METHODOLOGICAL REPORT

Impact measurement using WifOR's sustainability footprint method

Upstream calculation: Methodological background and data sources

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1 Methodological Background

This technical report describes the method of upstream impact calculation used and gives an overview of the required data sources and respective extrapolations which were necessary to meet the needs of WifOR's sustainability footprint methodology.

Upstream impacts can be evaluated using either a bottom-up or top-down approach. A widely used bottom-up approach is the process-based lifecycle assessment (LCA). Another is the collection of suppliers and / or sales data. The advantage of this method is the predominant use of primary data. However, the results are product or vendor specific and represent only a fraction of a company's overall impact. It is also considered a labor-intensive task.

In contrast, the top-down approach relies primarily on secondary data. A popular methodology is the Input-Output-Analysis (IO-Analysis which detects environmental and socio-economic hotspots with comparatively low effort. IO-Analysis is frequently used to estimate the up- and downstream impacts in a company's supply chain or of an economic sector. Unlike process-based methods, IO Analysis has a broader scope, enabling the evaluation of an entire value chain. It utilizes primary financial data (a detailed list with region-specific information regarding the amount and type of goods purchased and sold) that are then translated into economic, socio-economic, and environmental indicators.

As both approaches deliver valuable results, efforts were made to match bottom-up and top-down approaches (Beylot, Corrado, and Sala 2019). Integrating results from bottom-up assessments into the top-down Input-Output-Framework improves data quality without restricting the scope of analysis.

Input-Output analysis was originally developed by Wassily Leontief (Leontief 1936) to describe the industrial structure of an economy and understand how changes in one economic sector may affect other sectors. Leontief's pioneering work earned him the Nobel Prize in Economics in 1973. Applying the technique of IO-Analysis, it is possible to trace the inputs of production along the entire supply chain. In addition to the direct effects, which describe the immediate effects directly generated by a company, IO-Analysis allows for the calculation of (indirect) upstream effects. Upstream effects arise from the input a company demands from other economic agents. For example, order placements result in an increase of economic activity not only at commissioned agents, but also among their suppliers. This ripple effect increases the gross value added (GVA) and other key indicators along the supply chain, which are summarized under the term upstream effects. While the model is based on an array of assumptions[1], it is widely regarded as a robust tool for conducting impact analysis.

The basis for the calculation of indirect effects can be illustrated by the following equilibrium equation:

$$x = Ax + y \leftrightarrow x = (I - A)^{-1}y \qquad (1)$$

where x represents the vector of total gross output of a sector and y represents the vector of final demand and includes domestic consumer spending, assets, changes in inventories and exports. A represents the matrix of intermediate consumption per unit of output.

Equation (1), with $L = (I - A)^{-1}$ being the Leontief inverse, can be determined by the following mathematical transformation:

$$x = Ax + y$$

$$y = x - Ax$$

$$y = (1 - A)x$$

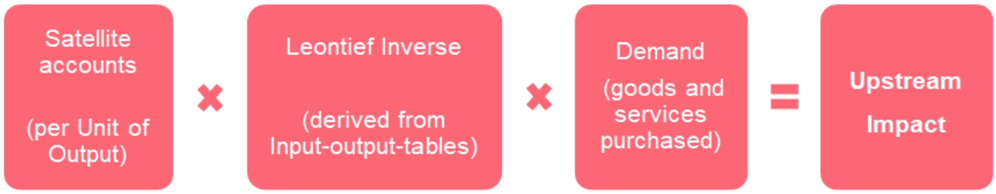
since $(I - A)^{-1} * (I - A) = 1$, with I being the identity matrix, $x = \frac{y}{1-A}$ equals

$$x = (1 - A)^{-1}y$$

[1] The assumptions of the Leontief model are: 1) Constant returns to scale, meaning that regardless of the level of production, the same quantity of inputs is needed per unit of output. 2) No Supply Constraints, meaning there are no restrictions to raw materials, services or other inputs such as employment. 3) Fixed Input Structure: meaning that there is no input substitution in response to a change in output.

With x, the output triggered by a given demand y, the corresponding GVA can be derived using country and sector specific ratios of GVA to output. Other effects (e.g. employment, air emissions, water pollution etc.) are calculated analogously using respective satellite accounts. In simple terms, the indirect (upstream) impact of a company is the result of the multiplication of three components (see *Figure 1*).

Figure 1: Components of upstream calculation



Source: Own depiction

As shown in *Figure 1*, the calculation of upstream impacts requires input-output tables to derive the Leontief Inverse, corresponding satellite accounts, and a detailed purchasing list / spend of the company under investigation. The next chapter describes a detailed explanation of the data sources used, along with the extrapolations performed.

2 Data Sources Base Year

2.1 Input-output-tables

When it comes to company-specific impact assessments using economic input output tables and the Leontief Inverse, selecting the appropriate data sources is crucial. The chosen data significantly influences the magnitude and respective characteristics of the impact factor being analyzed. There is no one-fits-all solution regarding the choice of the base data to use.

The compilation of input-output tables (IOT) is described in the System of National Accounts (European Commission et al. 2009). Similarly, the compilation of environmental satellite accounts is outlined in the System of Environmental-Economic Accounting (United Nations 2014). National statistical offices are responsible for producing these tables, which are particularly well suited for calculating and organization's national economic footprint.

To analyze global value chains and the increasing international fragmentation of production, a multi-regional input-output table (MRIOT) is needed. These kinds of tables can be regarded as a set of national input-output tables that relate to each other by bilateral international trade flows. They provide comprehensive summaries of all transactions in the global economy between industries and final users across countries in a particular year.[2]
The estimation of a multi-regional IOT requires significant individual data and computation capability and is labor intensive. For a detailed multi-regional IOT, it would be necessary to measure worldwide economic transactions consistently and uniformly across all sectors and production stages of the

[2] To date, statistical offices do not produce official MRIOs. One exception is the experimental FIGARO MRIO tables produced by Eurostat.

economy. Since such an approach is not feasible, MRIOTs are constructed with the help of national accounts and trade data.

The currently available tables differ with respect to the data sources, construction philosophy and the selection of countries. Not surprisingly, there are a lot of different approaches to deal with data gaps and inconsistencies. Each dataset was developed for specific questions with different intentions. Different methods were used in each case. This even leads to limited comparability of MRIOTs, which is a well-known and discussed phenomenon within the scientific community (Tukker and Dietzenbacher 2013; Arto, Rueda-Cantuche, and Peters 2014; Inomata and Owen 2014; Moran and Wood 2014; Owen 2017; Owen et al. 2014; 2016; Wieland et al. 2018; Giljum et al. 2019). Various data sources / models / IO Tables deliver different results (and operative conclusions) despite using the same model inputs (company spend and sales data).

The most prominent MRIO data sets (and related references) used for impact assessment are:

- FIGARO (Remond-Tiedrez and Rueda-Cantuche 2019; Eurostat and European Commission 2018; Eurostat 2008)
- OECD ICIO (Yamano and Webb 2018; Guilhoto et al. 2019)
- EORA (Lenzen et al. 2013; 2012)
- GTAP (Center for Global Trade Analysis, Purdue University et al. 2019; Walmsley, Aguiar, and Narayanan 2012)
- WIOD (Gouma et al. 2018; Timmer et al. 2016; 2015; Amores et al. 2019)
- ADB MRIO (Mariasingham 2011)
- EXIOBASE (Stadler et al. 2018; Tukker et al. 2013; Wood et al. 2014)
- Global MRIO Lab (Lenzen et al. 2017)

All selected databases have different methodical backgrounds and properties regarding regional, temporal, and sectoral coverage. Most of them are updated regularly and are therefore available in different versions, and they are differently equipped with additional information with respect to economic, environmental, and social satellite accounts (see Table 1 for an overview). A rigorous impact analysis framework relies on the choice of an appropriate model for the measurement and analysis of various impact factors of a company. The correct data choice makes it possible to adapt the modelling framework to the needs of the company more easily.

Table I: Overview of relevant MRIO Datasets

Source	Version	Resolution			sectoral classification standard	Satellite Accounts			License	Regular update	Institution	Info
		regional	temporal	sectoral		Economic	Environmental	Social				
FIGARO	experimental	27 Countries (EU-28 and USA)	2010 (production of time series in progress)	64 industries	ISIC Rev. 4	yes	not ready to use	not ready to use	free	experimental version, yearly updates and time-series planned	Eurostat	https://ec.europa.eu/eurostat/web/experimental-statistics/figaro
OECD ICIO	2018	65 Countries (37 OECD, 29 non-OECD, 1 RoW)	2005-2015	34 industries	ISIC Rev. 4	yes	not ready to use	not ready to use	free	yes	OECD	http://oe.cd/icio
EORA	EORA	187 countries	1990-2016	varying across countries; simplified version with 26 industries	ISIC Rev. 3	yes	good coverage (GHG, land, water, air pollution and biodiversity etc.)	no	not free	yes	KGM & Associates Pty (originally University of Sydney)	https://worldmrio.com/
EXIOBASE	3.8.1	44 countries, (5 RoW Aggregates)	1995-2024	163 industries, 200 products	ISIC Rev. 3	yes	very good coverage (Energy supply and use, GHG emissions, pollutants, water use, land use, material flows, nitrogen loads, phosphorus loads, LFC impact coefficients, etc.)	yes, few indicators are available (e.g. employment by skill-level and gender)	free	yes	Norwegian University of Science and Technologiy	http://exiobase.eu
GTAP	Version 10	121 Countries (20 RoW Aggregates)	2004, 2007, 2011, 2014	65 industries	ISIC Rev. 4	yes	good coverage (Co2 emissions, Energy volumes, land use)	Five labor skill categories	$320 - $6,240 (Versions 1 to 8 can be downloaded for free)	yes, on irregular basis	Center for Global Trade Analysis, Department of Agricultural Economics,Purdue University	https://www.gtap.agecon.purdue.edu/databases/v10/index.aspx
ADB MRIO	2019	62 countries (1 RoW)	2000, 2007-2018	varying SUT dimensions, harmonized to 35 industries	ISIC Rev. 3	yes	no	no	free	planned	Asian Development Bank	http://mrio.adbx.online/
WIOD	Release 2016	44 countries, 1 ROW	2000-2014	57 industries (some Zero-Sectors available)	ISIC Rev. 4	yes, full set of socio-economic variables	good coverage (GHG Emissions, Gross and emission relevant energy-use estimated by JRC, other environmental indicators just available for previous version)	labor by skill-level available for previous versions	free	yes, on irregular basis (depends on funding)	University Groningen	http://www.wiod.org
Global MRIO-Lab	-	All	as long as available	flexible (more than 5700 products)	flexibel	yes	covered (data availability depends on project purpose and sectoral resolution)	covered (data availability depends on project purpose and sectoral resolution)	depends on the workload	yes, realtime in nature	University of Sydney	https://ielab.info/

Source: Own depiction based on references and inspection of data.

To meet the needs of the sustainability footprint methodology, we employ a custom hybrid model that combines WIOD (high sectoral resolution and robust economic base-data), EORA (large country coverage) and EXIOBASE (extensive indicators available within the satellite accounts). In the current version, the WIOD database shows the global interdependence of 56 economies. It allows the analysis of the international interdependencies of 43 countries and an aggregate that summarizes the rest of the world. To be able to extend the impact analysis to other countries, this aggregate was distributed among the individual countries using the information from EORA. Due to the higher country resolution of EORA, a total of 188 countries and 57 sectors can be analyzed.

2.2 Satellite accounts

Satellite accounts are important extensions of MRIOT's, enabling the linkage of monetary flows of goods and services to other indicators of interest. The databases referred above already include a range of economic, environmental, and social indicators, such as land- and sector-specific data on gross value added, employment, compensation of employees, greenhouse gas emissions, water consumption, and land use.
However, the requirements of additional socio-economic and environmental indicators (see Table 2) could not be fulfilled using available MRIO datasets. As a results, we supplemented these datasets by gathering additional indicators from other sources and adapting them to align with the sectoral and geographical structure of the MRIO.

Table II: Scope of indicators

Economic	• Gross Value Added (GDP contribution) • Employment
Human & Social	• Child Labor • Disability Discrimination • Forced Labor • Freedom of Association • Gender Discrimination • Human Capital / Training • Land Eviction • Living Wages • Occupational Health & Safety • Rule of Law

	• Working Overtime
Environmental	• Air Emissions • GHG Emissions/Projections • Invasive Alien Species • Land Use • Resource Use • Resource Use - Wood • Waste • Water Consumption • Water Pollution

Source: WifOR

When creating the satellite accounts, we first determined whether the indicators and the respective specifications are available in a primary source / MRIO Database and mapped them onto the structure of our table. This was the case for GVA, GHGs, Air Pollution, Water Consumption, Land use and partially for supply of waste and water pollution. The remaining were not available, so we had to build the whole satellites on our own. This chapter describes the indicators and gives an overview of the relevant definitions and sources.

2.2.1 Economic indicators

2.2.1.1 GVA (GDP contribution)

Definition

Output (at basic prices) minus intermediate consumption (at purchaser prices). GVA can be broken down by industry and institutional sector. The sum of GVA across all industries or sectors plus taxes on products minus subsidies on products gives gross domestic product (GDP). The GVA thus captures the contribution to GDP.

