixel, the spatial dataset with the highest levels of detail with respect to a specific driver of forest loss is prioritised. Specific commodity-expansion data (e.g. soy extent), therefore, takes precedence over more broadly-classified land use data (e.g. cropland or pasture), followed by data on dominant forest loss drivers (e.g. commodity-driven deforestation).

Certain processing details require assumptions/decisions to be made: i) Forest is defined as areas with 25% or greater tree cover density for each 30 m pixel; ii) Where multiple MapBiomas datasets cover the same pixel, priority is given to data with higher specificity; for example forest loss in a pixel which can be linked to ‘oil palm’ will take precedence over a broad land use category; iii) Potential time lags between detected forest loss and establishment of agricultural land are accounted for by applying a four-year time window from the year of deforestation. For example, if forest loss occurs in 2001 and a dataset (e.g. MapBiomas) suggests cropland exists in that pixel in 2003 then that forest loss is attributed to cropland expansion. Within this four-year time window if the same pixel experiences different land uses then attribution to plantations is prioritised, followed by pasture, perennial crops, then temporary crops; iv) Any forest loss in agricultural land systems established prior to 2001 is excluded; v) After forest loss data has been attributed to commodities or other categories of land use, forest loss due to (spatio-temporally defined) fire (a dominant driver in temperate and boreal regions) is excluded from the analysis; vi) For any areas not covered by aforementioned data/assumptions the dataset provided by Curtis *et al.* (2018) which identifies forest loss drivers – complemented by a global forest management dataset to differentiate between managed and undisturbed forests for the year 2000 (Lesiv *et al.,* 2022) – is used to determine remaining agricultural-commodity driven and forestry-related deforestation post year-2000.

In some cases, results indicate that forest-loss is attributed to land use categories which cover multiple activities (e.g. ‘mosaics’). Here a statistical attribution approach is utilised using annual land use data from FAOSTAT. Land use data from FAOSTAT are available to 2023, allowing statistical expansion to be determined until 2022. To fill gaps in 2023, therefore, the last three-year average (i.e. 2020–2022) expansion data are used to apportion forest loss in later years. In cases where mosaics are identified to be a mix of cropland and pasture, forest loss is divided based on relative areas of FAOSTAT-defined land expansion (equivalent to methods in Pendrill *et al*., 2019a). When forest loss is categorised into broad-driver classifications or spatially unclassified regions, a cap is applied by selecting the lowest of either the proportionally distributed forest loss or land-use expansion estimates.

The final step in the forest loss categorisation stage is to sum spatial and statistical attributions associated with each individual land class, which results in the determined forest loss attributed to cropland, pasture and forest plantation expansion.

The use of spatially explicit land use and commodity information results in improved attribution of forest loss to agricultural and forestry-driven deforestation, where this spatially explicit information is available, compared to previous methods (Pendrill *et al*. 2019a, b). The utilisation of data on dominant drivers of forest loss also means that non-tropical forest loss can be allocated to commodity-production. However, it should be noted that the information on dominant forest-loss drivers is coarse (approximately in a 10-by-10 km pixel) and operates in a ‘binary’ manner (i.e. pixels are designated by their dominant driver of forest loss, meaning that forest loss within a pixel could potentially be a mix of several drivers – across space and time – which may include agriculture, but this may not be apparent). The important consequence of this is that the data quality for forest-loss attributions varies across the dataset, with better estimates existing for example in Latin America and Indonesia where spatially-explicit land use and certain crop-extent information is available.

4.2.2. Commodity attribution

Attribution of deforestation to individual crops depends on combinations of spatial and statistical attribution. It is assumed that remote sensing products utilised provide accurate estimates of crop-specific deforestation. These crop-specific products (see Supplementary Table 3 in Singh & Persson 2024) are: i) oil palm in Indonesia, Malaysia and globally (via alternative data layers); ii) soybeans in Argentina, Bolivia, Brazil, Chile, Paraguay and Uruguay; iii) rice in Northeast and Southeast Asia; iv) rapeseed in Argentina, Europe, United States and Canada; v) maize in China; vi) cocoa in Cote d’Ivoire and Ghana; vii) coconut across the tropics; and viii) sugarcane in Brazil. Spatially-specific attribution to forest loss is conducted first, where data are available, and statistical attribution is then employed to allocate any remaining forest loss to cropland expansion, based on relative crop expansions compared to total cropland expansion. Because FAOSTAT crop product data are available to 2023, this allows statistical crop-attribution to 2022, with data to 2023 calculated using a similar ‘nowcasting’ method as described above. If there is a surplus in forest loss attributed to cropland expansion compared with FAOSTAT’s records of cropland expansion, then this surplus is allocated proportionally based on annual harvested areas.

Because land may be productive many years following conversion (and thus production in subsequent years can be validly attributed to previous land use change), attributed deforestation for each commodity is spread over a five-year amortisation period. This means that that the total amount of deforestation embodied in production of a given commodity in a given year is calculated as the total deforestation attributed to the land use producing that commodity in the five previous years, divided by five. This amortisation step ensures that ‘responsibility’ for the original conversion is distributed over a number of subsequent years of production (which is a practice commonly applied to other metrics, including those used e.g. in greenhouse gas inventories).

4.2.3. Carbon emissions

Soil organic carbon (SOC) loss estimates are derived using a spatial SOC stock dataset and literature-based meta analysis to assess the percentage loss of SOC for different land uses in different biomes. Below-ground biomass emissions are estimated via a spatially-explicit root-to-shoot ratio dataset, with carbon emissions including stocks from deadwood and litter. The carbon stocks associated with replacement commodities (which are used in the calculation of net carbon emissions) are divided into 40 individual commodities and 11 commodity groups across different biomes. For peatland drainage emissions on deforested land, emission factors are specified by land use (cropland, pasture, plantation expansion) and by biome (tropical, temperate and boreal).

4.3. Data update plans

Chalmers researchers are looking for opportunities to ensure that continued updates to the deforestation and associated emissions data are possible. Updates to the data approximately yearly (or as soon as the underlying datasets are updated) are therefore considered likely.

4.4. Source(s)

This dataset is managed by the Chalmers University of Technology, Sweden. The key contact point is Martin Persson, who is an active collaborator with the SEI York team.

While the data incorporated into this release of the GEIC indicator were supplied directly by Chalmers researchers, the dataset they are based on is available, open source at: https://zenodo.org/record/4250532. Publications using this data (including as applied within the UK indicator framework) should properly reference this resource (and associated papers).

4.5. Application in the IOTA framework

Attribution data from the Zenodo dataset is utilised. This allows for the addition of the production linked deforestation and emissions estimates directly into the IOTA framework (to

FAOSTAT production categories) which are then translated, via our modelled trade-and-consumption system, into footprint indicators (for units refer to results sheets). The following notes are relevant to the application of this dataset in IOTA:

- The raw data are classified already into FAOSTAT production categories. We have created a library to ensure the correct matching where any alternative product labels are used (which occurs in a handful of cases). One crop (Guarana produced in Brazil) in the Pendrill dataset is not associated with FAOSTAT production/trade data and is therefore not included in the footprint;
- The dataset contains two listings relating to cattle production: “cattle meat” and “leather”. These impacts are both aggregated together and then assigned to the individual FAOSTAT commodities associated with cattle production (see above) in proportion to relative mass produced, before being aggregated post-modelling to form the “Cattle and buffalo meat, plus associated co-products” impact;
- The impacts are divided by associated commodity production quantities to create a set of impact per tonne intensities. These are then multiplied by the resolved mass flows to extend these to estimates of embedded impacts within those flows;
- These are applied to all commodities within the current database. Where any country/territory/commodities have no data within a given year/the time series, these are left empty.

5. Water footprint and water scarcity metrics

5.1. Overview

Our indicator for water consists of three metrics: 'blue water', which estimates the surface and groundwater consumed (i.e. not returned to the basin due to evaporation, inter-basin transfer, product integration or release to the sea) as a result of production; 'green water', which estimates rainwater consumed; and 'water-availability-adjusted blue water' (aka. Blue water scarcity equivalent), which scales the blue water footprint according to water availability in a region after human and aquatic ecosystem demands have been met. These indicators are applied only to crop products at the current time. A more detailed explanation of the differences between blue and green water can be found on the Water Footprint Network website.

5.2. Methodological summary

Tamea *et al.* (2021) details an approach to creating an annualised water footprint for crop products; expressed as a volume of water per unit weight (unit water footprint; uWF). As its basis, the uWF approach utilises the well-established 'Water Footprint Network' (WFN) crop-specific water-footprint data (Hoekstra and Chapagain, 2007; Mekonnen and Hoekstra, 2010). However, given that WFN data provide estimates solely for a single reference period, a 'fast track' method is utilised to provide water footprints of production (uWFp) that *vary over time*.

The uWFp Is based on a function of evapotranspiration calculated for the growing period of the crop and the crop yield. In Tamea *et al.* (2021), annualised uWFp's are created using the 'fast track' method introduced and substantiated in Tuninetti *et al.* (2017) that are in turn based on the use of the WaterStat database (Mekonnen and Hoekstra, 2010) for expressing the *spatial variations* in evapotranspiration and on a ratio of agricultural yields for expressing the *temporal variability* of the unit water footprint:

$$\mathrm{uWFp}_{c,p,t} = \overline{\mathrm{uWFp}_{c,p,T}} \cdot \frac{\overline{Y_{c,p,T}}}{Y_{c,p,t}}$$

where $\overline{\mathrm{uWFp}_{c,p,T}}$ is the reference unit water footprint provided by WaterStat (Mekonnen and Hoekstra, 2010) corresponding to an average in the period T = 1996–2005, $\overline{Y_{c,p,T}}$ is the average crop yield over the same period T, and $Y_{c,p,t}$ is the annual crop yield in a generic year t in the range 1961–2016. The average crop yield is obtained as an average of the annual yields in the years 1996–2005, weighted by the harvested areas across the years in country/territory c, based on FAOSTAT data. Effectively this function is estimating annual water consumption by taking the average yield over the reference period and scaling water consumption based on yield in a particular year

Because data released in Tamea *et al.* (2021) is present only to 2016 and only for aggregated (green and blue) water footprints, we use the equation above, along with the original WaterStat and FAO (FAOSTAT crop production statistics) sources to compile our own timeseries for both blue and green water footprints to match the availability of IOTA data and to allow us to readily update the data in future. An important limitation is that, in the absence of additional information, we retain the green:blue water requirement ratios of the original WaterStat reference period when annualising results, e.g. this assumes that increases in yield over time are achieved by proportionally fixed increase in both blue and green water requirements.

The blue water footprint refers to the volume of surface and groundwater consumed as a result of the production of a crop. Green water footprint refers to the rainwater consumed. The blue water footprint is then additionally scaled by a factor (from WULCA; Boulay *et al.,* 2018) which represents the relative Available wAter rEmaining per area in a country/territory (or watershed), after the demand of humans and aquatic ecosystems have been met. AWARE factors for use alongside agricultural water use are available and these are adopted in our indicator set.

5.2.1. Water Footprint Network data

The Water Footprint Network's 'product water footprints for crops' is utilised, which is described in full detail within Mekonnen and Hoekstra (2010 & 2011). This dataset contains an estimate of water footprint of crops based on a water-balance model applied at a 5 by 5 arc minute grid. This model computes a daily soil water balance and calculates crop water requirements, actual crop water use (both green and blue) and actual yields, and is used to estimate the crop water use of 126 primary crops, with requirements of an additional 20 minor crops estimated by application of the CROPWAT 8.0 model. For rain-fed crop production, blue water use (as irrigation) is zero and the green water use (m^3/ha) is calculated by summing up daily evapotranspiration values over the length of crop growing periods and compared to precipitation to derive the water consumption of crops. For irrigated crops, green and blue water use is calculated via a combination of two soil-balance scenarios: a first scenario is based on the modelled assumption that the soil receives no irrigation and uses crop parameters of irrigated crops (e.g. the same rooting depth as in an irrigated condition), with the calculated evapotranspiration in this scenario equalling the green water footprint estimate. A second scenario assumes actual irrigation sufficient to meet water requirements, applying the same parameters as in the first scenario, with the blue water use calculated as the difference between water use across the two scenarios. Crop growth is also modelled, accounting also for water stress, to provide estimates of actual yields which are scaled according to national FAOSTAT yield data. The green and blue water footprints of primary crops (m^3/ton) are then calculated by dividing the total volume of green and blue water by the quantity of production per year. The data provided by Water Footprint Network has a reference year of 2000, but represents the average over a period 1996–2005.

5.2.2. uWFp (unit water footprint of production) data

Tamea *et al.* (2021) present 'annualised' water footprint data based upon changes in productivity of crops over time. The authors apply annualised water footprints to the trade of agricultural commodities, as part of a European project: CWASI ('Coping with wAter Scarcity In a globalized world'), but the method for creating 'unit water footprints of production' (uWFp) are in turn based on a 'fast track' method for incorporating the *temporal* variability of water footprints into studies (Tuninetti *et al.,* 2017; which also describes the suitability of this approach for creating a simple but appropriate evaluation of a time-varying crop water footprint). The fast track method employed in Tamea *et al.* (2021) is replicated here with original data sources, with an annualised water footprint for each crop calculated by taking a reference water footprint value (obtained from the Water Footprint Network database) and multiplying this by the average yield (from FAOSTAT) for the crop for the same reference period (1996–2005), before dividing through by the crop yield (again from FAOSTAT) for the target year (see equation above). This fast-track method effectively keeps the rates of evapotranspiration per crop (as estimated originally by the Water Footprint Network model) constant, and thus it has monitored changes in yield which determine changes in the water volumes used.

When linking to trade data, a problem arises when a country/territory was not a crop producer in the 1996–2005 reference period and therefore does not have an associated reference water footprint. The approach adopted in cases where there are such gaps in country/territory data is to calculate a weighted average of neighbours within a distance threshold of 1110km (approximately equivalent to 10 degrees of latitude), with weighting exponentially decaying with increasing distance.

Specifically, the weighting for each neighbour is calculated via the equation:

$$w_x = \frac{\exp(-0.25 \cdot d_x)}{1-\exp(-2.5)} + \left(1 - \frac{1}{1-\exp(-2.5)}\right),$$

where w_x is the weighting for country/territory x, which is an angular d_x from the focal country/territory (calculated as the Euclidean distance between coordinates). Figure 1 shows a plot of this decay function, demonstrating how the function takes maximum weighting (i.e. 1) at zero distance, before decaying to no weighting (i.e. 0) beyond the threshold distance of 10 degrees.

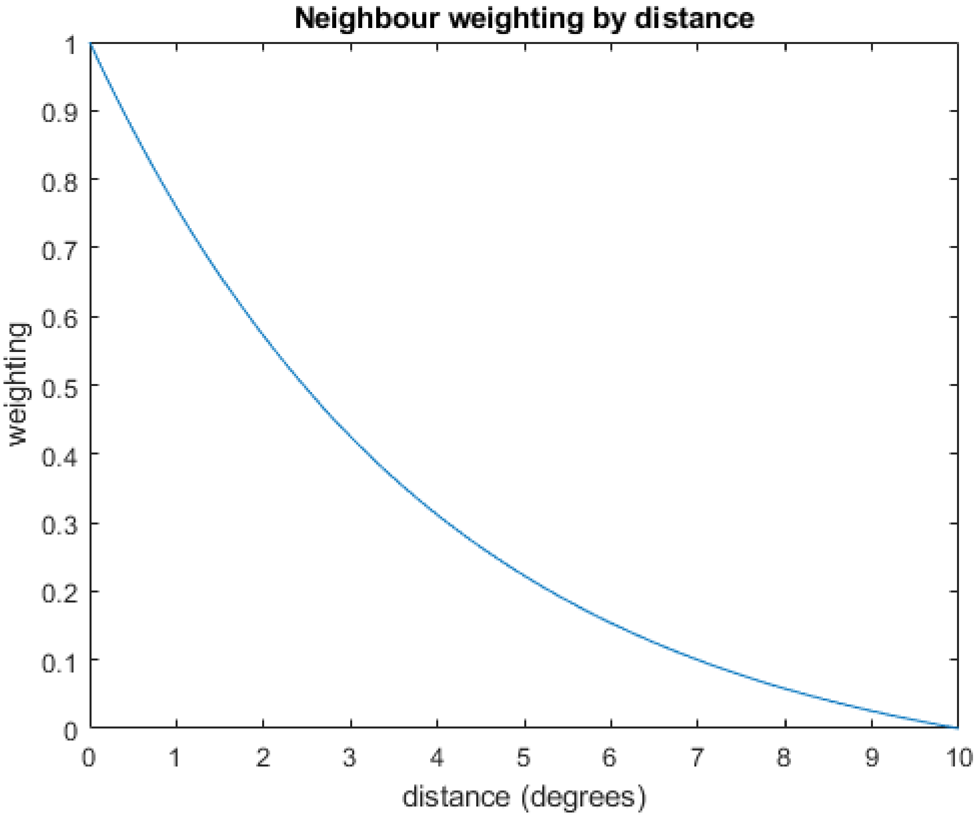

Figure 1. Exponential decay function utilised to establish relative weighting of neighbours in the calculation of weighted averages to fill gaps within the water indicator dataset.

