TACKLING
ENVIRONMENTAL
SPILLOVERS

GLOBAL COMMONS STEWARDSHIP INDEX 2022

Technical Appendix

SUSTAINABLE DEVELOPMENT SOLUTIONS NETWORK
A GLOBAL INITIATIVE FOR THE UNITED NATIONS

Yale Center for Environmental Law & Policy

CENTER FOR GLOBAL COMMONS

Acknowledgements

This Technical Appendix was prepared by the Sustainable Development Solutions Network (SDSN), Paris; the Yale Center for Environmental Law & Policy, New Haven, CT; and the Center for Global Commons at the University of Tokyo. The analysis and report production were undertaken by T. Reed Miller, Zachary A. Wendling, Salma Dahir, Eamon Drumm, and Akiyuki Kawasaki under the direction of Guillaume Lafortune, Daniel C. Esty, and Naoko Ishii.

Please cite this Technical Appendix as:

> SDSN, Yale Center for Environmental Law & Policy, and Center for Global Commons at the University of Tokyo. 2023. *Global Commons Stewardship Index 2022: Technical Appendix*. Paris; New Haven, CT; and Tokyo.

We are grateful for statistical support, guidance, and inputs provided by researchers from the following organizations:

SDSN	Grayson Fuller, Max Gruber, Sara Kasim, and Ruben Andino
University of Tokyo	Zhao Han
Sea Around Us	Maria L.D. Palomares
Global Forest Watch	James MacCarthy
UN Environment Programme World Conservation Monitoring Centre	Jessica Vitale, Kelly Malsch, and Katia Sanchez-Ortiz

The report benefited from numerous comments and inputs provided during an online public consultation in October 2022. The authors are grateful for contributions and feedback provided by the Yale Center for Environmental Law & Policy, SYSTEMIQ, the World Resources Institute, the Potsdam Institute for Climate Impact Research, and the Institute for Future Initiatives at the University of Tokyo. The Center for Global Commons at the University of Tokyo provided financial support for this work.

Table of Contents

Abbreviations

AR5	Fifth Assessment Report of the IPCC
AWARE	Available WAter Remaining
BHI	Biodiversity Habitat Index
CBA	Consumption-Based Accounting
CITES	Convention on International Trade in Endangered Species of Wild Fauna and Flora
CO_2	Carbon dioxide
CSIRO	Commonwealth Scientific and Industrial Research Organisation (Australia)
EDGAR	Emissions Database for Global Atmospheric Research
EE	environmentally extended
EEZ	Exclusive Economic Zone
FAO	Food and Agriculture Organization of the United Nations
FE	Fishing Entity
FUBC	Fertilizer Use By Crop
GCS	Global Commons Stewardship
GFW	Global Forest Watch
GHG	Greenhouse gas
GLORIA	Global Resource Input-Output Assessment
GWP100	Global Warming Potential (100-year)
IFA	International Fertilizer Association
IPCC	Intergovernmental Panel on Climate Change
KBA	Key Biodiversity Area
ML	megaliter
MRIO	Multi-Regional Input-Output
N_2O	Nitrous oxide
NO_X	Nitrogen oxides
ODS	Ozone Depleting Substances
OECD	Organisation for Economic Co-operation and Development
PBA	Production-Based Accounting
PDF	Potentially Disappeared Fraction of species
SAU	*Sea Around Us*
SCP-HAT	Sustainable Consumption and Production Hotspot Analysis Tool
SDG	Sustainable Development Goals
SDSN	Sustainable Development Solutions Network
SO_2	Sulfur dioxide
UNEP	United Nations Environment Programme
WCMC	World Conservation Monitoring Centre (UNEP)
WOE	Whole Organism Equivalent

This Technical Appendix contains the details behind the methods and assumptions used in the 2022 Global Commons Stewardship (GCS) Index. Nardo et al. (2008) describe the general techniques of composite indexing, and we follow the best practices of this field. Here, we elaborate on our data and other choices in the construction of the 2022 Index and subsequent analyses. In doing so, we invite feedback and critiques from researchers and other stakeholders. Future iterations of this Index will incorporate constructive suggestions for improvement.

1. Conceptual framework

Measuring countries' impacts on the Global Commons requires many indicators, and building a coherent narrative requires organizing these indicators. The GCS Index is a composite index, with a hierarchy of indicators, sub-pillars, and pillars within the overall Index (see Figure 1). This section explains the logic of the Index hierarchy.

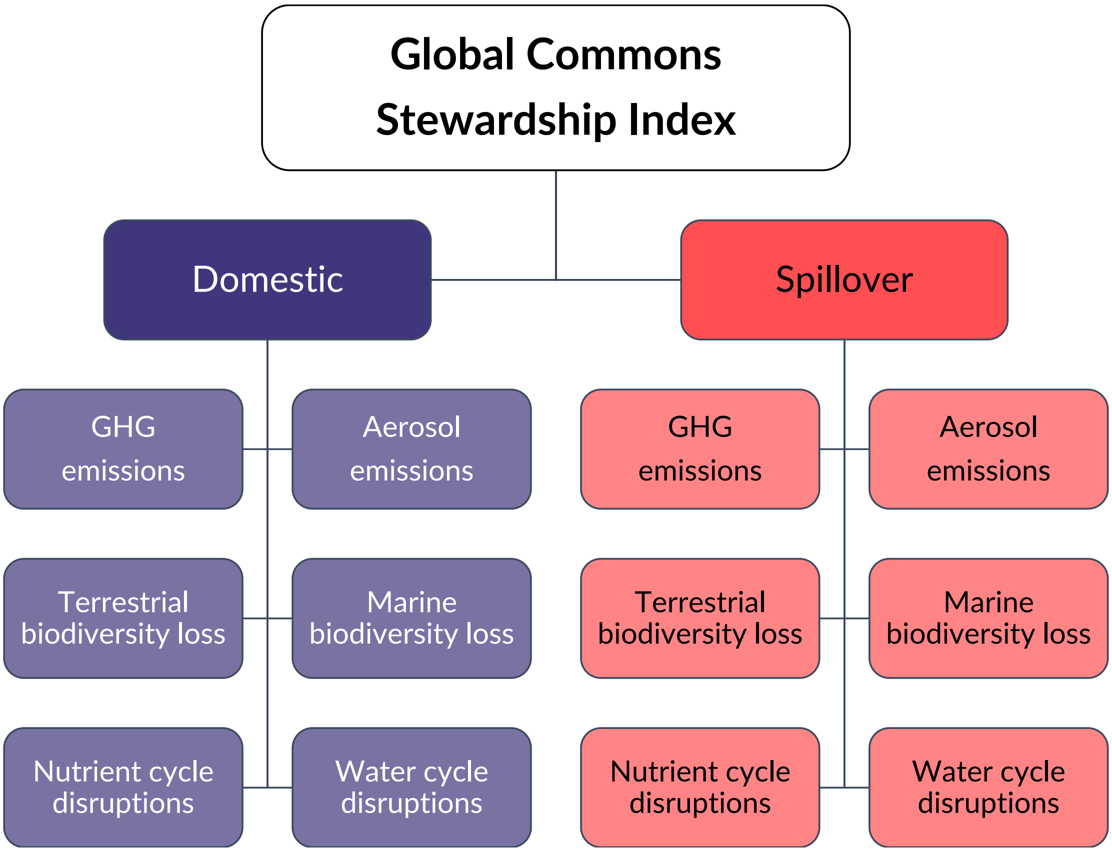

Figure 1. Conceptual framework of pillars and sub-pillars within the 2022 Global Commons Stewardship Index.

1.1 Pillars

Focusing on the Global Commons means contrasting domestic environmental impacts with the extra-territorial environmental impacts resulting from transboundary issues, especially impacts embodied in traded goods and services. We therefore divide the GCS Index into two pillars as shown in Figure 1: Domestic, which covers impacts to the Global Commons that occur within countries' territorial boundaries, and Spillover, which covers environmental impacts that occur beyond territorial boundaries.

1.2 Sub-pillars

As discussed in Section 4.4 of the 2022 GCS Index Report, the Index seeks to categorize available data on impacts to the Global Commons in thematically coherent sub-pillars. These categories reflect Earth system science as well as levers for policymaking. Measuring countries' impacts on these commons often entails crossing causal pathways. Emissions of CO_2, for example, contribute to both climate change and ocean acidification. Our sub-pillars also reflect the current state of data availability. Despite the importance of the ozone layer, we could identify virtually no indicators on impacts to stratospheric ozone that satisfy our inclusion criteria. Alternative categorizations are possible, especially if future research closes important gaps in the available data. Our scheme, however, is meant to provide a recognizable and useful framework for a broad audience. We have grouped our indicators into six sub-pillars: Aerosols, GHG Emissions, Terrestrial and Marine Biodiversity Loss, and disruptions to the Nutrient and Water Cycles.

2. Spillover calculations

2.1 Environmental accounting

Two major accounting methods (Peters & Hertwich, 2008) exist for attributing environmental impacts across countries: production-based accounting (PBA) and consumption-based accounting (CBA). PBA examines the domestic emissions and impacts which take place within a country due to production and use of products. CBA accounts for impacts that occur along the global supply chains of final products in order to satisfy a country's final demand. Final demand includes final consumption (household and government expenditures) as well as investment in fixed capital assets. There are several ways to approach these calculations; one useful calculation is shown below.

Production = domestic production for domestic final demand + domestic production for exports + use phase

Consumption = domestic production for domestic final demand + imports embodied in domestic final demand + use phase

As illustrated in Figure 2, both methods include use-phase emissions associated with households and government consumption, *e.g.*, tailpipe emissions from driving personal vehicles or combustion emissions from home heating and cooking. The "imports embodied in domestic final demand" dimension refers to the creation of goods and services in foreign countries along the supply chain for a final product consumed domestically. For instance, the environmental impacts of producing bananas in India for export to Iran would be attributed to Iran. This metric also captures more complex situations, such as attributing to the US the impacts of creating tires in Mexico that are imported by the US and installed on cars sold to consumers in the US.

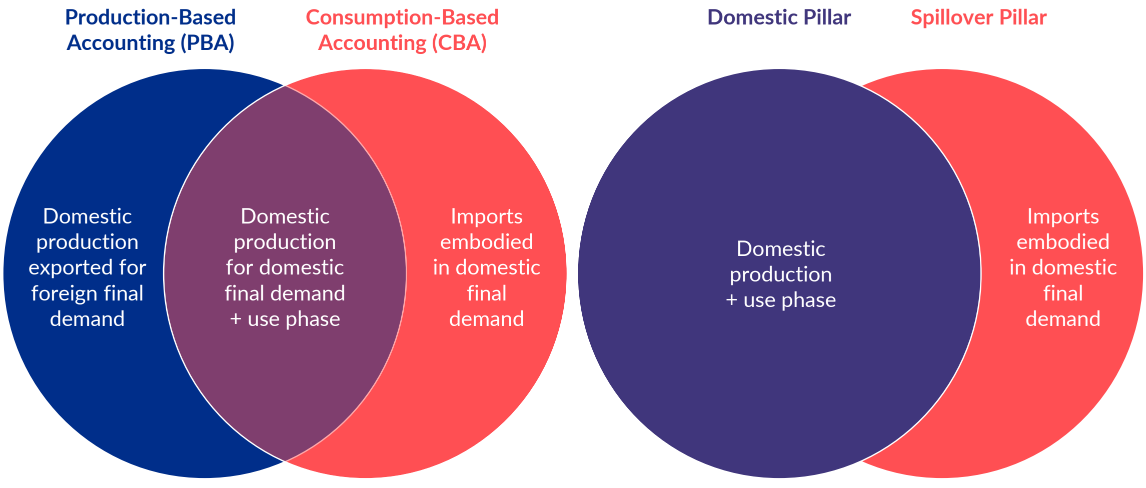

Figure 2. Production- and Consumption-based accounting (left) versus GCS Index Domestic and Spillover accounting (right).