Primary Sources

- World Input Output Database (WIOD)
- EORA

Additional Sources

- Eurostat National Accounts (Table “nama_10_a64”)
- OECD National Accounts (Table “SNA_TABLE6A”)

	Eurostat	OECD	WIOD	EORA	IMF (Forecasts)
Data Source	https://ec.europa.eu/eurostat/data/database Table «nam_10_64»	https://stats.oecd.org/ Table «SNA_TABLE 6A»	https://www.rug.nl/ggdc/valuechain/wiod/wiod-2016-release?lang=en	https://www.worldmrio.com/	World Economic Outlook (WEO) Database (imf.org)
Frequency of update	Multiple times a year	Yearly	Non regular	Non regular	Yearly
Country coverage (extent & scope)	27 European countries	16 Non-EU OECD countries	6 Non-EU Non OECD countries	Rest of the World	197 countries
Sector granularity	64 sectors aggregated to 57	Chemical & Pharmaceutical sectors combined	56 sectors	-	None
% of global value	~19%	~36%	~16%	~24%	~100%
Reliability (1-5)	5	5	4	2	3
GVA Rate (GVA/Output)	**Average: 0.85** Country Range: 0.2 to 0.9 Sector Range: 0 to 0.79				

Publisher	Statistical Authority	Statistical Authority	University (large research consortium)	University	International Organization

Data processing

There is full country coverage of economic variables by existing satellites of MRIO Sources. The additional sources are used to get the most recent values.

Estimation procedure

Eurostat and OECD offer reliable data on GVA across various levels of aggregation. For other countries, estimates were generated by distributing the values from the WIOD Rest-of-the-World aggregate to EORA countries based on output shares. Data is provided up to the present, and any forecasts are based on the IMF's World Economic Outlook.

Unit of measure

Million USD

2.2.1.2 Employment

Definition

The employment level is defined as the number of people engaged in productive activities in an economy. The concept includes both employees and the self-employed.

Primary Sources

- World Input Output Database (WIOD)
- EORA
- ILO Database

Additional Sources

- Eurostat (Table “nama_10_a64e”)
- OECD (Table “SNA_TABLE7A”)

	WIOD	EORA	Eurostat	OECD	ILO
Data Source	https://www.rug.nl/ggdc/valuechain/wiod/wiod-2013-release	https://www.worldmrio.com/	https://ec.europa.eu/eurostat/databrowser/view/nama_10_a64/default/table?lang=en Table «nama_10_a64»	OECD Data Explorer - Archive • 7A. Labour input by activity, ISIC rev4, 2019 archive Table «SNA_TABLE7A»	https://rshiny.ilo.org/dataexplorer44/?lang=en&id=POP_XWAP_SEX_DSB_LMS_NB_A «POP_XWAP_SEX_DSB_LMS_NB_A» «EAR_4MTH_SEX_DSB_CUR_NB_A»
Frequency of update	Non regular	Non regular	Yearly	Yearly	Monthly
Country coverage (extent & scope)	6 Non-EU Non OECD countries	Rest of the World	EU27 and 12 European countries	OECD countries	114/93 countries
Sector granularity	56 sectors	-	56 sectors	56 sectors	-
% of global value	-	shares	~9%	~13%	~30%
Reliability (1-5)	4	2	5	5	3
Employment Rate (EMP/Output)	**Average: 0.07** Country Range: 0.0006 to 0.71 Sector Range: 0.012 to 0.57				
Publisher	University (international research consortium)	University	Statistical Authority	International Organization	Statistical Authority

Data processing

There is nearly full country coverage of economic variables by existing satellites of MRIO Sources. WIOD is used as the main source accompanied with EORA employment shares for countries missing in WIOD. Missing or implausible values in EORA are filled with the help of the ILO employment data. The additional sources are used to get the most current values.

Unit of measure

Thousand persons

2.2.2 Environmental indicators

2.2.2.1 Air Pollution

Definition

Air pollution is the presence of substances in the atmosphere that are harmful to the health of humans and other living beings, or cause damage to the climate or to materials. There are different types of air pollutants, such as gases, particulates, and biological molecules. Both human activity and natural processes can generate air pollution.

Sub indicators

- Ammonia (NH_3)
- Nitrogen Oxides (NO_x),
- Sulfur Oxides (SO_x)
- Non-Methane Volatile Organic Compounds (NMVOC)
- Particulates ($PM_{2.5}$, PM_{10})

Specifications

Four locations:

- Urban
- Peri-urban
- Rural
- Transport

Primary Sources

- EDGAR v8.1
- EXIOBASE 3.8.1.
- EORA

Additional Sources

- Eurostat Air Emission Accounts (Table “env_ac_ainah_r2”)
- OECD Air Emission Accounts (Table “AEA”)
- OECD Air Transport CO2 emissions (Table "AIRTRANS_CO2”)
- UNCTAD Merchant fleet by country of beneficial ownership, annual
- Location mapping

	EDGAR	EXIO	EORA	Eurostat	OECD		UNCTAD
Data Source	JRC (European Comission), version 8.1	EXIOBASE version 3	https://www.worldmrio.com/	https://ec.europa.eu/eurostat/databrowser/view/env_ac_ainah_r2/default/table?lang=en Table «env_ac_ainah_r2»	https://stats.oecd.org/Index.aspx?DataSetCode=AEA Air Emission Accounts «Table AEA»	https://stats.oecd.org/ Table «AIRTRANS_CO2»	https://unctadstat.unctad.org/datacentre/ Table «Merchant fleet by country of beneficial ownership, annual»
Frequency of update	Yearly	-	Non regular	Yearly	Yearly		Yearly
Country coverage (extent & scope)	All Countries	44 countries, 5 Rest of the World regions	Rest of the World	EU 27 and 9 European countries	EU 27 and 13 Non-EU OECD countries	186 countries	241 countries and regions
Sector granularity	Inventories	163 sectors aggregated to 57	-	56 sectors	89 sectors	Aviation sector	-
% of global value (only NO_x)	91.7%	Only shares	Only shares	7.5%	0%	Only shares	Only shares
Reliability (1-5)	5	4	2	5	5		5
Air Pollution Rate 2023 (only NO_x)	**Average: 3,029.93 kg/mUSD** Country Range: 23.02 to 31,058.9 kg/mUSD Sector Range: 18.7 to 42,854.9 kg/mUSD						
Publisher	International Organization	University (international research consortium)	University	Statistical Authority	Statistical Authority		International Organization

Data processing

There is full country coverage of indicators by existing satellites of MRIO Sources. EXIOBASE has a higher sectoral disaggregation than WIOD (163 versus 57 sectors) so that we had to map the EXIOBASE sectors into the WIOD classification. Data from EORA is used to get the values for all sectors in 188 countries. The transformed EXIOBASE data (with aggregated sectors and disaggregated regions) serves as a basis for the sectoral split of emissions within each of the 188 countries.

We then consider EDGAR data. It contains total emissions for all air pollutants for all 188 countries. While the data contains emission inventories, it also delivers international sea and air emissions. These emissions are distributed to countries according to the residence principle to derive air pollutant accounts for each country. The distribution of international sea emissions is done according to UNCTAD's data set on Merchant fleet by country of beneficial ownership (UNCTAD, 2024). Each country receives a share of international sea emissions according to its share in global ship ownership in terms of deadweight tons (not number of ships). International air emissions are distributed according to OECD's Air Transport CO_2 emissions data set, which we use to calculate the exact yearly amount of CO_2 emissions attributable to a country based on the residence principle. As a second step, the yearly share of each country within OECD's total international emissions is calculated. Under the assumption that international air transport air pollution has similar shares as CO_2, these shares are used to distribute EDGAR international air pollution.

Moreover, for some countries, EDGAR gives only combined values. It combines Serbia and Montenegro, Israel and Palestine, Italy and San Marino, Sudan and South Sudan, France and Monaco, Spain and Andorra, Switzerland and Liechtenstein. To separate the emissions for these pairs, we use the gross output of each country. For example, the 2022 yearly NO_x emissions of France and Monaco are distributed to each country according to the 2023 share of each country in their combined gross output. All the other country pairs and years are calculated analogously.

The EDGAR data contains values for each year from 2014 (beginning year for WifOR's dataset) until 2022. The total country values for all air pollutants were distributed to sectors according to the transformed EXIOBASE dataset.

Moreover, for countries covered by both Eurostat, OECD and EDGAR, Eurostat was used as the preferred source over EDGAR. For countries covered by OECD and EDGAR, OECD was used as the preferred source.

Depending on where emissions are released, the magnitude of air pollutants varies. Therefore, a split between four main locations (urban, peri-urban, rural and transport) was done.

Unit of measure

Kilograms

2.2.2.2 GHG

Definition

Emissions of greenhouse gases (GHGs) induce global warming by creating a greenhouse effect in the earth's atmosphere. Due to climate change, we will experience an increase in extreme weather events and rising sea levels, as well as a decrease in surface and ground water resources. Greenhouse gases included in the analysis are the most contributing and dominating ones: carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O) and F-gases (NF_3, SF_6, HFCs, HCFCs, PFCs). GHGs are accounted for according to their global warming potential (GWP), whereby CO_2 is taken as a baseline and the GWP of other gases is measured relative to the same mass of CO_2 (called CO_2 equivalents, short CO_2e). They are evaluated for a specific timescale, in this case a 100-year time horizon. The applied GWP factors are in line with the sixth assessment report of the inter-governmental panel on climate change (IPCC). More specifically we use the following GWPs: CO_2: 1 CO_2e; CH_4: 29.8 CO_2e; N_2O: 265 CO_2e.

Air pollution, and (greenhouse gas) GHG emissions as a part of it, can be measured according to two different approaches, as air emission accounts and air emission inventories. They differ in the principles they follow: Emission accounts are built according to the residence principle, while inventories follow the territorial principle[3]. Thus, one country's accounts measure the emissions of all residents of this country, irrespective of where these residents are located, while its inventories measure the emissions occurring on its territory, irrespective of whether the emitter is a resident or not. Because the residence principle is consistent with national accounts, a satellite with GHG emissions must contain the GHG accounts, not inventories. However, GHG emission data is usually collected as inventories. The only exceptions are Eurostat and OECD that report both inventories and accounts.

Primary Sources

- WIOD
- EDGAR v8.0

Additional Sources

- Eurostat Air Emission Accounts (Table "env_ac_ainah_r2")
- OECD Air Emission Accounts (Table "AEA")
- OECD Air Transport CO2 emissions (Table "AIRTRANS_CO2")
- Global Warming Potentials (based on the IPCC's Sixth Assessment Report AR6)
- EORA
- UNCTAD Merchant fleet by country of beneficial ownership, annual

[3] Eurostat: https://ec.europa.eu/eurostat/cache/metadata/en/env_ac_ainah_r2_sims.htm.

	Eurostat	OECD		EDGAR	WIOD	EORA	UNCTAD
Data Source	https://ec.europa.eu/eurostat/data/database Table «env_ac_ainah_r2»	https://stats.oecd.org/ Table «AEA»	https://stats.oecd.org/ Table «AIRTRANS_CO2»	JRC (European Comission), version 8.0	https://www.rug.nl/ggdc/valuechain/wiod/wiod-2013-release	https://www.worldmrio.com/	https://unctadstat.unctad.org/datacentre/ Table «Merchant fleet by country of beneficial ownership, annual»
Frequency of update	Multiple times a year	Yearly		Yearly	Non regular	Non regular	Yearly
Country coverage (extent & scope)	27 European countries	16 Non-EU OECD countries	186 countries	All Countries	6 Non-EU Non OECD countries	Rest of the World	241 countries and regions
Sector granularity	64 sectors aggregated to 57	64 sectors aggregated to 57	Aviation sector	Inventories	56 sectors	-	-
% of global value	11%	25%	Only shares	64%	Only shares	Only shares	Only shares
Reliability (1-5)	5	5		5	4	2	5
GHG Rate 2023 (GHG/Output)	**Average: 0.83 kg CO2eq/USD** Country Range: 0.007-6.00 Sector Range: 0.059-2.83						
Publisher	Statistical Authority	Statistical Authority		International Organization	University (large research consortium)	University (large research consortium)	International Organization

Data processing

Regarding the main types of GHGs (CO_2, CH_4, N_2O), there is full country coverage of indicators by existing satellites of MRIO Sources. WIOD has a higher sectoral disaggregation than EORA (57 versus 26 sectors) such that we mapped the WIOD sectors onto the EORA classification. Data from EORA is used to get the values for all sectors in 188 countries. The combined GHG data from WIOD and EORA serves as a basis for the sectoral split of emissions within each of the 188 countries.

We then consider EDGAR data. It contains total emissions for CO_2, CH_4, N_2O for all 188 countries. While the data contains emission inventories, it also delivers international sea and air emissions. These emissions are distributed to countries according to the residence principle to derive GHG emission accounts for each country. The distribution of international sea emissions is done according to UNCTAD's data set on Merchant fleet by country of beneficial ownership (UNCTAD, 2024). Each country receives a share of international sea emissions according to its share in global ship ownership in terms of deadweight tons (not number of ships). International air emissions are distributed according to OECD's Air Transport CO_2 emissions data set, which we use to calculate the exact yearly amount of CO_2 emissions attributable to a country based on the residence principle. As a second step, the yearly share of each country within OECD's total international emissions is calculated and used to distribute EDGAR international air emissions (not only for CO_2, but also CH_4 and N_2O).