The weighted average is then calculated over all neighbours based on these weightings. Where no data exist for a country, and no suitable value is established via the above neighbour-based routine, the global average is adopted.

5.2.3. AWARE data

AWARE factors represent the relative Available WAter REmaining per area in a river basin, after the demand of humans and aquatic ecosystems have been met (Boulay *et al.,* 2018). They are a result of a 2-year consensus building process by ‘Water Use in Life Cycle Assessment’ (WULCA), a working group of the UNEP-SETAC (United Nations Environment Programme – Society of Environmental Toxicology and Chemistry) Life Cycle Initiative, on the development of a water scarcity method for use in LCA (Life Cycle Assessment) and water scarcity footprint assessments (Boulay *et al.,* 2018). AWARE factors assess the water deprivation potential, to either humans or ecosystems, with the assumption that the less water remaining available per area, the more likely another user will be deprived. Water availability minus demand (AMD) of humans and aquatic ecosystems is first calculated in terms of m^3 per m^2 per month. Values are then normalised with a world average result (AMD = 0.0136 $m^3.m^{-2}.month^{-1}$) and inverted, to derive the relative value in comparison with the average m^3 consumed in the world.

The indicator is limited to a range from (i.e. subjected to thresholds between) 0.1 to 100, with a value of 1 corresponding to the world average, and a value of 10, for example, representing a region where there is 10 times less available water remaining per area than the world average. Data is calculated at the sub-watershed scale and for monthly timesteps, but is available aggregated to country/territory, with an annual average. Aggregations can be conducted differently to better represent an agricultural water use or a domestic/industrial use, based on the time and region of water use. Characterization factors for agricultural and non-agricultural use are therefore provided.

To calculate AWARE factors (see Figure 2), actual water availability was obtained from the WaterGAP2.2 (Müller Schmied *et al.,* 2014) model for more than 11,000 global watersheds (with the largest watersheds divided into sub-watersheds), using climatic data over the period 1960–2010 to model runoff based on precipitation and evapotranspiration. Current human water consumption (the fraction of water withdrawal not returning to the watershed after use) represents human demand, with data obtained from the WaterGAP model (Florke *et al.,* 2013). This includes domestic, industrial, agricultural, livestock and energy production sectors modelled for the year 2010 on a 0.5 degree global resolution. Water requirements for freshwater ecosystems are used as a proxy for ecosystem demand, with a monthly model from Pastor *et al.* (2013) chosen that evaluates minimum water requirements as a fraction of the available flow to ecosystems in “fair” conditions. Water requirements of terrestrial and groundwater-dependent ecosystems are not included since the link between blue water consumption (for which AWARE is used) and water deprivation of terrestrial ecosystems is unclear at the current time.

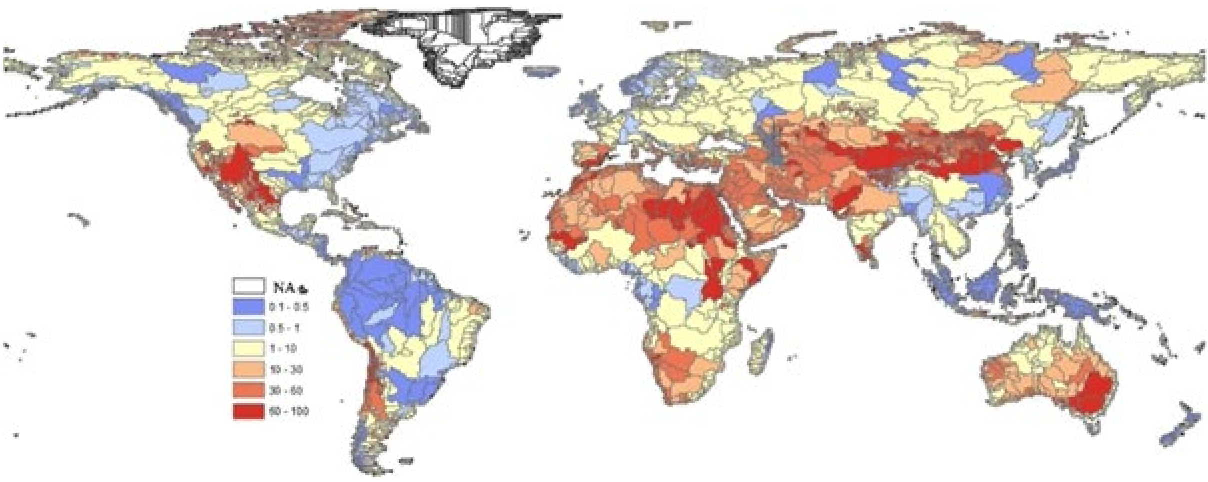

Figure 2. Annualised AWARE characterization factors for non-agricultural use in m^3 world eq./m^3. Reproduced from Boulay *et al*., 2018.

5.3. Data update plans

Water Footprint Network baseline water footprint statistics, and AWARE scarcity factors present ‘snapshots’ around baseline periods of 1996–2005, and 2010 respectively. The authors are unaware as to whether there are any plans to update these reference datasets at the time of writing.

The ‘fast-track’ method presented above represents a credible attempt to develop annualised water footprint statistics from baseline WFN data.

The simplicity of the fast-track method means that it is relatively easy to provide annual water footprint data for future years as this is only dependent on the release of FAOSTAT crop production data. However, at the present time an important limitation is that the original reference ratio of blue:green water use is retained in our annualised results. Future work could scope out whether improvements to this approach could be made (e.g. via consideration of recorded rainfall or information on national irrigation rates).

In addition to exploring the opportunities to update water scarcity data going forward, it is also worth noting that future developments may allow the utilisation of basin-specific water footprint and water-scarcity metrics, that may be combined with geographically specific crop-production data to provide more granularity. At the present time, only national averages have been deployed.

5.4. Source(s)

Water footprint estimates from the Water Footprint Network are sourced from: https://waterfootprint.org/en/resources/waterstat/product-water-footprint-statistics/

Statistics necessary to annualise these factors are sourced from FAO: http://www.fao.org/faostat/en/#data/QCL

AWARE factors are sourced from WULCA country/territory-level values: https://wulca-waterlca.org/aware/download-aware-factors/

All sources are currently publicly, and freely, available.

5.5. Application in the IOTA framework

Unit water footprint data for crop production are compiled for all crops present in the IOTA dataset. Water footprints of crop production are then converted, via our modelled trade-and-consumption system, into consumption-based footprint indicators (for units refer to results sheets). The following notes are relevant to the application of this dataset in IOTA:

- National average estimates are extracted for the reference period 1996–2005 for each available crop from the WFN dataset.
- From FAOSTAT production statistics the mean yield is calculated for the same reference period by summing total production values over that period and dividing through by total land use requirements for that period. In line with Tamea *et al.* (2021), for each year of crop production relevant to the current UK indicator timeseries, the yield is extracted from FAO. The reference yield is divided by the focal-year yield and then multiplied by the reference water footprints to estimate water intensities (unit water per unit production). Reference water footprints are used for blue and green water individually, in order to calculate annualised results for both blue and green water. An important limitation is that the ratio of blue:green water used in the annualised data is fixed to that of the reference period.
- Cross-referencing the annualised water footprint data against the crop production datasets reveals gaps in the data for certain countries/territories. These gaps are filled following the method described above in section 5.2.2.
- This process provides annualised green and blue water intensities for each year, crop and country/territory. The blue water footprints are also then multiplied by country/territory-level AWARE characterisation factors for agricultural use to provide an estimate of the scarcity-weighted blue water footprint. A handful of small producing countries/territories (mainly Oceanic island states) do not have water scarcity values in the AWARE database. No attempt was made to provide scarcity estimates for these countries.
- These indicators are only applied to crop commodities within the dataset.

6. Biodiversity 1: Predicted species loss metric

6.1. Overview

The GEIC indicator offers three biodiversity metrics, with each based on different methods and input data, to provide multiple estimates of consumption risks to biodiversity. This section describes the methods behind the predicted species loss metric; see sections 7 and 8 for details of the other metrics. Note that – if users choose to only use one of the three – we recommend the LIFE metric as the 'first choice' biodiversity metric, the methods for which are described in section 8.

For this metric, using the countryside species area relationship (cSAR) model, biodiversity impacts are estimated as the number of regional species lost as a result of agricultural land use. Chaudhary and Kastner (2016) provide crop- and country-specific characterisation factors to estimate the impact per tonne of production for 152 crops/crop groups in 171 countries/territories (Table S1 in Chaudhary & Kastner, 2016). In GEIC, these were linked to respective crop production statistics within the IOTA framework to estimate the 'predicted regional species loss' associated with consumption activities.

6.2. Methodological summary

Countryside SAR can be used to predict the final level of species extinctions per ecoregion but does not specify the timing of extinctions. In other words, SARs provide an estimate of species 'committed to extinction' in the absence of habitat restoration (Chaudhary & Kastner, 2016). The extinction risk associated with land use change and occupation was estimated for each of the 804 terrestrial ecoregions for mammals, birds, amphibians and reptiles (Chaudhary *et al.,* 2015). These were then allocated to different land use types according to the relative area of each land use within the ecoregion and the estimated species 'affinity' for that land use. This provides characterisation factors per ecoregion and broad land use type, that Chaudhary and Kastner (2016) then further disaggregated to specific crops using crop maps and yields from Monfreda *et al.* (2008), which modelled harvested area at 5 minute pixel resolution for, nominally, the year 2000. For the indicator, these country/territory and crop specific characterisation factors (in terms of 'predicted regional species loss per tonne') were applied directly to IOTA to estimate biodiversity losses.

See Chaudhary and Kastner (2016) and references therein for more detailed descriptions of data sources and methods.

6.3. Data update plans

The Chaudhary and Kastner (2016) dataset was released as an application of the cSAR-based approach to estimating potential species loss alongside crop-specific production and trade (at FAOSTAT commodity level). More recently, the methods have been developed (e.g. Chaudhary and Brooks, 2018) and applied in the preparation, for example, of characterisation factors for use in life cycle assessment (LCA) e.g. within LC-IMPACT. Future work could explore the application of the Chaudhary and Brooks (2018) factors alongside FAOSTAT production statistics. However, it should be noted that these still depend on land use information from the Monfreda *et al.* (2008) dataset with reference year 2000. With additional effort, it may be possible also to create a cSAR-based biodiversity metric using more recent crop production data.

6.4. Source(s)

Characterisation factors are taken from the Supplementary Information (Table S1) of Chaudhary and Kastner (2016), which is not currently an open access publication, and has been accessed via an institutional licence.

6.5. Application in the IOTA framework

Characterisation factors for “Total regional species lost per ton” were taken from Table S1 of Chaudhary and Kastner (2016). These were first cleaned to remove duplicated entries for ‘Chillies and peppers, green’ and then a concordance table was constructed to map the country/territory and commodity names to their respective FAOSTAT codes for joining to IOTA.

The characterisation factors are already in a production intensity form (i.e. per unit mass), and so the mass flows resolved by the framework are simply multiplied by the corresponding factor to provide estimates of regional species loss embedded in these flows.

If no value is available, it is left as zero. This indicator is applied only to crop commodities within the dataset.

7. Biodiversity 2: Species richness weighted hectares metric

7.1. Overview

The GEIC indicator offers three biodiversity metrics, with each based on different methods and input data, to provide multiple estimates of consumption risks to biodiversity. This section describes the methods behind the predicted species richness weighted hectares (species-area) metric; see sections 6 and 8 for details of the other metrics. Note that – if users choose to only use one of the three – we recommend the LIFE metric as the 'first choice' biodiversity metric, the methods for which are described in section 8.

This metric is based on the global mapped ranges of 11,145 bird species (BirdLife 2020), 6,707 amphibians, 5,537 terrestrial mammals (IUCN 2020) and 10,196 reptiles (IUCN 2021). These can be used as a proxy for biodiversity importance across the world's terrestrial surface. We intersected these biodiversity layers with 42 modelled crop production layers from MapSPAM (IFPRI & IIASA 2016; IFPRI 2019) for the relevant (see below) reference years of 2005 and 2010 to estimate, for each crop, the number of hectares of production (physical hectares) within each species' range. This is then summed across all species to estimate the biodiversity loss from the production of each crop in terms of 'species-hectares' (i.e. the species richness-weighted extent of crop production). The measure accounts for the high degree of spatial variation in species richness, and can also respond to information on agricultural expansion.

7.2. Methodological summary

Data on species' ranges are a mainstay of global biodiversity mapping and analyses. Detailed information on the data are provided by Birdlife International and the International Union for Conservation of Nature (BirdLife International and Handbook of the Birds of the World, 2020; IUCN, 2020). Figure 3 describes how species-hectares are calculated.

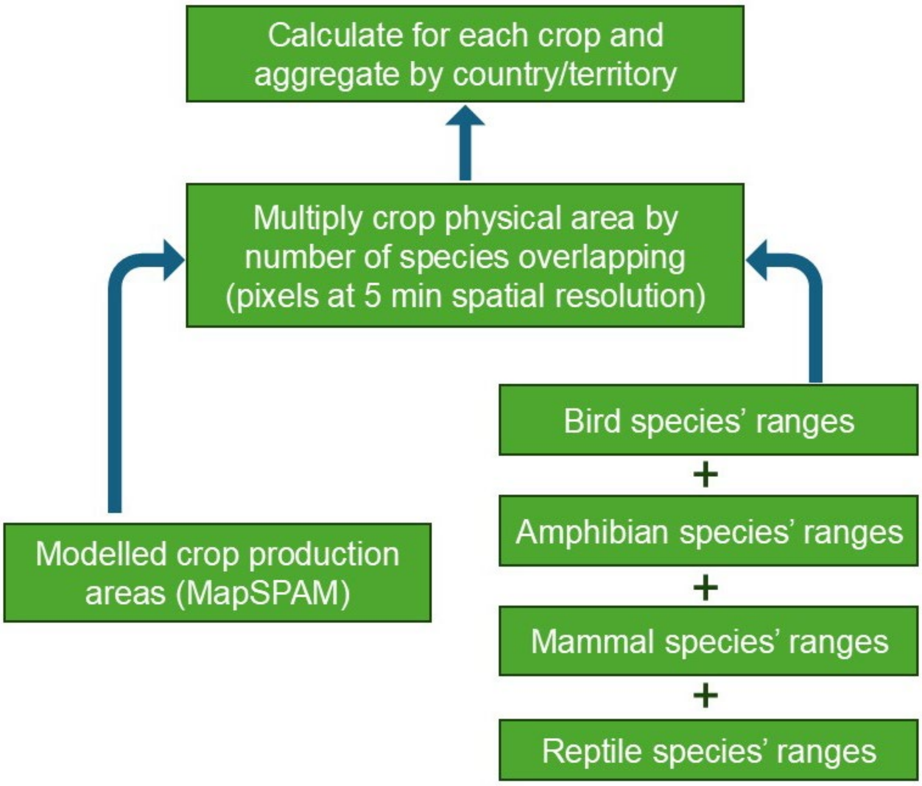

Figure 3. Visual summary of the method for calculating species-hectares.

We conducted the integration of data illustrated in Figure 3 and described below in the [Google Earth Engine] platform.