Figure 2 shows how the two accounting frameworks overlap: There is typically a high level of correlation between impacts measured by CBA and PBA. To avoid double counting the portion of impacts labeled, "domestic production for domestic final demand and use phase," the GCS Index does not use straightforward CBA estimates. Instead, while the Domestic pillar is equivalent to PBA, the Spillover pillar isolates "imports embodied in domestic final demand," making importing countries accountable for negative environmental impacts generated abroad. Overall, at the country-level, the most significant component is domestic production for domestic final demand, which accounted for roughly 74% of global GHG emissions in 2015.

PBA is the most commonly used framework. Under the Paris Climate Change Agreement, the methods used to track the evolution of GHG emissions as part of the National Inventory Report of the Intergovernmental Panel on Climate Change (IPCC) and the UN Framework Convention on Climate Change focus, for practical reasons, on PBA (Afionis et al., 2017). Methods used to generate PBA estimates of CO_2 emissions (or other types of impacts) are rather straightforward. By contrast, CBA relies on more complex input-output matrices and sophisticated modeling techniques, and, therefore, it is generally more subject to debates among experts than PBA.

Yet there is a crucial need to better integrate CBA within monitoring and policy frameworks, including in tracking and reducing GHG emissions (Kander et al., 2015). CBA incorporates carbon leakages and attributes them to the countries that externalize CO_2 emissions. While PBA rightfully emphasizes the principle of "product liability," which states that producers are responsible for the quality and safety of their products, CBA emphasizes the responsibility of consumers and international trade policies and agreements. In the contexts of the SDGs and Agenda 2030, domestic decarbonization should not be achieved by outsourcing certain high-emitting sectors to other countries, such as cement or steel, and then re-importing the final production (Sachs et al., 2017; Schmidt-Traub et al., 2019).

The GCS Index uses both accounting methods. The Domestic pillar makes use of indicators calculated using PBA or related approaches. Doing so underlines the need for countries to take domestic actions in order to clean their industries and implement effective strategies to curb negative impacts on the Global Commons. The Spillover pillar, by contrast, uses indicators calculated using CBA and attributes negative impacts to importing countries. Poor scores on the Spillover pillar highlight areas where countries need to take further actions related to consumption and also to closely monitor trade relationships that might generate negative impacts abroad.

2.2 Impact matrices

Calculations using MRIO models can provide us with a matrix of impacts. Along the rows of these matrices are the countries where the impacts occurred, in which, for instance, a factory released pollution while making a part. Along the columns are the countries which purchased the final goods and services, for instance, where a homeowner purchased a laptop incorporating a part made abroad. The arrows in the matrix indicate the flow from the Country of Impact to the Country of Final Demand. Note that there may be several steps along the supply chain between the first Country of Impact and the Country of Final Demand; the arrow does not necessarily represent direct imports. Consider a world with three countries trading with each other: A part made in a factory in Country A could be assembled into a laptop in Country B before it is imported into Country C.

We can evaluate this matrix from several perspectives. The boxes along the diagonal of the matrix represent "domestic production for domestic final demand + use phase." The off-diagonal boxes could be considered from the perspective of the producer (Country of Impact) or the final product importer (Country of Final Demand).

In the first perspective, we can calculate CBA impacts. The CBA impacts are the column sums, representing the impacts that are driven by final demand. These impacts include the "domestic production for domestic final demand + use phase" and "imports embodied in domestic final demand." Therefore, the sum of $A \rightarrow A$, $B \rightarrow A$, and $C \rightarrow A$ is CBA_A, as shown in Table 1.

Table 1. Matrix of impacts, CBA perspective.

		Country of Final Demand		
		A	B	C
Country of Impact	A	$A \rightarrow A$	$A \rightarrow B$	$A \rightarrow C$
	B	$B \rightarrow A$	$B \rightarrow B$	$B \rightarrow C$
	C	$C \rightarrow A$	$C \rightarrow B$	$C \rightarrow C$
	Sum	CBA_A	CBA_B	CBA_C

Legend:

Domestic production for domestic final demand + use phase
Imports embodied in domestic final demand
Domestic production of exports
Domestic Pillar
Spillover Pillar

The PBA impacts are the sums across the rows, representing the impacts that occur within that country due to production and use of products. Taking the perspective of the exporter (the Country of Impact), the off-diagonal boxes represent "domestic production of exports." The row sum of $A \rightarrow A$, $A \rightarrow B$, and $A \rightarrow C$ is PBA_A, as shown in Table 2. The Domestic pillar in the GCS Index is equivalent to PBA for the indicators calculated using MRIO models.

Table 2. Matrix of impacts, PBA and Domestic Pillar perspective.

		Country of Final Demand			
		A	B	C	Sum
Country of Impact	A	$A \rightarrow A$	$A \rightarrow B$	$A \rightarrow C$	$Domestic_A = PBA_A$
	B	$B \rightarrow A$	$B \rightarrow B$	$B \rightarrow C$	$Domestic_B = PBA_B$
	C	$C \rightarrow A$	$C \rightarrow B$	$C \rightarrow C$	$Domestic_C = PBA_C$

Lastly, we can focus on the off-diagonal boxes to calculate the Spillover pillar. In this perspective, the Country of Final Demand is said to drive the impacts which occurred elsewhere. Thus, the purchase of a laptop in Country C results in spillover impacts in Country A where a part was made and in Country B where the laptop was assembled. Here, the sum of just $B \rightarrow A$ and $C \rightarrow A$ is $Spillover_A$, as shown in Table 3.

Table 3. Matrix of impacts, Spillover perspective.

		Country of Final Demand		
		A	B	C
Country of Impact	A		$A \rightarrow B$	$A \rightarrow C$
	B	$B \rightarrow A$		$B \rightarrow C$
	C	$C \rightarrow A$	$C \rightarrow B$	
	Sum	$Spillover_A$	$Spillover_B$	$Spillover_C$

2.3 Matrix calculations

There are several key matrices in MRIO analysis. Data needed to compile the monetary MRIO matrices are derived from national statistical offices and trade statistics. Balancing techniques are then applied to misaligned data so that the model is internally consistent. The 2022 Index uses Release 055 of the GLORIA global environmentally extended MRIO database (Lenzen et al., 2022), constructed in the Global MRIO Lab (Lenzen et al., 2017) at the University of Sydney, for spillover indicators not calculated by other research groups.

The square intermediate demand matrix, $\boldsymbol{T}$, shows the expenditures between and within product sectors in a given year. The rows of $\boldsymbol{T}$ list products, i, from countries, r, that are used to make products, j, in countries, s, across the columns. For instance, $\boldsymbol{T}$ estimates that the UK cereal products sector purchased \$2.24 million of US wheat products in 2018.

The final demand matrix, $\boldsymbol{Y}$, includes components, *d* of the expenditures on final products by households and governments, as well as investments in equipment, structures, and intellectual property products by households (real estate), businesses, and governments. The matrix $\boldsymbol{Y}$ estimates that Brazilians purchased \$16.24 billion of Brazilian beef in 2018. We find the total final demand per for each Country of Final Demand, *s*, summing over the components *d*.

$$\boldsymbol{Y}_s = \sum_d \boldsymbol{Y}_{s,d}$$

The combined row sums of the intermediate $\boldsymbol{T}$ and final demand $\boldsymbol{Y}$ matrices is total output, $\boldsymbol{x}$.

$$\boldsymbol{x} = \boldsymbol{T} + \boldsymbol{Y}$$

The intermediate demand matrix $\boldsymbol{T}$ is normalized by the total output $\boldsymbol{x}$ to create $\boldsymbol{A}$, the direct requirements matrix. The columns in $\boldsymbol{A}$ have technical coefficients, which are effectively 'recipes' showing how many units of an input product i from region r are directly needed to produce one unit of output of a final product j in region s. For instance, producing 1 dollar of basic copper in Japan directly requires 0.195 dollars of Chilean copper ores, 0.063 dollars of Indonesian copper ores, 0.007 dollars of Japanese electricity, and so on.

$$\boldsymbol{A} = \boldsymbol{T}\hat{\boldsymbol{x}}^{\boldsymbol{-1}}$$

The Leontief inverse, $\boldsymbol{L}$, or total requirements matrix, takes another step and quantifies the indirect inputs needed across the entire supply chain. For instance, while $\boldsymbol{A}$ shows how much petroleum is a direct input into truck transportation, $\boldsymbol{L}$ would additionally include the petroleum needed along the supply chain to create other goods and services used by truck transportation. Note that total output $\boldsymbol{x} = \boldsymbol{LY}$.

$$\boldsymbol{L} = (\boldsymbol{I} - \boldsymbol{A})^{-\boldsymbol{1}}$$

Extensions with direct environmental impact data, $\boldsymbol{Q}$, are appended to MRIO tables, making them "environmentally extended" (EE-MRIO). These data could be derived from national statistics or third-party databases. These data may be very disaggregated, and therefore characterization factors, $\boldsymbol{C}$, are applied. For instance, raw values of GHG emissions can all be converted to global warming potentials by multiplying a matrix of CO_2 equivalencies, *e.g.*, 1 kg of methane becomes 28 kg CO_2-eq. (following IPCC AR5).

The subset $\boldsymbol{Q_T}$ are impacts from production and the subset $\boldsymbol{Q_Y}$ are impacts from use of final products. Summing both per Country of Impact, r, is the PBA approach, which is equivalent to the Domestic Pillar.

$$Domestic_r = \boldsymbol{CQ}_{\boldsymbol{T}_r} + \boldsymbol{CQ}_{\boldsymbol{Y}_r}$$

To derive spillover estimates, it is critical that the extension data distinguish the production of which product *i* in region *r* directly creates the environmental impact. A common challenge is that the classification of products in environmental data differs from the classification in MRIO tables, and therefore allocation procedures must be applied to distribute the impacts across the products.