Moreover, for some countries, EDGAR gives only combined values. It combines Serbia and Montenegro, Israel and Palestine, Italy and San Marino, Sudan and South Sudan, France and Monaco, Spain and Andorra, Switzerland and Liechtenstein. To separate the emissions for these pairs, we assume that the total emissions ratio between each pair of countries is constant over time (e.g., Italy has the same ratio of the combined emissions with San Marino each year). Then, an allocation ratio was established using each country's emissions data from the combined WIOD and EORA dataset, allowing for the distribution of combined emissions to the individual countries. For example, Italy's emissions for a given year are calculated as a portion of the combined emissions for Italy and San Marino, based on Italy's share of the total emissions for both countries as provided in the WIOD-EORA dataset. The EDGAR data contains values for each year from 2014 (beginning year for WifOR's dataset) until 2022. The total country values for CO_2, CH_4, N_2O were distributed to sectors according to the combined WIOD-EORA dataset.

Additionally, EDGAR contains data for F-gases. This data was distributed to economic sectors based on Eurostat's Technical Note on "Allocating emissions of fluorinated gases to NACE industries in air emissions accounts" (Eurostat, 2017).

Lastly, for countries covered by both Eurostat, OECD and EDGAR, Eurostat was used as the preferred source over EDGAR. For countries covered by OECD and EDGAR, OECD was used as the preferred source.

Unit of measure

Kilograms

2.2.2.3 GHG Projections, Scenarios and Pathways

Future GHG emissions will have significant impact on societies and, hence, companies. In order to capture these developments, we provide short and long-term GHG forecasts drawn from climate models used for the IPCC report. Three fundamental ways of thinking about future GHG emissions can be distinguished. Each is connected to different methods:

Scenario	Projections of what *can* happen by creating plausible, coherent, and internally consistent **descriptions of possible climate change futures**. *Not* a forecast of what will happen but used to compare different potential trajectories and implications of various developments and actions.	How *could* the future unfold?
Pathway	Plausible, coherent, and internally consistent descriptions of **pathways towards certain goals**, e.g., limiting global warming to 2°C, or achieving certain SDGs.	What *should* happen to reach a certain goal?
Near-term Projection	Projection of what is **likely** to happen in the coming years given current policies.	What will *likely* happen based on current status?

Source: WifOR

Near-term projections are used for developing the forecast until 2030, as these reflect the implications for current policies. Scenarios represent a long-term view given different assumptions about socio-economic developments and the GHG emission trajectory and hence different extents of radiative forcing leading to temperature change.

Studies on future GHG emissions are typically performed for sectors that are akin to emission *inventories*, i.e., they are process-based. For example, they distinguish between energy-based emissions, emissions due to specific industrial processes (not their energy use) or as cattle emit methane. In IO tables, however, the satellite accounts are emission *accounts,* i.e. based on economic activities. Emission accounts can include different emission inventory types. For example, animal rearing activities lead to emissions through cattle as well as from tractors burning fossil fuels, which are two different processes. Absolute values in IO satellite accounts can thus not be directly compared with sources on future emissions.

To generate forecasts for emission accounts, we first identify which process-sectors are the main drivers of emissions in each economic sector. We invert the “Eurostat Correspondence Table”, showing for each process-based category the NACE sectors in which they occur. This basic mapping can then be adjusted to the specific differentiations of emission inventories in the different data sources.

The forecast of emission accounts is then done based on the development of the dominating process-sectors. For this purpose, we calculate the percentage changes of the process-sectors' emissions for each year relative to the latest year for which actual emissions are available.

Near-term projections

A variety of academic studies and governmental data can be used for the construction of a "likely" or "realistic" near-term forecast. A summary of relevant sources identified is provided in the table on the following page.

We use EEA (2019/2020) and CAT sectoral detail (2020) for the countries available. For all other countries, the IEA (2021) projections for CO2 and US EPA (2019) projections for CH4 and N2O are used. The resulting individual gas emissions are then aggregated using the same warming potentials as described for the base year. Missing years are interpolated linearly.

	Source	Description	Regional coverage	Sectors	Years
GHG	**European Environmental Agency (EEA)** (2019/20)	States' harmonized projections with ***existing measures***, taking into consideration any policies and measures adopted at Union level	EU 27, United Kingdom, Iceland, Norway, Liechtenstein	UNFCCC Common Reporting Framework (CRF) level 1	Yearly until 2035
	Climate Action Tracker (CAT) sectoral detail (2020)	Projected emissions based on ***current policies*** (min & max estimates)	China, USA	Agriculture, Industry, Transport, Waste; Total fossil CO2 emissions	2025,2030, 2050
	Climate Action Tracker (CAT) total (2020/21)	Post-covid emission projections based on ***current policies*** (min & max estimates)	30 major economies not in EEA	Total	Yearly until 2030
CO2	**IEA STEPS model** (from Net Zero 2050 Report 2021)	Stated Policies Scenario: takes account only of specific ***policies that are in place or have been announced*** by governments.	"Advanced" vs. "emerging & developing" countries	Electricity, Industry, Transport, Buildings, Other	2020-50 in 5-year steps
CH4 & N2O	**US EPA** (2019)	Harmonized ***BAU baseline*** with fixed emission factors. Does not model policies explicitly but does incorporate historic emission declines	175 countries	Agriculture, Energy, Industrial Processes, Waste	Yearly until 2050

Table 3: Summary of Key Sources for Near-Term Emission Forecasts (source: own illustration)

Scenarios

As for the near-term projections, there are a large number of studies providing future emission scenarios for emission inventories. An overview of identified sources is provided in the Table 6.

The scenarios are outcomes of the Coupled Model Intercomparison Projects (CMIP), serving as the modelling backbone for the IPCC report.

The CIMP6 scenarios have several advantages:

- Broad range of possible futures covered.
- Scenarios form the basis for IPCC 6th Assessment Report, have been developed in long, comprehensive, collaborative, and peer-reviewed processes.
- Region/country- and sector-specific projections for CO2, and CH4, global projection for N2O. Region/country- and sector-specific projections for other air pollutants (NH3, NOx, Sulfur, VOC) are also available.
- Further available information (e.g., GDP, population by education levels) which might be used to enhance economic and employment forecasts in the future.

In the CIMP scenarios, five different so called Shared Socio-Economic Pathways (SSPs) are considered. Those five pathways set the baseline for storylines describing the future socio-economic development of the planet which is necessary to obtain emission scenarios. Table 4 provides an overview of the storylines.

SSP1 Taking the Green Road: A world of sustainability-focused growth and equality	• Gradual but pervasive shift towards a more sustainable path; more inclusive development that respects perceived environmental boundaries • Rapid technological development, relative global equality of income and focus on environmental sustainability • Increasing commitment to achieving SDGs • Consumption oriented towards low material growth & lower resource and energy intensity
SSP2 Middle of the Road: Trends broadly follow their historical patterns	• Development and income growth proceeds unevenly • Global and national institutions work toward but make slow progress in achieving SDGs • Environmental systems experience degradation, although there are some improvements • Overall, the intensity of resource and energy use declines • Income inequality persists or improves only slowly
SSP3 Regional Rivalry: A fragmented world of “resurgent nationalism”	• Resurgent nationalism, concerns about competitiveness and security, and regional conflicts push countries to increasingly focus on domestic or, at most, regional issues • Countries focus on achieving energy and food security goals within their own regions at the expense of broader-based development

	• Economic development is slow, consumption is material-intensive, and inequalities persist or worsen over time
SSP4 Inequality: **A world of ever-increasing inequality**	• A gap widens between an internationally-connected society that contributes to knowledge- and capital-intensive sectors of the global economy, and a fragmented collection of lower-income, poorly educated societies that work in a labor intensive, low-tech economy. Conflict and unrest become common • Development is high in the high-tech economy and sectors
SSP5 Fossil-fueled Development **A world of rapid and unconstrained growth in economic output and energy use**	• Increasing faith in competitive markets, innovation and participatory societies to produce rapid technological progress and development of human capital as the path to sustainable development • Exploitation of abundant fossil fuel resources and the adoption of resource and energy intensive lifestyles around the world • Local environmental problems like air pollution are successfully managed • Faith in the ability to effectively manage social and ecological systems, including by geo-engineering if necessary.

Table 4: Shared Socio-Economic Pathways (SSPs) and Their Storylines (source: Riahi et al., 2017)

The SSPs do not directly provide information about the associated emission trajectories. However, they are often presented alongside Representative Concentration Pathways (RCPs). RCPs describe different levels of greenhouse gases (GHGs) in the atmosphere and other factors contributing to radiative forcing by 2100, as well as the associated pathways of GHGs and subsequent change in the climate system. Climate effects are expressed as radiative forcing which represents the change in energy flux in the atmosphere caused by natural and anthropogenic factors of climate change and measured in watts per square meter (W/m^2). Positive radiative forcing means that the Earth receives more incoming energy from sunlight than it radiates back to space, leading to a net energy gain, and consequently, global warming. The combination of socioeconomic assumptions with compatible emission pathways gives the GHG scenarios. Table 5 shows the available combinations and associated temperature changes by 2100.

GHG_SSP1_19	SSP1 *Sustainability* with 1.9 W/m2 radiative forcing, <1.5° warming until 2100
GHG_SSP1_26	SSP1 *Sustainability* with 2.6 W/m2 radiative forcing, <2° warming until 2100
GHG_SSP2_45	SSP2 *Middle of the Road* with 4.5 W/m2 radiative forcing, ~2.6° warming until 2100

GHG_SSP3_70_Baseline	SSP3 *regional rivalry* with 7.0 W/m2 radiative forcing, ~3.6 warming until 2100
GHG_SSP4_34	SSP4 *Inequality* with 3.4 W/m2 radiative forcing, ~2.2° warming until 2100
GHG_SSP4_60	SSP4 *Inequality* with 6.0 W/m2 radiative forcing, ~3.3° warming until 2100. A 'no-additional-climate policy' reference scenario under socio-economic conditions that pose small challenges to mitigation
GHG_SSP5_34_OS	SSP5 *Fossil Fuel Growth* with 3.4 W/m2 and overshoot (OS), ~2.2° warming until 2100
GHG_SSP5_85_Baseline	SSP5 *Fossil Fuel Growth* with 8.0 W/m2 radiative forcing, ~4.4° warming until 2100. A high reference scenario with no additional climate policy

Table 5: SSP-RCP Combinations and Temperature Outcomes by 2100
(source: IPCC, 2021)

Unit of measure

Kilograms

Source	Description	Regional coverage	Sectors	Years	Emissions
EIA Energy Outlook (2019)	• Reference • High / Low oil price • High / low economic growth	• 8 regions • Specification of 10 countries	-	Yearly until 2050	CO2
IEA Announced Pledges Case (from Net Zero 2050 Report 2021)	All announced national net zero pledges are achieved in full and on time, even if not underpinned by specific policies.	Global	Electricity, industry, transport, buildings, other	2020-50 in 5-year steps	CO2
IEA net zero 2050 pathway (2021)	Pathway to net zero 2050 that relies on little carbon dioxide removal to stay below 1.5°	• Global • "Advanced" vs. "emerging&developing" countries only for industrial emissions	Electricity & heat; other energy, industry, transport, buildings		CO2 CH4 in energy-sector
CMIP6 (2017) Scenarios in preparation of next IPCC report	SSP1-19/26: "sustainability"	26 countries/regions	Agriculture, Energy, Industry, Residential Commercial, Transportation, Waste; Forest Burning, Peat Burning, Grassland Burning, and Agricultural Waste Burning	2020-2100 in 5-year steps	CO2 and CH4 sectoral + regional, N2O global; Other air pollution: NH3, NOx, Sulfur, VOC
	SSP2-45: "middle of the road"	10 countries/regions			
	SSP3-70: "regional rivalry"	17 countries/regions			
	SSP4 -34 and SSP4-60: "inequality"	32 countries/regions			
	SSP5-34-OS: "fossil fuel development"	11 countries/regions			
US EPA (2019)	% reductions relative to the projection baseline	175 countries	Agriculture, Energy, Industrial Processes, Waste	2015-50 in 5-year steps	CH4, N20

Table 6: Key Emission Scenarios, Regional Coverage, and Sectoral Breakdown (source: own illustration)

2.2.2.4 Invasive Alien Species

Definition

Invasive alien species (IAS) are non-native plants, animals, fungi, or microorganisms that are introduced to regions outside their natural habitat due to human activities, either intentionally or accidentally. Once established, these species can spread rapidly, outcompeting native species and causing significant harm to biodiversity, ecosystems, and human well-being. IAS can disrupt ecosystem services, lead to economic losses, and sometimes cause irreversible environmental damage.

