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Comparing Emissions Embodied in Imports from Four Global MRIO Databases

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Comparing emissions embodied in imports from four global MRIO databases

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Abstract

Recent years have seen an increased interest in consumption-based approaches to estimating national GHG emissions. To calculate consumption-based accounts, global multi-regional input-output (MRIO) data with environmental extensions are needed and researchers must choose which of the various MRIO databases, each with its own strengths and limitations, to employ. Exploring the effects of these choices contributes to the improvement of national consumption-based emissions accounts and aids understanding the impacts of climate change policy on emissions. This research investigates differences in emission estimates from four global MRIO databases: EXIOBASE, the Global Resource Input-Output Assessment (GLORIA), the OECD's Inter-Country Input-Output tables (ICIO), and Eurostat's Full International and Global Accounts for Research in input-Output analysis (FIGARO). These databases are commonly used, but intercomparison is currently understudied. We ask how the imported component of a country's environmental footprint differs when using each of these datasets. We do this to evaluate the most appropriate database to use in different contexts and to understand the implications of choosing one of these datasets over another. We investigate data from the years 2010-2018, as data for these years is published for all four databases. We calculate consumption-based emissions for all countries and sectors in each MRIO table, and then aggregate these to a common set of countries in sectors. Our final analysis contains 43 countries and one Rest of World region and 36 sectors.

To quantify differences, we run pairwise comparisons of all MRIO pairings. We analyse absolute differences in emissions estimates and the similarity in trend meaning whether two MRIOs increase and decrease concurrently over time. Initial findings indicate that ICIO and FIGARO produce the most similar results to each other, followed by the EXIOBASE and GLORIA comparison.

Keywords: Multi-regional input output database; consumption-based accounts; footprints

Introduction

A globalised economy means that the goods and services which are produced in one territory can be consumed in elsewhere. Looking at a consumption-perceptive, which calculates a country's total footprint linked to final demand, thus, provides a different picture to territorial approaches, around which national targets are usually set. In addition, the effect of many demand side strategies such as 'the sharing economy' and 'low meat diets' can only be determined using consumption calculations.

To calculate consumption-based emissions (CBE), global multi-regional input-output (MRIO) data are needed. However, various such databases exist, each with their its own set of strengths and limitations. As accounting from a consumption perspective moves up the political agenda in the effort to reduce emissions (IPCC, 2022), the creation and improvement of such policy relevant databases are crucial. Consequently, the availability of such databases and ensuring these are as robust as possible can impact, for instance, trade policies, carbon agreements, and national demand side mitigation strategies.

In this research, we investigate four current MRIO databases. These include EXIOBASE (Stadler et al., 2018), the Global Resource Input-Output Assessment (GLORIA) (Lenzen et al., 2023), the OECD's the OECD's Inter-Country Input-Output tables (ICIO) (OECD, no date), and Eurostat's Full International and Global Accounts for Research in input-Output analysis (FIGARO) (Eurostat, no date). These are four MRIO databases, which are currently maintained and updated, as well as widely used by researchers and governments. Moreover, while researchers have investigated differences between MRIO databases (Moran and Wood, 2014; Owen et al., 2014; Inomata and Owen, 2014; Arto et al., 2014), these four have not yet been assessed in their current format.

While previous MRIO databases were mainly constructed by academic institutions, multilateral institutions are now involved in the construction of MRIO tables. The tables had many different assumptions, leading to notable differences both within the data (Owen et al., 2014), and in the CBE calculated with them (Moran and Wood, 2014). In this analysis we add a comparison of these databases developed by academics to more recently developed ones by Eurostat and OECD. This allows us to compare which database is best for which context and provide an overview of their differences when calculating CBEs.

Methods and Data

2.1. MRIO Data

The MRIO databases we analyse offer very different coverage (Table 1). This includes the number of countries, sectors and final demand categories, the years data are available for, and the extension variables available. Moreover, the MRIO tables are made by different organisations. While EXIOBASE and GLORIA are made by a collaboration of mainly academic institutions, ICIO and FIGARO are constructed by OECD and Eurostat respectively.

Table 1. MRIO metadata differences.