The impact per unit output, $\boldsymbol{q}$, is found by normalizing $\boldsymbol{Q_T}$ by the total output, $\boldsymbol{x}$, just as was done before with matrices $\boldsymbol{T}$ and $\boldsymbol{A}$. Note that the use phase impacts are not included in the Spillover pillar, because they do not happen abroad, but instead happen domestically in the Country of Final Demand.

$$\boldsymbol{Cq} = \boldsymbol{CQ_T}\hat{\boldsymbol{x}}^{-\boldsymbol{1}}$$

In order to distinguish by Country of Impact for spillover analyses, the impacts are diagonalized. It is necessary to perform this step separately for each impact, *c*, considered, creating an array of matrices. The columns of $\boldsymbol{Y}$ already distinguish the Country of Final Demand. The total footprint matrix, $\boldsymbol{F_c}$, is found by multiplying the impact per output of products made in the Country of Impact, $\widehat{\boldsymbol{Cq}}_{\boldsymbol{c}}$, by the total output needed to satisfy final demand for those products, $\boldsymbol{LY_s}$.

$$\boldsymbol{F_c} = \widehat{\boldsymbol{Cq}}_{\boldsymbol{c}}\boldsymbol{LY_s}$$

In order to separate the spillover footprint from the total footprint, the domestic production for domestic final demand is set to zero. This is done by element-wise multiplying the total footprint with a matrix of 1s with 0s across the diagonal, since domestic impacts for domestic final demand are in the diagonal.

$$Spillover_{c,r,s,i,j} = \boldsymbol{F}_c \times (\mathbf{1} - \boldsymbol{I})$$

Finally, the spillover impacts per impact, *c*, Country of Impact, *r,* and Country of Final Demand, *s*, are found by taking sums over products *i* and *j*.

$$Spillover_{c,r,s} = \sum_{i,j} Spillover_{c,r,s,i,j}$$

3. Data selection

3.1 Inclusion criteria

With a wide variety of environmental data on impacts to the Global Commons, the GCS Index requires some criteria for selecting appropriate indicators for a composite index. The data we use come from a variety of sources, including international agencies, academia, and non-governmental organizations. The indicator selection will evolve over time as new data and statistics become available.

We selected data for inclusion based on five selection criteria:

1. **Global relevance and applicability to a broad range of country settings:** The indicators should be relevant and allow for direct comparison of impacts across countries. In particular, they should allow for the definition of quantitative thresholds that signify goal achievement.
2. **Statistical adequacy:** The indicators selected should represent valid and reliable measures.
3. **Timeliness:** The indicators selected should be up-to-date and published on a reasonably prompt schedule.
4. **Data quality:** Data series should represent the best available measure for a specific issue and be collected according to methods either peer-reviewed by the academic community or endorsed by an international organization or other reputable sources.
5. **Country coverage:** Data should be available for a large range of countries.

3.2 Indicators

After careful review of available sources, we identified 39 indicators that met our inclusion criteria and could be assembled with the necessary expedience (see Table 4). We also acknowledge that there are gaps in how we measure impacts to the Global Commons, either because there are data sources unknown to us or because further research is needed. We welcome suggestions for additional datasets that meet our inclusion criteria for incorporation into future versions of the GCS Index.

Table 4. Indicators included in the 2022 Global Commons Stewardship Index.

Sub-pillar	Indicator	Spillover
Aerosols	SO_2 emissions	✓
	NO_X emissions	✓
	Black Carbon emissions	✓
GHG Emissions	Greenhouse Gas emissions	✓
	CO_2 emissions embodied in fossil fuel exports	
Terrestrial Biodiversity	Unprotected terrestrial Key Biodiversity Areas	
	Unprotected freshwater Key Biodiversity Areas	
	Land use biodiversity loss	✓
	Freshwater biodiversity threats	✓
	Deforestation	✓
	Red List Index of species survival	
	CITES-listed terrestrial organisms	✓
	Biodiversity Habitat Index	
Marine Biodiversity	Unprotected marine Key Biodiversity Areas	
	Marine biodiversity threats	✓
	CITES-listed marine organisms	✓
	Fish caught from vulnerable taxa	✓
	Fish caught from overexploited or collapsed fish stocks	
	Fish caught by trawling	
Nutrient Cycles	Sustainable Nitrogen Management Index	
	Nitrogen surplus	✓
	Phosphorus fertilizer	✓
Water Cycle	Scarce water consumption	✓
	Water stress	✓

Note: All indicators listed are included in the Domestic pillar; only those indicators with a ✓ are included in the Spillover pillar.

3.2.1 Domestic indicators

For the Domestic pillar we present 24 indicators that meet our selection criteria (Table 5). Aerosol indicators consist of emissions of sulfur dioxide (SO_2), nitrogen oxides (NO_X), and black carbon. GHG Emissions are a combination of carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and fluorinated gases (F-gases) – the latter three converted to CO_2-equivalents. We also include a measure of GHG emissions embodied in exported fossil fuels.

Terrestrial Biodiversity Loss is our most expansive sub-pillar, with indicators on terrestrial and freshwater protection, as measured by the percentage of a country's Key Biodiversity Areas (KBA) (BirdLife International, 2022) that are not in protected areas. These KBA indicators are the only measures in the current indicator set that track policy intentions and not outcomes. Human activities also impact species in terrestrial and freshwater ecosystems whose conservation status is threatened. As a biome of critical importance for many ecosystem services, we include a measure of deforestation. The 2022 Index also includes a pilot indicator of domestic export of CITES-protected terrestrial animals. Two additional indicators provide a more holistic picture of biodiversity loss: the Red List Index (IUCN, 2022) and the Biodiversity Habitat Index (Ferrier et al., 2022; Hoskins et al., 2020; Mokany et al., 2020).

For Marine Biodiversity Loss, we also include measures of unprotected KBAs and threats to species. As a classic example of the commons, we include measurements of fish stocks, with a status indicator of percentage of catches that come from over-exploited or collapsed stocks and a measure of percentage of catches that use trawling or longlines, especially destructive fishing gear. These indicator are based on data from the Sea Around Us using methods described by Pauly et al. (2020). Two pilot indicators measure domestic export of CITES-protected marine animals and fisheries catch from vulnerable taxa. Impacts to the Nutrient Cycles are largely driven by agriculture. We use the Sustainable Nitrogen Management Index (Zhang et al., 2022), a measure of nitrogen surplus, and a measure of phosphorus used as fertilizer. Water Cycle disruptions include consumption of scarce water resources and water stress due to crops.

3.2.2 Spillover indicators

The 15 indicators in the Spillover pillar (Table 6) are derived from CBA (isolating the imported for final demand dimension) using MRIO tables that link traded goods with environmental and biodiversity impacts. These derivations are only possible for those datasets in which impacts can be mapped onto the economic sectors described in the MRIO models. The Spillover indicators include all of the Aerosol emissions; GHG emissions; threats to terrestrial, freshwater, and marine species; deforestation; trade in CITES-protected organisms (does not use MRIO tables); vulnerable marine taxa; nitrogen surplus and phosphorus fertilizer; and scarce water consumption and water stress due to crops.

Table 5. Domestic indicators in the 2022 GCS Index.

Indicator	Description	Input Data Sources	Section
Domestic SO_2 emissions	SO_2 emissions embodied in domestic production of goods and services for domestic consumption and export.	EDGAR 6.1 (European Commission Joint Research Centre, 2019)	
Domestic NO_X emissions	Nitrogen oxides (NO_X) emissions embodied in domestic production of goods and commodities for domestic consumption and export.		
Domestic black carbon emissions	Black carbon emissions embodied in domestic production of goods and services for domestic consumption and export.		
Domestic GHG emissions	Greenhouse gas emissions (CO_2, CH_4, N_2O, F-Gasses [HFCs, PFCs, SF_6]) in CO_2-equivalent embodied in domestic production for domestic consumption and exports.	EDGAR 7.0 (European Commission Joint Research Centre, 2022)	4.1
CO_2 emissions embodied in fossil fuel exports	CO_2 emissions embodied in the exports of coal, gas, and oil. Calculated using a 5-year average of fossil fuel exports and converting exports into their equivalent CO_2 emissions. Exports for each fossil fuel are capped at the country's level of production.	UN Comtrade (UN Department of Economic and Social Affairs, 2022)	
Unprotected terrestrial biodiversity sites	The mean percentage area of terrestrial Key Biodiversity Areas that is not covered by protected areas and remains at risk.	Birdlife International (2022)	
Unprotected freshwater biodiversity sites	The mean percentage area of freshwater Key Biodiversity Areas that is not covered by protected areas and remains at risk.	Birdlife International (2022)	
Domestic land use related biodiversity loss	Fraction of global species that are committed to extinction as a result of domestic anthropogenic land use for crops, pasture, and forestry, for domestic consumption and export.	GLORIA	4.2.1
Domestic freshwater biodiversity threats	Number of freshwater species threatened as a result of domestic production of goods and services for domestic consumption and export.	Peterson et al. (2020)	4.2.2
Domestic deforestation	Three-year average tree cover loss due to urbanization, commodity production, the forestry sector, and certain types of small-scale agriculture. It does not include temporary loss due to wildfires.	The Sustainability Consortium et al. (2022)	4.2.3

Indicator	Description	Input Data Sources	Section
Domestic export of CITES-listed terrestrial animals	Direct export of CITES-listed terrestrial and freshwater species, converted to Whole Organism Equivalents.	CITES Trade Database (UNEP-WCMC, 2022)	4.2.4
Red List Index of species survival	The change in aggregate extinction risk across groups of species. The index is based on genuine changes in the number of species in each category of extinction risk on The IUCN Red List of Threatened Species.	IUCN (2022)	
Biodiversity Habitat Index	Estimates the effects of habitat loss, degradation, and fragmentation on the expected retention of terrestrial biodiversity. CSIRO calculates the BHI from remote sensing data and other studies of ecological diversity. A score of 100 indicates that a country has experienced no habitat loss or degradation, and a score of 0 indicates complete habitat loss.	CSIRO	
Unprotected marine biodiversity sites	The mean percentage area of marine Key Biodiversity Areas that is not covered by protected areas and remains at risk.	Birdlife International (2022)	
Domestic marine biodiversity threats	Number of marine species threatened as a result of domestic production of goods and services for domestic consumption and export.	Peterson et al. (2020)	4.2.2
Domestic export of CITES-listed marine animals	Direct export of CITES-listed marine species, converted to Whole Organism Equivalents.	CITES Trade Database (UNEP-WCMC 2022)	4.2.4
Domestic vulnerable marine animals	Catch of marine species within a country's EEZ classified as vulnerable (or unable to be classified due to insufficient reporting).	*Sea Around Us*	4.2.5
Fish caught from overexploited or collapsed stocks	The percentage of a country’s total catch, within its EEZ, that is comprised of species that are overexploited or collapsed.	*Sea Around Us*	
Fish caught by trawling	The percentage of a country's total fish catch caught by trawling.	*Sea Around Us*	
Sustainable Nitrogen Management Index	The Sustainable Nitrogen Management Index is a one-dimensional ranking score that combines two efficiency measures in crop production: Nitrogen Use Efficiency and land use efficiency (crop yield).	Zhang Lab at University of Maryland	

Indicator	Description	Input Data Sources	Section
Domestic nitrogen surplus	Excess nitrogen embodied in domestic production of crops for domestic consumption and export	Vishwakarma et al. (2022)	4.3.1
Domestic phosphorus fertilizer	Phosphorus fertilizer applied to erodible soils embodied in domestic production of goods and services for domestic consumption and export.	FAO (2022), IFA (2021)	4.3.2
Domestic scarce water consumption	Volume of scarce water embodied in domestic production of goods and services for domestic consumption and export.	GLORIA	4.4.1
Domestic water stress	Volume of water stress-weighted blue water use embodied in domestic production of crops for domestic consumption and export.	GLORIA	4.4.2

Table 6. Spillover indicators in the 2022 GCS Index.