Invasions can be attributed to both anthropogenic activities and natural phenomena (Hulme et al., 2023). Human-induced drivers encompass direct factors such as the intentional or accidental introduction of IAS, natural resource exploitation, pollution, and climate change, as well as indirect factors like international trade. Natural drivers include environmental hazards such as tsunamis, hurricanes, and biodiversity loss.

The diverse array of factors contributing to species invasions complicates the understanding of their mechanisms. Additionally, there is often a significant delay between the occurrence of an invasion and its documentation. For instance, it may take years for an invasive plant species to be detected in a new region, with only the year of its discovery typically being recorded. This lag can obscure the timeline and dynamics of the invasion process.

Owing to the difficulty of understanding the channels through which invasive species migrate, it is even more difficult to directly link the activities of specific companies to the emergence of IAS. Moreover, even if there is definitive data that a company introduces a species from one country in another country, where it is alien, this species needs to establish a population over time to be considered an IAS.

Hence, WifOR follows a top-down approach that links global trade data to the introduction of IAS. To the best of our knowledge, the most comprehensive analysis of global trade and invasive species is by Seebens et al. (2015). They link global trade data with biodiversity and climate information, to predict the spread of naturalized alien plant species across different regions.[4] Given the strong correlation between the number of established alien species and a country's import value, as well as the impact of changes in global trade on the introduction and establishment of species to new environments, trade data serves as a robust predictor for mapping species invasions. Additional country-specific environmental data and biodiversity indicators are used to enhance the accuracy of invasion predictions.

WifOR takes the model of Seebens et al. (2015) as a starting point and estimates it using more recent trade, plant invasions, and environmental data. As a result, we

[4] The taxonomic group of plants has the most extensive and comprehensive global data currently available (Seebens et al., 2015).

calculate an expected number of invasions uniquely for each country pair out of a set of 188 different countries separately for each year in the period 2014-2030, as well as for 2050 and 2100.

The Model

The model combines bilateral trade data with environmental and geographic distances between countries and native plant species richness from donor countries to calculate the invasion risk of a single country - the probability that a vascular plant species native to country i and non-native to country j is introduced to j and establishes a population within a time period τ.

The model incorporates three probabilities to estimate the risk of invasion, accounting for the complex interplay of globalization, biological invasions, and climate change. The three probabilities refer to the three conditions that must be fulfilled for an invasion: (i) that a species native to one country is alien in another, (ii) that this species is introduced in the latter country, (iii) that the introduced alien species establishes a population in the new country. The probabilities of each of these events are defined as follows:

1. $\boldsymbol{P_{ij}(Alien)}$**,** which describes the likelihood that species native to country i are non-native to country *j*:

$$P_{ij}(Alien) = \left(1 + \frac{\gamma}{D_{ij}}\right)^{-\beta},$$

where D_{ij} is the great circle distance between countries i and j, β is a shape parameter, and γ denotes the characteristic distance below which $P_{ij}(Alien)$ changes at a disproportionately low rate.

2. $\boldsymbol{P_{ij}(Intro)}$, the probability of introduction, which depends on the cumulative amount of trade between countries and the species richness of the donor country:

$$P_{ij}(Intro) = \left(1 - e^{-\delta G_{ijy}}\right)\left(1 - e^{-\lambda S_i}\right),$$

where G_{ijy} is the cumulative trade value between countries i and j up to year y, S_i is the species richness of the donor country i, and δ and λ are characteristic constants. Here, we deviate from Seebens et al. (2015). While they consider the cumulative trade value as an explanatory variable for the probability of introduction, we take only cumulative imports from country i in country j, as it is via imports that species can be introduced. Thus, we do not run the risk of predicting more invasions in countries with *ceteris paribus* higher exports.

3. $\boldsymbol{P_{ij}(Estab)}$, the probability of establishment, which is a function of environmental similarity between donor and recipient regions:

$$P_{ij}(Estab) = \alpha e^{-\frac{0.5}{3}\left(\frac{\Delta T_{ij}}{\sigma_T} + \frac{\Delta P_{ij}}{\sigma_P} + \frac{\Delta A_{ij}}{\sigma_A}\right)}$$

where ΔT_{ij}, ΔP_{ij}, ΔA_{ij} are the differences in annual mean temperature, annual mean precipitation, and mean altitude between countries i and j, respectively, and σ_T, σ_P, and σ_A are their respective standard deviations. α denotes the initial probability of invasion.

Under the assumption of statistical independence of these three events, the probability of invasion(s) from country i to j, defined as $P_{ij}(Inv)$, is the product of the three probabilities considered above:

$$P_{ij}(Inv) = P_{ij}(Alien)P_{ij}(Intro)P_{ij}(Estab).$$

Since these probabilities are not defined for just one species, their product represents the probability that at least one species invades country j from country i within the considered period τ.

The model can be used to estimate the expected number of invasions for the period of consideration. For this purpose, additional definitions and assumptions are required.

1. Normalize the length of the period to one year, $\tau = 1$.
2. Define the number of trips made from country i to j during the period as n_{ij} and the probability of invasion per trip as p_{ij}.

Then, the probability of at least one invasion during the period is given by:

$$P_{ij}(Inv) = 1 - (1 - p_{ij})^{n_{ij}}.$$

If we suppose that the number of trips gets very large ($n_{ij} \to \infty$), and the probability of invasion per trip gets very small ($p_{ij} \to 0$), such that the expected number of invasions, $E_{ij}(Inv) = n_{ij}p_{ij}$, remains a finite positive constant, then in the limit $(1 - p_{ij})^{n_{ij}} = e^{-n_{ij}p_{ij}}$.

Thus, the probability simplifies to:

$$P_{ij}(Inv) = 1 - e^{-n_{ij}p_{ij}} = 1 - e^{E_{ij}(Inv)}.$$

Solving for the expected number of invasions, we get

$$E_{ij}(Inv) = -\ln\left(1 - P_{ij}(Inv)\right).$$

Estimation of Model Parameters

The model has eight unknown parameters: $\alpha, \beta, \gamma, \delta, \lambda, \sigma_T, \sigma_P, \sigma_A$. The three standard deviations ($\sigma_T, \sigma_P, \sigma_A$) can be estimated directly as the standard deviations of mean annual temperature, precipitation, and altitude of all world countries. Furthermore, we use environmental, trade, and invasions data to estimate the remaining parameters using non-linear least squares optimization, where the number of invasions N_{ij}, are regressed against the predicted invasions, i.e.:

$$N_{ij} = -\,ln\left(1 - P_{ij}(Inv)\right) = -\,ln\left(1 - P_{ij}(Alien)P_{ij}(Intro)P_{ij}(Estab)\right). \qquad (1)$$

Application of IAS model to IO Model

Once the model parameters are estimated, year-specific probability of invasions ($P_{ij}(Inv)$) are calculated for all country pairs among the 188 countries in WifOR's database, based on WifOR's imports data (derived from the Input-Output transaction matrix), and the same environmental data used for parameter estimation. A probability for invasion within a country is fixed at zero.[5] These probabilities are then used to calculate the expected number of invasions for all country pairs. Dividing the expected invasions by imports (measured in million USD) yields the expected invasions per million USD of imports. Finally, for each sector in WifOR's IO model, the imports per unit of output from a given country were multiplied with that country's specific expected invasions per million USD of imports. Summing across all importing countries provides a sector-specific number of expected invasions per million USD of output. Finally, multiplying this number with the sector's gross output gives the number of invasions per year due to the sector's activities (via imports) in its country of operation.

Data Sources

Overview

Data Type	Primary Source	Data Format
Invasions data	EASIN, European Commission	Spatial Database
Plant origins data	The World Checklist of Vascular Plants (WCVP), Royal Botanic Gardens, Kew	Tabular/Taxonomic Database
Trade data	IMF Direction of Trade Data Statistics (DOTS)	Statistical Dataset
Distances data	Derived using GeoPandas (Python)	Spatial Analysis / Geospatial
Native species data	Global Naturalized Alien Flora (GloNAF)	Spatial/Species Distribution
Altitude data	CIA Worldfactbook	Geographic Dataset
Precipitation data	Our World in Data	Statistical Dataset
Temperature data	Our World in Data	Statistical Dataset

Invasions Data

Data on invasions is sourced from the European Commission's EASIN database, providing first records in Europe by year and country per plant species. The data was extracted for the period of 1990-2016, providing data on 812 unique alien plant taxa. Invasion data only from 2000 onward is used, as there can be a significant lag between the introduction of a species and its discovery. Thus, we lower the probability of observing an invasion that has occurred before our trade data observations start. While this data provides the exact country of invasion, it does not specify the plant's origin. To address this, the plants' taxon names are matched to their region of origin using data on plant origins.

Plant origins data

Data on plant origin regions comes from The World Checklist of Vascular Plants (WCVP) database, managed by the Royal Botanic Gardens, Kew (see also Govaerts

[5] This is not entirely accurate, as large countries such as Russia may experience invasions from one part of the country in another. However, the model is not granular enough to capture such invasions.

et al. (2021)). As of April 2021, the WCVP database includes 1,383,297 plant names, 996,093 at species level, representing 342,953 accepted vascular plant species.

For the period under consideration, the EASIN database categorizes 452 unique taxa as alien. Of these, 440 were successfully matched to plant records in the WCVP database, while 12 were excluded due to unknown origins. Additionally, 1 taxon was excluded because it was listed as introduced in its WCVP region (thus, it is not native). A further 77 taxa were dropped because, while present in the WCVP database, their region of origin was not specified. As a result, 362 unique taxa with known origin regions and recorded invasions in EASIN were retained for analysis.

Furthermore, some taxa have (i) multiple countries of origin within the same region and/or (ii) multiple regions of origin. In these cases, we assigned the modal region as the sole region of origin. That is, if a taxon has x_1 origin countries in region y_1 and x_2 origin countries in region y_2, we used region y_1 if $x_1 > x_2$. The final dataset includes 121 unique country-region invasion observations, with altogether 1878 invasions.

Trade data

The source for trade data is the Direction of Trade Statistics (DOTS) database from the IMF, which provides comprehensive annual data on imports, reported on a cost, insurance and freight (CIF) basis. Annual data was extracted for a 69-year period, spanning from 1954 to 2023. This data covers all IMF member states and some non-member countries, covering all 188 countries required by the WifOR-model, with the exception of Liechtenstein.

For the purposes of the analysis, we use only data from 1980 to 2015. The starting year is set 20 years prior to the initial year of observed invasions in the final invasions dataset. Here the main assumption is that trade influences observed invasions for up to 20 years, meaning newly observed invasive plants from 2000 onwards are not subject to longer observation lags. Since invasions data extends to 2016, 2015 is chosen as the final year where trade could results in and observable invasion within the period. Lastly, data for all years was inflated to 2020 values and expressed in 2020 million USD.

Distances data

The data used from the calculation of distances between countries originates from a combination of various sources. The Geopandas module in Python provides robust tools for geospatial data analysis and manipulation and was used to extract the centroid coordinates for 177 countries, 165 of these aligning with the WifOR model requirements. To ensure comprehensive coverage, the remaining 23 countries not included in the Geopandas module, are sourced from the “world-countries-centroids” repository on GitHub[6] and supplemented with coordinates provided by ChatGPT for

[6] world-countries-centroids/dist/countries.csv at master · gavinr/world-countries-centroids · GitHub

23 countries.[7] The ChatGPT data was checked for accuracy based on coordinates of neighbouring countries (nearby islands in the case of island nations).

Using the extracted centroid coordinates, the distances between countries were calculated with the haversine formula, which determines the shortest distance over the earth's surface between two points using their latitudes and longitudes. The formula accounts for the spherical shape of the Earth, providing an accurate measure of distance between two geographical points and is defined as follows:

$$d = 2r \times asin(\sqrt{hav(\Delta\phi) + cos(\phi_1)cos(\phi_2) \cdot hav(\Delta\lambda)})$$

where d is the distance between the two points along the surface of the sphere, r is the radius of the sphere (Earth≈6,371 km), ϕ_1 and ϕ_2 are the latitudes of the two points in radians, λ_1 and λ_2 are the longitudes of the two points in radians, $\Delta\phi = \phi_2 - \phi_1$ is the difference in latitude, $\Delta\lambda = \lambda_2 - \lambda_1$ is the difference in longitude, and hav is the haversine function, defined as $hav(\theta) = sin^2(\frac{\theta}{2})$.

Native species data

Data on native species per country stems from several sources. The main source is the article from Pyšek et al. (2017). Using the Global Naturalized Alien Flora (GloNAF) database, the authors provide data for the number of natural plant species per country for 179 out of the 188 countries in WifOR's database. For three additional countries, species numbers are derived from World Conservation Monitoring Centre of the United Nations Environment Programme (UNEP-WCMC), 2004.[8] The 6 remaining countries (Andorra, Netherlands Antilles, Monaco, Palestine, San Marino, and Moldova) lack data. To estimate their native species count, we follow Pyšek et al. (2017), and regress the logarithm species numbers on the logarithm of land area for all countries with available species data (we excluded Antarctica as an outlier due to

[7] The countries for which ChatGPT was used to get coordinates are Aruba, Andorra, Netherlands Antilles, Antigua and Barbuda, Bahrain, Bermuda, Barbados, Cape Verde, Cayman Islands, Hong Kong, Liechtenstein, Macao, Monaco, Maldives, Malta, Mauritius, French Polynesia, Singapore, San Marino, São Tomé and Príncipe, Seychelles, British Virgin Islands, Samoa.