	EXIOBASE	ICIO	FIGARO	GLORIA
Organisations involved in construction	NTNU, TNO, SERI, Uni. Leiden, WU, 2.-0 LCA Consultants	OECD	Eurostat	Uni. of Sydney, CSIRO, Uni.Wien, UNSW Sydney
Year range	1995 - 2021	1995 - 2020	2010 - 2021	1990 - 2027
Countries/regions	49	67	46	164
Sectors	163	45	64	120
Extension variables[1]	1115 including CO_2	CO_2 only	CO_2 only	5677 including CO_2
Final demand categories	7	6	9	6

2.2. Calculation of footprints

We calculate consumption-based emissions for each country and sector in each MRIO database using environmentally-extended input-output analysis. This allows us to link environmental impacts that occur throughout the global supply chain to the final demand of a specific country or region (Miller and Blair, 2009). Equation (1) shows how the the fundamental Leontief equation, $\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-\mathbf{1}}\mathbf{y}$ can be used to estimated CBEs at a product-level. Here, $\mathbf{s}$ is a vector showing direct industry emissions[2], $\mathbf{A}$ is the product of the input-

[1] This shows all extension variables available, not only environmental variables.
[2] In this analysis we do not add direct household emissions.

output matrix (**Z)** and the total industry output vector, and **y** is final demand (see Miller and Blair, 2009; Wood et al., 2019b).

$$(1) \qquad \boldsymbol{p} = \boldsymbol{s}(\boldsymbol{I} - \boldsymbol{A})^{-1}\hat{\boldsymbol{y}}$$

After carbon footprints are calculated, we aggregate countries and sectors, so that emission estimates from all four databases contain the same countries and sectors. Aggregation is kept to the minimum possible level. In other words, countries are aggregated with the dual aim of maintaining as many countries and sectors as possible, while ensuring they are consistent across all four databases (see Appendix A).

2.3. Footprint comparison methods

Following Kilian et al.'s (2023) approach, we analyse various characteristics of the footprints. First, we look at the absolute difference by calculating the root mean squared error (RMSE) as shown in Equation (2). Here, N is the number of years analysed. We calculate this at a country level, across years and for each data pairing. This means that, for instance, the RMSE of the total footprint for Australia between GLORIA and FIGARO provides an indication of the absolute difference in GLORIA and FIGARO results across the years 2010-2018. As this RMSE is relative to the emission estimates, in this case of Australia by GLORIA and FIGARO, we report the RMSE as a percentage of the mean emission estimate of the pairing analysed, as shown in Equation (3). We are thereby able to control for the difference in magnitudes between the emissions of the different countries and sectors analysed and can compare these proportional RMSEs between countries and sectors.

$$(2) \qquad \boldsymbol{RMSE} = \sqrt{\sum(\boldsymbol{x_{Datset\,A}} - \boldsymbol{x_{Datset\,B}})^2 / \boldsymbol{N}}$$

$$(3) \qquad \boldsymbol{proportional\ RMSE_{Datasets\ A\ and\ B}} = \frac{\boldsymbol{RMSE_{Datasets\ A\ and\ B}}}{\boldsymbol{Mean\ emissions_{Datasets\ A\ and\ B}}} * \boldsymbol{100}$$

In addition to absolute difference, we also assess differences in trend over time. For this, we code emissions from one year to the next as increasing or decreasing and then calculate the number of times for which the direction of change is the same. Using the FIGARO, GLORIA pairwise comparison for Australia as an example again, Table 2 shows how the similarity in direction variable is calculated.

Table 2. Example method for calculating the similarity difference for Australia for the FIGARO, GLORIA comparison.

Year	FIGARO Emissions	GLORIA Emissions	FIGARO change	GLORIA change	Match
2010	450813	407480	-	-	
2011	461178	417599	Increase	Increase	Yes
2012	472002	429089	Increase	Increase	Yes
2013	441819	421573	Decrease	Decrease	Yes
2014	419984	389509	Decrease	Decrease	Yes
2015	417136	373403	Decrease	Decrease	Yes
2016	407254	372439	Decrease	Decrease	Yes
2017	414985	369532	Increase	Decrease	No
2018	402200	362386	Decrease	Decrease	Yes
	Number of ‘Yes’ as a percentage of total comparisons:				87.5%

Results

3.1. Country-level differences

Consumption-based CO_2 emissions are calculated for each country in each MRIO dataset, and then aggregated to 43 countries which overlap in all four datasets, as well as one rest of world region. Mean aggregated emission estimates are comparable across the four datasets

(Figure 1). However, differences occur in the proportion of emissions imported, where the ICIO and FIGARO data estimate a higher proportion of imported emissions than the EXIOBASE and GLORIA data. For all years and countries, EXIOBASE estimates that only 23% of global CBEs are imported. GLORIA estimates this to be 27%, ICIO 46% and FIGARO 47%. Despite similarities in country rankings, we find two groupings of estimates in imported emissions: EXIOBASE and GLORIA, and FIGARO and ICIO.