7.2.1. Species data

Species range polygons are available from Birdlife International and IUCN/Birdlife's online data portals. IUCN data include information on birds (via Birdlife), mammals, amphibians and reptiles (IUCN 2020 and 2021). These delineate the geographical limits to species' ranges, also known as a species' extent of occurrence, but are not refined by known habitat preferences or altitudinal limits, so will contain commission errors. These polygons therefore contain the smallest area that encompasses all known or inferred species occurrences and can include large extents of habitat which are unsuitable for species. However, these data are highly useful for showing the potential biodiversity value in terrestrial areas, relative to global biodiversity.

The spatial data are associated with information on the species' threat status, presence, origin, and seasonality (Appendix 4, Table 6). We therefore estimated biodiversity loss by filtering the original data according to specific criteria. This included using all extant species (i.e. presence is "Extant" and they are not listed as "Extinct" or "Extinct in the Wild") and species that are either native to the area or originate from reintroductions or assisted colonisation (i.e. conservation interventions). All parts of seasonal ranges were included (BirdLife, n.d.; IUCN, 2018).

7.2.2. Crop data

Outputs from the Spatial Production Allocation Model (MapSPAM) (IFPRI & IIASA 2016; IFPRI 2019) were used to estimate the distribution of cropland under each of 33 crops and 9 crop aggregates (Table 4, Appendix 4). Physical area was used, which refers to the actual area where a crop is grown; measured in hectares. Use of physical area means that pressures associated with, for example, double-cropping activities are not explicitly captured, i.e. we provide a species richness-weighted *extent* of crop production which does not account for the differing impacts associated with different production systems and land use intensities. Data are provided globally at 5 minute resolution nominally for 2000, 2005, 2010 and 2020 (data from 2000 falls outside our indicator period). In practice these data are compiled by MapSPAM authors from a variety of sources and timestamps centred, where possible, on the three years around the nominal date.

7.2.3. Calculating species-hectares

For the two years that align with the IOTA timeseries for which crop models were available (2005 and 2010), Google Earth Engine was used to create a global species richness layer across mammal, amphibian and bird datasets. For each crop/crop group, the physical area of cropland in every pixel (5 min resolution) was multiplied by this combined species richness layer i.e. number of species range polygons that overlapped it. This, then, is the estimated ‘species-hectares’ measure for that crop in that pixel. Summing these pixel values for each country/territory using the simplified Large Scale International Boundaries dataset (LSIB; USDS, 2017), allows an estimate of how many ‘species-hectares’ are impacted by the production of that crop in the reference year.

7.3. Data update plans

The species range data hosted by IUCN and BirdLife International are one of the most important conservation datasets globally. These are regularly updated on an annual basis and up to date information added. MapSPAM has data for 2005, 2010 and 2020 with more recent data available for specific regions of the world but the authors are unaware of any plans to update global datasets for later years. Species and crop data used in calculating species impacts are freely available for non-commercial purposes with the requisite citations.

7.4. Source(s)

Species ranges for birds are sourced from: http://datazone.birdlife.org/species/requestdis

Species ranges for mammals, amphibians and reptiles are sourced from: https://www.iucnredlist.org/

Crop-distribution estimates for reference years 2005 and 2010 are sourced from: https://www.mapspam.info/data/

All sources are currently publicly, and freely, available.

7.5. Application in the IOTA framework

- Summed species richness data for mammals, birds, amphibians and reptiles was compiled from source data within Google Earth Engine.

- For each crop/crop group, species richness per pixel is multiplied by the associated estimate of physical area of crop production. Resulting 'species-hectares' are then aggregated to country/territory level. This step is conducted using 2005, 2010 and 2020 crop extents.
- MapSPAM provides crop models for 2005, 2010 and 2020, which does not match the time series data available for the IOTA consumption dataset. The approach to overcome this incompatibility, linking a crop model with each year in the IOTA time series, is described below in section 7.5.1.
- Of the 42 crop layers mapped in MapSPAM, nine are aggregate crop groups:
    - If the indicator data concords to a single commodity within the FAOSTAT classification, that impact is assigned directly to the production of that commodity.
    - If the indicator data concords to multiple commodities, the impact is distributed across the production of those commodities in proportion to the relative land area used in their production. If no land area data are available within FAOSTAT for a given country/territory/commodity/year, then an estimate is derived based on global average yields, and this is then used to apportion the share of the indicator data to the crop.
- Once total impacts have been assigned to the production of corresponding crops, they are converted to intensities by dividing through by associated annual FAOSTAT-provided crop production masses. The resolved mass flows are then multiplied by the corresponding factors to estimate the species richness-weighted hectares embedded within those flows.
- This indicator is only applied to the crop commodities within the dataset.

A concordance was developed (Table 4, Appendix 3) to provide alignment between the commodities provided by MapSPAM and those used in IOTA. A concordance is also necessary to align countries/territories/regions covered by the two datasets.

To map the impacts calculated per country/territory using LSIB (USDS, 2017), a table was developed to provide concordance between the country/territory names resulting from the application of the LSIB country/territory boundaries used to derive country/territory-level species-hectares estimates, and those countries/territories used within IOTA. This is provided in Table 5 in Appendix 4.

7.5.1. Applying MapSPAM crop models across the IOTA time series

The species richness weighted hectares (species-area) and LIFE score (section 8) biodiversity metrics are both underpinned by the MapSPAM spatial crop production data. Consequently, the data files used as inputs within the IOTA methodology are classified according to the standards adopted within MapSPAM, namely MapSPAM's own commodity classification, with metrics then aggregated to country scale using the LSIB geographic classification. Concording these to the FAOSTAT country and commodity classifications within IOTA is relatively straightforward (Table 5, Appendix 4). More challenging is adapting the temporal coverage (2005, 2010 and 2020 MapSPAM data for the species-area metric, and 2020 MapSPAM data for the LIFE score metric) to span the time series employed within IOTA.

For the species-area metric, an approach is adopted whereby species richness is assumed to remain constant for all years sharing data from a given reference year but that, as area use goes up or down through time, the corresponding estimate of species-ha value goes up or down, respectively, in proportion to this change.

A challenge here is that whilst FAOSTAT provide annualised cropland area data (which is used within IOTA for the cropland use metric), this is a measure of “harvested” area, whereas the relevant value for scaling species-ha values is “physical area”. Whilst the former potentially includes activities like double-cropping (where crops are grown more than once in a given year on a given piece of land), the latter refers purely to the physical area of land which is used for production, regardless of how many harvests are performed within a year. Although MapSPAM provide values for both harvested and physical areas, these are limited to the 2005, 2010 and 2020 reference years.

To tackle these limitations and accommodate the assumptions, for the reference years within MapSPAM, the ratios between the reported MapSPAM physical area and the reported FAOSTAT harvested areas have been calculated for each country/crop pairing. Each year within the time series is matched to its closest reference year (with 2015 paired to 2020 due to better resolution), and a scaling is used based on relative land area between the reference year, and other years adopting the MapSPAM data from the same reference year.and a scaling is used based on relative land area between the reference year, and other years adopting the MapSPAM data from the same reference year.

Before applying this approach, steps need to be taken to address issues around missing data within the cropland area dataset. A hierarchical approach is adopted, whereby the best possible methods are adopted in each case depending on available data. In the best case, appropriate data are available directly within the FAOSTAT dataset. Where these are missing, checks are made to see what approach can be adopted to estimate the missing values.

Here, a first approach is to check if FAOSTAT include yield data. The production dataset typically includes three related data points for each year/country/commodity context, namely a production value (tonnes), an associated area value (hectares), and a corresponding yield value (hundred grams per hectare). These three data points triangulate, with any two allowing the calculation of the third. In some instances, whilst area data are not given, yield data are, in which case it is trivial to calculate the missing area values from the production and yield values.

If no yield data are available for a given year, a check is made to see if yield data are available for any other years within the time series. If this is the case, methods are applied to interpolate/extrapolate for missing years. This is applied by extending the first or last year’s value for any years prior/after these points, respectively, and by linearly interpolating for any years between provided data points. The linear interpolation part of this method provides a simple and robust way to estimate gaps within the series, whilst the extrapolation at either end of the series ensures that values never exceed provided values, and prevents potentially erroneous extremes driven by observed trends at either end of the available data window.

Finally, where no yield data are available for a given country/commodity across the time series, a global average yield value is adopted. Once yield values have been calculated across all gaps, these are used in conjunction with reported production values to provide estimates of the associated harvested land area.

It is worth noting that these area values, whether included in the original FAOSTAT dataset or calculated, are still used ultimately as “relative” values for the application of the MapSPAM data. Even in the “worst case” where global yield values have to be adopted, this is not directly determining the biodiversity values but rather being used to scale on an inter-annual basis, with the reference year values remaining unchanged from the input datasets.

For the species-area metric, with these harvested area values present for nearly all cases (there are some commodities, namely “Mushrooms and truffles” and “Brazil nuts, in shell”, for which no area data are available for any years/countries), the ratios between these areas and the areas in the corresponding reference years are calculated (e.g. 2012 area data are compared to corresponding 2010 area data, with 2010 being the closest MapSPAM reference year). These ratios are then used to scale the species-area values available for 2005, 2010 and 2020 and apply them across the time series to provide a full series of year/country/commodity total species-area impact values. Finally, these values are then divided by the respective production values to give a material (i.e. per-tonne) intensity value which can be assigned to each material flow corresponding to a given country (of production)/commodity pairing.

Further details for the approach taken for the LIFE metric are given in section 8.5.1.

7.5.1.1. Outstanding cases

It is worth noting that not all values from the MapSPAM/species-area/LIFE outputs end up being mapped to associated production and flows within IOTA. There are a number of explanations that can give rise to this.

One of the most common is the presence of what are believed to be “false-positives” within the underlying MapSPAM-derived dataset (prepared by this project team) that provides crop area aggregated to national scale, whereby production/land use is being assigned to countries which do not report production of the respective commodities. This is believed to be an artefact of the methods and resolution employed, and specifically due to pixels on country borders being split across countries. As such, we ignore these values and do not to take additional steps to try and map them into the IOTA framework.

Notes on further outstanding cases relevant to the LIFE metric are given in section 8.5.1.1.

8. Biodiversity 3: LIFE score metric

8.1. Overview

The GEIC indicator offers three biodiversity metrics, with each based on different methods and input data, to provide multiple estimates of consumption risks to biodiversity. This section describes the methods behind the LIFE metric; see sections 6 and 7 for details of the other metrics. Note that – if users choose to only use one of the three – we recommend the LIFE metric as the 'first choice' biodiversity metric, the methods for which are described in this section.

The LIFE score is a metric that provides quantitative estimates of the marginal changes in the expected number of extinctions (both increases and decreases) across ~30k terrestrial vertebrate species, using changes in their modelled area of habitat in the absence of human activity. The impact of changes in area of habitat are related to the proportion that has been lost already, so that per unit area losses in habitat will have the greatest impacts on extinction risk for those species which have faced the greatest losses of habitat. The metric provides an estimate of the probable number of species committed to extinction over approximately 100 years, but which are not yet already extinct (i.e. effective restoration and conservation efforts within this time period could re-establish a stable population).

The approach integrates information on species richness, endemism, and past habitat loss to estimate the impact of land cover change on extinctions. The method assumes that the impacts of restoration are equal and opposite to the impacts of conversion of a given land area (i.e. restoring cropland to natural habitat would eventually lead to original conditions and repopulation – which may not be the case in reality). Following this assumption, in areas that have already been converted, the inverse of the 'LIFE restore' layer is used to estimate extinction pressure from the conversion of the land from its natural habitat. In GEIC, we use this inverse 'restore' layer data as well as crop production layers from MapSPAM to calculate the impacts of conversion to cropland, with the data presented in the form of predicted extinctions (assuming the land is not restored).

A score of 1 is equivalent to one global extinction (though in reality the change in extinction risk is shared across many species). Consequently, results show the sum of the each country's contribution to global future extinctions across all the world as a result of that country's consumption of crop commodities.

8.2. Methodological summary

Methods used to calculate the LIFE metric (and the description provided below) are adapted from Eyres *et al.* (2025) and, in particular, Ball *et al*. (2025), upon which the data are based. Please refer to these references for a more detailed description of the underlying concept and methods.

8.2.1. Species data

To derive global maps of the LIFE score for future land-cover changes, we use species range polygons and information on the habitat and altitudinal preferences of each species from Birdlife International and IUCN. The species range data (which are equivalent to those used in the species hectares metric) delineate the geographical limits to species' ranges, also known as a species' extent of occurrence. These are then refined further to provide area of habitat (AOH) maps using information on species habitat preferences and altitudinal limits to their ranges.

Excluded species ranges: The spatial data are associated with information on the species' threat status, presence, origin, and seasonality. The parts of a species' range where its presence is 'extant' or 'possibly extinct', its origin is 'native', 'reintroduced' or 'uncertain' were included. 'Possibly extinct' is used rather than 'extinct' due to uncertainty related to extinction data. All parts of seasonal ranges were included. When generating original AOH maps the parts of range polygons that are coded as 'extinct' were also included. Species that are listed as 'marine', 'terrestrial+marine', 'freshwater', or 'freshwater+marine' were excluded. Exclusion of marine and freshwater species is because their much higher (and in many cases exclusive) dependence on marine and fresh-water means that their inclusion would be inconsistent with the other data that we use for conversion. Species with missing data, those which inhabit caves or subterranean habitats, or those where mismatches between range maps, habitat maps and habitat preferences result in no measurable AOH were also excluded. This gives information for ~30k species.

In order to calculate LIFE scores, current and original AOHs are needed for each species. For current AOH the map of habitat distribution in 2016 from Jung (2020) and Jung *et al*. (2020) was used. Original AOH uses the map of Potential Natural Vegetation (PNV) (Jung, 2020; Jung *et al*., 2020), which estimates habitat distributions in the absence of humans as a baseline. Habitats in the PNV layer are mapped at IUCN level 1, so natural habitats mapped at level 1 (broader habitat classes) and artificial habitats at level 2 (more refined habitat classes) were used. These habitat surfaces were overlaid with species' range maps from IUCN and Birdlife International and a Digital Elevation Model (see data sources, below), and estimated per-species AOH as those parts of its range which are (or were) suitable based on its elevation and habitat preferences. For species which exhibit seasonal habitat preferences AOH was calculated separately for the breeding and non-breeding season.

8.2.2. Crop data

For consistency with the species-hectare indicator, the LIFE layer was recalculated using the crop layers from the Spatial Production Allocation Model (MapSPAM) for 2020 (IFPRI 2024), rather than the GAEZ data used in the version published by Ball *et al.* (2025). These crop layers are provided globally at 5 minute resolution and were used to estimate the distribution of cropland under each of the 37 crops and 9 crop aggregates. The physical area of each crop was then intersected with the Jung *et al*. (2020) habitat map to calculate current AOH, as per Ball *et al*. (2025).

8.2.3. Calculating LIFE scores

Impact values are derived from the LIFE score (per unit area) for the spatially explicit locations in which that commodity is produced. To derive these estimates, we followed Ball *et al.* (2025) to intersect a partially modified (to generate a continuous surface of biodiversity opportunity cost) version of the LIFE 'restore' layer (Eyres *et al.,* 2025) with crop production layers from the MapSPAM crop layer. Summing these pixel values for each country/territory using the Global Administrative areas data from GADM (see sources, below) gives a per-country estimate of the potential biodiversity lost to commodity crop production in the reference year, in terms of how it contributes to global extinctions.

8.2.4. Caveats

LIFE is a metric of marginal change – the certainty of results reduces as cell values are aggregated (see Eyres *et al*., 2025, for some discussion on this deviation). Moreover, as the trade and consumption accounts from the MRIO move further from the reference year for the biodiversity impact layer (i.e. 2020), so the actual impacts will be increasingly different from the marginal change for which they were calculated. In general, a positive impact will be more positive and a negative impact more negative than appears. We are exploring the development of multiple reference years in future releases, which will mitigate this issue (see next section).

8.3. Data update plans

The species range data hosted by IUCN and BirdLife International are one of the most important conservation datasets globally. These are regularly updated. We use MapSPAM data for 2020, but earlier data are also available – for 2000, 2005 and 2010. With the anticipated release of later years, alongside harmonisation with earlier years, we would like to recalculate LIFE at 1–5 year time steps. Species and crop data used in calculating species impacts are freely available for non-commercial purposes with the requisite citations.