Indicator	Description	Input Data Sources	Section
Spillover SO_2 emissions	SO_2 emissions occurring in foreign countries and embodied in domestic final demand.	EDGAR 5.0 (European Commission Joint Research Centre, 2016b)	
Spillover NO_X emissions	Nitrogen oxides (NO_X) emissions occurring in foreign countries and embodied in domestic final demand.		
Spillover black carbon emissions	Black carbon emissions occurring in foreign countries and embodied in domestic final demand.		
Spillover GHG emissions	Greenhouse gas emissions (CO_2, CH_4, N_2O, F-Gasses [HFCs, PFCs, SF_6]) in CO_2-equivalent occurring in foreign countries and embodied in domestic final demand.	EDGAR 6.0 (European Commission Joint Research Centre, 2016a)	4.1
Spillover land use related biodiversity loss	Fraction of global species that are committed to extinction as a result of anthropogenic land use for crops, pasture and forestry in foreign countries, embodied in domestic final demand.	GLORIA	4.2.1
Spillover freshwater biodiversity threats	Number of freshwater species threatened as a result of imports of final products for domestic final demand.	Peterson et al. (2020)	4.2.2
Spillover deforestation	Tree loss occurring in foreign countries and embodied in domestic final demand (excluding wildfires and urbanization).	The Sustainability Consortium et al. (2022)	4.2.3
Spillover CITES-listed terrestrial animals	Final import of CITES-listed terrestrial and freshwater species, converted to Whole Organism Equivalents.	CITES Trade Database (UNEP-WCMC 2022)	4.2.4
Spillover marine biodiversity threats	Number of marine species threatened as a result of imports of final products for domestic final demand.	Peterson et al. (2020)	4.2.2

Indicator	Description	Input Data Sources	Section
Spillover CITES-listed marine animals	Final import of CITES-listed marine species, converted to Whole Organism Equivalents.	CITES Trade Database (UNEP-WCMC 2022)	4.2.4
Spillover vulnerable marine animals	Catch of marine species by foreign fishing entities embodied in domestic final demand and classified as vulnerable (or unable to be classified due to insufficient reporting).	*Sea Around Us*	4.2.5
Spillover nitrogen surplus	Excess nitrogen from crop production occurring in foreign countries and embodied in domestic final demand.	Vishwakarma et al. (2022)	4.3.1
Spillover phosphorus fertilizer	Phosphorus fertilizer applied to erodible soils in foreign countries and embodied in domestic final demand.	FAO (2022), IFA (2021)	4.3.2
Spillover scarce water consumption	Volume of scarce water occurring in foreign countries and embodied in domestic final demand.	GLORIA	4.4.1
Spillover water stress	Volume of water stress-weighted blue water use occurring in foreign countries and embodied in domestic final demand.	GLORIA	4.4.2

3.2.3 Data gaps

Despite an extensive data search and expert consultations, there are many impacts to the Global Commons for which appropriate metrics are unknown or unavailable to the research team. Some datasets are excluded by our inclusion criteria (see Section 3.1 of this Technical Appendix), and some are yet to be developed by scientific researchers. These persistent data gaps limit the comprehensiveness of the 2022 GCS Index, and our results should be interpreted in light of these limitations. Future versions of the Index will work with the scientific community and national and international organizations to close these gaps, with the following being of special note:

- GHG Emissions
    - CO_2 fluxes from anthropogenic land use change, including those fluxes embodied in trade
- Terrestrial Biodiversity Loss
    - Functional biodiversity loss
    - Loss of intact areas and wilderness, including those losses attributable to trade
- Marine Biodiversity Loss
    - Fish stock depletion embodied in trade, including overfishing in international waters
    - Coastal pollution, especially of plastics, including those releases embodied in trade
- Nutrient Cycles
    - Hypoxia attributable to sources, including eutrophication embodied in trade
- Water Cycle
    - Water use disaggregated at the basin level
    - Groundwater depletion, including embodied in trade
- Stratospheric Ozone Depletion
    - Unreported or illegal production of ozone depleting substances (ODS), including those ODS embodied in trade
    - Mitigation of ODS in existing products or temporary storage
- Novel entities
    - Toxic pesticides, including those embodied in trade
- Physical flows of pollutants across country boundaries in air and water.

4. Methods for indicator development

While Tables 5 & 6 provide basic descriptions of the indicators and the sources for input data, this section provides additional information about the calculation of metrics, including citations of relevant documentation or additional steps needed to replicate our results.

For most of the Spillover indicators, we calculated the indicators using GLORIA Release 055 (Lenzen et al., 2017, 2022) model following the methods described above in Section 2. Spillover calculations. The technical documentation for the Sustainable Consumption and Production Hotspots Analysis Tool (SCP-HAT Version 2.0) (Piñero et al., 2021) is rich in additional details about data sources and how those datasets were applied to GLORIA.

A handful of Spillover indicators derived from other trade data:

- Nitrogen surplus, Freshwater biodiversity threats, and Marine biodiversity threats were calculated with the Eora MRIO, and the values used in the 2022 GCS Index are the same as those used in previous versions.
- Indicators about CITES-listed animals did not involve an MRIO model.

4.1 GHG emissions

Our indicator for GHG emissions is expressed in CO_2-eq. based on GWP100 using the IPCC AR5 factors (Myhre et al., 2013). Table 7 provides the characterization factors, ***C*** (see Section 2.3 Matrix calculations), used in the conversion, with the first two columns corresponding to the GLORIA satellite accounts.

Table 7. Characterization factors for Greenhouse gases based on 100-year Global Warming Potential.

Lfd_Nr	Sat_indicator	CO_2	CH_4	N_2O	F-Gas	Total
1	C4F8	0	0	0	9540	9540
2	C2F6	0	0	0	11100	11100
3	C3F8	0	0	0	8900	8900
4	C4F10	0	0	0	9200	9200
5	C5F12	0	0	0	8550	8550
6	C6F14	0	0	0	7910	7910
7	C7F16	0	0	0	7820	7820
8	CF4	0	0	0	6630	6630
9	HFC_23	0	0	0	12690	12690
10	HFC_32	0	0	0	705	705
11	HFC_43	0	0	0	1470	1470
12	HFC_125	0	0	0	3450	3450
13	HFC_134A	0	0	0	1360	1360
14	HFC_143A	0	0	0	5080	5080
15	HFC_152A	0	0	0	148	148
16	HFC_227EA	0	0	0	3140	3140
17	HFC_236FA	0	0	0	7680	7680
18	HFC_245FA	0	0	0	880	880
19	HFC_365MFC	0	0	0	810	810
20	NF3	0	0	0	15750	15750
21	SF6	0	0	0	23500	23500
22	CO2 excluding short cycle organic C	1	0	0	0	1
23	CO2 short cycle organic C	1	0	0	0	1
24	N2O	0	0	265	0	265
25	CH4	0	28	0	0	28

4.2 Terrestrial and marine biodiversity loss

4.2.1 Land use biodiversity loss

We derive the domestic and spillover land use biodiversity loss indicators using the GLORIA Release 055 model and the provided satellite extension. These data were based on modeled land use per sector and the estimated potential species loss associated with each class of land use. According to the satellite extension documentation for the Sustainable Consumption and Production Hotspot Analysis Tool (SCP-HAT) (Piñero et al., 2021):

> Following UNEP's recommendations, country-level average characterization factors for global species loss from Chaudhary et al. (2015) are used in the SCP-HAT, aggregated over five taxa (mammals, reptiles, birds, amphibians, and vascular plants) for each of the six land use categories. The unit of this indicator is PDF*year which stands for the Potentially Disappeared Fraction of species for the duration of a year. Land use impact modelling assumes that once an activity (land use) stops, the system will slowly return to its natural state. The indicator therefore does not reflect full extinction of species but a temporary decline in biodiversity. (12)

4.2.2 Freshwater & marine biodiversity threats

The domestic and spillover Freshwater and Marine biodiversity threats indicators were provided as custom calculations by the authors of "The Ecological Cost of Consumption", based on the Eora MRIO (Peterson et al., 2020).

4.2.3 Deforestation (Pilot Indicator)

In the 2021 GCS Index we recognized 'Forest cover loss embodied in trade' as a data gap that limited the comprehensiveness of our report. For the 2022 Index, we seek to close this gap by developing a pilot spillover indicator and updating the domestic deforestation indicator accordingly. Global Forest Watch (GFW) uses satellite data to create spatial models of global tree cover loss (Hansen et al., 2013; Weisse & Potapov, 2021). GFW states that "This data set indicates the dominant driver of tree cover loss for 10 km grid cells, based on nearly 5,000 sample points and a model built on data for tree cover, tree cover loss, tree cover gain, population density, land cover, and fires" (GFW, 2023). GFW attributes the tree cover loss to several drivers, following Curtis et al. (2018). GFW provided a dataset of tree cover loss by dominant drivers (The Sustainability Consortium et al., 2022). We are grateful to James MacCarthy at GFW for his expert guidance on this indicator.

Table 8 describes the drivers of tree cover loss in the GFW data and different approaches to indicator construction. Only two of these drivers are considered permanent: commodity-driven deforestation and urbanization. We did not include urbanization in our Spillover indicator due to difficulty in assigning it to economic sectors within GLORIA. Following Hoang & Kanemoto (2021), we also exclude wildfires from both versions of our indicators due to the difficulty in attributing fire to human activity (rather than natural causes) by Curtis et al. (2018). Shifting-agriculture and forestry are included in our indicator construction despite not always being permanent. Hoang & Kanemoto (2021) argue that shifting-agriculture is the dominant driver in much of Africa as well as Central and South America, so excluding it would result in an underestimate of those impacts. They also argue for including forestry since regrowth of harvested forests in the long-term could pose challenges for climate neutrality targets on shorter time horizons.

Table 8. Drivers of tree cover loss.

Driver	GFW definition	Hoang & Kanemoto (2021)	Included in Domestic Indicator?	Included in Spillover Indicator?
Commodity-driven	"Large-scale deforestation linked primarily to commercial agricultural expansion."	X	X	X
Urbanization	"Deforestation for expansion of urban centers"	X	X	
Shifting-agriculture	"Temporary loss or permanent deforestation due to small- and medium-scale agriculture"	X	X	X
Forestry	"Temporary loss from plantation and natural forest harvesting, with some deforestation of primary forests."	X	X	X
Wildfire	"Temporary loss, does not include fire clearing for agriculture."			