In addition, countries with more open economies tend to have smaller footprints (Figure 1). These are often smaller countries, who are more reliant on trade. Despite this, even for countries with high levels of imported emissions, the estimate for the percentage of emissions that is imported vary between datasets, where ICIO and FIGARO often report a higher percentage of imported emissions than EXIOBASE and GLORIA. As openness of the economy is defined by the proportion of imports and exports, countries with higher levels of openness also have higher proportions of imported emissions and vice versa.

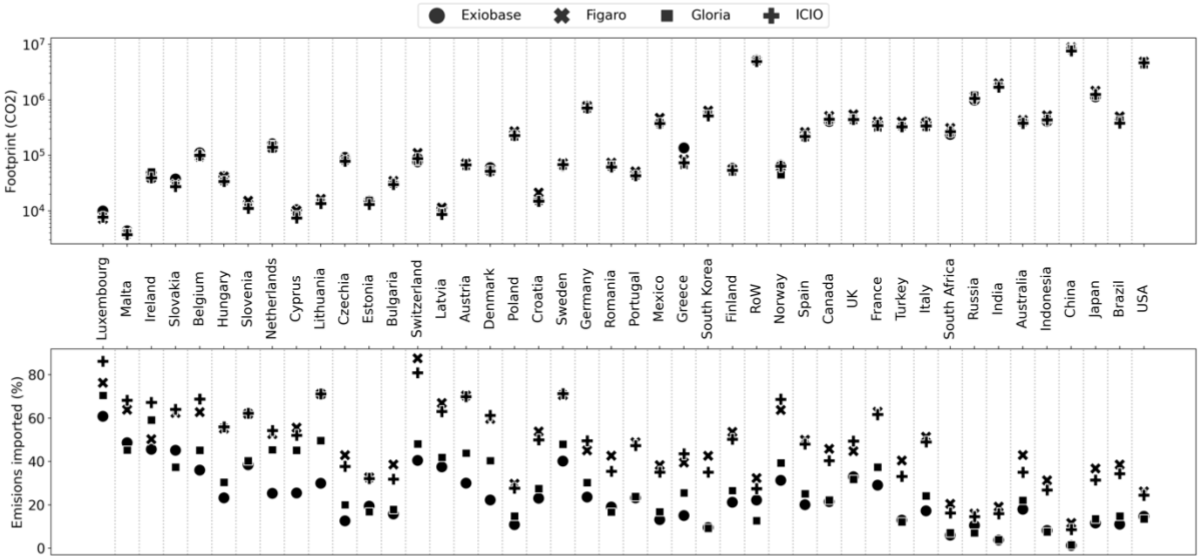

Figure 1. Mean emissions from 2010-2018 (top) and percentage of emissions imported (bottom) by consumer country and MRIO data.

** Note: Countries on the x-axis are sorted from highest (left) to lowest (right) economic openness.

To quantify differences between each data pairing, we calculate the difference as an error as well as the frequency in which the direction of the footprint trend changes over time. For the error, we calculate the proportional RMSE across the years 2010-2018. To estimate similarity in direction we count the number of times to datasets increase or decrease simultaneously for each year and express this as a percentage. In other words, this value shows the number of years in which the estimates of two datasets both increase together, or both decrease as a percentage of the total number of years analysed.

As shown in Figure 2, proportional RMSEs are lower and similarity in direction is higher for countries with higher emissions. The four countries with the highest total CBEs, which make up over 68% of the global footprint have a proportional RMSEs of under 17% (mean=6.86%) for all pairings and a directional similarity of over 50% (mean=80.73%) for all pairings. However, while these countries and regions have the highest total emissions, they do not necessarily have the highest per capita emissions. Of China, the USA, India and the RoW region, only the USA is in the top 3 highest per capita emissions, while India and the RoW have the lowest and second lowest per capita emissions (see Appendix B). Thus, while the majority of the global footprint is comparable between the datasets, the four MRIO databases can provide drastically different results for some countries with the highest per capita emissions - countries where having accurate results is vital for reducing global carbon inequality. Indeed, some countries with the lowest directional similarity, such as Luxembourg, Norway, and

Australia, are all within the top ten highest emitters per capita. Selecting a dataset that best fits each country's needs is therefore essential.