8.4. Source(s)

Species ranges for birds are sourced from: http://datazone.birdlife.org/species/requestdis
Species ranges for mammals and amphibians are sourced from: https://www.iucnredlist.org/

Crop-distribution estimates for reference years 2020 are sourced from: https://www.mapspam.info/data/.

Elevation data are from:

- Global SRTM. NASA Shuttle Radar Topography Mission (SRTM) Distributed by OpenTopography. 2013. Available from: http://dx.doi.org/10.5069/G9445JDF
- USGS. USGS 30 ARC-second Global Elevation Data, GTOPO30. Boulder, CO: Research Data Archive at the National Center for Atmospheric Research, Computational and Information Systems Laboratory; 1997. Available from: https://doi.org/10.5065/A1Z4-EE71

Administrative boundaries are the 50 m GADM level0, available from https://www.naturalearthdata.com/downloads/.

All sources are currently publicly, and freely, available.

8.5. Application in the IOTA framework

In 2020, the LIFE score is calculated for each crop/crop group, according to the methods described above. The biodiversity impact intensity is then the ‘biodiversity opportunity cost’, which is calculated as LIFE score divided by physical area.

The ratio between harvested and physical area is also calculated for 2020 for each crop/crop group, using the MapSPAM data (more details in section 8.5.1).

We currently calculate the LIFE score for 2020 only. Therefore, for other years in the IOTA time series, the same data (i.e. 2020 layer) are applied, but impacts are recalculated based on the amount of consumption. This is done by:

- For each crop/crop group, the physical area is estimated using the harvested area, provided by the FAO on an annual basis and a previously calculated (MapSPAM derived) relationship to physical area (see sections 7.5.1 and 8.5.1).
- This estimated physical area for each year is then multiplied by the biodiversity impact intensity calculated for 2020, which gives an estimate of the 'biodiversity opportunity cost' for each year.

Of the 46 crop layers mapped in MapSPAM, nine are aggregate crop groups:

- If the indicator data concords to a single commodity within the FAOSTAT classification, that impact is assigned directly to the production of that commodity.
- If the indicator data concords to multiple commodities, the impact is distributed across the production of those commodities in proportion to the relative land area used in their production. If no land area data are available within FAOSTAT for a given country/ territory/commodity/year, then an estimate is derived based on global average yields, and this is then used to apportion the share of the indicator data to the crop.

This indicator is only applied to crop commodities within the dataset.

A concordance was developed (Table 4, Appendix 4) to provide alignment between the commodities provided by MapSPAM and those used in IOTA.

8.5.1. Applying MapSPAM crop models across the IOTA time series

The species richness weighted hectares (species-area) (section 7) and LIFE score biodiversity metrics are both underpinned by the MapSPAM spatial crop production data, which is provided for three years of the IOTA time series: 2005, 2010 and 2020. The approach taken to apply this data across the full IOTA time series for the species-area metric is described in section 7.5.1.

For the LIFE metric, a similar approach to that described in 7.5.1 is taken, but using only the 2020 MapSPAM data. Here the ratio between MapSPAM physical area and FAOSTAT harvested area in 2020 is calculated to provide an explicit conversion factor. This step isn't necessary for the species-area calculations since the input species-area values are totals, and so this conversion was effectively implicit within the calculations. In contrast, LIFE metric inputs are an area-intensity, and thus need to be multiplied by the physical area to calculate the total value. Once calculated, these total values are divided by the 2020 FAOSTAT harvested area values to create a harvested-area intensity. This can then be multiplied by the harvested area value across the time-series to give an estimated total value for each year/country/commodity. Finally, as with the species-area values, these are divided by respective production values to provide a per-tonne material intensity to be applied to the model outputs.

8.5.1.1. Outstanding cases

It is worth noting that not all values from the MapSPAM/species-area/LIFE outputs end up being mapped to associated production and flows within IOTA. See comments on how this can be caused by the presence of "false-positives", in section 7.5.1.1.

In the LIFE dataset, there are also cases where impacts are reported but no corresponding production occurs in 2020. In some investigated cases, production is reported as taking place in other years near to 2020, and this is believed to be being captured within the LIFE scores as a result of its use of various datasets across different years to estimate inputs used to calculate the 2020 LIFE values. In such cases, these have been left unassigned within IOTA rather than taking additional steps to use values from other years to estimate linkages for two main reasons. Firstly, given only one reference year (2020) is being used to apply the LIFE metric across IOTA's full time-series, basing this around additional estimations for the one available reference year would undermine confidence in the results. Secondly, given the infancy of the LIFE metric and available input data for use within IOTA, there is a strong possibility that in future additional reference years will be available which should go some way to eliminating the issues described, but would also invalidate additional efforts made now to circumvent the issue.

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Weblinks

Table 2. Full URLS for weblinks used in the text.

Weblink text	Full URL
AWARE	https://wulca-waterlca.org/aware/what-is-aware/
BirdLife International	http://datazone.birdlife.org/species/requestdis#.YVRyP5rMKUI
Code of Practice for Statistics	https://code.statisticsauthority.gov.uk/the-code/
Convention on Biological Diversity (CBD)'s Kunming-Montreal Global Biodiversity Framework	https://www.cbd.int/gbf/
CROPWAT 8.0	http://www.fao.org/land-water/databases-and-software/cropwat/en/
Dasgupta Review	https://www.gov.uk/government/publications/final-report-the-economics-of-biodiversity-the-dasgupta-review
Environmental Improvement Plan 2023	https://www.gov.uk/government/publications/environmental-improvement-plan
EXIOBASE	https://doi.org/10.5281/zenodo.3583070
EXIOBASE 3.8.1 MRIO model	https://zenodo.org/record/4588235
Food and Agriculture Organisation (FAO) of the United Nations	http://www.fao.org/faostat/en/#data
GLAD	https://glad.umd.edu/
GLORIA	https://ielab.info/labs/ielab-gloria
Global Trade Analysis Project (GTAP)	https://www.gtap.agecon.purdue.edu/databases/default.asp
Google Earth Engine	https://earthengine.google.com/
Interactive dashboard	http://www.commodityfootprints.earth/
International Union for the Conservation of Nature (IUCN)	https://www.iucnredlist.org/
MapSPAM	https://www.mapspam.info/
National Food Strategy	https://www.nationalfoodstrategy.org/
UK Statistics Authority website	https://uksa.statisticsauthority.gov.uk/about-the-authority/uk-statistical-system/types-of-official-statistics/
Original publication in 2021	https://webarchive.nationalarchives.gov.uk/ukgwa/20220901105341/https:/jncc.gov.uk/our-work/ukbi-a4-global-biodiversity-impact/
SPAM 2005	https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/DHXBJX
SPAM 2010	https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/PRFF8V

Weblink text	Full URL
Water Footprint Network	https://www.waterfootprint.org/
WULCA	https://wulca-waterlca.org/aware/what-is-aware/
Publication of this indicator as a UK Biodiversity Indicator	https://jncc.gov.uk/our-work/ukbi-global-biodiversity-impact/
UK Carbon Footprint	https://www.gov.uk/government/statistics/uks-carbon-footprint
UK Material Footprint	https://www.ons.gov.uk/economy/environmentalaccounts/ articles/materialfootprintintheuk/2018
25 Year Environment Plan	https://www.gov.uk/government/publications/25-year-environment-plan

Appendix 1: Supplementary graphs for the UK (2025)

The UK official statistic includes basic graphs on total worldwide estimates for:

- area of deforestation risk associated with UK consumption (headline result);
- predicted regional species loss associated with UK consumption (biodiversity metric 1);
- species richness-weighted crop area associated with UK consumption (biodiversity metric 2);
- LIFE score (change in probability of extinction – biodiversity metric 3);
- deforestation linked GHG emissions (including peatland drainage) associated with UK consumption;
- scarcity-weighted blue water use equivalent associated with UK consumption;
- cropland area harvested associated with UK consumption;
- material footprint associated with UK consumption.

However, it was not possible to include all graphs produced in the UK Biodiversity Indicator fiche itself. This Appendix presents additional graphs, showing intensities (impact per tonnes of production) related to each of the above metrics rather than totals, as well as emissions excluding peatland drainage, blue water footprint and green water footprint.

Graphs for the global dataset (for example, from the perspective of different consuming countries/territories) can be generated, and the underlying data downloaded, at the interactive dashboard.

Cropland

UK consumption of **crop** commodities in 2023 was associated with an estimated total land use footprint intensity of 150 ha per thousand tonnes of embedded production worldwide, a decrease of 8.0% since 2005 (Figure 4). Comparing the 2023 footprint with 2018 reveals a short-term decrease of 3.8% (five years is the standard short-term comparison used for the UKBIs and, although the metrics presented here do not officially form part of the UKBI itself, the same comparisons are made for consistency with the rest of the dataset). For the latest year (2023 compared to 2022) a 0.3% increase is observed. UK consumption-based intensities are below that of the global average (orange line) for most years, although are closer to the global average in more recent years. Estimates are for crop commodities only.

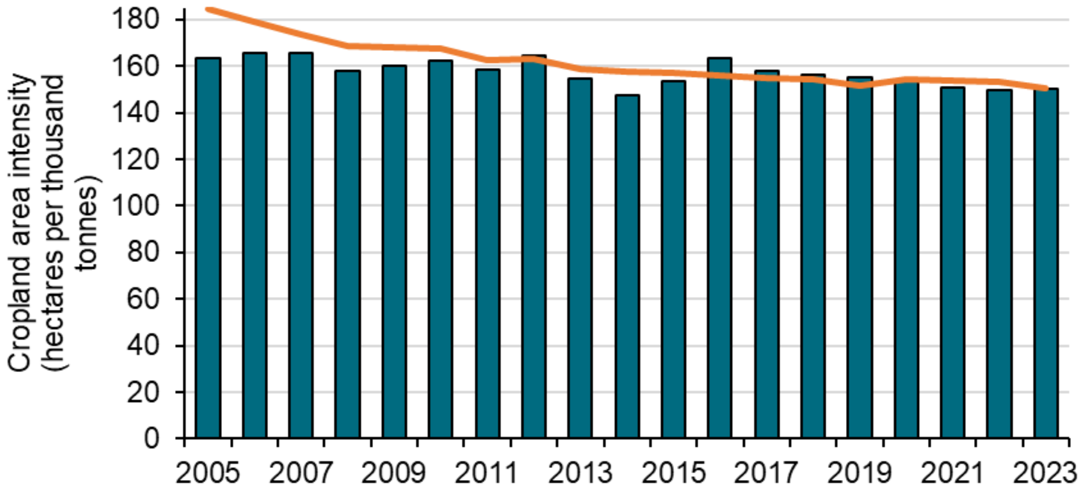

Figure 4. Cropland area intensity (hectares per thousand tonnes of embedded production) worldwide associated with UK consumption. The orange line compares this to intensities associated with average global consumption.

Deforestation

UK consumption of **crop, cattle-related and timber** commodities in 2023 was associated with an estimated agriculture-driven deforestation intensity of 0.22 ha per thousand tonnes of embedded production worldwide, a decrease of 45.4% since 2005. Comparing the 2023 footprint with 2018 reveals a short-term decrease of 35.5% (Figure 5). For the latest year (2023 compared to 2022) a 4.3% decrease is observed. UK consumption-based intensities are below that of the global average (orange line) for all years in the timeseries. Estimates are for deforestation as a result of crop, cattle-related and timber commodities only. Note that – as per the quality scores in the underpinning deforestation data – confidence in the most recent years of data tends to be lower.

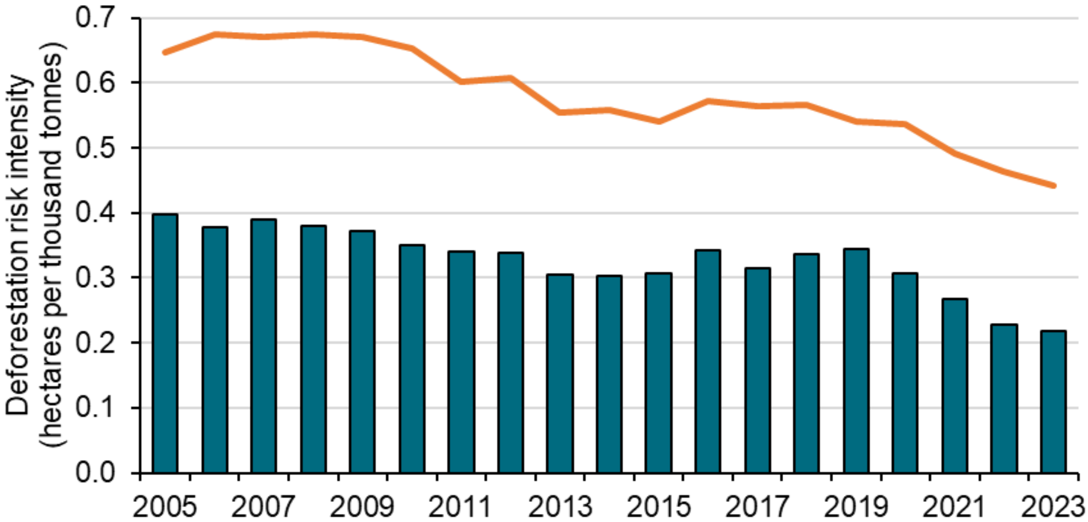

Figure 5. Deforestation intensity (hectares per thousand tonnes of embedded production) worldwide associated with UK consumption. The orange line compares this to intensities associated with average global consumption.

Deforestation linked emissions

UK consumption of **crop, cattle-related and timber** commodities in 2023 was responsible for an estimated 7.9 million tonnes of CO_2 emissions linked to deforestation worldwide, exclusive of peat drainage, a decrease of 63.4% since 2005 (Figure 6). Comparing the 2023 footprint with 2018 reveals a short-term decrease of 41.8%. For the latest year (2023 compared to 2022) an 8.4% decrease is observed. Estimates are for deforestation as a result of crop, cattle-related and timber commodities only. Note that – as per the quality scores in the underpinning deforestation data – confidence in the most recent years of data tends to be lower.

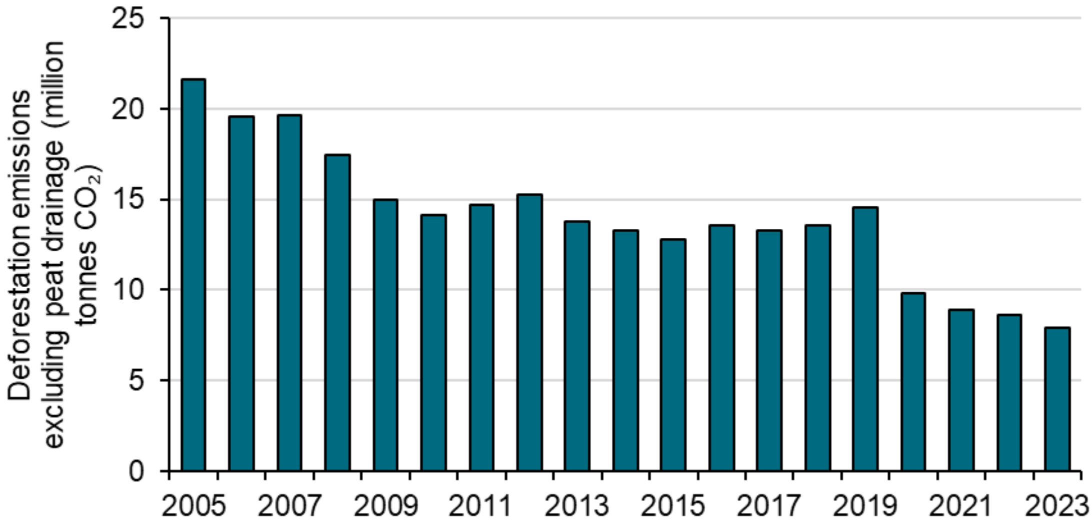

Figure 6. Deforestation emissions (excluding peat drainage) worldwide associated with UK consumption (million tonnes CO_2).

UK consumption of **crop, cattle-related and timber** commodities in 2023 was associated with an estimated deforestation linked emissions intensity worldwide, inclusive of peat drainage, of 70.0 tonnes of CO_2 per thousand tonnes of embedded production, a decrease of 48.2% since 2005 (Figure 7). Comparing the 2023 footprint with 2018 reveals a short-term decrease of 34.2%. For the latest year (2023 compared to 2022) a 6.5% decrease is observed. UK consumption-based intensities are below that of the global average (orange line) for all years in the time series. Estimates are for deforestation as a result of crop, cattle-related and timber commodities only.