[8] Source website: https://worldrainforests.com/03plants.htm (last visited on 18.11.2024).

its vast area and minimal native species). The fitted regression (Figure 3) was used to estimate species numbers for these 6 countries based on their land area.

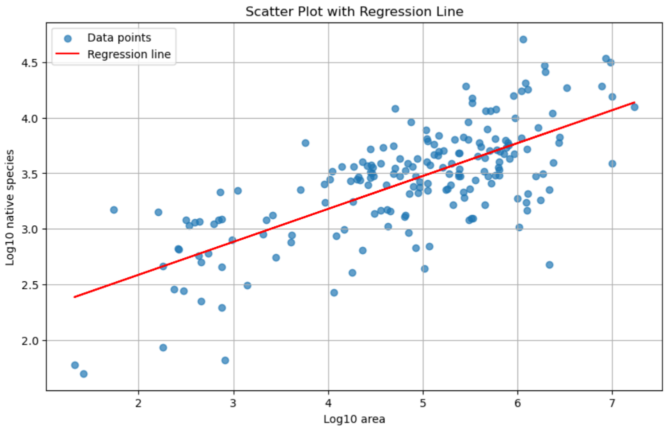


Figure 3: Logarithmic relationship between native species count and country area.

Altitude data

The main source for altitude data is the CIA World Factbook, which provides mean elevation measurements. This data is expressed in meters and covers 168 countries. Elevation data for most of the remaining countries is extracted from the website https://en-in.topographic-map.com.[9]

Precipitation data

The main source for precipitation data is Our World in Data, which provides average annual precipitation measurements in millimeters per year. Collected by the Food and Agriculture Organization of the United Nations (FAO), this data spans from 1961 to 2020 and encompasses 286 countries. However, many countries listed lack data. Altogether, there is data for 173 out of the 188 countries covered in WifOR's database. The remaining 15 countries' mean annual precipitation is sourced from Wikipedia. The analysis uses the most recent precipitation values from 2020.

Temperature data

The main source for temperature data is Our World in Data, which provides monthly average surface temperatures by decade, measuring the temperature of the air 2 meters above the ground, covering land, sea, and inland water surfaces. Sourced from the Copernicus Climate Change Service (2019), the dataset spans from the 1940s to the 2020s and is measured in degrees Celsius (°C). This dataset covers 175 of the 188 countries in WifOR's dataset. Data for the remaining 13 countries is

[9] In addition, altitude data for French Polynesia was extracted from https://www.confiduss.com/en/jurisdictions/french-polynesia/geography/, data for Malta from https://www.confiduss.com/en/jurisdictions/malta/geography/, Netherlands Antilles from https://www.confiduss.com/en/jurisdictions/netherlands-antilles/geography/, and Sao Tome and Principe is sourced from Wikipedia (https://en.wikipedia.org/wiki/S%C3%A3o_Tom%C3%A9).

sourced from Wikipedia, as well as https://weatherandclimate.com/countries. In the analysis, we use the most recent data from the 2020s.

Estimation procedure

To estimate the parameters, we begin with temperature, altitude, and precipitation data, which provide direct values for the standard deviation parameters (see estimated values in Table 4 below). Using the standard deviation parameters, as well as all data described above, the remaining parameters are derived through non-linear regression of Equation 1 (results reported in Table 7). However, one challenge arises: the parameter α is estimated at above unity, implying that the invasion probabilities could surpass one for countries with similar temperature, altitude, and precipitation. This issue is addressed later in the analysis.

	Parameter Values
α	3,308015
β	2,518141
γ	-361,476
δ	0,0096
λ	2,01E-06
σ_T	7,716936
σ_P	671,7932
σ_A	572,9466

Table 7: Estimated parameters (source: own calculation).

Using the estimated parameters, we calculate the probability of invasion $P_{ij}(Inv)$ for all country pairs across the years 2014-2030, 2050, and 2100. The median probability for all country pairs and years is 0.00043, while the mean is significantly higher at 0.068. The discrepancy arises because, for some country pairs (those above the 99.8th percentile), the model predicts probabilities above unity. Table 8 shows the 75th, 90th, 95th, and 99th percentiles of all calculated probabilities for each year. The percentiles show an upward trend over time due to the increase in value of imports.

	p75	**p90**	**p95**	**p99**
2014	0,0024	0,0161	0,0378	0,1354
2015	0,0024	0,0163	0,0381	0,1368
2016	0,0025	0,0164	0,0384	0,1378
2017	0,0026	0,0168	0,0389	0,1379
2018	0,0027	0,0171	0,0395	0,1379
2019	0,0028	0,0174	0,0400	0,1380
2020	0,0030	0,0178	0,0407	0,1391
2021	0,0034	0,0186	0,0422	0,1409
2022	0,0040	0,0197	0,0442	0,1431
2023	0,0041	0,0201	0,0450	0,1434
2024	0,0043	0,0204	0,0455	0,1441

2025	0,0044	0,0207	0,0462	0,1452
2026	0,0046	0,0211	0,0468	0,1461
2027	0,0048	0,0215	0,0474	0,1469
2028	0,0050	0,0218	0,0481	0,1487
2029	0,0052	0,0220	0,0487	0,1488
2030	0,0053	0,0223	0,0492	0,1491
2050	0,0077	0,0266	0,0558	0,1571
2100	0,0129	0,0361	0,0704	0,1835

Table 8: 75th, 90th, 95th, 99th percentile of the country pair probabilities for all countries (source: own calculation).

Now, we deal with the high probabilities predicted for some country pairs. The model assumes that invasions are rare events (the main assumption behind the derivation of the expected number of invasions). Thus, it is unlikely that the model would be able to accurately predict invasions that take place regularly (because such invasions may have other explanations). To be on the safe side, we assume that all predicted probabilities above the 95th percentile are too high probabilities and thus outliers. Then, we set all values above the 95th percentile to be equal to the 95th percentile (for each year). In this way, we aim to not overestimate the probability of an invasion.
Finally, we estimate the expected number of invasions for all country pairs and years based on the calculated probabilities. Globally, the number of predicted invasions is lowest in 2014 (around 157) and highest in 2100 (around 226), with approximately 202 invasions predicted for 2023. This increase over time reflects growing trade and rising probabilities. These results are slightly above the historical average of reported plants invasions. According to Seebens et al. (2017), the 5-year average first record rate of established alien vascular plants has remained between 600 and 800 over the past century (see Figure 2b in Seebens et al. (2017)), equating to a global annual average between 120 and 160. Considering the projected increase in trade until 2100, our results are align with the historical average.

Unit of measure

Expected number of invasions

2.2.2.5 Land Use

Definition

Land use involves the management and modification of natural environment or wilderness into built environments such as settlements and semi-natural habitats such as arable fields, pastures, and managed woods. Most land use is due to agricultural activities. We distinguish between eleven types of land use, nine of them attributed to different forms of agricultural activity.

Sub indicators

- Agriculture
- Forestry
- Paved

Specifications

- Wheat
- Vegetables, fruit, and nuts
- Cereal grains (not elsewhere classified)
- Oilseeds
- Sugarcane and sugarbeet
- Plant-based fibers
- Crops (not elsewhere classified)
- Animal rearing
- Paddy rice

Primary Sources

- EXIOBASE 3.8.1.
- EORA

	EXIO	WIOD	EORA
Data Source	EXIOBASE 3.8.1	https://www.rug.nl/ggdc/valuechain/wiod/wiod-2013-release	https://www.worldmrio.com/
Frequency of update	-	Non regular	Non regular
Country coverage (extent & scope)	44 countries, 5 Rest of the World regions	6 Non-EU Non OECD countries	Rest of the World?
Sector granularity	163 sectors aggregated to 57	56 sectors	-
% of global value	~75%	Only shares	Only shares
Reliability (1-5)	4	4	2
Landuse Rate (only Paved)	**Average: 86.91 ha** Country Range: 0.03 to 565.1 ha Sector Range: 0 to 4,905.4 ha		
Publisher	University (international research consortium)	University (large research consortium)	University (large research consortium)

Estimation procedure

There is full country coverage of indicators by existing satellites of MRIO sources. EXIOBASE has a higher sectoral disaggregation than WIOD (163 versus 57 sectors) such that we had to map the EXIOBASE sectors into the WIOD classification.

EXIOBASE provides 20 types of land use[10], which are transferred / partially aggregated to the requested specifications. Countries which are not covered by WIOD were estimated by using EORA output shares.

General remark

The quality of the data is not very good for some countries. Nevertheless, it is the best source available at the moment.

Unit of measure

Hectare

2.2.2.6 Resource Use / Natural Resources

Definition

Resources encompass all accessible materials and minerals found in nature, which we extract or process for use across economic activities, transportation, and societal well-being (Ali & Kamraju, 2023). The three categories within this indicator are metals and minerals (including iron, ferroalloys, non-ferrous metals, alkali metals, and industrial minerals), fossil fuels (such as oil and gas), and biomass materials (from forestry and agriculture) (World Mining Data, 2024).

The first resource category encompasses metals and minerals, further broken down into four categories, visible in Table 9 below.

Table 9: Minerals/Metals Classifications

Category	Subcategory	Resources
Minerals/Metals	Iron and Ferroalloy Metals	Chromium, Cobalt, Iron, Manganese, Molybdenum, Nickel, Niobium, Tantalum, Titanium, Tungsten and Vanadium
	Non-Ferrous Metals	Aluminium, Antimony, Arsenic, Beryllium, Bismuth, Cadmium, Copper, Gallium, Germanium, Hafnium, Indium, Lead, Magnesium, Mercury, Precious Metals, Rare Earth Elements, Rhenium, Selenium, Tellurium, Tin, Thallium, Thorium, Uranium, Zinc and Zirconium
	Alkali Metals	Caesium, Lithium, Potassium, Rubidium and Sodium

[10] For more information, see the supporting information S6 in Stadler et al. (2018) on the construction of the air emission accounts, available at: https://onlinelibrary.wiley.com/action/downloadSupplement?doi=10.1111%2Fjiec.12715&file=jiec12715-sup-0006-SuppMat-6.pdf

	Industrial Minerals	Asbestos, Baryte, Boron, Calcium, Diamond, Diatomite, Feldspar, Fluorspar, Graphite, Gypsum, Kaolin, Magnesite, Perlite, Phosphates and Phosphate Rock, Potash, Sulphur, Talc and Vermiculite

Fossil fuels are categorized separately due to their high carbon content and significant role in emissions, being essential for transportation, industry, and electricity. This category includes **Coal, Lignite, Natural Gas and Oil resources.**

Biomass data includes products such as **Crop residues, Fishery products, Fodder crops, Forestry, Grazing, and Primary crops**. Known for their renewable nature, biomass goods support emissions reduction and are increasingly used as a renewable energy source.

We are also considering the EU's 2020 critical raw materials list, which identifies 33 materials as "critical" due to their economic importance and high supply risk in extraction or processing stages (European Commission, 2020). Our dataset includes all of these resources except Borate, Natural Rubber, Phosphorus, Scandium, and Silicon metal.

The European Union (2018) identifies various approaches to measuring metal mining output. For our database, we report resources at their pure metal level - net output after metal separation - rather than the 'run-of-mine' (ROM) concept, which measures gross ore, including all extracted materials. Pure metal data provides a clearer basis for global comparison since metal content in gross ore varies widely by country and mine. Using this approach also aligns better with industry standards, facilitates accurate forecasting, and offers clearer insights into the economic value of resources, benefiting operational and financial planning by indicating recoverable valuable elements.

Sub indicators

- Minerals/ Metals
- Fossil Fuels
- Biomass

Primary Sources

- World Mining Data (2022)
- EXIOBASE 3.8.1. (2022)

Additional Sources

- British Geological Survey (2022)

	World Mining Data	EXIO	British Geological Survey
Data Source	https://www.world-mining-data.info/?World_Mining_Data	EXIOBASE version 3	https://www.bgs.ac.uk/geological-data/
Frequency of update	Annual	-	Annual
Country coverage (extent & scope)	168 countries	44 countries, 5 Rest of the World regions	229 countries and territories
Sector granularity	-	163 sectors aggregated to 57	-
% of global value (only Iron)	100%	-	-
Reliability (1-5)	5	4	5
Resource Rate (only Iron)	**Average: 4.94 kilotons** Country Range: 0 to 531.6 Sector Range: 0 to 281.8		
Publisher	Statistical Authority	University (International Research Consortium)	Governmental Research Organization

Data processing

There is full country coverage of indicators by existing satellites of MRIO Sources. The World Mining Data covers a time frame from 2014 for fossil fuels, minerals and other materials. The British Geological Survey is thus used to cover gaps in the resources data frame. While Biomass goods are distributed throughout all NACE sectors, Fossil Fuels and the rest of the Minerals and Metals are only assigned to NACE sector B. Additionally we adjusted Country names as well as the metric unit, to have all resources measured in metric tons. Natural Gas is the only exception as it's measured in cubic square meter. To account for the biomass information the EXIOBASE database is used.