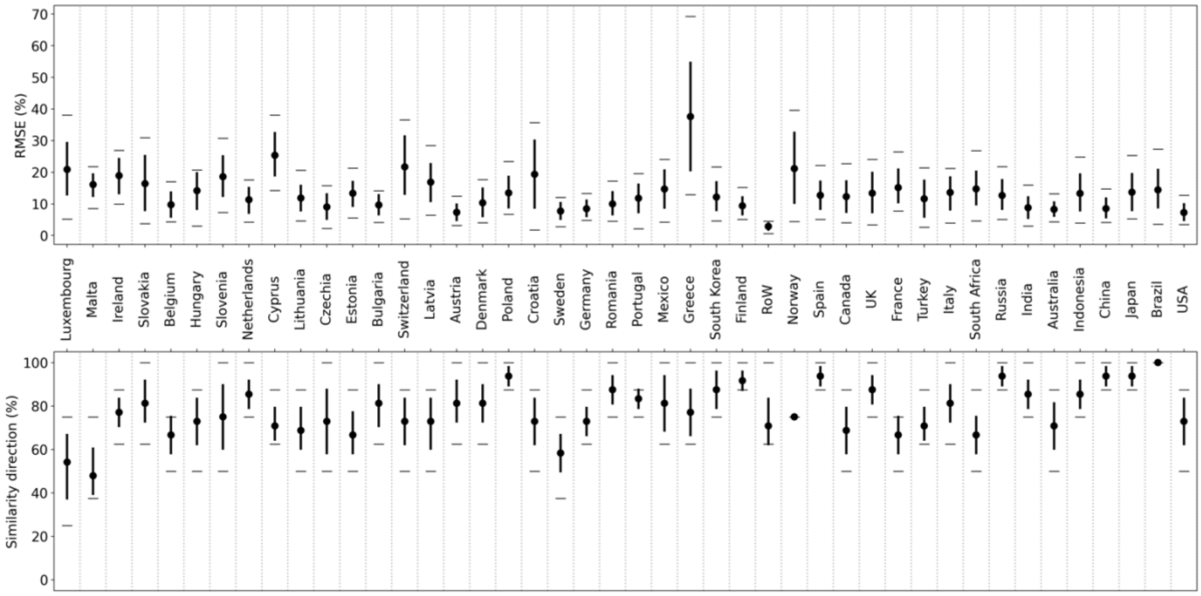

Figure 2. Mean and standard deviation total emission RMSE as a percentage of mean emission (top) and similarity in direction of change (bottom) by consumer country for all MRIO data pairings.

** Note: Countries on the x-axis are sorted from highest (left) to lowest (right) economic openness. Error bars show +/-1 standard deviation. Horizontal lines show minimum and maximum values.

When zooming in on imported emissions, proportional RMSEs get higher and directional similarity gets lower. In other words, uncertainty increases (Figure 3). proportional RMSEs appear to be lower for countries with more open economies (Figure 1). However, these countries also appear to have lower levels of directional similarity in imported emissions. Thus, while absolute differences in imported emissions are lower for countries with more open economies, the direction of change in imported emissions over time is not necessarily the same across the four datasets for these countries. More closed economies show more similarity in direction of change over time for both imported (Figure 3) and total (Figure 2) emissions.