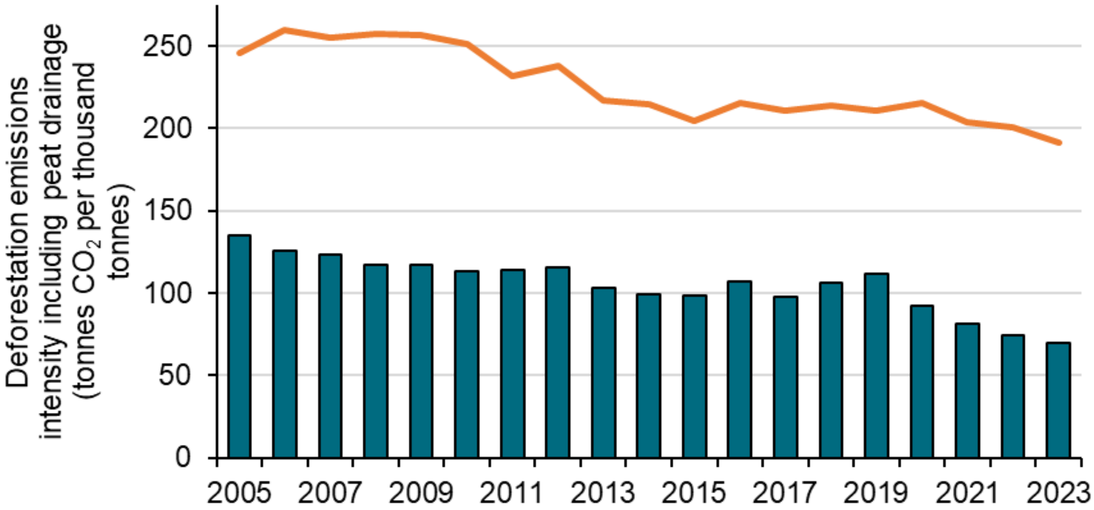

Figure 7. Deforestation emissions intensity (including peat drainage) worldwide associated with UK consumption (tonnes CO_2 per thousand tonnes of embedded production). The orange line compares this to intensities associated with average global consumption.

UK consumption of **crop, cattle-related and timber** commodities in 2023 was associated with an estimated deforestation linked emissions intensity worldwide, excluding peat drainage, of 58.7 tonnes of CO_2 per thousand tonnes of embedded production, a decrease of 55.3% since 2005 (Figure 8). Comparing the 2023 footprint with 2018 reveals a short-term decrease of 38.0%. For the latest year (2023 compared to 2022) a 7.8% decrease is observed. UK consumption-based intensities are below that of the global average (orange line) for all years in the timeseries. Estimates are for deforestation as a result of crop, cattle-related and timber commodities only.

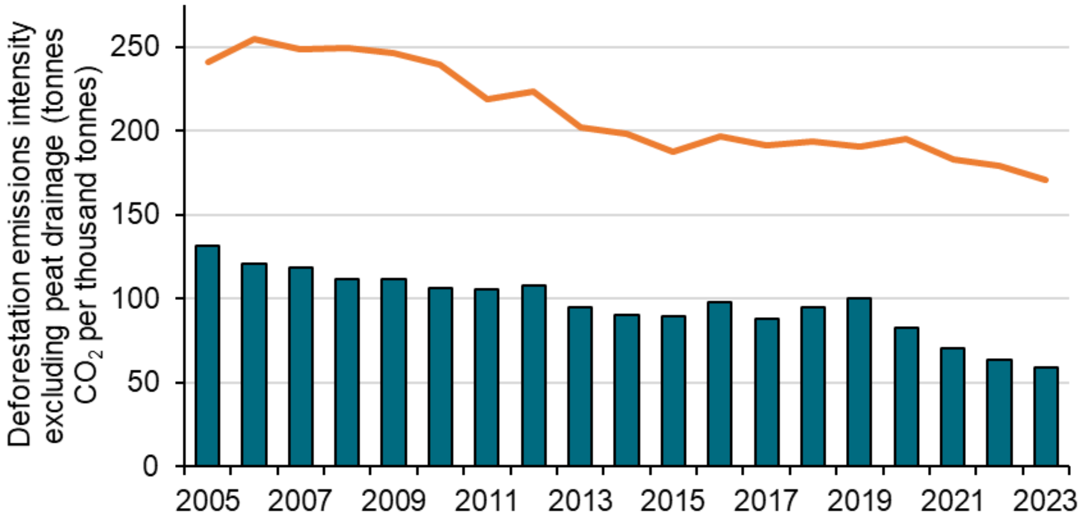

Figure 8. Deforestation emissions intensity (excluding peat drainage) worldwide associated with UK consumption (tonnes CO_2 per thousand tonnes of embedded production). The orange line compares this to intensities associated with average global consumption.

Green water use

UK consumption of **crop** commodities in 2023 was associated with an estimated 68.4 billion cubic metres of green water use worldwide, a decrease of 23.9% since 2005 (Figure 9). Comparing the 2023 footprint with 2018 reveals a short-term decrease of 9.1%. For the latest year (2023 compared to 2022) a 0.3% decrease is observed. Estimates are for crop commodities only.

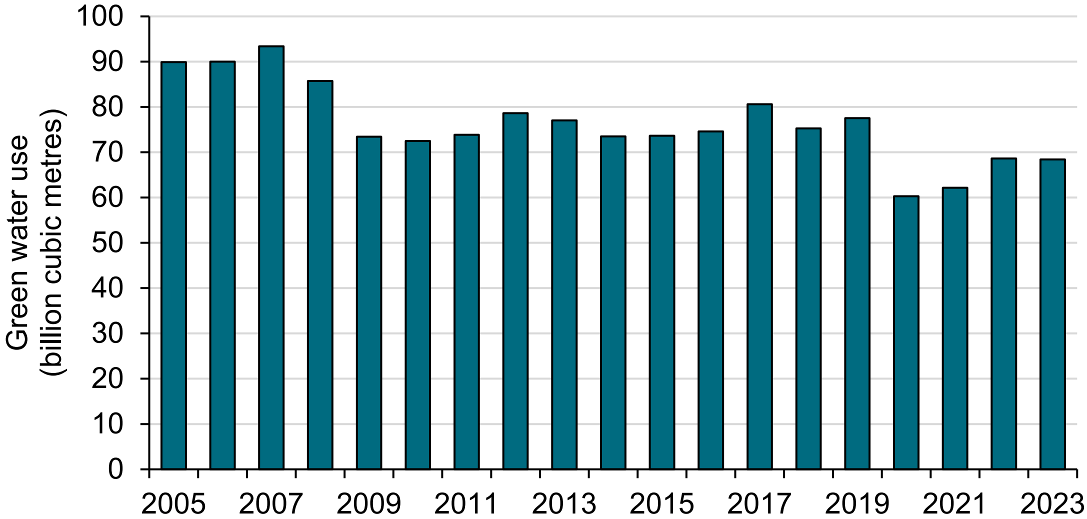

Figure 9. Green water use worldwide associated with UK consumption (billion cubic metres).

UK consumption of **crop** commodities in 2023 was associated with an estimated green water use intensity worldwide of 641 cubic metres per tonne of embedded production, a decrease of 10.7% since 2005 (Figure 10). Comparing the 2023 footprint with 2018 reveals a short-term decrease of 4.6%. For the latest year (2023 compared to 2022) a 0.1% decrease is observed. UK consumption-based intensities are below that of the global average (orange line) for all years. Estimates are for crop commodities only.

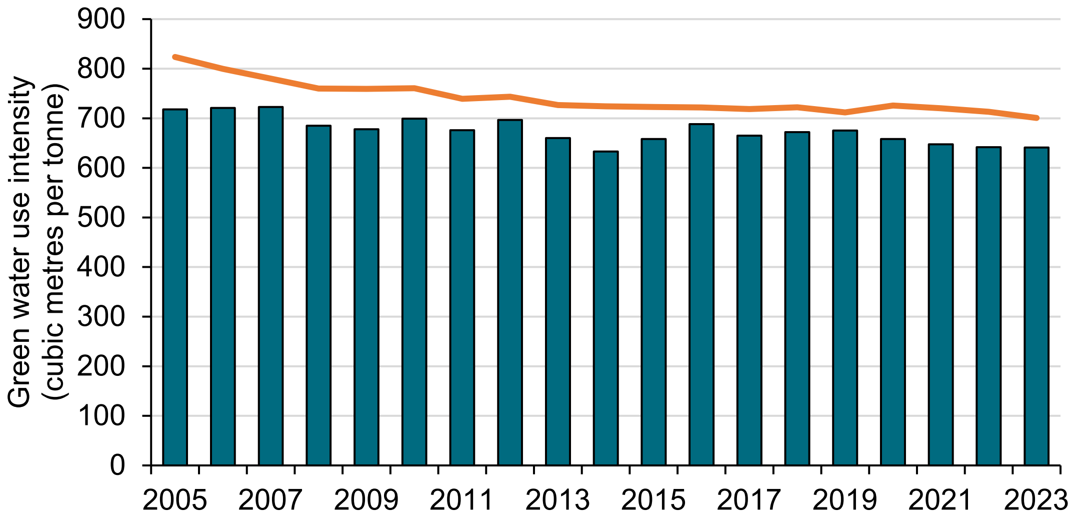

Figure 10. Green water intensity (cubic metres per tonne of embedded production) worldwide associated with UK consumption. The orange line compares this to intensities associated with average global consumption.

Blue water use

UK consumption of **crop** commodities in 2023 was associated with an estimated 6.6 billion cubic metres of blue water use worldwide, a decrease of 36.2% since 2005 (Figure 11). Comparing the 2023 footprint with 2018 reveals a 18.4% decrease. For the latest year (2023 compared to 2022) a 0.3% increase is observed. Estimates are for crop commodities only.

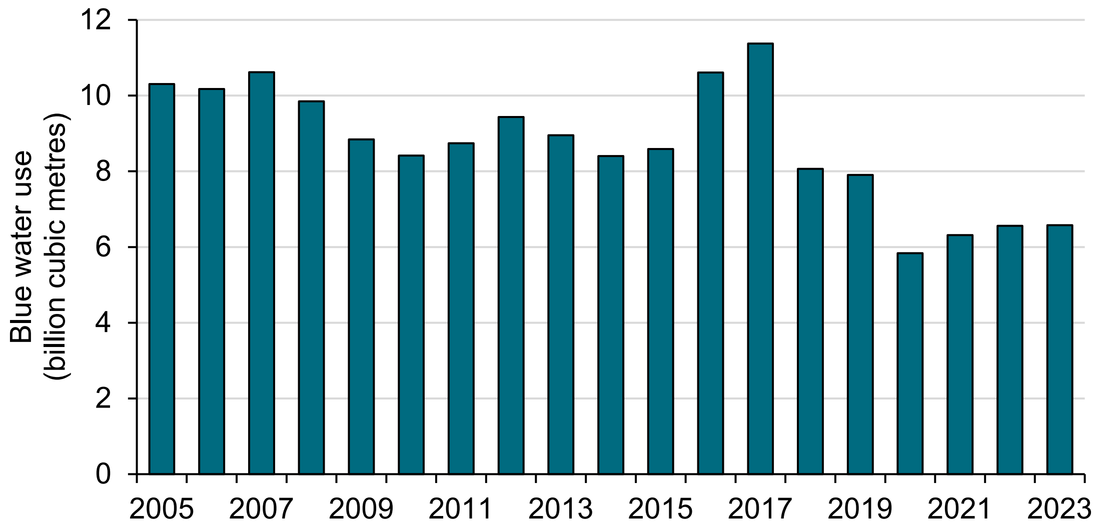

Figure 11. Blue water use worldwide associated with UK consumption (billion cubic metres).

UK consumption of **crop** commodities in 2023 was associated with an estimated blue water use intensity of 62 cubic metres per tonne of embedded production worldwide, a decrease of 25.1% since 2005 (Figure 12). Comparing the 2023 footprint with 2018 reveals a short-term decrease of 14.4%. For the latest year (2023 compared to 2022) a 0.4% increase is observed. UK consumption-based intensities are below that of the global average (orange line) for all years in the timeseries. Estimates are for crop commodities only.

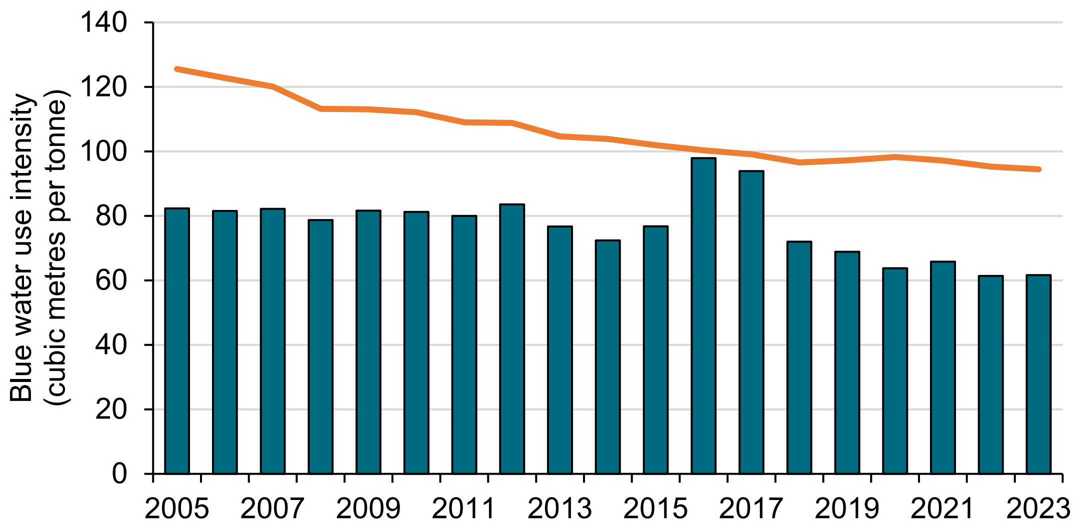

Figure 12. Blue water use intensity (cubic metres per tonne of embedded production) worldwide associated with UK consumption. The orange line compares this to intensities associated with average global consumption.

UK consumption of **crop** commodities in 2023 was associated with an estimated scarcity-weighted blue water use intensity of 2,580 cubic-metres per tonne of embedded production worldwide, a decrease of 30.7% since 2005 (Figure 13). Comparing the 2023 footprint with 2018 reveals a short-term decrease of 13.4%. For the latest year (2023 compared to 2022) a 1.4% decrease is observed. UK consumption-based intensities are below that of the global average (orange line) for all years across the timeseries. Estimates are for crop commodities only.

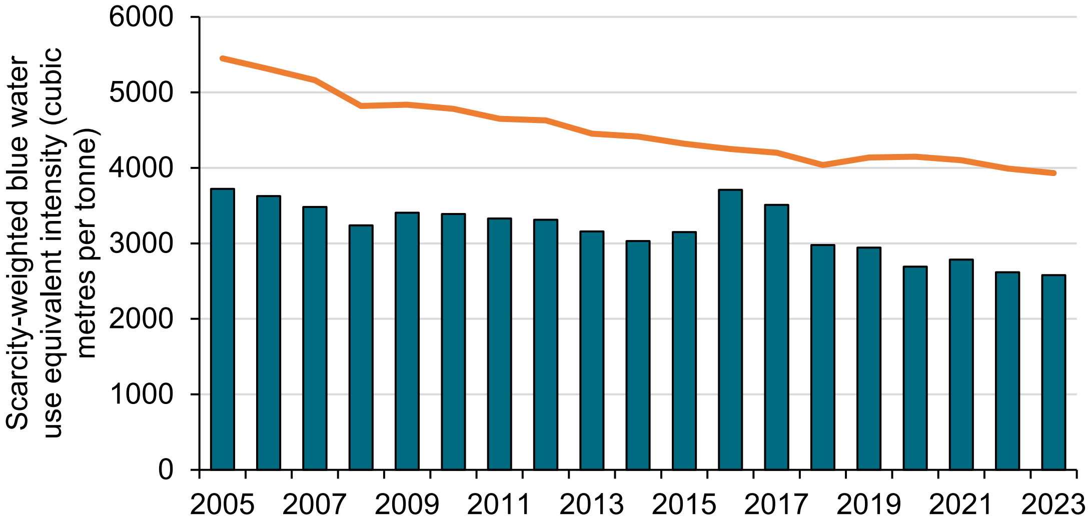

Figure 13. Scarcity-weighted blue water use equivalent intensity (cubic metres per tonne of embedded production) worldwide associated with UK consumption. The orange line compares this to intensities associated with average global consumption.