For the spillover indicator, we assigned annual tree cover loss data from select drivers to economic sectors within GLORIA. Forestry-driven tree cover loss mapped to the "Forestry & Logging" sector. We summed tree cover loss attributed to commodities and shifting agriculture then attributed this loss to GLORIA agricultural sectors in proportion to agricultural land use in each country. This proportional allocation is a proxy for the actual allocation of tree cover loss by economic sectors, and more detailed data about commodity-specific drivers could improve the accuracy of this indicator. Further, commodity-driven tree cover loss also includes non-agricultural commodities, such as energy and mining, but these may be considered minor uses of land. The implication of our mappings is that tree cover loss has been embodied in the goods traded captured by the GLORIA sectors.

4.2.4 CITES-Protected animals (Pilot Indicators)

In the 2021 GCS Index we recognized trade in endangered species as a data gap that limited the comprehensiveness of our report. For the 2022 Index, we seek to close this gap by developing four pilot indicators (domestic and spillover, terrestrial and marine). In light of the repercussions of global trade on biodiversity, the Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES) collects international trade data on endangered species and aims to protect them from extinction, since trade is a threat to species survival (Wilcove, 2022). CITES came into force in 1975 and became the largest multilateral agreement on regulating and conserving international trade for over 40,900 species and currently has a membership of 183 countries and the EU (CITES, 2023). We are grateful to Jessica Vitale, Kelly Malsch, and Katia Sanchez-Ortiz at the UN Environment Programme World Conservation Monitoring Centre for their expert guidance on these pilot indicators.

The CITES parties annually report volume of trade per species; countries of origin, export, and import; and the source of traded organisms and their purposes at the destination. We assigned Domestic impacts to the country of origin and Spillover impacts to the country of final destination. Note that this is unlike other Spillover indicators, which were analyzed through the GLORIA MRIO model.

In the CITES database, wild animals (alive or dead) are included, while plants are excluded. The basic unit of trade volume for these animals is Whole Organism Equivalents (WOE). According to Harfoot et al. (2018), for example, one head, two ears, or four feet (from dead animals) would each be counted as one WOE. The database only includes the following purposes of these traded WOE: commercial purposes (Code T), personal possessions (Code P), hunting trophies (Code H), and unknown. We excluded animals sourced from captivity (not wild, Codes A, C, F, and D).

Tracing the flows of WOE across countries required us to adjust reported data for cases of re-exportation when there were three trade partners. We did not assign trade volumes from re-exporters in our spillover indicator, as they are passthrough countries. To distinguish between terrestrial and marine indicators (placed in different sub-pillars), we classified species in the CITES database as terrestrial, marine, or both (50/50 split) using the World Register of Marine Organisms (Ahyong et al., 2023) and Wikipedia.org. Landlocked countries were not considered to be possible origins of marine species.

As pilot indicators, we are aware of several limitations in our approach to constructing metrics around endangered species. Beyond the restriction to only covering animals and not plants, the domestic indicator does not include endangered species that are sourced and purchased entirely within the same country, i.e., not traded. Since the CITES database also includes data reported by both importers and exporters, there is an opportunity for substantial disagreement between trade partners. In cases where trade volumes did not agree, we used the maximum value. Trade relationships that involve more than three trade partners, i.e., multiple re-exportation, also present a challenge when constructing our indicators, and further refinements could account for these situations. Accounting for all nodes in the supply chains for WOE is further frustrated by the fact that the EU is a party to CITES and reports data as a bloc. Intra-EU trade, therefore, is not fully captured in the database and is underreported. For the purposes of our spillover indicator, we consider EU countries that import WOE as the final destination, even though these countries may re-export elsewhere in the EU. Additional limitations include reported trade that could not be converted into WOE, and so were excluded, and the trade of products derived from animals, such as skins for shoes, was also not able to be captured. Despite these problems, we feel that our pilot indicators are still useful for understanding the negative environmental impacts of trade in endangered species and point the way for future work.

4.2.5 Vulnerable marine animals (Pilot Indicators)

For the 2022 Index, we developed pilot domestic and spillover indicators for vulnerable marine animals. Global data on the health of marine life and harvests come from the *Sea Around Us* (SAU) using methods described by Pauly et al. (2020). For these indicators, we focus on those marine animals (fish, crustaceans, and mollusks) that could be considered vulnerable by at least one published criterion. Each country sets the catch policies within their EEZs and, theoretically, could take action to reduce the catch of vulnerable taxa. We also include catches reported at such a high taxonomic level that the vulnerability could not be determined. A country can also improve its reporting practices to record fish catches at more granular taxonomic levels, which would enable more accurate assessments of the vulnerability of those catches. We are grateful to Maria L.D. Palomares for her expert guidance on these indicators.

We requested *SAU* data on the mass fish catch disaggregated by taxa, fishing entity (FE), exclusive economic zone (EEZ), and fishing category. The FEs and EEZs match with countries and regions within GLORIA, and we assigned the taxa to either the "Fishing" or "Crustaceans & mollusks" GLORIA sectors. We limited our analysis to only fish catches classified by *SAU* as "Industrial" and "Artisanal."

Developing these indicators also requires assigning a vulnerability status to each taxon. *SAU* provided vulnerability criteria from FISHBASE and other sources merged with marine catch data. Ultimately, we relied on four vulnerability metrics from the scientific literature and experts.

Resilience: "The capacity of a system to tolerate impacts without irreversible change in its outputs or structure. In species or populations often understood as the capacity to withstand exploitation" (Froese et al., 2017)

- **Range:** Very Low – High
- **Vulnerable:** Very Low & Low
- **Not Vulnerable:** Medium & High

IUCN Red List: "Established in 1964, the International Union for Conservation of Nature's Red List of Threatened Species has evolved to become the world's most comprehensive information source on the global extinction risk status of animal, fungus and plant species" (IUCN, 2022)

- **Range:** 1–8
- **Vulnerable:** >1
- **Not Vulnerable:** Least Concern (1) or Data Deficient

Vulnerability to fishing: "[F]uzzy expert system that integrates life history and ecological characteristics of marine fishes to estimate their intrinsic vulnerability to fishing." (Cheung et al., 2005)

- **Range:** 10–90
- **Vulnerable:** ≥25
- **Not Vulnerable:** <25

Vulnerability to climate change: "[S]pecies-specific estimates of exposure, and ecological and biological traits to undertake an assessment of vulnerability (sensitivity and adaptive capacity) and risk of impacts (combining exposure to hazards and vulnerability) of climate change (including ocean acidification) for global marine fishes and invertebrates." (Jones & Cheung, 2018)

- **Range:** 0–100
- **Vulnerable:** ≥25
- **Not Vulnerable:** <25

If vulnerability had been assessed, we classified a taxon as 'vulnerable' if it met *any* of the vulnerability criteria and 'not vulnerable' if it met *none* of the criteria. If vulnerability for a taxon had not been assessed – of if the level of taxonomic reporting was too high to clearly identify the vulnerability – we created a complex decision tree to assign 'vulnerable' or 'not vulnerable' status based on the taxonomic level reported and whether the vulnerability status could be inferred from other species in the genus or family. We chose to double the impact of the catch reported at the highest taxonomic level, such as the generic "marine species not elsewhere specified," as a penalty for under-reporting.

With these data, we created domestic and spillover indicators. The Domestic indicator is a sum of the mass of vulnerable taxa caught within each country's EEZs. The Spillover indicator is the sum of the mass of vulnerable taxa caught due to final demand in a country, caught by other FEs. Unlike other data on fisheries, the proportional versions of these indicators are denominated on a per capita basis.

As pilot indicator, we are aware of the limitations of our metrics and opportunities for further refinement. Our data do not include catches on the high seas (only those within EEZs), bycatch, or discards. Vulnerability criteria are not available for all marine species; funding should be allocated for research to enable these vulnerability assessments. Additional vulnerability criteria also may be appropriate for assessing taxa, such as sustainability yield level, though such criteria may be more complicated to apply due to spatial variability. An alternative perspective on the definition of the Spillover indicator would be to distinguish catch occurring in other countries' EEZs to satisfy a country's final demand, regardless of the FE. Future work on these indicators will yield more useful and accurate metrics to guide the protection of marine commons.

4.3 Nutrient cycle disruptions

4.3.1 Nitrogen surplus

Disaggregated nitrogen surplus (N surplus, or Soil Nutrient Balance) data were provided by the authors of Vishwakarma et al. (2022), which covered 218 countries, 170 crop types, and 55 years through 2015. Negative values in this dataset represent extraction of N from the soil; We set these negative values to zero in our calculations so as not to incidentally give a country a benefit for this activity. Crop types in these data were mapped to the crop sectors in Eora, which vary by country. The domestic indicator is simply the sum of N surplus across all crop types. The spillover indicator derive from using the N surplus per country – crop sector and running the Eora MRIO model. Given the wide variation of annual estimates for N surplus across datasets (Zhang et al., 2021), we elected to not update these indicators from the 2021 GCS Index versions until high quality disaggregated updates are available.

4.3.2 Phosphorus fertilizer

Phosphorus (P) fertilizer entering waterways can cause freshwater eutrophication and ocean anoxia. These impacts point to the recognition of disruptions to the phosphorus cycle as a Planetary Boundary, especially through the mining of phosphorus to fertilize soils (Steffen et al., 2015).

Four datasets provide the foundation for estimating the annual P_2O_5 fertilizer applied per country:

1. UN Food and Agriculture Organization (FAO) data on annual P_2O_5 consumption per country (FAO, 2022)
2. International Fertilizer Association (IFA) data on annual P_2O_5 consumption per country (IFA, 2021)
3. IFA timeseries data on fertilizer use by crop (FUBC) (Ludemann et al., 2022)
4. GLORIA satellite extension on land use per sector

Our domestic indicator is a simple composite of the annual P_2O_5 consumption per country, as found in either Source (1) or, if missing, Source (2). For the spillover indicator, we distributed the country-level consumption of phosphorus by mapping the crop groups in Source (3) across the economic sectors in Source (4). Over the period 2014–2018, we calculated the sum of P_2O_5 per GLORIA crop sector. We allocated any fertilizer use for "Grassland" to the GLORIA sectors based on the proportion of "Pasture land" in the GLORIA land use satellite extension for each country. We then normalized the fertilizer use across all GLORIA sectors by dividing by the IFA FUBC total to find the percent of P_2O_5 per GLORIA sector, country, and year. We interpolated and extrapolated data linearly for missing years. We assigned the mean percent for each GLORIA sector per ISO subregion to countries not present in the IFA FUBC dataset. Finally, we multiplied these percents by the annual P_2O_5 consumption per country to arrive at the annual P_2O_5 consumption per country and GLORIA sector.