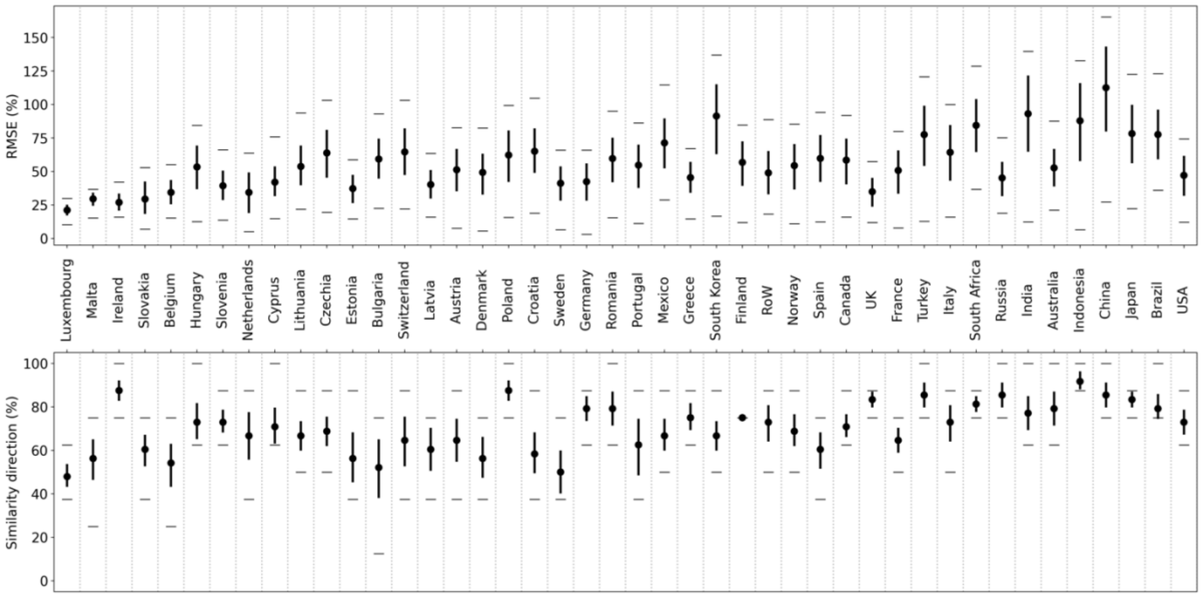

Figure 3. Mean and standard deviation imported emissions RMSE as a percentage of mean emission (top) and similarity in direction of change (bottom) by consumer country for all MRIO data pairings.

** Note: Countries on the x-axis are sorted from highest (left) to lowest (right) economic openness. Error bars show +/-1 standard deviation. Horizontal lines show minimum and maximum values.

Displayed by pairwise comparison, it becomes even clearer that the EXIOBASE and GLORIA comparison and the ICIO and FIGARO comparison have lower RMSEs than other comparison for imported emissions (Figure 4). Interestingly, the ICIO and FIGARO comparison has the lowest directional similarity for total emissions, but the highest for imported emissions.

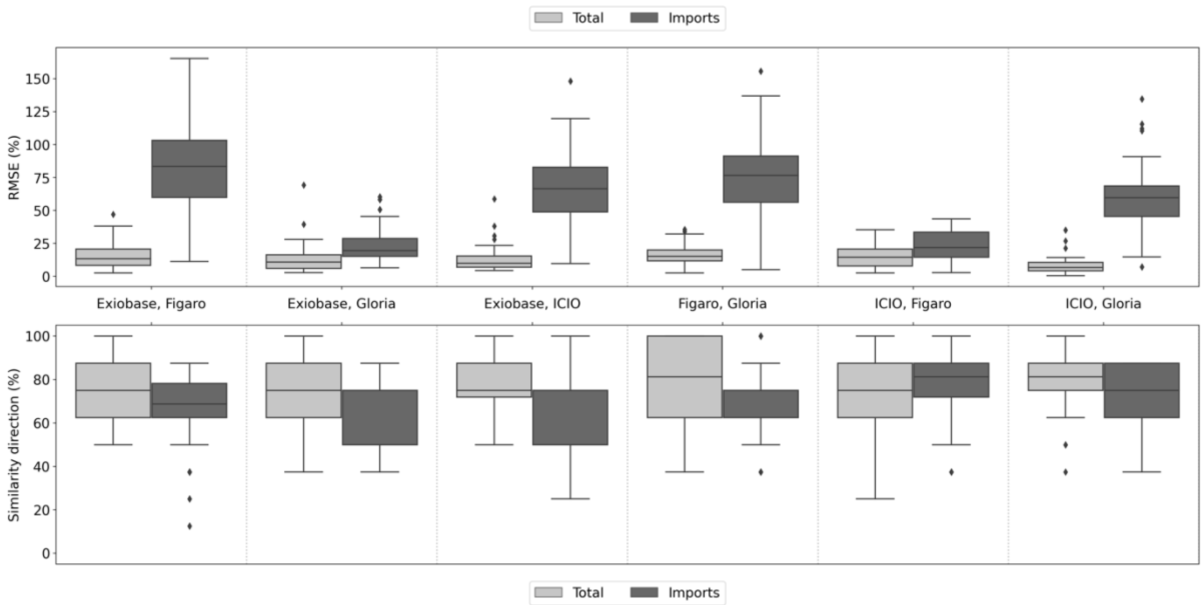

Figure 4. Total and imported emissions RMSE as a percentage of mean emission (top) and similarity in direction of change (bottom) by MRIO data pairing.