Unit of measure

Kilotons (exception: "Natural Gas": cubic square meter)

2.2.2.7 Resource Use - Wood

Definition

Resource use of wood is measured as solid weight of roundwood production by type of (primary) wood product and certification scheme.

Subindicators

- Industrial roundwood
- Wood fuel (incl. pellets)

Specifications

- Certified
- Non-certified

Primary Sources

- Food and Agriculture Organization of the UN (FAO) – Forestry Production and Trade Database
- Food and Agriculture Organization of the UN (FAO) – SDG Indicators Data Portal - Indicator 15.2.1 - Progress towards sustainable forest management

Additional Sources

- Methodological appendix from EXIOBASE – Conversion factors to transform m^3 wood in kg, by type of wood

	Food and Agriculture Organization (FAO)		EXIOBASE
Data Source	https://www.fao.org/faostat/en/#data/FO	https://www.fao.org/sustainable-development-goals-data-portal/data/indicators/1521-sustainable-forest-management/en «15.1.1 Forest area»	EXIOBASE version 3
Frequency of update	Yearly	Yearly	-
Country coverage (extent & scope)	278 countries	249 countries	44 countries, 5 Rest of World regions
Sector granularity	-	-	163 sectors aggregated to 57
% of global value	-	-	Only conversion factors
Reliability (1-5)	4		4
Wood fuel (certified) Rate	**Average: 12,288.82 kg** Country Range: 0 to 435,222.6 kg Sector Range: 0 to 698,862.9		
Publisher	International Organization		University (international research consortium)

Data processing / estimation procedure

The estimation process entails gathering country-specific data on roundwood production from the FAO, ensuring that only primary data is used to avoid issues with double counting. This data, initially recorded in cubic meters, is converted to kilograms using conversion factors provided by EXIOBASE. Following this, FAO wood area information on the percentage of certified wood areas is applied to refine weight specifications. In the final step, all data is mapped to Sector A02, aligning it within the forestry and logging sector framework for consistency.

Unit of measure
Kilograms

2.2.2.8 Waste

Definition
The indicator is defined as the weight of waste generated by a certain company. The quantity is expressed in kilogram.

Sub indicators
- Hazardous waste
- Non-Hazardous waste

Specifications
- Disposed (landfill)
- Disposed (incinerated)
- Recovered (recycling or downcycling)

Primary Sources
- EXIOBASE HYBRID (Merciai and Schmidt 2018)

Additional Sources
- Eurostat Waste accounts (Table "env_wastrt")

	EXIOBASE HYBRID	Eurostat
Data Source	(Merciai and Schmidt 2018)	https://ec.europa.eu/eurostat/databrowser/view/env_wastrt/default/table?lang=en Table «env_wastrt»
Frequency of update	-	Biannually
Country coverage (extent & scope)	44 countries and 5 Rest of World regions	EU27 and 11 European countries
Sector granularity	163 sectors aggregated to 57	-
% of global value	~82%	~22%
Reliability (1-5)	4	5
Waste Rate	**Average: 54,788.5 kg** Country Range: 228.8 to 181,690.6 kg Sector Range: 234 to 1,383,221 kg	
Publisher	University (international research consortium)	Statistical Authority

Estimation procedure

Because not all specifications for the indicator "waste" are given by EXIOBASEHYBRID, we used Eurostat to split the sub indicators to meet the specifications needed.

Unit of measure

Kilograms

2.2.2.9 Water Consumption

Definition

Water consumption describes the proportion of water withdrawal, which is not returned to surface waters after use, as it is lost in the manufacturing process via evaporation, or incorporated into the finished product, byproducts, or solid waste. Water consumption refers to "blue water", i.e. water sourced from surface or groundwater resources.

Primary Sources

- EXIOBASE 3.8.1.
- EORA

	EXIO	EORA
Data Source	EXIOBASE version 3	https://www.worldmrio.com/
Frequency of update	-	Non regular
Country coverage (extent & scope)	44 countries, 5 Rest of World regions	Rest of the World
Sector granularity	163 sectors aggregated to 57	-
% of global value	~71%	~29%
Reliability (1-5)	4	2
Consumption Rate	**Average: 6,314.02 m3** Country Range: 10.74 to 125,654.2 m3 Sector Range: 0.55 to 297,889.9 m3	
Publisher	University (international research consortium)	University (large research consortium)

Estimation procedure

There is full country coverage of indicators by existing satellites of MRIO Sources. EXIOBASE has a higher sectoral disaggregation than WIOD (163 versus 57 sectors) such that we had to map the EXIOBASE sectors into the WIOD classification.

Unit of measure

Cubic meter (m^3)

2.2.2.10 Water Pollution

Definition

Water pollution is the contamination of water bodies, usually as a result of human activities. Water bodies include for example lakes, rivers, oceans, aquifers, and groundwater. Twelve different water pollutants are integrated in the analysis: Nitrogen, Phosphorus, Antimony, Arsenic, Cadmium, Chromium, Copper, Lead, Mercury, Nickel, PAHs and Zinc.

Sub indicators

- Nitrogen
- Phosphorus
- Antimony
- Arsenic
- Cadmium
- Chromium
- Copper
- Lead
- Mercury
- Nickel
- PAHs
- Zinc

Primary Sources

- EXIOBASE HYBRID (Merciai and Schmidt 2018)

Additional Sources

- DESTATIS
- EEA WATERBASE – aggregated Database

	EXIO HYBRID	DESTATIS	EEA Waterbase
Data Source	(Merciai and Schmidt 2018)	GENESIS-Online	Waterbase - Water Quality ICM Aggregated Database
Frequency of update	Multiple times a year	-	Yearly
Country coverage (extent & scope)	44 countries and 5 Rest of World regions	1 country	22 European countries

Sector granularity	163 sectors aggregated to 57	-	WIOD grey water usage is used to distribute across sectors
% of global value	~74%	Only shares	~11%
Reliability (1-5)	4	5	4
Water Pollution Rate (only Arsenic)	**Average: 0.29 kg** Country Range: 0.0001 to 5.2 kg Sector Range: 0.0041 to 4.16 kg		
Publisher	Statistical Authority	Statistical Authority	International Organization

Estimation procedure

The indicator distinguishes between three types of water bodies that get contaminated: freshwater, marine water, and unspecified water bodies. The availability of data on water pollution is highly restricted, both in terms of pollutant and impacted water bodies. Our primary data source features data on Nitrogen and Phosphorus in the sectoral granularity needed. These form the baseline to allocate the further ten pollutants to the respective countries and industries. The relation of Phosphorus and Nitrogen to the other ten Pollutants are taken from Destatis and EEA Waterbase and are used to extrapolate values for the missing pollutants, following the assumption of structural constancy. Unfortunately, just one specification was assessable (unspecified) with this approach and available datasets.

Unit of measure

Kilograms

2.2.3 Human rights & social indicators

2.2.3.1 Child labor

Definition

A case of child labor is defined as a child engaged in economic activities for more than one hour per week if aged 5-11, for more than 14 hours per week if aged 12-14, and for more than 43 hours per week if aged 15-17. This includes, but is not limited to, hazardous work but excludes household chores (ILO & UNICEF, 2021).

Primary Sources

- ILOSTAT (2021)
- UNICEF (2021)

Additional Sources

- ILO and UNICEF (2021)

	ILO	UNICEF	ILO & UNICEF
Data Source	https://rshiny.ilo.org/dataexplorer31/?lang=en&id=SDG_B871_SEX_AGE_RT_A Table «SDG_A871_SEX_AGE_RT_A (2021)»	Percentage of Children (Aged 5-17 Years) Engaged in Child Labour (Economic Activities)	https://www.ilo.org/publications/major-publications/child-labour-global-estimates-2020-trends-and-road-forward Report «Child Labor: Percentage and number of children aged 5 to 17 years in child labor (2020)»
Frequency of update	Yearly	Yearly	-
Country coverage (extent & scope)	80 Countries	62 countries	6 Regions + World
Sector granularity	Country level	-	3 Sectors. Distributes data across sectors + excludes household work
% of global value	~62%	~33%	-
Reliability (1-5)	3	4	3
Child Labor Rate	**Average: 4.36** Country Range: 0 to 56.8 Sector Range: 0 to 33.2		
Publisher	Statistical Authority	International Organization	International Organization

Data processing

We combine country-level estimates of the percentage of children engaged in economic activity with estimates for the number of children aged 5 to 17 per country to generate the absolute number of children working at the country level. We apply a recent estimate of the distribution across the three aggregate sectors agriculture, industry, and services by SDG region (ILO and UNICEF (2021)) and assume close to no child labor in 15 sectors with mainly high-skilled employment. Within the aggregate sectors, child labor cases are distributed proportionally to employment. Finally, we account for children working yet not engaged in supply chains. We assume that this is most relevant for the agricultural sector and thus exclude the percentage of children working as part of a family operation according to regional estimates from ILO and UNICEF (2021). Finally, as the ILO currently provides no reliable child labor data for high-income countries, it is assumed that no child labor has occurred. As high family income and stronger legal frameworks effectively reduce child labor prevalence, this likely does not lead to a large distortion.

Unit of measure

Number of cases

2.2.3.2 Disability Discrimination

Definition

The Disability Discrimination indicator measures the risk of discrimination against individuals with disabilities in the labor market. This indicator captures the wage differences between employees with and without disabilities, represented as a disability pay gap.

Sub indicators

- Employment without disability
- Employment with disability
- Disability Pay Gap

Primary Sources

- International Labour Organization (ILO) (Table "POP_XWAP_SEX_DSB_LMS_NB_A")
- International Labour Organization (ILO) (Table "EAR_4MTH_SEX_DSB_CUR_NB_A")

Additional Sources

- EXIOBASE

	ILO		EXIO
Data Source	ILOSTAT Data Explorer POP_XWAP_SEX_DSB_LMS_NB_A	ILOSTAT Data Explorer EAR_4MTH_SEX_DSB_CUR_NB_A	EXIOBASE version 3
Frequency of update	Monthly	Monthly	-
Country coverage (extent & scope)	96 countries + 20 regions	86 countries + 19 regions	44 countries, 5 Rest of the World regions
Sector granularity	-	-	163 sectors aggregated to 57
% of global value	-	-	-
Reliability (1-5)	3		4
Page Gap Rate	**Average: 3,888.8 USD** Country Range: -578.2 – 5,094.7 Sector Range: 756 – 15,432.8		
Publisher	UN		University (large research consortium)

Data processing

The ILO database is used to identify the working population categorized by disability status across 188 countries. Gaps in data are filled with regional averages, following ILO definitions. The wage gap is estimated by calculating the ratio of average incomes for employees with and without disabilities and applying this to general compensation data to estimate the Disability Pay Gap across sectors. Due to the lack of sectoral differentiation, it is assumed that the share of employees with disabilities and the associated pay gap are uniformly distributed across all industries.

Unit of measure

Employment: Number of persons

Disability Pay Gap: USD

2.2.3.3 Forced labor

Definition

Forced labor exploitation is defined as work forcefully imposed by private agents, including bonded labor, forced domestic work, and work imposed in the context of slavery or vestiges of slavery. Other forms of forced labor are forced sexual exploitation and state-imposed forced labor. The aggregate "modern slavery" further includes forced marriage (ILO and Walk Free Foundation 2017).

Primary Sources

- Walk Free Foundation (2018)

Additional Sources

- ILO and Walk Free Foundation (2017)

	Walk Free Foundation	ILO & Walk Free Foundation
Data Source	https://cdn.walkfree.org/content/uploads/2023/04/13181704/Global-Slavery-Index-2018.pdf GSI Report (2018) «Table 4 p.190»	https://www.ilo.org/publications/global-estimates-modern-slavery-forced-labour-and-forced-marriage ILO-GSI Report (2017) «Table 1&2 p.18-19»
Frequency of update	Yearly	Every 5 Years
Country coverage (extent & scope)	186 countries	World
Sector granularity	57 sectors	Excludes irrelevant data in main source
% of global value	~100%	-
Reliability (1-5)	3	3

Forced Labor Rate	**Average: 0.82 cases** Country Range: 0.002 to 8.99 Sector Range: 0 to 7.99	
Publisher	Independent NGO	UN + Independent NGO

Data processing

The Global Slavery Index (GSI) provides country-level estimates for the number of people in modern slavery at the country level for 186 countries. For missing countries, the absolute number of modern slavery cases is estimated using the income region medians of Modern Slaves per Employees for the countries covered by the GSI dataset and the total number of employees in the country missing information.
As forced marriage, state-imposed forced labor and sexual exploitation are not driven by global supply chains, we exclude these using global and regional estimates from ILO and Walk Free Foundation (2017). The forced labor estimates are then allocated to sectors using the distribution of employees by country and excluding certain sectors (ILO and Walk Free Foundation 2017).

Unit of measure

Number of cases

2.2.3.4 Freedom of Association

Definition

The Freedom of Association & Collective Bargaining indicator measures the risk of violations of the right to freedom of association and collective bargaining. This indicator focuses on countries with a high risk of such violations to assess the number of employees potentially affected.