4.4 Water cycle disruptions

Both water cycle disruption indicators are based on the modeled 'Blue water consumption' satellite extension data provided with GLORIA Release 055. The indicators use the sum of 'Agriculture' and 'Non-Agriculture' blue water consumption. According to the satellite extension documentation for the Sustainable Consumption and Production Hotspot Analysis Tool (SCP-HAT) (Piñero et al., 2021):

> Blue water is defined as water stemming from surface water sources (e.g., rivers or lakes) or groundwater bodies. Water consumption is defined as the difference between overall water withdrawals and direct return flows. Blue water consumption hence encompasses water withdrawn from surface water sources or groundwater bodies that is either incorporated into products or evaporated during the growth period of a crop or the production process of a good. (15)

The difference between the two sets of indicators described below is the choice of country-level characterization factors applied to convert from consumption to scarce water or water stress. It is important to multiply these characterization factors to each country's blue water consumption data prior to performing the spillover MRIO calculations.

4.4.1 Scarce water consumption

These indicators were derived mimicking the approach established by Lenzen et al. (2013):

> In order to incorporate water scarcity into the virtual water flow calculus we construct a new satellite account where water use entries are weighted so that they reflect the scarcity of the water being used. As a weight we choose a measure of water withdrawals as a percentage of the existing local renewable freshwater resources. We use the Water Scarcity Index for converting total water use into scarce water use. Global data for this measure are provided by the [FAO AQUASTAT]. According to the FAO, "this parameter is an indication of the pressure on the renewable water resources". Note that we use resource and scarcity information only as an input into a weighting procedure, and that we do not determine water stress or water scarcity as a result of our calculations. (80)

The characterization factors here were based on the equivalent FAO AQUASTAT indicator for pressure on water resources: "MDG 7.5 Freshwater withdrawal as percent of total renewable water resources" (FAO, 2020) since the Water Scarcity Index data is no longer available. Data were linearly interpolated for countries lacking data points for specific years.

4.4.2 Water stress

The Water stress indicators were derived using the GLORIA Release 055 model and its precalculated satellite extensions (Piñero et al., 2021). These satellite extensions incorporate the Available WAter Remaining (AWARE) water stress characterization factors (Boulay et al., 2018), which "represent the relative Available WAter REmaining per area in a watershed, after the demand of humans and aquatic ecosystems has been met."

5. Country coverage

The GCS Index seeks to provide information on the widest set of countries for which an assessment of impacts to the Global Commons would be useful. The major constraint on country coverage is data availability, especially the trade data that underpins our spillover indicators. GLORIA Release 055 expands the coverage in the 2022 GCS Index to 145 countries and the European Union, for a total of 146 entities.

Albania	Colombia	Hungary	Moldova	Singapore
Algeria	Congo, Dem. Rep.	Iceland	Mongolia	Slovakia
Angola	Congo, Rep.	India	Morocco	Slovenia
Argentina	Costa Rica	Indonesia	Mozambique	Somalia
Armenia	Cote d'Ivoire	Iran	Myanmar	South Africa
Australia	Croatia	Iraq	Namibia	Spain
Austria	Cuba	Ireland	Nepal	Sri Lanka
Azerbaijan	Cyprus	Israel	Netherlands	Sweden
Bahrain	Czechia	Italy	New Zealand	Switzerland
Bangladesh	Denmark	Jamaica	Nicaragua	Tajikistan
Belarus	Dom. Rep.	Japan	Niger	Tanzania
Belgium	Ecuador	Jordan	Nigeria	Thailand
Belize	Egypt	Kazakhstan	N. Macedonia	Togo
Benin	El Salvador	Kenya	Norway	Tunisia
Bhutan	Eritrea	South Korea	Oman	Turkey
Bolivia	Estonia	Kuwait	Pakistan	Uganda
Bosnia & Herz.	Ethiopia	Kyrgyzstan	Panama	Ukraine
Botswana	EU27	Laos	Papua New Guinea	UAE
Brazil	Finland	Latvia	Paraguay	United Kingdom
Brunei	France	Lebanon	Peru	United States
Bulgaria	Gabon	Liberia	Philippines	Uruguay
Burkina Faso	Gambia	Lithuania	Poland	Uzbekistan
Burundi	Georgia	Luxembourg	Portugal	Venezuela
Cambodia	Germany	Madagascar	Qatar	Vietnam
Cameroon	Ghana	Malawi	Romania	Zambia
Canada	Greece	Malaysia	Russia	Zimbabwe
Cen. Afr. Rep.	Guatemala	Mali	Rwanda	
Chad	Guinea	Malta	Saudi Arabia	
Chile	Haiti	Mauritania	Senegal	
China	Honduras	Mexico	Sierra Leone	

6. Indicator construction

6.1 Standardization

We present the indicators in two forms: *proportional* and *absolute*. Proportional indicators are standardized to allow cross-country comparison, regardless of country size. We standardize most metrics by population rather than GDP. Population sizes tend to be more stable over time, and the MRIO databases from which the CBA indicators are calculated with GDP as a denominator.

Absolute indicators present unstandardized metrics of environmental impacts. While the proportional indicators emphasize that governments and citizens in small countries can strengthen policies and actions for sustainable development, the absolute indicators emphasize the efforts and leadership needed from large countries who have the greatest global impacts. This two-track approach reflects the growing trend in the field of industrial ecology, where researchers tend to present both *per capita* and absolute results in peer-reviewed papers (e.g., Lenzen et al., 2018).

6.2 Rescaling

To make the data comparable across indicators, we rescale each variable between 1 and 100, with 1 being the lowest bound denoting worst impacts and 100 denoting thresholds met or surpassed. We truncate each dataset so that all countries exceeding the threshold score no more than 100 and all countries falling below the lowest bound score 1.

We select the sustainability thresholds, or upper bounds, using a decision tree reflecting the approach used by the SDSN (Sachs et al., 2023) and the OECD (2019, Table 3.1) to compute distance to SDG targets (see Figure 3). Optimally, sustainability thresholds set for each indicator should be based on international agreements such as the SDGs and Paris Climate Change Agreement. When such a target is not available, we rely on scientific input and expert judgment. Finally, if neither of these two options are available, the upper bound is based on the average of top performing countries. A public consultation was organized in October 2022 to collect feedback from experts on the indicator selection, the quality of the data, the methodological choices and sustainability thresholds assigned, and the potential uses of this work. We welcome further comments and feedback at GCSIndex@unsdsn.org.

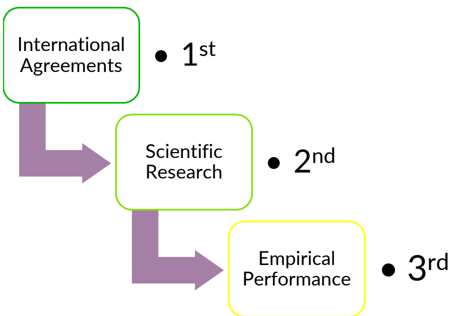

Figure 3. Hierarchy of sources for thresholds.

Three indicators illustrate this decision tree for threshold selection. First, international agreements, especially the Paris Climate Change Agreement, seek to limit global warming to below 1.5°C. Meeting this goal requires limiting per capita emissions of GHG to 2.0–2.5 tonnes CO_2-eq. by 2030 (UNEP, 2020). Considering the upper end of that range as a generous target, we set our 2050 threshold two decades later at the lower end: 2 tonnes CO_2-eq. per capita. Second, the Sustainable Nitrogen Management Index (Zhang et al., 2022) is a relatively novel indicator, and therefore unlikely to have yet been incorporated into international agreements. Based upon the logic of the underlying scientific research, the optimal value on a unitless scale is zero. Third, neither international agreements nor scientific research offers strict guidance on the target for water stress from crops. For this indicator, we selected the 2.5^{th}-percentile of all observed values as the threshold.

We rescale all indicators using a distance-to-target technique described by the following equation.

$$\textit{Indicator Score} = (X - L) / (U - L) \times 99 + 1$$

where X is a raw data value and U and L denote the upper and lower bounds, respectively. Our selection of bounds ensures that for all rescaled variables, higher values indicate better mitigation of impacts on the global commons (Table 9). Thus, a country that scores 50 on an indicator is halfway toward achieving the optimum value. A country with a score of 75 has covered three-quarters of the distance from the lower to the upper bound.

6.3 Transformation

One of the best practices in composite indexing is inspecting metrics for skewness and mitigating its effects. Skewed data are distributed with many countries at one end of the spectrum of values and fewer countries spread into the opposite end. Such datasets pose problems on both empirical and theoretical grounds. When thresholds are selected by percentiles (see previous section), outliers can bias the scale by drawing thresholds into extreme ranges (see Nardo et al., 2008). Aggregating skewed datasets can also give undue emphasis to indicators with relatively small variation in scores among the clustered observations. On theoretical grounds, skewness also obscures differentiation between nations, reducing the usefulness of the indicator (see Wendling et al., 2020, pp. 171–172). Based upon statistical examination of our underlying datasets, it is warranted to transform certain indicators through a natural logarithmic normalization, namely, all indicators used in the GHG Emissions and Water Cycle sub-pillars, within both the Domestic and Spillover pillars. Data were transformed prior to scaling, and the thresholds were likewise also transformed.

Table 9. Thresholds used to score indicators in the 2022 GCS Index on a 1–100 scale.

		Proportional			Absolute	
Indicator	Unit	Upper Bound	Lower Bound	Unit	Upper Bound	Lower Bound
Domestic SO_2 emissions	kg/capita	0.87 [a]	64.39 [e]	Gg	1.10 [a]	7,551 [f]
Spillover SO_2 emissions	kg/capita	0.72 [a]	26.04 [f]	Gg	8.33 [a]	2,079 [f]
Domestic NO_X emissions	kg/capita	4.89 [a]	53.27 [e]	Gg	15.37 [a]	9,768 [f]
Spillover NO_X emissions	kg/capita	0.634 [a]	26.36 [d]	Gg	7.67 [a]	2,311 [f]
Domestic black carbon emissions	kg/capita	0.097 [a]	1.19 [c]	Gg	0.13 [a]	233.76 [f]
Spillover black carbon emissions	kg/capita	0.0279 [a]	1.00 [f]	Gg	0.24 [a]	100.91 [f]
Domestic GHG emissions	t CO_2e/capita	2 [h]	25.66 [e]	Tg	3.84 [a]	3,722 [f]
Spillover GHG emissions	t CO_2e/capita	0.41 [a]	13.87 [f]	Tg	4.91 [a]	1,614 [f]
CO_2 emissions embodied in fossil fuel exports	t CO_2e/capita	8.09E-09 [i]	43.15 [e]	Tg	1.55E-07 [a]	960.60 [f]
Unprotected terrestrial biodiversity sites	%	2.33 [a]	100 [j]	%	2.33 [a]	100 [j]
Unprotected freshwater biodiversity sites	%	4.17 [a]	100 [j]	%	4.17 [a]	100 [j]
Domestic land use related biodiversity loss	global PDF/capita	1.82E-14 [a]	7.44E-11 [e]	global PDF	3.53E-08 [a]	4.73E-03 [f]
Spillover land use related biodiversity loss	global PDF/capita	5.12E-13 [a]	1.70E-11 [e]	global PDF	6.52E-06 [a]	3.43E-03 [f]
Domestic freshwater biodiversity threats	per million people	2.00E-03 [a]	5.36 [d]	species	5.57E-03 [a]	256.62 [f]
Spillover freshwater biodiversity threats	per million people	2.21E-03 [a]	0.85 [e]	species	1.18E-02 [a]	120.55 [f]
Domestic deforestation	%	9.86E-06 [i]	1.32 [e]	hectares	0.39 [i]	1,333,792 [f]
Spillover deforestation	ha/capita	1.45E-04 [a]	6.89E-03 [e]	hectares	2,111.82 [a]	996,935 [f]
Red List Index of species survival	scale 0–1	0.9885 [g]	0.67 [b]	scale 0–1	0.99 [g]	0.67 [b]
Biodiversity Habitat Index	scale 0–1	0.9885 [g]	0.29 [a]	scale 0–1	0.99 [g]	0.29 [a]
Domestic export of CITES terrestrial animals	WOE/million	7.74E-09 [i]	9.50E-03 [f]	WOE	0.33 [i]	762,807 [f]
Spillover CITES terrestrial animals	WOE/capita	3.66E-09 [i]	8.46E-03 [e]	WOE	2 [i]	852,233 [f]