3.2. *Sector-level differences*

To gain a complete overview of CBEs, we also analyse sector-level emissions. Most emissions come from a few sectors. Globally, the 10 sectors with the highest total and imported CBEs make up over 71% of total emissions and over 75% of imported emissions, and 5 sectors with the highest total and imported CBEs make up over 55% of total emissions and over 52% of imported emissions (Table 3). In this section, we analyse these 5 most polluting sectors in more detail.

Analysing results by MRIO dataset and pairwise comparison, we find large sector-level differences. As shown in Figure 5, total global CBEs from sectors can vary strongly by MRIO. In the top 3 highest emitting sectors alone, we observe notable differences between the datasets. FIGARO and ICIO find much lower total global emissions from construction, but much higher emissions from electricity, gas, steam and air-conditioning and basic metals than EXIOBASE and GLORIA. Results from pairwise comparisons are worse at a sectoral than at a country level. The FIGARO and ICIO pairing shows mostly lower RMSEs and higher directional similarity than other pairings. For the construction and the machinery, computer, electronic and other equipment sectors, RMSE findings also show more similarity between the EXIOBASE and GLORIA pairing, than between other pairings. However, most pairings perform poorly at a sectoral level with RMSEs as a percentage of mean emissions over 100% and directional similarity only around 50%.

Table 3. Global total and imported CBEs by sector.

	Total Emissions			Imported Emissions		
	Global emissions (ktCO2/ year)	Ranked	Perc. of global CO2 (%)	Global emissions (ktCO2/ year)	Ranked	Perc. of global CO2 (%)
Electricity, gas, steam and air con.	9,221,896	1	31.80	1,201,570	1	21.92
Construction	3,091,094	2	10.66	16,842	25	0.31
Basic metals	1,615,284	3	5.57	623,326	2	11.37
Other non-metallic mineral products	1,316,888	4	4.54	268,341	7	4.89
Land and pipeline transport	991,341	5	3.42	212,240	11	3.87
Food, beverages and tobacco	967,350	6	3.34	154,019	14	2.81
Chemical, pharma. and botanical products	930,432	7	3.21	398,719	3	7.27
Coke and refined petroleum products	859,193	8	2.96	283,579	6	5.17
Machin., computer, electronic, and other equipment	857,090	9	2.96	345,122	4	6.30
Public admin. and defence; compuls. social security	835,885	10	2.88	7,866	30	0.14
Mining and quarrying, energy producing products	678,006	11	2.34	305,989	5	5.58
Agriculture, hunting, forestry	667,544	12	2.30	123,346	15	2.25
Manufacturing; repair and installation of machinery	658,341	13	2.27	242,644	10	4.43
Air transport	617,926	14	2.13	244,776	9	4.46
Human health and social work activities	579,394	15	2.00	3,290	34	0.06
Water transport	520,961	16	1.80	259,056	8	4.73
Wholesale and retail trade; repair of motor vehicles	503,982	17	1.74	59,477	18	1.08
Motor vehicles, trailers and semi-trailers	499,008	18	1.72	157,508	13	2.87
Admin., support and other prof. transport services	422,711	19	1.46	69,663	17	1.27
Real estate activities	395,934	20	1.37	4,823	32	0.09
Textiles, textile products, leather and footwear	372,869	21	1.29	166,170	12	3.03
Other service activities	318,238	22	1.10	7,147	31	0.13
IT, postal, communication services and publishing	301,000	23	1.04	21,793	23	0.40
Education	288,183	24	0.99	3,424	33	0.06
Accommodation and food service activities	267,868	25	0.92	23,299	22	0.42
Rubber and plastics products	253,469	26	0.87	76,699	16	1.40
Paper products and printing	187,508	27	0.65	47,009	20	0.86
Water supply, sewerage, waste management	173,793	28	0.60	19,728	24	0.36
Fabricated metal products	168,640	29	0.58	42,070	21	0.77
Other transport equipment	166,616	30	0.57	52,910	19	0.97
Financial and insurance activities	164,279	31	0.57	10,887	27	0.20
Fishing and aquaculture	50,724	32	0.17	7,881	29	0.14
Wood and products of wood and cork	40,252	33	0.14	11,142	26	0.20
Activities of households as employers	19,545	34	0.07	9,814	28	0.18

Differences for imported emissions are even higher (Figure 6). Estimates for global imported emissions are, again, similar between the FIGARO and ICIO datasets and between the EXIOBASE and GLORIA datasets. Only the FIGARO and ICIO pairings has median RMSE results of under 100%. Indeed, RMSE as a percentage of mean emissions is under 30% for all sectors except chemical, pharmaceutical and botanical products for this comparison. Median similarity in direction is over 75% for this pairing for all sectors except mining, quarrying, and energy producing products.