Biodiversity

UK consumption of **crop** commodities in 2023 was associated with an estimated intensity of 50.6 species richness-weighted hectares per tonne of embedded production worldwide (Figure 14), a 7.9% decrease since 2005. Comparing the 2023 footprint with 2018 reveals a short-term decrease of 2.3%. For the latest year (2023 compared to 2022) a 0.5% increase is observed. UK consumption-based intensities are below that of the global average (orange line) for all years in the timeseries. Estimates are for crop commodities only.

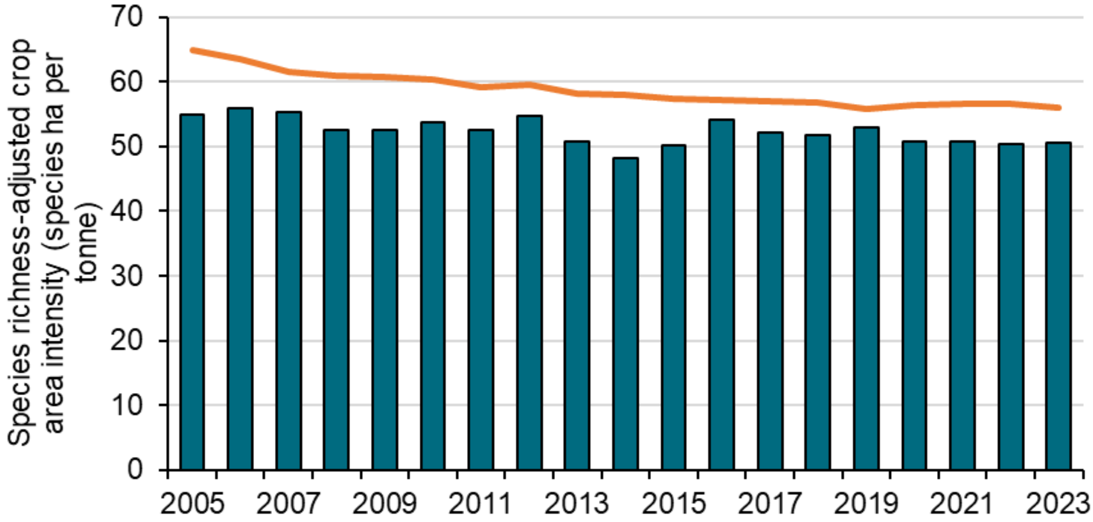

Figure 14. Species richness-weighted crop area intensity (species-hectares per tonne of embedded production) worldwide associated with UK consumption. The orange line compares this to intensities associated with average global consumption.

UK consumption of **crop** commodities in 2023 was associated with a predicted regional species loss intensity of 0.00058 species per thousand tonnes of embedded production worldwide, a decrease of 8.3% since 2005 (Figure 15). Comparing the 2023 footprint with 2018 reveals a short-term decrease of 5.7%. For the latest year (2023 compared to 2022) a 2.6% decrease is observed. UK consumption-based intensities are below that of the global average (orange line) for all years in the timeseries. Estimates are for crop commodities only.

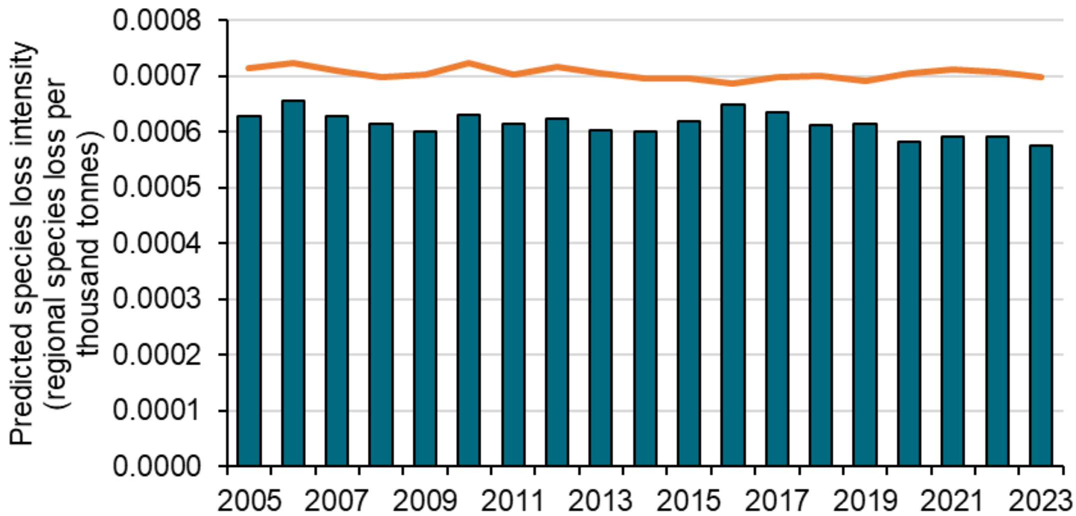

Figure 15. Predicted species loss intensity (regional species loss per thousand tonnes of embedded production) worldwide associated with UK consumption. The orange line compares this to intensities associated with average global consumption.

UK consumption of **crop** commodities in 2023 was associated with a 'LIFE score' (change in probability of extinction) intensity (impact per thousand tonnes of production) of 0.000031 worldwide, a decrease of 23.1% since 2005 (Figure 16). Comparing the 2023 footprint with 2018 reveals a short-term decrease of 5.8%. For the latest year (2023 compared to 2022) a 4.6% decrease is observed. UK consumption-based intensities are below that of the global average (orange line) for all years in the timeseries. Estimates are for crop commodities only.

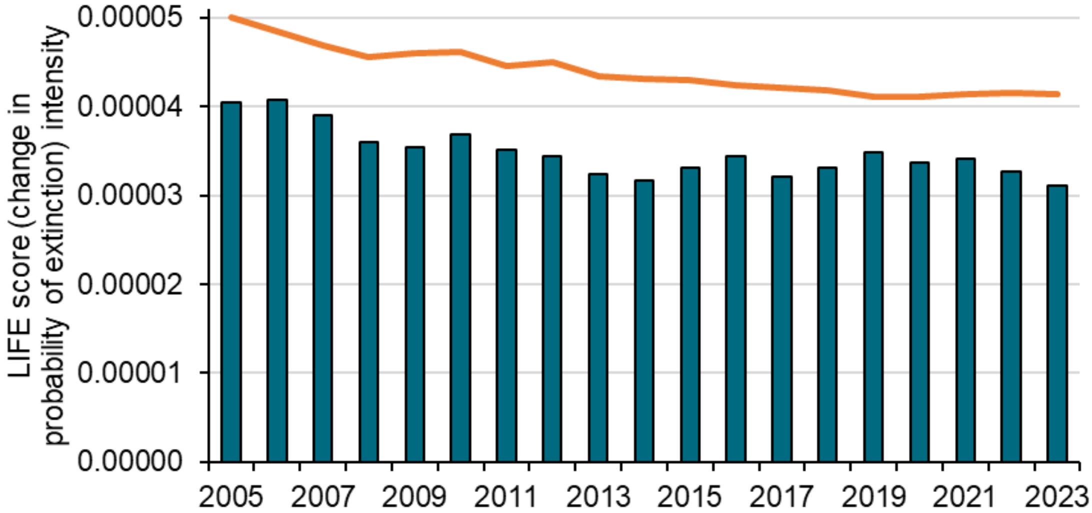

Figure 16. LIFE score intensity (change in probability of extinction per thousand tonnes of production) worldwide associated with UK consumption. The orange line compares this to intensities associated with average global consumption.

Appendix 2: Consideration of alignment and consistency with the UK Carbon Footprint and UK Material Footprint

The University of Leeds also compile an MRIO-based indicator about two aspects of the UK's consumption impacts, in the form of the UK Carbon Footprint and the UK Material Footprint. The GEIC project recognised the potential for alignment as it could be useful if other environmental indicators developed in this body of work are produced in a consistent and comparable way with existing UK indicators. In particular, the GEIC indicator is producing a material footprint of its own, on which the impact metrics are based, and a GHG emissions from deforestation indicator (an aspect of GHG emissions not currently included within the UK Carbon Footprint). The project team, therefore, met with those who work on the UK Carbon Footprint in February 2021 to discuss potential alignment opportunities.

However, the nature of the UK Carbon/Material Footprints does not allow for a detailed breakdown in terms of commodities and countries/territories of origin, unlike the indicator developed under this project. For example, carbon emissions linked to agricultural commodities are presented at an aggregate 'agricultural' sector level, which cannot be broken down into specific commodities such as soy, wheat, palm oil, etc., and geographic resolution is limited to that of the MRIO. This is because the Carbon/Material Footprints aim to quantify the overall pressure that the UK is exerting, whilst the work within this project aims to understand in greater detail the location of impacts and their associated drivers, to inform action. As understanding countries/territories and commodities of impact is key to many of the current indicator's use cases across both the steering group and the stakeholder group, it was decided that in this case alignment would not be immediately beneficial. GHG emissions are also less sensitive to spatial heterogeneity compared to impacts such as deforestation and biodiversity.

It should therefore be flagged that the results from these two indicators will not be directly comparable. They are not in the same format, and they also use separate methodologies. However, the project team will keep channels of communication open with the University of Leeds as future use cases may emerge where direct harmonisation in approaches is useful. One such use case would be in an instance where the land-use emissions estimates resulting from the work conducted for this report could be considered as a 'supplement' to UK GHG accounts (which currently do not include LULUCF (Land Use, Land Use Change and Forestry) emissions).

Appendix 3: Summary of methodological updates

Since its original publication in 2021, GEIC has been updated annually. While based on the same core methods, each update has incorporated methodological developments and an extension to the time series. Table 3 provides a summary of the main changes since the indicator's release in 2021. Full details of the methods used for each previous release can be found on The National Archives website.

Table 3. Summary of GEIC methodological updates since its original release in 2021. See relevant report section for details of current methods.

Report section	Description of change
2. Overview of modelling framework	In the original (2021) release, results were generated for the years 2005-2017. GEIC's time series is extended on an annual basis, with results for the latest release available for 2005-2023.
2.3 MRIO data	In 2021-2024 indicator releases, EXIOBASE 3.8.1 MRIO was the underlying data model. In the 2025 release we for the first time utilised GLORIA as the underlying data model due to the current version of EXIOBASE running only to 2022. Results published in 2025 are therefore not directly comparable to results published in previous years (although the full time series has been recalculated, so all of 2025's results are comparable with each other). However, in most cases the magnitude of the change this has created has been small.
2.4.1. Re-exports and trade balancing	Prior to 2023, the trade balancing step was done using a simpler approach: where exports exceeded available supply for a given country/territory, all exports from this country/territory were scaled down to be equal to their supply (see Croft *et al*., 2018 for technical details of the original method). Since this would reduce other countries/territories' imports, potentially making supply less than reported imports plus production, the process would then run iteratively until all constraints were satisfied. Details of the methods adopted since 2023 are given in section 2.4.1.
2.5.2. Forestry	In the 2021 and 2022 indicator release, FAOSTAT trade data were used instead of Comtrade to map trade in wood products, but data from this source have not been updated in recent years, with no data available for 2019 onwards, necessitating the adoption of an alternative dataset (Comtrade) from the 2023 release onwards.
4. Deforestation and associated carbon emissions metrics	The deforestation (and associated deforestation-linked emissions) metrics are based on a series of datasets provided by the Chalmers University of Technology, which have been updated several times during the development of GEIC. The original 2021 indicator release was based on the statistical 'land-balance' approach described in Pendrill *et al*. (2019a, b). From 2023, deforestation-attribution methods were substantially revised by Chalmers researchers, with the outcome of enhancing the dataset (via the use of spatialised land use and commodity datasets for certain regions and commodities used in combination with land-balance approaches where geospatial land use data is unavailable) and expanding its coverage to estimate non-tropical deforestation. Subsequent indicator releases have been based on these improved datasets, with the 2023 release based on

Report section	Description of change
	Singh & Persson (2023), the 2024 release based on Singh & Persson (2024), and the 2025 release based on an updated dataset using the latest available deforestation and crop information (provided directly by the University of Chalmers).
5.2.2. uWFp (unit water footprint of production) data	In the 2021 and 2022 indicator releases, as per Tamea *et al*. (2021), gaps in country/territory data were filled using the value of the "nearest neighbour" within a distance threshold of 1110km (approximately equivalent to 10 degrees of latitude). In cases where no alternative country/territory-value is available the global average value was adopted. Details of the methods adopted since 2023 are given in section 2.4.1.
7. Biodiversity 2: Species richness weighted hectares metric	In the 2021 release, the species richness-weighted hectares metric made use of IUCN data, which included information on birds, mammals and amphibians. From the 2022 release onwards (for the entire time series published), additional data are included on reptiles, which were not previously comprehensively covered, yet subsequently underwent a global assessment, the data for which are also available from the IUCN. These reptile data have been used in addition to the data for other taxa and (via inclusion of these data) simply serve to increase the counts of species present per pixel. A result of this is that estimates of 'species hectares' provided since 2023 are inflated compared to the 2021 and 2022 releases as more species are accounted for. Note that for non-reptiles, the same data as in the 2021 release have been used in subsequent releases (see references for the data in section 7).
7.5.1 and 8.5.1. Applying MapSPAM crop models across the IOTA time series in the species richness weighted hectares and LIFE metrics	Methods to adapt the temporal coverage within MapSPAM (and LIFE) to span the data window employed within IOTA were updated in 2024. In the 2021, 2022 and 2023 releases for the species-ha data (where MapSPAM data were previously only available for the years 2005 and 2010, and in which the LIFE score was not included as a metric), for any other year (i.e. years aside from 2005 or 2010) a simple approach was taken to adopt the data from the nearest reference year and apply it. The manner in which this was executed preserved the total species-ha value for a given crop/country of production across all years that adopted a given reference year, regardless of changes in land use for crop production within that period. This effectively meant that if land use changed for a given country/commodity context, an implicit assumption was being made that species richness was changing inversely to keep the product of species richness and area a constant value. A more logical approach is to assume that species richness remains constant for all years sharing data from a given reference year but that, as area use goes up or down through time, the corresponding estimate of species-ha value goes up or down, respectively, in proportion to this change. This change was applied in 2024, as described in section 7.5.1.

Report section	**Description of change**
8. Biodiversity 3: LIFE score metric	The 2024 release included the addition of a new biodiversity loss metric – the LIFE score metric. This provides a more nuanced understanding that integrates information on species richness, endemism, and past habitat loss to estimate the impact of land cover change on extinctions, rather than simply relying on estimates from species area curves or overlaying land use with expected species richness.
Appendix 4: Concordances	Within the time series covered by this work, there are two instances of changing jurisdictional classifications, namely 'Serbia and Montenegro' splitting to become 'Serbia' and 'Montenegro' in 2006, and 'Sudan (former)' splitting in 2012 to form 'Sudan' and 'South Sudan'. These changes are reflected appropriately in the production and trade data used within the framework; however, for some input indicator files this is not the case due to time stamps or classification choices. In these instances, separate entries have had to be aggregated to form entries for the pre-split jurisdictions, or pre-split entries disaggregated/ extrapolated to apply to post-split jurisdictions, as appropriate on a case-by-case basis. This method has been adopted since the 2023 indicator release.

References for Appendix 3

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Appendix 4: Concordances

This Appendix provides concordance information between MapSPAM crops and FAO/IOTA data (Table 4); concordance information between LSIB country/territory names and FAO country/territory names (Table 5); attributes associated with spatial data adapted from IUCN (2012, 2018) and BirdLife International (n.d.) (Table 6); and concordance information between FAO commodities and appropriate producing sectors within the MRIO database (Table 7). All FAO data come from FAOSTAT.

Table 4. MapSPAM crops and concordance with FAO/IOTA.