Primary Sources

- International Labour Organization (ILO) (Table “SDG_0882_NOC_RT_A”)

	ILO
Data Source	ILOSTAT Data Explorer « SDG_0882_NOC_RT_A »
Frequency of update	Monthly
Country coverage (extent & scope)	170 countries
Sector granularity	-
% of global value	-
Reliability (1-5)	3

xxx Rate	**Average: 12.32 cases** Country Range: 0 to 196.4 Sector Range: 2.5 to 68.2
Publisher	UN

Data processing/Estimation procedure

The indicator is derived from the ILO compliance index, which assigns a score from 0 to 10 for each country. A threshold score of 5 is established to classify countries into high-risk (score ≥ 5) and low-risk (score < 5) groups. The binary indicator is then multiplied by the total number of employees in each country-sector combination to estimate the absolute number of affected employees in high-risk countries. Missing data in country datasets is imputed based on historical territorial affiliations, the prevailing economic system, or regional benchmarks. Due to a lack of sectoral differentiation, it is assumed that violations occur uniformly across all industries based on general national political circumstances.

Unit of measure

Number of cases

2.2.3.5 Gender Discrimination

Definition

The Gender Pay Gap measures the difference in average earnings between men and women, indicating what women earn relative to men in the same economic activity. It serves as a quantifiable indicator of gender inequality in the workplace. According to the International Labour Organisation (ILO), the Gender Pay Gap reflects the gap in average wages between all working men and women, whether on a salary, hourly, or daily wage basis. It is calculated as the difference between men’s and women’s average earnings, expressed as a percentage of men’s average earnings.

Sub indicators

- Pay Gap
- Female Employment

Primary Sources

- ILOSTAT – Wage and Working Time Statistics (COND) (Table “EAR_4MTH_SEX_ECO_CUR_NB_A”)

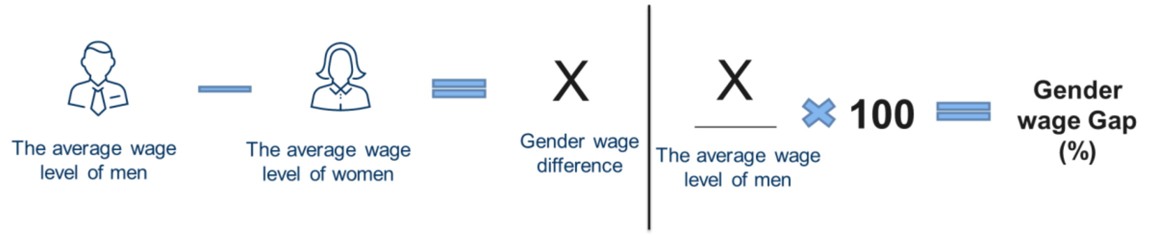
Additional Sources

- EXIOBASE
- WIOD
- EORA

	ILO
Data Source	ILOSTAT Data Explorer « EAR_4MTH_SEX_ECO_CUR_NB_A »
Frequency of update	Monthly
Country coverage (extent & scope)	135 countries
Sector granularity	21 sectors
% of global value	-
Reliability (1-5)	3
xxx Rate	**Average:** Country Range: Sector Range:
Publisher	UN

Data processing/Estimation procedure

The basic methodology for estimating the Gender Pay Gap is the subtraction of average wage level for women from that of men, and then dividing the remainder by the average wage level of men (ILO 2020b). Therefore, the methodology in the simpler form looks the following way.



For a NACE code-wise estimation of gender pay gap, the average level of wages code-wise would be needed, however the ILO database provides data only for mean monthly earnings of employees by sex and economic activity. Thus, for the NACE code-wise estimation of the Gender Pay Gap, the existing ILO database of mean monthly earnings was sub-divided using the WifOR's existing labour compensation (LAB), total employment (EMP), number of males employed (EMP-M) and the number of females employed (EMP-F). The earnings ratio is one of the most important inputs to this exercise which was derived from the ILO's database of mean monthly earnings of employees by sex and economic activity. The earnings ratio is the mean monthly earnings of male to female by country and economic activity.

Step 1

Estimate Compensation per Employment (Female).

$$COMP_F\ per\ EMP_F = \frac{Total\ Average\ Compensation}{EMP_F + (EMP_M * Earnings\ Ratio)}$$

Step 2

Estimate Compensation per Employment (Male)

$$COMP_M\ per\ EMP_M = COMP_F\ per\ EMP_F \times Earnings\ Ratio$$

Step 3

Estimate Total Compensation of Females in sector category

$$Total\ COMP_F = COMP_F\ per\ EMP_F \times EMP_F$$

Step 4

Estimate Total Compensation of Males in sector category

$$Total\ COMP_M = COMP_M\ per\ EMP_M \times EMP_M$$

Thus, the Gender Pay gap is the difference between Total Compensation estimated for the female subtracted from the total compensation estimated for the male. There exists even a cross-check mechanism in this methodology where the summation of the total compensation by male and female estimated here equals to the labour compensation sourced from WifOR's model.

It was assumed during the estimation that the earnings ratio of one economic activity is same across all the sub-sectors included in that economic activity and also that this ratio remains constant across all the years. The data on the mean monthly earnings of male to female by country and economic activity was available for specific countries only i.e., for 88 countries, therefore, for the rest 100 countries, the ratios were estimated using the regional averages from the data given for the existing countries.

Unit of measure

Pay Gap: USD

Employment: Number of persons

2.2.3.6 Human Capital / Training

Definition

Continuing vocational training (CVT) courses involve activities primarily aimed at developing new skills or enhancing existing ones and are funded, at least in part, by enterprises for their workforce. This workforce includes employees with contracts, as well as unpaid family and casual workers who directly benefit from their work within the enterprise. Time spent on CVT courses refers specifically to the paid working hours (in total hours) that participants dedicated to training during the reference year.

Primary Sources

- Eurostat: Hours spent in CVT courses by NACE Rev. 2 activity - hours per person employed in all enterprises (Table “trng_cvt_23n2”)

Additional Sources

- Employment data

	Eurostat
Data Source	https://ec.europa.eu/eurostat/databrowser/view/trng_cvt_23n2/default/table?lang=en&category=educ.educ_part.trng_cvt.trng_cvt_04 Table «trng_cvt_23n2»
Frequency of update	Multiple times a year
Country coverage (extent & scope)	30 European countries
Sector granularity	5 sector groups
% of global value	~11%
Reliability (1-5)	5
Training Rate	**Average: 475.86 h** Country Range: 6.1 to 5,109.6 h Sector Range: 0 to 5,046 h
Publisher	Statistical Authority

Estimation procedure

In general, there is no dataset with global coverage. Eurostat provides datapoints for 30 countries and for the EU28 on sectoral level. The data of the other countries are estimated based on the EU28 average training hours per person employed.

Unit of measure

Hour

2.2.3.7 Land Eviction

Definition

The Land Eviction indicator measures the risk of unlawful violations of land rights. This indicator captures the potential impact on workers in the agricultural sector who lose their employment and income due to illegal land eviction deals.

Primary Sources

- GIZ and Global and Area Studies – Land Matrix (2023)

Additional Sources

- EXIOBASE

	GIZ & Global and Area Studies	EXIO
Data Source	Land Matrix | Land Matrix Land Matrix (2023)	EXIOBASE version 3
Frequency of update	Yearly	-
Country coverage (extent & scope)	15 countries	44 countries, 5 Rest of the World regions
Sector granularity	1 sector	163 sectors aggregated to 57
% of global value	100%	-
Reliability (1-5)	4	4
Xxx Rate	**Average: 0.05 cases** Country Range: 0 to 3.17 Sector Range: 0 to 2.14	
Publisher	Governmental Development Agency	University (large research consortium)

Data processing/Estimation procedure

The indicator uses data from the Land Matrix, which records large-scale land acquisitions, to estimate affected people by calculating the density of agricultural employment per hectare and applying it to land eviction deals. Employment density serves as a proxy for workers at risk. Given the limited data, an average across years is used for each country-sector combination to stabilize estimates. For countries not represented in the dataset, it is assumed that no unlawful deals have occurred.

Unit of measure

Number of affected persons.

2.2.3.8 Living Wage Gap (+ People affected)

Definition

The living wages indicators is meant to assess the quality of employment through the wages paid to employees. For this purpose, wages are evaluated against a threshold, the “living wage”. The living wage is defined as “a basic but decent level of life that allows a household to get good nutrition, housing, health and education” and is available at country level. Employees paid below the living wage cannot maintain a basic but decent level of life despite their work. They thus experience negative effects on quality of life and life expectancy.

Sub indicators

- Net Gap
- Positive Gap
- Negative Gap
- People Over Living Wage
- People Under Living Wage

Specifications

- Single working parent family Living Wage
- Typical family Living Wage

Sub-specifications

- High-skilled
- Medium-skilled
- Low-skilled

Primary Sources

- Valuing Nature – Global Living Wage dataset (2024 update)
  - The latest Living Wage dataset from Valuing Nature provides both rural and urban Living Wages per country (and additionally for several cities) – an average value per country is not available
  - As our wage data is not (yet) available with this granularity, we calculate the (unweighted) mean value between rural and urban per country, as proposed by Sam Vionnet (Valuing Nature)

Additional Sources

- WIOD
- EORA

	WIOD	EORA	Valuing Nature
Data Source	https://www.rug.nl/ggdc/valuechain/wiod/wiod-2013-release	https://www.worldmrio.com/	https://www.valuingnature.ch/post/global-living-wage-dataset-2023 (recent update) Global Living Wage dataset (2024)
Frequency of update	Non regular	Non regular	Yearly
Country coverage (extent & scope)	6 Non-EU Non OECD countries	Rest of the World	218 countries * 2 spatial classifications
Sector granularity	56 sectors	-	-
% of global value	~72%	Only shares	~100%
Reliability (1-5)	4	2	3

People Under LW (TFLW) Rate	**Average: 59.21** Country Range: 0 to 759.6 Sector Range: 0 to 438.5		
Publisher	University (large research consortium)	University (large research consortium)	Valuing Nature (Collaborative Research Initiative)

Estimation Procedure

The Living Wage Gap is calculated, subtracting the (gross) living wage of a country from the (gross) labor compensation per employee. The Living Wage data was derived from Valuing Nature (and adapted as indicated above). The compensation and employment data were partly derived from WIOD and partly from EORA, both are available not by spatial category but by skill levels: highly-skilled, medium-skilled and low-skilled. Dividing the compensation per sector, country and skill level by the respective number of employees gives us the average wage. As the living wage is a nationally uniform value and not dependent on the skill level, we were able to calculate Living Wage Gaps by skill level which makes the indicator more granular. The analysis further derives the number of people earning above (positive) and below (negative) the living wage.

Unit of measure

Pay Gaps: USD
People Over/Under Living Wage: Number of persons

2.2.3.9 Occupational Health & Safety

Occupational health deals with all aspects of health and safety in the workplace and has a strong focus on primary prevention of hazards. The focus of these indicators is on the societal impacts arising from injuries and illnesses resulting from incidents that happen during the course of employment.

2.2.3.9.1 Injuries

Definition

A non-fatal occupational injury refers to an injury sustained by a worker due to a workplace accident that does not result in death. In contrast, a fatal occupational injury occurs when a workplace accident leads to the worker's death within one year of the accident date.

Specifications

Injuries by severity:

- Short absence
- Long absence
- Partial incapacity
- Full incapacity
- Fatality

Primary Sources

- Eurostat (Tables "hsw_n2_01" and "hsw_n2_02")
- Database of the International Labour Organization (ILO) - Occupational safety and health statistics (OSH): Incidence rates for fatal and non-fatal occupational injuries by economic activity

Additional Sources

- Study by Kharel (2016): The global epidemic of occupational injuries: Counts, costs, and compensation.
- Study by Hämäläinen et al (2017): Global Estimates of Occupational Accidents and Work-Related Illnesses
- Study of the Australia and National Occupational Health and Safety Commission (2015)
- Data on employment (see "Economic indicators")

	Eurostat	ILO	US BLS	Safe Work Australia
Data Source	https://ec.europa.eu/eurostat/databrowser/view/hsw_n2_01/default/table?lang=en https://ec.europa.eu/eurostat/databrowser/view/hsw_n2_02/default/table?lang=en Tables «hsw_n2_01» «hsw_n2_02»	Occupational safety and health statistic (OSH)	https://www.bls.gov/iif/nonfatal-injuries-and-illnesses-tables/soii-summary-historical.htm Table «SNR07» (2018)	"Study of the Australia and National Occupational Health and Safety Commission (2015)"
Frequency of update	Multiple times a year	Multiple times a year	Yearly	Yearly
Country coverage (extent & scope)	27 European countries	147 countries	1 country	Rest
Sector granularity	111 sectors aggregated to 57	50 sectors	17 sectors	-
% of global value	~3%	~92%	~1%	~2%
Reliability (1-5)	5	3	5	2
Range of quota across countries	**Average: 4.38** Country Range: 0.00012-194.3 Sector Range: 0.46-32.2			
Publisher	Statistical Authority	UN	Statistical Authority	Governmental agency

Estimation procedure
Eurostat and ILO data provide incidence rates for fatal and nonfatal injuries at different sector disaggregation levels and completeness. These data are based only on official records, such as declarations to national social security systems, private accident insurance, labor inspections, or other relevant authorities. We calculated average incidence rates by income region to estimate missing values for entire countries and missing sectors. Incidence rates are then adjusted using academic studies to account for the well-recognized problem of underreporting. Furthermore, there was no data for all five severity levels. We use the ratios of the study of the Australia and National Occupational Health and Safety Commission (2015) to break down the non-fatal injuries according to the requested severity levels.