		Proportional			Absolute	
Indicator	Unit	Upper Bound	Lower Bound	Unit	Upper Bound	Lower Bound
Domestic export of CITES marine animals	WOE/million	9.50E-08 [i]	2.91E-03 [f]	WOE	5 [i]	194,728 [f]
Spillover CITES marine animals	WOE/capita	1.74E-08 [i]	1.55E-03 [f]	WOE	1 [i]	110,924 [f]
Unprotected marine biodiversity sites	%	3.40E-04 [i]	100 [j]	%	3.40E-04 [i]	100 [j]
Domestic marine biodiversity threats	per million people	6.11E-03 [a]	8.06 [f]	species	2.94E-02 [a]	272.66 [f]
Spillover marine biodiversity threats	per million people	2.79E-04 [a]	1.01 [f]	species	5.21E-03 [a]	122.50 [f]
Fish caught from overexploited or collapsed stocks	%	0.04 [i]	62.0 [e]	%	0.04 [i]	62.0 [e]
Fish caught by trawling	%	0.17 [i]	60.5 [e]	%	0.17 [i]	60.5 [e]
Domestic vulnerable fisheries catch	tonnes/capita	0.09 [a]	169.07 [e]	Tg	0.0008 [a]	12.48 [f]
Spillover vulnerable fisheries catch	tonnes/capita	0.19 [a]	73.12 [e]	tonnes	0.0056 [a]	6.04 [f]
Sustainable Nitrogen Management Index	scale 0–1.4	0.0115 [i]	1.15 [f]	scale 0–1.4	0.0115 [i]	1.15 [f]
Domestic nitrogen surplus	kg/capita	0.48 [b]	34.84 [d]	Gg	0.22 [a]	7,376 [f]
Spillover nitrogen surplus	kg/capita	0.12 [a]	22.35 [e]	Tg	2.54 [a]	1,672 [f]
Domestic phosphorus fertilizer	kg/capita	0.75 [b]	30.49 [d]	kt	6.10 [a]	6,968 [f]
Spillover phosphorus fertilizer	g/capita	0.37 [a]	9.06 [e]	kt	3.03 [a]	1,222 [f]
Domestic scarce water consumption	m^3/capita	0.035 [a]	233.29 [e]	Mm^3	0.019 [a]	40,822 [f]
Spillover scarce water consumption	m^3/capita	5.06 [a]	227.22 [f]	Mm^3	34.33 [a]	14,145 [f]
Domestic water stress	ML/capita	0.0072 [a]	15.51 [e]	Bm^3	0.0063 [a]	4,231 [f]
Spillover water stress	m^3/capita	0.199 [a]	9.14 [e]	Mm^3	1.91 [a]	564.13 [f]

Note: *PDF* = potentially disappeared fraction of species; *WOE* = whole organism equivalent
Rationale for bounds: *a* = 2.5th-percentile, *b* = 5th-percentile, *c* = 90th-percentile, *d* = 92.5th-percentile, *e* = 95th-percentile, *f* = 97.5th-percentile, *g* = expert judgment, *h* = international target, *i* = minimum non-zero observation, *j* = technical bound (all percentiles adjusted for outliers).

7. Weighting & Aggregation

Aggregating individual indicator scores to the levels of sub-pillars and pillars requires two choices. The first choice is to select how to weight each subcomponent. Within the sub-pillars, we weight each indicator equally, for the sake of simplicity. Within each pillar, we give the greatest weight, 75% of the total, to GHG Emissions, in recognition of the urgent importance of this impact on the Global Commons. The balance of the weight is distributed equally across the remaining five sub-pillars.

The second choice is the method of aggregation. While we used arithmetic means for the Pilot GCS Index, our subsequent analysis (Wendling et al., 2021) showed that this method allows countries to balance low scores on some indicators with high scores in others. This effect would be warranted if the indicators are compensatory, but on both theoretical and empirical grounds, this assumption is not warranted. Therefore, we use geometric means in the 2022 GCS Index, a method that results in a steeper penalty for low scores in any of the indicators.

8. Missing data

Data for our indicators may be missing for two reasons. First, data may not be applicable for a country due to its geography. For example, landlocked countries will have no indicators on marine resources. In these cases, no score is recorded, and the indicator and sub-pillar will receive no weight in the aggregation step. For spillover scores, however, even landlocked countries may import environmental impacts to Marine Biodiversity Loss, and so no such materiality filter is applied to these spillover indicators. Second, our data sources may fail to report relevant data. In these cases, missing values are imputed using the population-weighted means of the other countries in a given region. The only exception is the European Union: When observations are not available from, or computable from, original datasets, missing values are calculated from the population-weighted averages of the member states. We note here that there are some indicators for which we do not yet have absolute values. In these cases, the proportional values are used in both the absolute and proportional versions.

9. Dashboards

For ease of communicating the results, we provide a dashboard color for each score and for overall impacts. These colors classify countries on an ordinal scale by how seriously they are impacting the Global Commons (see Table 10).

Table 10. Legend for dashboard categories and trajectories in the 2022 GCS Index.

Dashboard Score	Impacts on the Global Commons
95–100	None or limited
90–95	Low
80–90	Medium-low
70–80	Medium-high
50–70	High
30–50	Very High
0–30	Extreme

Arrow	Meaning
↑	Projected to meet 2050 Threshold
↗	Projected to meet only 2030 Threshold
→	Insufficient progress toward threshold
↓	Trajectory headed in wrong direction

10. Trajectories

Because the 2022 GCS Index uses time-bound thresholds, this report includes an assessment of the trajectories of countries' impacts. The scores provide a snapshot of the level of impacts based on the most recent year of data, but we also calculate an annual average growth rate over the past five years of data. Projecting these growth rates into the future, we can determine whether countries are on- or off-track to meet sustainability threshold. We classify impacts into four categories (Table 10).

Interim thresholds are based on aggregate global impacts in proportional terms. Given the most recent levels of impact, we calculate the average annual growth rate for the world as a whole to meet the 2050 threshold. The interim threshold is then the projected value in the year 2030, which coïncides with the target date for many of the SDGs.

Even if a country is currently meeting the interim or 2050 threshold, we categorize their trajectory as being off-track if it is trending in the wrong direction. This would allow a country with a "green" dashboard to still receive a ↓ trajectory. We aggregate trajectories from indicators to higher levels using the methods described in Sachs et al. (Sachs et al., 2019, pp. 46–47).

References

Afionis, S., Sakai, M., Scott, K., Barrett, J., & Gouldson, A. (2017). Consumption-based carbon accounting: Does it have a future? Consumption-based carbon accounting. *Wiley Interdisciplinary Reviews: Climate Change*, *8*(1), e438. https://doi.org/10.1002/wcc.438

Ahyong, S., Boyko, C. B., Bailly, N., Bernot, J., Bieler, R., Brandão, S. N., Daly, M., De Grave, S., Gofas, S., Hernandez, F., Hughes, L., Neubauer, T. A., Paulay, G., Boydens, B., Decock, W., Dekeyzer, S., Vandepitte, L., Vanhoorne, B., Adlard, R., … Zullini, A. (2023). *World Register of Marine Species (WoRMS)*. WoRMS Editorial Board. https://www.marinespecies.org

BirdLife International. (2022). *World Database of Key Biodiversity Areas* [Data set]. http://www.keybiodiversityareas.org

Boulay, A.-M., Bare, J., Benini, L., Berger, M., Lathuillière, M. J., Manzardo, A., Margni, M., Motoshita, M., Núñez, M., Pastor, A. V., Ridoutt, B., Oki, T., Worbe, S., & Pfister, S. (2018). The WULCA consensus characterization model for water scarcity footprints: Assessing impacts of water consumption based on available water remaining (AWARE). *The International Journal of Life Cycle Assessment*, *23*(2), 368–378. https://doi.org/10.1007/s11367-017-1333-8

Chaudhary, A., Verones, F., de Baan, L., & Hellweg, S. (2015). Quantifying Land Use Impacts on Biodiversity: Combining Species–Area Models and Vulnerability Indicators. *Environmental Science & Technology*, *49*(16), 9987–9995. https://doi.org/10.1021/acs.est.5b02507

Cheung, W. W. L., Pitcher, T. J., & Pauly, D. (2005). A fuzzy logic expert system to estimate intrinsic extinction vulnerabilities of marine fishes to fishing. *Biological Conservation*, *124*(1), 97–111. https://doi.org/10.1016/j.biocon.2005.01.017

CITES. (2023). *The CITES species*. CITES. https://cites.org/eng/disc/species.php

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

European Commission Joint Research Centre. (2016a). *EDGAR (Emissions Database for Global Atmospheric Research) Community GHG Database version 6.0* [Data set]. https://edgar.jrc.ec.europa.eu/dataset_ghg60

European Commission Joint Research Centre. (2016b). *EDGAR (Emissions Database for Global Atmospheric Research) Global Air Pollutant Emissions version 5.0* [Data set]. https://edgar.jrc.ec.europa.eu/dataset_ap50

European Commission Joint Research Centre. (2019). *EDGAR (Emissions Database for Global Atmospheric Research) Global Air Pollutant Emissions version 6.1* [Data set]. https://edgar.jrc.ec.europa.eu/dataset_ap61

European Commission Joint Research Centre. (2022). *EDGAR (Emissions Database for Global Atmospheric Research) Community GHG Database version 7.0* [Data set]. https://edgar.jrc.ec.europa.eu/dataset_ghg70

FAO. (2020). *AQUASTAT Database* [Data set]. https://www.fao.org/aquastat/statistics/query/index.html?lang=en

FAO. (2022). *Fertilizers by Nutrient* [Data set]. https://www.fao.org/faostat/en/#data/RFN

Ferrier, S., Ware, C., Austin, J. M., Grantham, H. S., Harwood, T. D., & Watson, J. E. M. (2022). *An integrative indicator linking area-based actions to national and global outcomes for forest biodiversity*. EcoEvoRxiv. https://doi.org/10.32942/osf.io/3eyvs