MapSPAM NAME	FAO ITEM NAME	FAO ITEM CODES	FAO GROUP
WHEAT	WHEAT	15	CEREALS
RICE	RICE	27	CEREALS
MAIZE	MAIZE	56	CEREALS
BARLEY	BARLEY	44	CEREALS
PEARL MILLET	MILLET	79	CEREALS
SMALL MILLET	MILLET	79	CEREALS
SORGHUM	SORGHUM	83	CEREALS
OTHER CEREALS	OTHER CEREALS ++	71; 75; 89; 92; 94; 97; 101; 103; 108;	CEREALS
POTATO	POTATO	116	ROOTS&TUBERS OR STARCHY ROOTS
SWEET POTATO	SWEET POTATO	122	ROOTS&TUBERS OR STARCHY ROOTS
YAMS	YAM	137	ROOTS&TUBERS OR STARCHY ROOTS
CASSAVA	CASSAVA	125	ROOTS&TUBERS OR STARCHY ROOTS

MapSPAM NAME	FAO ITEM NAME	FAO ITEM CODES	FAO GROUP
OTHER ROOTS	YAUTIA ++	135; 136; 149	ROOTS&TUBERS OR STARCHY ROOTS
BEAN	BEANS; DRY	176	PULSES
CHICKPEA	CHICKPEA	191	PULSES
COWPEA	COWPEA	195	PULSES
PIGEONPEA	PIGEON PEA	197	PULSES
LENTIL	LENTILS	201	PULSES
OTHER PULSES	BROAD BEANS ++	181; 187; 203; 205; 210; 211	PULSES
SOYBEAN	SOYBEAN	236	OILCROPS
GROUNDNUT	GROUNDNUT; WITH SHELL	242	OILCROPS
COCONUT	COCONUT	249	OILCROPS
OILPALM	PALMOIL	254	OILCROPS
SUNFLOWER	SUNFLOWER SEED	267	OILCROPS
RAPESEED	RAPESEED	270; 292	OILCROPS
SESAMESEED	SESAME SEED	289	OILCROPS
OTHER OIL CROPS	OLIVES ++	260; 261; 263; 265; 268; 271; 275; 277; 280; 281; 290; 296; 299; 305; 310; 329; 331; 333; 334; 336; 339;	OILCROPS

MapSPAM NAME	**FAO ITEM NAME**	**FAO ITEM CODES**	**FAO GROUP**
SUGARCANE	SUGAR CANE	156	SUGAR CROPS
SUGARBEET	SUGARBEET	157	SUGAR CROPS
COTTON	SEED COTTON	328	FIBRES
OTHER FIBRE CROPS	OTHER FIBRES ++	773; 777; 778; 780; 782; 788; 789; 800; 809; 813; 821;	FIBRES
ARABICA COFFEE	COFFEE	656	STIMULANT
ROBUSTA COFFEE	COFFEE	656	STIMULANT
COCOA	COCOA	661	STIMULANT
TEA	TEA	667	STIMULANT
TOBACCO	TOBACCO LEAVES	826	STIMULANT
BANANA	BANANA	486	FRUITS
PLANTAIN	PLANTAIN	489	FRUITS
TROPICAL FRUIT	ORANGES ++	490; 495; 497; 507; 512; 567; 568; 569; 571; 572; 574; 577; 587; 591; 600; 603;	FRUITS
TEMPERATE FRUIT	APPLES ++	515; 521; 523; 526; 530; 531; 534; 536; 541; 542; 544; 547; 549; 550; 552; 554; 558; 560; 592; 619;	FRUITS

MapSPAM NAME	FAO ITEM NAME	FAO ITEM CODES	FAO GROUP
VEGETABLES	CABBAGES AND OTHER BRASSICAS ++	358; 366; 367; 372; 373; 388; 393; 394; 397; 399; 401; 402; 403; 406; 407; 414; 417; 420; 423; 426; 430; 446; 449; 459; 461; 463;	VEGETABLES
REST OF CROPS	ALL INDIVIDUAL OTHER CROPS (EG SPICES; TREE NUTS; OTHER SUGAR CROPS; MATE; RUBBER)	161; 216; 217; 220; 221; 222; 223; 224; 225; 226; 234; 671; 677; 687; 689; 692; 693; 698; 702; 711; 720; 723; 748; 754; 767; 836; 839;	

Table 5. To align the species-hectare indicator calculated per country/territory using the LSIB country/territory boundaries (USDS, 2017) to IOTA, we developed a table to provide concordance between the LSIB country/territory names to those names and codes used by the FAO (from FAOSTAT).

LSIB NAME	FAOSTAT NAME	FAOSTAT CODE
Afghanistan	Afghanistan	2
Akrotiri	Cyprus	50
Albania	Albania	3
Algeria	Algeria	4
American Samoa	American Samoa	5
Andorra	Andorra	6
Angola	Angola	7
Anguilla	Anguilla	258

LSIB NAME	FAOSTAT NAME	FAOSTAT CODE
Antarctica	Antarctica	30
Antigua & Barbuda	Antigua and Barbuda	8
Argentina	Argentina	9
Armenia	Armenia	1
Aruba	Aruba	22
Australia	Australia	10
Austria	Austria	11
Azerbaijan	Azerbaijan	52
Bahamas, The	Bahamas	12
Bahrain	Bahrain	13
Bangladesh	Bangladesh	16
Barbados	Barbados	14
Belarus	Belarus	57
Belgium	Belgium	255
Belize	Belize	23
Benin	Benin	53
Bermuda	Bermuda	17
Bhutan	Bhutan	18

LSIB NAME	FAOSTAT NAME	FAOSTAT CODE
Bolivia	Bolivia (Plurinational State of)	19
Bosnia & Herzegovina	Bosnia and Herzegovina	80
Botswana	Botswana	20
Bouvet Island	Bouvet Island	31
Brazil	Brazil	21
British Virgin Is	British Virgin Islands	239
Brunei	Brunei Darussalam	26
Bulgaria	Bulgaria	27
Burkina Faso	Burkina Faso	233
Burma	Myanmar	28
Burundi	Burundi	29
Cabo Verde	Cabo Verde	35
Cambodia	Cambodia	115
Cameroon	Cameroon	32
Canada	Canada	33
Cayman Is	Cayman Islands	36
Central African Rep	Central African Republic	37
Chad	Chad	39

LSIB NAME	FAOSTAT NAME	FAOSTAT CODE
Chile	Chile	40
China	China, Mainland	41
Christmas I	Christmas Island	42
Cocos (Keeling) Is	Cocos (Keeling) Islands	43
Colombia	Colombia	44
Comoros	Comoros	45
Cook Is	Cook Islands	47
Coral Sea Is	Australia	10
Costa Rica	Costa Rica	48
Cote d'Ivoire	Côte d'Ivoire	107
Croatia	Croatia	98
Cuba	Cuba	49
Curacao	Curaçao	279
Cyprus	Cyprus	50
Czechia	Czechia	167
Dem Rep of the Congo	Democratic Republic of the Congo	250
Denmark	Denmark	54
Dhekelia	Cyprus	50

LSIB NAME	FAOSTAT NAME	FAOSTAT CODE
Djibouti	Djibouti	72
Dominica	Dominica	55
Dominican Republic	Dominican Republic	56
Dragonja River Mouth	Croatia	98
Dramana-Shakatoe Area	China, Mainland	41
Ecuador	Ecuador	58
Egypt	Egypt	59
El Salvador	El Salvador	60
Equatorial Guinea	Equatorial Guinea	61
Eritrea	Eritrea	178
Estonia	Estonia	63
Ethiopia	Ethiopia	238
Falkland Islands	Falkland Islands (Malvinas)	65
Faroe Is	Faroe Islands	64
Fed States of Micronesia	Micronesia (Federated States of)	145
Fiji	Fiji	66
Finland	Finland	67
France	France	68

LSIB NAME	FAOSTAT NAME	FAOSTAT CODE
French Polynesia	French Polynesia	70
French S & Antarctic Lands	French Southern Territories	71
Gabon	Gabon	74
Gambia, The	Gambia	75
Georgia	Georgia	73
Germany	Germany	79
Ghana	Ghana	81
Gibraltar	Gibraltar	82
Greece	Greece	84
Greenland	Greenland	85
Grenada	Grenada	86
Guadeloupe	Guadeloupe	87
Guam	Guam	88
Guatemala	Guatemala	89
Guernsey	Channel Islands	259
Guinea	Guinea	90
Guinea-Bissau	Guinea-Bissau	175
Guyana	Guyana	91

LSIB NAME	FAOSTAT NAME	FAOSTAT CODE
Haiti	Haiti	93
Heard I & McDonald Is	Heard and McDonald Islands	92
Honduras	Honduras	95
Hong Kong	China, Hong Kong SAR	96
Hungary	Hungary	97
Iceland	Iceland	99
India	India	100
Indonesia	Indonesia	101
Invernada Area	Brazil	21
Iran	Iran (Islamic Republic of)	102
Iraq	Iraq	103
Ireland	Ireland	104
Isla Brasilera	Uruguay	234
Isle of Man	Isle of Man	264
Israel	Israel	105
Italy	Italy	106
Jamaica	Jamaica	109
Jan Mayen	Svalbard and Jan Mayen Islands	260

LSIB NAME	FAOSTAT NAME	FAOSTAT CODE
Japan	Japan	110
Jersey	Jersey	283
Jordan	Jordan	112
Kalapani Area	India	100
Kazakhstan	Kazakhstan	108
Kenya	Kenya	114
Kiribati	Kiribati	83
Korea, North	Democratic People's Republic of Korea	116
Korea, South	Republic of Korea	117
Korean Is. (UN Jurisdiction)	Republic of Korea	117
Kosovo	Serbia*	272
Koualou Area	Benin	53
Kuwait	Kuwait	118
Kyrgyzstan	Kyrgyzstan	113
Laos	Lao People's Democratic Republic	120
Latvia	Latvia	119
Lebanon	Lebanon	121
Lesotho	Lesotho	122

LSIB NAME	FAOSTAT NAME	FAOSTAT CODE
Liberia	Liberia	123
Libya	Libya	124
Liechtenstein	Liechtenstein	125
Lithuania	Lithuania	126
Luxembourg	Luxembourg	256
Macau	China, Macao SAR	128
Macedonia	North Macedonia	154
Madagascar	Madagascar	129
Malawi	Malawi	130
Malaysia	Malaysia	131
Maldives	Maldives	132
Mali	Mali	133
Malta	Malta	134
Marshall Is	Marshall Islands	127
Martinique	Martinique	135
Mauritania	Mauritania	136
Mauritius	Mauritius	137
Mayotte	Mayotte	270

LSIB NAME	FAOSTAT NAME	FAOSTAT CODE
Mexico	Mexico	138
Moldova	Republic of Moldova	146
Monaco	Monaco	140
Mongolia	Mongolia	141
Montenegro	Montenegro*	273
Montserrat	Montserrat	142
Morocco	Morocco	143
Mozambique	Mozambique	144
Namibia	Namibia	147
Nauru	Nauru	148
Nepal	Nepal	149
Netherlands	Netherlands	150
Netherlands (Caribbean)	Netherlands Antilles (former)	151
New Caledonia	New Caledonia	153
New Zealand	New Zealand	156
Nicaragua	Nicaragua	157
Niger	Niger	158
Nigeria	Nigeria	159

LSIB NAME	FAOSTAT NAME	FAOSTAT CODE
Niue	Niue	160
Norfolk I	Norfolk Island	161
Northern Mariana Is	Northern Mariana Islands	163
Norway	Norway	162
Oman	Oman	221
Pakistan	Pakistan	165
Palau	Palau	180
Panama	Panama	166
Papua New Guinea	Papua New Guinea	168
Paraguay	Paraguay	169
Peru	Peru	170
Philippines	Philippines	171
Pitcairn Is	Pitcairn	172
Poland	Poland	173
Portugal	Portugal	174
Puerto Rico	Puerto Rico	177
Qatar	Qatar	179
Rep of the Congo	Congo	46

LSIB NAME	FAOSTAT NAME	FAOSTAT CODE
Reunion	Réunion	182
Romania	Romania	183
Russia	Russian Federation	185
Rwanda	Rwanda	184
S Georgia & S Sandwich Is	South Georgia and the South Sandwich Islands	271
Saint Lucia	Saint Lucia	189
Samoa	Samoa	244
San Marino	San Marino	192
Sao Tome & Principe	Sao Tome and Principe	193
Saudi Arabia	Saudi Arabia	194
Senegal	Senegal	195
Serbia	Serbia*	272
Seychelles	Seychelles	196
Sierra Leone	Sierra Leone	197
Sinafir & Tiran Is.	Saudi Arabia	194
Singapore	Singapore	200
Slovakia	Slovakia	199
Slovenia	Slovenia	198

LSIB NAME	FAOSTAT NAME	FAOSTAT CODE
Solomon Is	Solomon Islands	25
Somalia	Somalia	201
South Africa	South Africa	202
South Sudan	South Sudan*	277
Spain	Spain	203
Spain (Africa)	Spain	203
Spain (Canary Is)	Spain	203
Sri Lanka	Sri Lanka	38
St Barthelemy	Saint Barthélemy	282
St Helena	Saint Helena, Ascension and Tristan da Cunha	187
St Kitts & Nevis	Saint Kitts and Nevis	188
St Martin	Guadeloupe	87
St Pierre & Miquelon	Saint Pierre and Miquelon	190
St Vincent & the Grenadines	Saint Vincent and the Grenadines	191
Sudan	Sudan*	276
Suriname	Suriname	207
Svalbard	Svalbard and Jan Mayen Islands	260
Swaziland	Eswatini	209

LSIB NAME	FAOSTAT NAME	FAOSTAT CODE
Sweden	Sweden	210
Switzerland	Switzerland	211
Syria	Syrian Arab Republic	212
Taiwan	China, Taiwan Province of	214
Tajikistan	Tajikistan	208
Tanzania	United Republic of Tanzania	215
Thailand	Thailand	216
Timor-Leste	Timor-Leste	176
Togo	Togo	217
Tokelau	Tokelau	218
Tonga	Tonga	219
Trinidad & Tobago	Trinidad and Tobago	220
Tunisia	Tunisia	222
Turkey	Türkiye	223
Turkmenistan	Turkmenistan	213
Turks & Caicos Is	Turks and Caicos Islands	224
Tuvalu	Tuvalu	227
US Virgin Is	United States Virgin Islands	240

LSIB NAME	FAOSTAT NAME	FAOSTAT CODE
Uganda	Uganda	226
Ukraine	Ukraine	230
United Arab Emirates	United Arab Emirates	225
United Kingdom	United Kingdom of Great Britain and Northern Ireland	229
United States	United States of America	231
United States (Alaska)	United States of America	231
United States (Hawaii)	United States of America	231
Uruguay	Uruguay	234
Uzbekistan	Uzbekistan	235
Vanuatu	Vanuatu	155
Vatican City	Holy See	94
Venezuela	Venezuela (Bolivarian Republic of)	236
Vietnam	Viet Nam	237
Wake I	Wake Island	242
Wallis & Futuna	Wallis and Futuna Islands	243
Western Sahara	Western Sahara	205
Yemen	Yemen	249
Zambia	Zambia	251

LSIB NAME	FAOSTAT NAME	FAOSTAT CODE
Zimbabwe	Zimbabwe	181

* Within the time series covered by this work, there are two instances of changing jurisdictional classifications, namely 'Serbia and Montenegro' splitting to become 'Serbia' and 'Montenegro' in 2006, and 'Sudan (former)' splitting in 2012 to form 'Sudan' and 'South Sudan'. These changes are reflected appropriately in the production and trade data used within the framework, however for some input indicator files this is not the case due to time stamps or classification choices. In these instances, separate entries have had to be aggregated to form entries for the pre-split jurisdictions, or pre-split entries disaggregated/extrapolated to apply to post-split jurisdictions, as appropriate on a case-by-case basis.

Table 6. Attributes associated with spatial data (adapted from IUCN (2012, 2018) and BirdLife International (n.d.). Values indicated in bold and asterisked are those that were included in calculation of species-hectares. For more information on Red List classification criteria, see IUCN (2018).