Unit of measure
Number of cases

2.2.3.9.2 Illness/Disease

Definition
An occupational disease is any disease caused primarily by exposure at work to a physical, organizational, chemical or biological risk factor, or to a combination of these factors. Occupational diseases are mostly those listed in national legislation as resulting from exposure to risk factors at work. The recognition of an occupational disease may be linked to compensation if it is clear that there is a causal relationship between an occupational exposure and the disease. Many types of disease, including cancer, respiratory disorders, cardiovascular disease, skin diseases, musculoskeletal disorders and mental health problems, can be caused or made worse by work. Although the underlying causes of such diseases may be complex, certain workplace exposures are known to contribute to the development or progression of a disease, including:

- dangerous substances, such as chemical and biological agents, including carcinogens;
- radiation, including ionizing radiation and ultraviolet radiation from the sun;
- physical factors, including vibration, noise, manual lifting, and sedentary work;
- organizational and psychosocial risk factors, such as shift work and stress.

Specifications
Illness by severity:

- Short absence
- Long absence
- Partial incapacity
- Full incapacity

- Fatality

Primary Sources

- Study of the European Agency for Safety and Health at Work (2019) for Germany, Netherlands, Finland, Italy and Poland. Australian Data is taken from Australia and National Occupational Health and Safety Commission (2015).

Additional Sources

- Sectoral incidence rates (The incidence rates represent the number of illnesses per 10,000 full-time equivalent workers) from US data on occupational illnesses by major industry sector and category of illness in 2018 (https://www.bls.gov/iif/oshwc/ osh/os/snr07_00_2018.xlsx)
- Study of the International Labour Organization (2014) with estimates on fatal occupational diseases for 227 countries
- Data on employment (see "Economic indicators")

	ILO	Eurostat	US Bureau of Labor Statistics	Safe Work Australia
Data Source	https://www.ilo.org/resource/world-statistic	https://ec.europa.eu/eurostat/databrowser/view/hsw_pb6b/default/table?lang=en https://ec.europa.eu/eurostat/databrowser/view/hsw_hp_dinag/default/table?lang=en Tables: «hsw_pb6b» and «hsw_hp_dinag»	https://www.bls.gov/iif/nonfatal-injuries-and-illnesses-tables/soii-summary-historical.htm Table «SNR07» (2018)	The Costs of Workplace Injury and Illness 2012-13 (safeworkaustralia.gov.au)
Frequency of update	-	Non regular	Yearly	-
Country coverage (extent & scope)	227 countries	EU27 and 5 European countries	1 country	1 country
Sector granularity	-	5 sectors	14 sectors (private industry + state & local government)	-
% of global value	-	~9%	~2%	-
Reliability (1-5)	3	5	5	2
Disease/Illness Rate	**Average: 4.68** Country Range: 0.02 to 83.7 Sector Range: 0.45 to 38.62			
Publisher	Statistical Authority	Statistical Authority	Statistical Authority	Governmental Agency

Estimation procedure

The estimation of fatal illness cases for each country uses incidence rates from ILO (2014) (cases per 10,000 employees) combined with employment figures from the IO-

Table. For Germany, the Netherlands, Finland, Italy, and Poland, we use updated estimates from the European Agency for Safety and Health at Work (2019), and for Australia, data is sourced from the Australian National Occupational Health and Safety Commission (2015). Economy-wide fatal case estimates are distributed across sectors using 2018 U.S. data on occupational illnesses by major industry sector, mapped to WIOD sectors. This assumes that the sectoral distribution of fatal illnesses aligns with that of all illnesses, and relative incidence rates across sectors are consistent across countries. We then estimate cases for the four remaining severity categories by applying the fatal-to-non-fatal case ratio for each category from the Australian study. To validate, we compare the resulting global case numbers against global estimates from ILO (2015).

Remarks

The ILO database lacks regularly updated figures on work-related diseases, unlike the injury statistics that are frequently refreshed. Comparing data across countries is challenging due to varying definitions of “work-related diseases” and differences in national compensation schemes. Additionally, underreporting and underestimation are significant issues, as there is often a gap between reported cases and actual instances. This discrepancy can result from diseases not being recognized by authorities or differences in insurance systems, leading to a divergence between official figures and reality.

Unit of measure

Number of cases

2.2.3.10 Rule of Law

Definition

The Rule of Law indicator measures the risk of human rights abuses by security forces and other violations related to the enforcement of law, assessing following set of sub indicators: Constraints on government powers, Absence of corruption, Open government, Fundamental rights, Order and security, Regulatory enforcement, Civil justice and Criminal justice.

Primary Sources

- World Justice Project (WJP) – Rule of Law Index

Additional Sources

- World Bank – Rule of Law Index
- EXIOBASE

	World Justice Project	World Bank	EXIO
Data Source	WJP Rule of Law Index Rule of Law Index	Rule Of Law | Data | DataBank Rule of Law Index	EXIOBASE version 3
Frequency of update	Yearly	Yearly	-
Country coverage (extent & scope)	134 countries	48 countries	44 countries, 5 Rest of the World regions
Sector granularity	-	-	163 sectors aggregated to 57
% of global value	-	-	-
Reliability (1-5)	4	5	4
xxx Rate	**Average: 51.12 cases** Country Range: 0 to 470.1 Sector Range: 9.5 to 395.2		
Publisher	Non-profit organization	International Organization	University (large research consortium)

Data processing/Estimation procedure

The indicator uses the Rule of Law Index from the World Justice Project to evaluate compliance levels across countries. A threshold score of 0.5 is set to categorize countries into high-risk (score < 0.5) and low-risk (score ≥ 0.5) groups. To estimate the number of affected employees, the binary indicator (1 for high-risk countries) is multiplied by the total number of employees in each country-sector combination. For countries with missing data, values are filled using the World Bank's Rule of Law Index or by associating them with similar countries based on historical or political ties. Given the lack of sectorial differentiation, we assume that violations of the rule of law are uniformly distributed across sectors, reflecting that issues stem from broader national political circumstances.

Unit of measure

Number of cases

2.2.3.11 Working Overtime

Definition

The Working Overtime indicator measures the risk of excessive physical and mental fatigue in the workforce. This indicator captures the number of employees working over 48 hours per week on average, which is considered a human rights risk linked to occupational health and safety, potentially leading to negative health outcomes.

Primary Sources

- International Labour Organization (ILO) – Wages and Working Time Statistics (Table "EMP_TEMP_SEX_HOW_NB_A")
- International Labour Organization (ILO) – Employment data ILO_Average hours and prevalence of excessive working time_2022

Additional Sources

- EXIOBASE

	ILO		EXIO
Data Source	ILOSTAT Data Explorer EMP_TEMP_SEX_HOW_NB_A	Statistics on working time - ILOSTAT Average hours and prevalence of excessive working time	EXIOBASE version 3
Frequency of update	Monthly	Yearly	-
Country coverage (extent & scope)	152 countries	36 countries	44 countries, 5 Rest of the World regions
Sector granularity	-	-	163 sectors aggregated to 57
% of global value	-	-	-
Reliability (1-5)	3		4
Overtime Rate	**Average: 15.4 cases** Country Range: 0.09 to 198 Sector Range: 2.5 to 99		
Publisher	UN		University (large research consortium)

Data processing/Estimation procedure

The indicator draws on two ILO datasets: one offering absolute numbers of employees working overtime and another providing the proportion of such employees. Missing values are estimated using regional averages based on available data, if the sectoral distribution of affected employees reflects the overall employment distribution. For missing years, data is filled using the closest available values, applied both forward and backward.

Unit of measure

Number of cases

Summary

Table 10: Indicators and relevant sources

	Indicator	Sub indicators	Specifications	Sources		
				Primary Datasource (MRIO Databases)	Additional Sources	comment on coverage
Economic	**GVA**	-	-	WIOD, EORA	Eurostat, OECD	full coverage by existing satellites of MRIO Source
	Employment	-	-			
Environmental	**Greenhouse gas emissions**	GHG's	-	EXIOBASE, EORA	Air Emission Accounts (Eurostat, OECD), GHG protocol to get actual GWPs	full coverage by existing satellites of MRIO Source
	Air Pollution	Six air pollutants: NH3, Nox, PM10, PM 2.5, Sox, VOC	Urban, Peri-Urban, Rural, Transport	EXIOBASE, EORA	Air Emission Accounts (Eurostat, OECD)	full coverage by existing satellites of MRIO Source
	Water consumption	-	-	EXIOBASE, EORA	-	full coverage by existing satellites of MRIO Source
	Water pollution	12 water pollutants: Nitrogen, Phosporus, Antimony, Arsenic, Cadmium, Chronium, Copper, Lead, Mercury, Nickel, PAHs, Zinc	Freshwater, Marine, Unspecified	EXIOBASE HYBRID	DESTATIS, EEA WATERBASE – aggregated Database	2 pollutants covered by MRIO Source (Nitrogen and Phosphorus) and the rest was estimated based on assumptions and other sources, one specification assessable (unspecified)
	Land use	Agriculture, forestry, paved	11 land types	EXIOBASE	-	full coverage by existing satellites of MRIO Source
	Waste	Hazardous waste, non-hazardous waste	Disposed (landfill), Disposed (incinerated), Recovered (recycling or downcycling)	EXIOBASE HYBRID	Eurostat (env_wastrt)	specifications partially not covered by existing MRIO satellites

	Indicator	Sub indicators	Specifications	Sources		
				Primary Datasource (MRIO Databases)	Additional Sources	comment on coverage
	Invasive Alien Species	-	-	-	EASIN, WCVP, IMF DOTS, GloNAF, CIA World Factbook, Our World in Data	own research: no coverage via satellites so far
	Resource Use	Minerals/Metals, Fossil Fuels, Biomass	-	EXIOBASE	World Mining Data (2022), British Geological Survey (2022)	full coverage by existing satellites of MRIO Source
	Resource Use - Wood	Industrial roundwood, Wood fuel (inlc. pellets)	Certified, Non-certified	-	FAO– Forestry Production and Trade Database FAO - SDG Indicators Data Portal - Indicator 15.2.1	own research: no coverage via satellites so far

	Indicator	Sub indicators	Specifications	Sources		
				Primary Datasource (MRIO Databases)	Additional Sources	comment on coverage
Human & Social	**Disability Discrimination**	Employment without disability, Employment with disability, Disability Pay Gap	-	-	ILO (POP_XWAP_SEX_DSB_LMS_NA_A), ILO (EAR_4MTH_SEX_DSB_CUR_NA_A), EXIOBASE	own research: no coverage via satellites so far
	Forced Labor	-	-	-	Walk Free Foundation (2018) ILO and Walk Free Foundation (2017)	own research: no coverage via satellites so far
	Freedom of Association	-	-	-	ILO (SDG_0882_NOC_RT_A)	own research: no coverage via satellites so far
	Gender Pay Gap	Pay Gap, Female Employment	-	-	ILO (EAR_4MTH_SEX_ECO_CUR_NB_A)	own research: no coverage via satellites so far
	Human Capital / Training	Training hours	Not needed due to consistent reformulation of the proposed model	-	Eurostat (trng_cvt_23n2), World Bank, Enterprise Surveys (IC.FRM.TRNG.ZS)	no coverage via existing satellites so far, reformulation of the model allows for use of training hours only
	Land eviction	-	-	-	GIZ and Global and Area Studies – Land Matrix (2023), EXIOBASE	own research: no coverage via satellites so far
	Living Wages	Living wages for low, medium, and high skill employees	-	WIOD, EORA	Living wage dataset (Valuing Impact) Health gap (Valuing Impact)	no coverage via existing satellites so far

	Occupational health and safety	Injury	Short absence, Long absence, Partial incapacity, Full incapacity, Fatality	-	Eurostat (hsw_n2_01, hsw_n2_02), ILOSTAT, Kharel (2016), Hämäläinen, Takala, and Kiat (2017), Australia and National Occupational Health and Safety Commission (2015)	own research: no coverage via existing satellites so far, specifications are taken from Australia
		Disease/Illness	Short absence, Long absence, Partial incapacity, Full incapacity, Fatality	-	ILOSTAT, US BLS (TABLE SNR07), European Agency for Safety and Health at Work. et al. (2019), Australia and National Occupational Health and Safety Commission (2015),	
	Risk of Child Labor	-	-	-	ILOSTAT (2021) UNICEF (2021) ILO and UNICEF (2021)	own research: no coverage via satellites so far
	Rule of Law	-	-	-	World Justice Project (WJP) – Rule of Law Index, World Bank – Rule of Law Index, EXIOBASE	own research: no coverage via satellites so far
	Working Overtime	-	-	-	ILO (EMP_TEMP_SEX_HOW_NB_A), ILO (Employment Data) EXIOBASE	own research: no coverage via satellites so far

Source: Own depiction

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