Froese, R., Demirel, N., Coro, G., Kleisner, K. M., & Winker, H. (2017). Estimating fisheries reference points from catch and resilience. *Fish & Fisheries*, *18*(3), 506–526. https://doi.org/10.1111/faf.12190

Global Forest Watch. (2023). *Global | Dashboards | Global Forest Watch*. Global Forest Watch. https://www.globalforestwatch.org/dashboards/global/

Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S. V., Goetz, S. J., Loveland, T. R., Kommareddy, A., Egorov, A., Chini, L., Justice, C. O., & Townshend, J. R. G. (2013). High-Resolution Global Maps of 21st-Century Forest Cover Change. *Science*, *342*(6160), 850–853. https://doi.org/10.1126/science.1244693

Harfoot, M., Glaser, S. A. M., Tittensor, D. P., Britten, G. L., McLardy, C., Malsch, K., & Burgess, N. D. (2018). Unveiling the patterns and trends in 40 years of global trade in CITES-listed wildlife. *Biological Conservation*, *223*, 47–57. https://doi.org/10.1016/j.biocon.2018.04.017

Hoang, N. T., & Kanemoto, K. (2021). Mapping the deforestation footprint of nations reveals growing threat to tropical forests. *Nature Ecology & Evolution*, *5*(6), 845–853. https://doi.org/10.1038/s41559-021-01417-z

Hoskins, A. J., Harwood, T. D., Ware, C., Williams, K. J., Perry, J. J., Ota, N., Croft, J. R., Yeates, D. K., Jetz, W., Golebiewski, M., Purvis, A., Robertson, T., & Ferrier, S. (2020). BILBI: Supporting global biodiversity assessment through high-resolution macroecological modelling. *Environmental Modelling & Software*, *132*, 104806. https://doi.org/10.1016/j.envsoft.2020.104806

International Fertilizer Association. (2021). *IFASTAT* [Data set]. International Fertilizer Association. https://www.ifastat.org/databases/plant-nutrition

IUCN. (2022). *The IUCN Red List of Threatened Species. Version 2022-2*. [Data set]. https://www.iucnredlist.org

Jones, M. C., & Cheung, W. W. L. (2018). Using fuzzy logic to determine the vulnerability of marine species to climate change. *Global Change Biology*, *24*(2), e719–e731. https://doi.org/10.1111/gcb.13869

Kander, A., Jiborn, M., Moran, D. D., & Wiedmann, T. O. (2015). National greenhouse-gas accounting for effective climate policy on international trade. *Nature Climate Change*, *5*(5), 431–435. https://doi.org/10.1038/nclimate2555

Lenzen, M., Geschke, A., Abd Rahman, M. D., Xiao, Y., Fry, J., Reyes, R., Dietzenbacher, E., Inomata, S., Kanemoto, K., Los, B., Moran, D., Schulte in den Bäumen, H., Tukker, A., Walmsley, T., Wiedmann, T., Wood, R., & Yamano, N. (2017). The Global MRIO Lab – charting the world economy. *Economic Systems Research*, *29*(2), 158–186. https://doi.org/10.1080/09535314.2017.1301887

Lenzen, M., Geschke, A., West, J., Fry, J., Malik, A., Giljum, S., Milà i Canals, L., Piñero, P., Lutter, S., Wiedmann, T., Li, M., Sevenster, M., Potočnik, J., Teixeira, I., Van Voore, M., Nansai, K., & Schandl, H. (2022). Implementing the material footprint to measure progress towards Sustainable Development Goals 8 and 12. *Nature Sustainability*, *5*(2), 157–166. https://doi.org/10.1038/s41893-021-00811-6

Lenzen, M., Moran, D., Bhaduri, A., Kanemoto, K., Bekchanov, M., Geschke, A., & Foran, B. (2013). International trade of scarce water. *Ecological Economics*, *94*, 78–85. https://doi.org/10.1016/j.ecolecon.2013.06.018

Lenzen, M., Sun, Y.-Y., Faturay, F., Ting, Y.-P., Geschke, A., & Malik, A. (2018). The carbon footprint of global tourism. *Nature Climate Change*, *8*(6), 522–528. https://doi.org/10.1038/s41558-018-0141-x

Ludemann, C. I., Gruere, A., Heffer, P., & Dobermann, A. (2022). Global data on fertilizer use by crop and by country. *Scientific Data*, *9*(1), Article 1. https://doi.org/10.1038/s41597-022-01592-z

Mokany, K., Ferrier, S., Harwood, T. D., Ware, C., Di Marco, M., Grantham, H. S., Venter, O., Hoskins, A. J., & Watson, J. E. M. (2020). Reconciling global priorities for conserving biodiversity habitat. *Proceedings of the National Academy of Sciences*, *117*(18), 9906–9911. https://doi.org/10.1073/pnas.1918373117

Myhre, G., Shindell, D., Bréon, F. M., Collins, W., Fuglestvedt, J., Huang, J., Koch, D., Lamarque, J. F., Lee, D., Mendoza, B., Nakajima, T., Robock, G., Stephens, G., Takemura, T., & Zhang, H. (2013). Anthropogenic and Natural Radiative Forcing. In T. F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex, & P. M. Midgley (Eds.), *Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press. https://www.ipcc.ch/site/assets/uploads/2018/02/WG1AR5_Chapter08_FINAL.pdf

Nardo, M., Saisana, M., Saltelli, A., Tarantola, S., Hoffmann, A., & Giovannini, E. (2008). *Handbook on constructing composite indicators: Methodology and user guide*. OECD.

OECD. (2019). *Measuring Distance to the SDG Targets 2019: An Assessment of Where OECD Countries Stand*. OECD. https://doi.org/10.1787/a8caf3fa-en

Pauly, D., Zeller, D., & Palomares, M. L. D. (Eds.). (2020). *Sea Around Us Concepts, Design and Data*. seaaroundus.org

Peters, G. P., & Hertwich, E. G. (2008). Post-Kyoto greenhouse gas inventories: Production versus consumption. *Climatic Change*, *86*(1), 51–66. https://doi.org/10.1007/s10584-007-9280-1

Peterson, I., Selinske, M., Lenzen, M., & Moilanen, A. (2020). *The Ecological Cost Of Consumption* [Preprint]. In Review. https://doi.org/10.21203/rs.3.rs-46089/v1

Piñero, P., Sevenster, M., Lutter, S., & Giljum, S. (2021). *Technical documentation of the Sustainable Consumption and Production Hotspots Analysis Tool (SCP-HAT) Version 2.0*. Commissioned by UN Life Cycle Initiative, One Planet Network, and UN International Resource Panel. http://scp-hat.lifecycleinitiative.org/wp-content/uploads/2021/11/SCP-HAT-2.0_Technical-documentation_Oct2021_final02.pdf

Sachs, J. D., Lafortune, G., Fuller, G., & Drumm, E. (2023). *Sustainable Development Report 2023: Implementing the SDG Stimulus*. SDSN, Dublin University Press. https://doi.org/10.25546/102924

Sachs, J. D., Schmidt-Traub, G., Kroll, C., Durand-Delacre, D., & Teksoz, K. (2017). *SDG Index and Dashboards Report 2017. Global Responsibilities—International Spillovers in Achieving the Goals*. Bertelsmann Stiftung and Sustainable Development Solutions Network. http://sdgindex.org/

Sachs, J. D., Schmidt-Traub, G., Kroll, C., Lafortune, G., & Fuller, G. (2019). *Sustainable Development Report 2019. Transformations to achieve the Sustainable Development Goals.* Bertelsmann Stiftung and Sustainable Development Solutions Network. http://sdgindex.org/

Schmidt-Traub, G., Hoff, H., & Bernlöhr, M. (2019). *International spillovers and the Sustainable Development Goals (SDGs)* [SDSN Policy Brief]. Sustainable Development Solutions Network (SDSN).

Steffen, W., Richardson, K., Rockström, J., Cornell, S. E., Fetzer, I., Bennett, E. M., Biggs, R., Carpenter, S. R., de Vries, W., de Wit, C. A., Folke, C., Gerten, D., Heinke, J., Mace, G. M., Persson, L. M., Ramanathan, V., Reyers, B., & Sörlin, S. (2015). Planetary boundaries: Guiding human development on a changing planet. *Science*, *347*(6223), 1259855. https://doi.org/10.1126/science.1259855

The Sustainability Consortium, World Resources Institute, & University of Maryland. (2022). *Tree Cover Loss by Dominant Driver.* Global Forest Watch. www.globalforestwatch.org

UN Department of Economic and Social Affairs. (2022). *UN Comtrade Database* [Data set]. https://comtrade.un.org/data/

United Nations Environment Programme. (2020). *The Emissions Gap Report 2020*.

United Nations Environment Programme World Conservation. (2022). *CITES Trade Database* [Data set]. https://trade.cites.org

Vishwakarma, S., Zhang, X., & Mueller, N. D. (2022). Projecting future nitrogen inputs: Are we making the right assumptions? *Environmental Research Letters*, *17*(5), 054035. https://doi.org/10.1088/1748-9326/ac6619

Weisse, M., & Potapov, P. (2021, April 28). Assessing Trends in Tree Cover Loss Over 20 Years of Data. *Global Forest Watch*. https://www.globalforestwatch.org/blog/data-and-research/tree-cover-loss-satellite-data-trend-analysis

Wendling, Z. A., Emerson, J. W., de Sherbinin, A., Esty, D. C., & et al. (2020). *2020 Environmental Performance Index*. Yale Center for Environmental Law & Policy. epi.yale.edu

Wendling, Z. A., Miller, R., Dahir, S., Lafortune, G., Esty, D. C., Schmidt-Traub, G., Ishii, N., & Kawazaki, A. (2021). *Global Commons Stewardship Index: A Statistical Review of the Pilot Methodology* [Working Paper]. Sustainable Development Solutions Network (SDSN). https://irp.cdn-website.com/be6d1d56/files/uploaded/WP_GCSIndex_Pilot_Methods%2020210618.pdf

Wilcove, D. S. (2022). Conservation: Trading species to extinction? *Current Biology*, *32*(7), R313–R315. https://doi.org/10.1016/j.cub.2022.02.070

Zhang, X., Wang, Y., Schulte-Uebbing, L., Vries, W. D., Zou, T., & Davidson, E. A. (2022). Sustainable nitrogen management index: Definition, global assessment and potential improvements. *Frontiers of Agricultural Science and Engineering*, *0*(0), 0. https://doi.org/10.15302/J-FASE-2022458

Zhang, X., Zou, T., Lassaletta, L., Mueller, N. D., Tubiello, F. N., Lisk, M. D., Lu, C., Conant, R. T., Dorich, C. D., Gerber, J., Tian, H., Bruulsema, T., Maaz, T. M., Nishina, K., Bodirsky, B. L., Popp, A., Bouwman, L., Beusen, A., Chang, J., … Davidson, E. A. (2021). Quantification of global and national nitrogen budgets for crop production. *Nature Food*, *2*(7), 529–540. https://doi.org/10.1038/s43016-021-00318-5