Attribute	Value	Description
Threat classification	Extinct	No reasonable doubt that the last individual has died. Exhaustive surveys in known and expected habitat, at appropriate times and throughout its historic range have failed to record an individual
Threat classification	Extinct in the Wild	As above, except that it survives in cultivation, in captivity or as a naturalized population(s) outside its past range.
Threat classification	**Critically Endangered***	**Considered to be facing an extremely high risk of extinction in the wild.**
Threat classification	**Endangered***	**Considered to be facing a very high risk of extinction in the wild.**
Threat classification	**Vulnerable***	**Considered to be facing a high risk of extinction in the wild.**
Threat classification	**Near Threatened***	**Close to qualifying for or is likely to qualify for a threatened category in the near future.**
Threat classification	**Least Concern***	**Does not qualify as threatened or Near Threatened. Widespread and abundant taxa are included in this category.**

Attribute	Value	Description
Threat classification	**Data Deficient***	**Inadequate information to make an assessment of extinction risk based on its distribution and/or population status. A taxon in this category may be well studied, and its biology well known, but appropriate data on abundance and/or distribution are lacking. Data Deficient is therefore not a category of threat.**
Threat classification	**Not Evaluated***	**Species has not yet been evaluated against the criteria.**
Presence	**Extant***	**Species is known or thought very likely to occur currently in the area, which encompasses localities with current or recent records where suitable habitat at appropriate altitudes remains.**
Presence	Probably Extant	Species' presence is considered probable, based on extrapolations of known records, or realistic inferences (e.g. distribution of suitable habitat at appropriate altitudes and proximity to areas where it is known to be extant). IUCN has discontinued use of this value for reasons of ambiguity.
Presence	Possibly Extant	No record of the species in the area, but may occur, based on the distribution of potentially suitable habitat at appropriate altitudes. The degree of probability of the species occurring is lower (e.g. because the area is beyond a geographic barrier, or because the area represents a considerable extension beyond areas of known or probable occurrence).
Presence	Possibly Extinct	Species was formerly known or very likely to occur (post 1500 AD), but is most likely now extirpated from the area because of habitat loss and/or other threats, No confirmed recent records despite searches.
Presence	Extinct (post 1500)	Species was formerly known or very likely to occur (post 1500 AD), but extirpation confirmed through exhaustive searches alongside knowledge of the intensity and timing of threats that could plausibly have extirpated the species.
Presence	Presence Uncertain	Record exists of the species' presence in the area, but it requires verification or is rendered questionable owing to uncertainty over the identity or authenticity of the record, or accuracy of the location.
Origin	**Native***	**Species is/was native to the area.**

Attribute	Value	Description
Origin	**Reintroduced***	**Species is/was reintroduced within its known historical range through either direct or indirect human activity.**
Origin	Introduced	Species is/was introduced outside of its known historical distribution range through either direct or indirect human activity. Includes species intentionally moved outside of native range to perform a specific ecological function, but does not include species subject to assisted colonisation.
Origin	Vagrant	Species is/was recorded once or sporadically, but it is known not to be native to the area.
Origin	Origin Uncertain	Species' provenance in an area is not known (it may be native, reintroduced or introduced)
Origin	**Assisted Colonisation***	**Species intentionally moved and released outside its native ranges to reduce extinction risk.**
Seasonality	**Resident***	**Species known or very likely resident throughout the year**
Seasonality	**Breeding Season***	**Species known or very likely to occur during breeding season and to breed and be capable of breeding.**
Seasonality	**Non-breeding Season***	**Species known or very likely to occur during non-breeding season. In the Eurasian and North American contexts, this encompasses 'winter'.**
Seasonality	**Passage***	**Species known or very likely to occur during relatively short period(s) of the year on migration between breeding and non-breeding ranges.**
Seasonality	**Seasonal occurrence uncertain***	**Species present, but not known if it is present during part or all of the year.**

Table 7. Concordance table showing how FAO commodities (from FAOSTAT) were concorded to appropriate producing sectors within the MRIO database.

FAO Commodity Code	FAO Commodity	GLORIA Sector Code	Allocation Factor
-3	Non-coniferous timber	21	1
-2	Coniferous timber	21	1
-1	Cattle and buffalo meat, plus associated co-products	NA	1
15	Wheat	1	1
16	Wheat and meslin flour	47	1
17	Bran of wheat	47	1
19	Germ of wheat	47	1
21	Bulgar	47	1
27	Rice	5	1
28	Husked rice	5	1
29	Rice, milled (husked)	5	1
30	Rice, paddy (rice milled equivalent)	5	1
31	Rice, milled	5	1
32	Rice, broken	5	1
35	Bran of rice	5	1
36	Oil of rice bran	53	1
37	Cake of rice bran	53	1
44	Barley	3	1
45	Pot barley	47	1
46	Barley, pearled	47	1
47	Bran of barley	47	1
48	Barley flour and grits	47	1
49	Malt, whether or not roasted	47	1
56	Maize (corn)	2	1
58	Flour of maize	47	1
59	Bran of maize	47	1
60	Oil of maize	53	1
61	Cake of maize	53	1
71	Rye	3	1
72	Flour of rye	47	1
73	Bran of rye	47	1
75	Oats	3	1
76	Oats, rolled	47	1
77	Bran of oats	47	1
79	Millet	3	1

80	Flour of millet	47	1
81	Bran of millet	47	1
83	Sorghum	3	1
84	Flour of sorghum	47	1
85	Bran of sorghum	47	1
89	Buckwheat	3	1
90	Flour of buckwheat	47	1
91	Bran of buckwheat	47	1
92	Quinoa	3	1
94	Fonio	3	1
95	Flour of fonio	47	1
96	Bran of fonio	47	1
97	Triticale	3	1
98	Flour of triticale	47	1
99	Bran of triticale	47	1
101	Canary seed	3	1
103	Mixed grain	3	1
104	Flour of mixed grain	47	1
105	Bran of mixed grain	47	1
108	Cereals n.e.c.	3	1
116	Potatoes	6	1
117	Flour, meal, powder, flakes, granules and pellets of potatoes	47	1
118	Potatoes, frozen	48	1
119	Starch of potatoes	48	1
120	Potato offals	48	1
121	Tapioca of potatoes	48	1
122	Sweet potatoes	6	1
125	Cassava, fresh	6	1
126	Flour of cassava	48	1
127	Tapioca of cassava	48	1
128	Cassava, dry	6	1
129	Starch of cassava	48	1
135	Yautia	6	1
136	Taro	6	1
137	Yams	6	1
149	Edible roots and tubers with high starch or inulin content, n.e.c., fresh	6	1
156	Sugar cane	7	1
157	Sugar beet	7	1
158	Cane sugar, centrifugal	51	1
159	Beet sugar	51	1

161	Other sugar crops n.e.c.	7	1
163	Cane sugar, non-centrifugal	51	1
164	Refined sugar	51	1
169	Beet pulp	51	1
170	Bagasse	51	1
176	Beans, dry	4	1
181	Broad beans and horse beans, dry	4	1
187	Peas, dry	4	1
191	Chick peas, dry	4	1
195	Cow peas, dry	4	1
197	Pigeon peas, dry	4	1
201	Lentils, dry	4	1
203	Bambara beans, dry	4	1
205	Vetches	4	1
210	Lupins	4	1
211	Other pulses n.e.c.	4	1
216	Brazil nuts, in shell	12	1
217	Cashew nuts, in shell	12	1
220	Chestnuts, in shell	12	1
221	Almonds, in shell	12	1
222	Walnuts, in shell	12	1
223	Pistachios, in shell	12	1
224	Kola nuts	12	1
225	Hazelnuts, in shell	12	1
226	Areca nuts	12	1
229	Brazil nuts, shelled	50	1
230	Cashew nuts, shelled	50	1
231	Almonds, shelled	50	1
232	Walnuts, shelled	50	1
233	Hazelnuts, shelled	50	1
234	Other nuts (excluding wild edible nuts and groundnuts), in shell, n.e.c.	12	1
236	Soya beans	4	1
237	Soya bean oil	53	1
238	Cake of soya beans	53	1
242	Groundnuts, excluding shelled	4	1
243	Groundnuts, shelled	50	1
244	Groundnut oil	53	1
245	Cake of groundnuts	53	1
246	Prepared groundnuts	50	1
247	Peanut butter	50	1

249	Coconuts, in shell	4	1
250	Coconuts, desiccated	50	1
251	Copra	4	1
252	Coconut oil	53	1
253	Cake of copra	53	1
254	Oil palm fruit	4	1
256	Palm kernels	4	1
257	Palm oil	53	1
258	Oil of palm kernel	53	1
259	Cake of palm kernel	53	1
260	Olives	4	1
261	Olive oil	53	1
262	Olives preserved	50	1
263	Karite nuts (sheanuts)	4	1
265	Castor oil seeds	4	1
266	Oil of castor beans	53	1
267	Sunflower seed	4	1
268	Sunflower-seed oil, crude	53	1
269	Cake of sunflower seed	53	1
270	Rape or colza seed	4	1
271	Rapeseed or canola oil, crude	53	1
272	Cake of rapeseed	53	1
273	Olive residues	53	1
274	Oil of olive residues	53	1
275	Tung nuts	4	1
277	Jojoba seeds	4	1
280	Safflower seed	4	1
289	Sesame seed	4	1
290	Oil of sesame seed	53	1
291	Cake of sesame seed	53	1
292	Mustard seed	4	1
293	Mustard seed oil, crude	53	1
294	Cake of mustard seed	53	1
295	Flour of mustard seed	50	1
296	Poppy seed	4	1
299	Melonseed	4	1
305	Tallowtree seeds	4	1
306	Vegetable tallow	53	1
307	Stillingia oil	4	1
310	Kapok fruit	4;9	0.66;0.34
311	Kapokseed in shell	4;9	0.66;0.34

312	Kapokseed, shelled	4;9	0.66;0.34
328	Seed cotton, unginned	4;9	0.63;0.37
329	Cotton seed	4	1
331	Cottonseed oil	53	1
332	Cake of cottonseed	53	1
333	Linseed	4	1
334	Oil of linseed	53	1
335	Cake of linseed	53	1
336	Hempseed	4	1
339	Other oil seeds, n.e.c.	4	1
358	Cabbages	6	1
366	Artichokes	6	1
367	Asparagus	6	1
372	Lettuce and chicory	6	1
373	Spinach	6	1
378	Cassava leaves	6	1
388	Tomatoes	6	1
389	Tomato juice, concentrated		1
390	Tomato juice	50	1
391	Paste of tomatoes	50	1
392	Tomatoes, peeled (o/t vinegar)	50	1
393	Cauliflowers and broccoli	6	1
394	Pumpkins, squash and gourds	6	1
397	Cucumbers and gherkins	6	1
399	Eggplants (aubergines)	6	1
401	Chillies and peppers, green (Capsicum spp. and Pimenta spp.)	6	1
402	Onions and shallots, green	6	1
403	Onions and shallots, dry (excluding dehydrated)	6	1
406	Green garlic	6	1
407	Leeks and other alliaceous vegetables	6	1
414	Other beans, green	4	1
417	Peas, green	4	1
420	Broad beans and horse beans, green	4	1
423	String beans	4	1
426	Carrots and turnips	6	1
430	Okra	6	1
446	Green corn (maize)	6	1
447	Sweet corn, frozen	48	1
448	Sweet corn, prepared or preserved	48	1
449	Mushrooms and truffles	6	1

450	Dried mushrooms	48	1
451	Canned mushrooms	48	1
459	Chicory roots	6	1
461	Locust beans (carobs)	4	1
463	Other vegetables, fresh n.e.c.	6	1
486	Bananas	12	1
489	Plantains and cooking bananas	12	1
490	Oranges	12	1
491	Orange juice	49	1
492	Orange juice, concentrated	49	1
495	Tangerines, mandarins, clementines	12	1
496	Juice of tangerine	49	1
497	Lemons and limes	12	1
498	Juice of lemon	49	1
499	Lemon juice, concentrated	49	1
507	Pomelos and grapefruits	12	1
509	Grapefruit juice	49	1
510	Grapefruit juice, concentrated	49	1
512	Other citrus fruit, n.e.c.	12	1
515	Apples	12	1
518	Apple juice	49	1
519	Apple juice, concentrated	49	1
521	Pears	12	1
523	Quinces	12	1
526	Apricots	12	1
527	Apricots, dried	49	1
530	Sour cherries	12	1
531	Cherries	12	1
534	Peaches and nectarines	12	1
536	Plums and sloes	12	1
537	Plums, dried	49	1
541	Other stone fruits	12	1
542	Other pome fruits	12	1
544	Strawberries	12	1
547	Raspberries	12	1
549	Gooseberries	12	1
550	Currants	12	1
552	Blueberries	12	1
554	Cranberries	12	1
558	Other berries and fruits of the genus vaccinium n.e.c.	12	1

560	Grapes	11	1
561	Raisins	49	1
562	Grape juice	49	1
564	Wine	55	1
566	Grapes, marc	49	1
567	Watermelons	12	1
568	Cantaloupes and other melons	12	1
569	Figs	12	1
570	Figs, dried	49	1
571	Mangoes, guavas and mangosteens	12	1
572	Avocados	12	1
574	Pineapples	12	1
575	Pineapples, otherwise prepared or preserved	49	1
576	Pineapple juice	49	1
577	Dates	12	1
583	Juice of mango	49	1
584	Mango pulp	49	1
587	Persimmons	12	1
591	Cashewapple	12	1
592	Kiwi fruit	12	1
600	Papayas	12	1
603	Other tropical fruits, n.e.c.	12	1
619	Other fruits, n.e.c.	12	1
656	Coffee, green	13	1
657	Coffee, decaffeinated or roasted	50	1
661	Cocoa beans	13	1
662	Cocoa paste not defatted	50	1
663	Cocoa husks and shells	50	1
664	Cocoa butter, fat and oil	53	1
665	Cocoa powder and cake	53	1
667	Tea leaves	13	1
671	Maté leaves	13	1
677	Hop cones	13	1
687	Pepper (Piper spp.), raw	14	1
689	Chillies and peppers, dry (Capsicum spp., Pimenta spp.), raw	14	1
692	Vanilla, raw	14	1
693	Cinnamon and cinnamon-tree flowers, raw	14	1
698	Cloves (whole stems), raw	14	1
702	Nutmeg, mace, cardamoms, raw	14	1

711	Anise, badian, coriander, cumin, caraway, fennel and juniper berries, raw	14	1
720	Ginger, raw	14	1
723	Other stimulant, spice and aromatic crops, n.e.c.	14	1
748	Peppermint, spearmint	14	1
754	Pyrethrum, dried flowers	10	1
767	Cotton lint, ginned	9	1
769	Cotton waste	4;9	0.63;0.37
770	Cotton linters	53	1
771	Flax, raw or retted	9	1
773	Flax, processed but not spun	9	1
777	True hemp, raw or retted	9	1
778	Kapok fibre, raw	9	1
780	Jute, raw or retted	9	1
782	Kenaf, and other textile bast fibres, raw or retted	9	1
788	Ramie, raw or retted	9	1
789	Sisal, raw	9	1
800	Agave fibres, raw, n.e.c.	9	1
809	Abaca, manila hemp, raw	9	1
813	Coir, raw	9	1
821	Other fibre crops, raw, n.e.c.	9	1
826	Unmanufactured tobacco	8	1
836	Natural rubber in primary forms	10	1
866	Cattle	16	1
867	Meat of cattle with the bone, fresh or chilled	41	1
868	Edible offal of cattle, fresh, chilled or frozen	41	1
869	Cattle fat, unrendered	52	1
870	Meat of cattle boneless, fresh or chilled	41	1
871	Cattle, butcher fat	52	1
872	Bovine meat, salted, dried or smoked	41	1
873	Extracts and juices of meat, fish, crustaceans, molluscs or other aquatic invertebrates	41	1
874	Sausages and similar products of meat, offal or blood of beef and veal	41	1
875	beef and veal preparations nes	41	1
919	Raw hides and skins of cattle	58	1
920	Hides, wet-salted of cattle	58	1
922	Hides, cattle nes	58	1
928	Skins, wet-salted of calves	58	1

947	Meat of buffalo, fresh or chilled	41	1
948	Edible offal of buffalo, fresh, chilled or frozen	41	1
949	Buffalo fat, unrendered	52	1
957	Raw hides and skins of buffaloes	58	1