For the sector with the highest emissions, electricity, gas, steam, and air conditioning, levels of similarity are particularly poor. This is in line with findings from Rodrigues et al. (2018) who find the electricity sector to contribute most strongly to high levels of uncertainty in consumption-based accounting. In our analysis, differences are in part due to EXIOBASE estimating imported emissions to be 0 or close to 0 for almost all countries, and thus EXIOBASE pairings showing high absolute differences and low directional similarity.

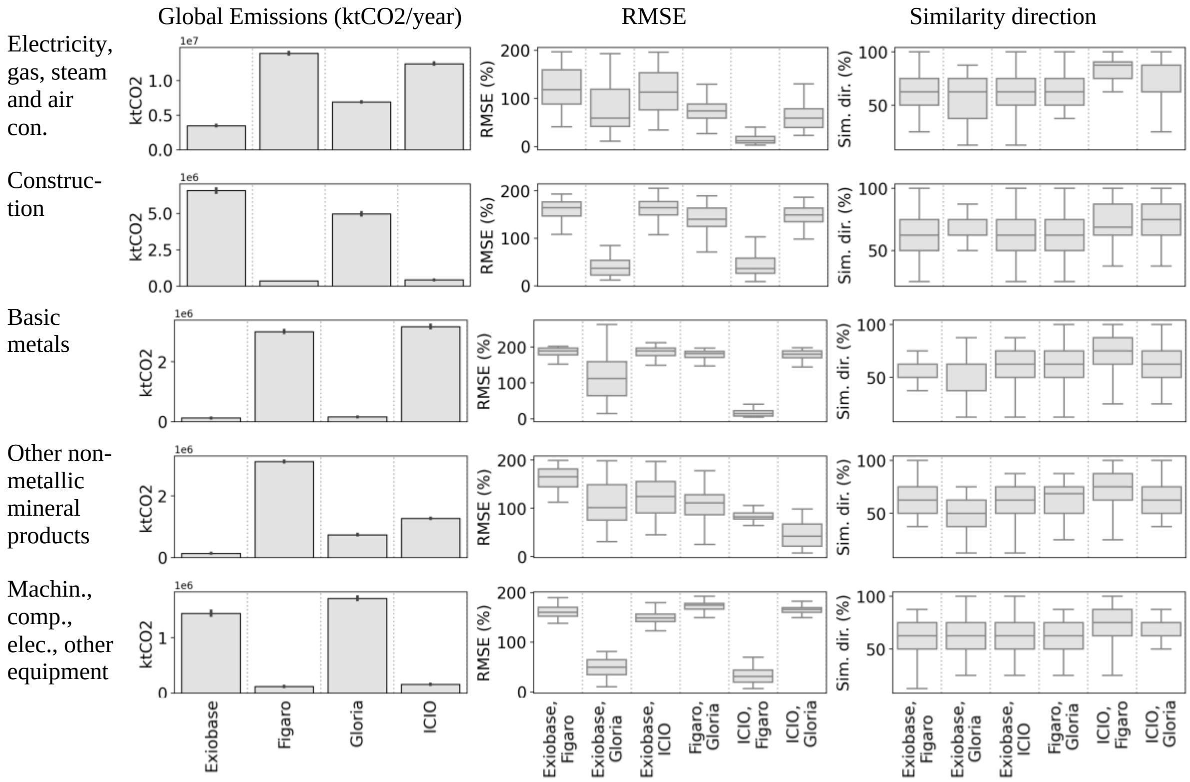

Figure 5. Total global emissions, RMSE as a percentage of mean emission, and similarity in direction of change (bottom) by sector.

** Note: Total emissions are shown as a global sum, while RMSE and Similarity direction results show country level results. Errorbar in global emissions shows +/-1 standard deviation from the mean.

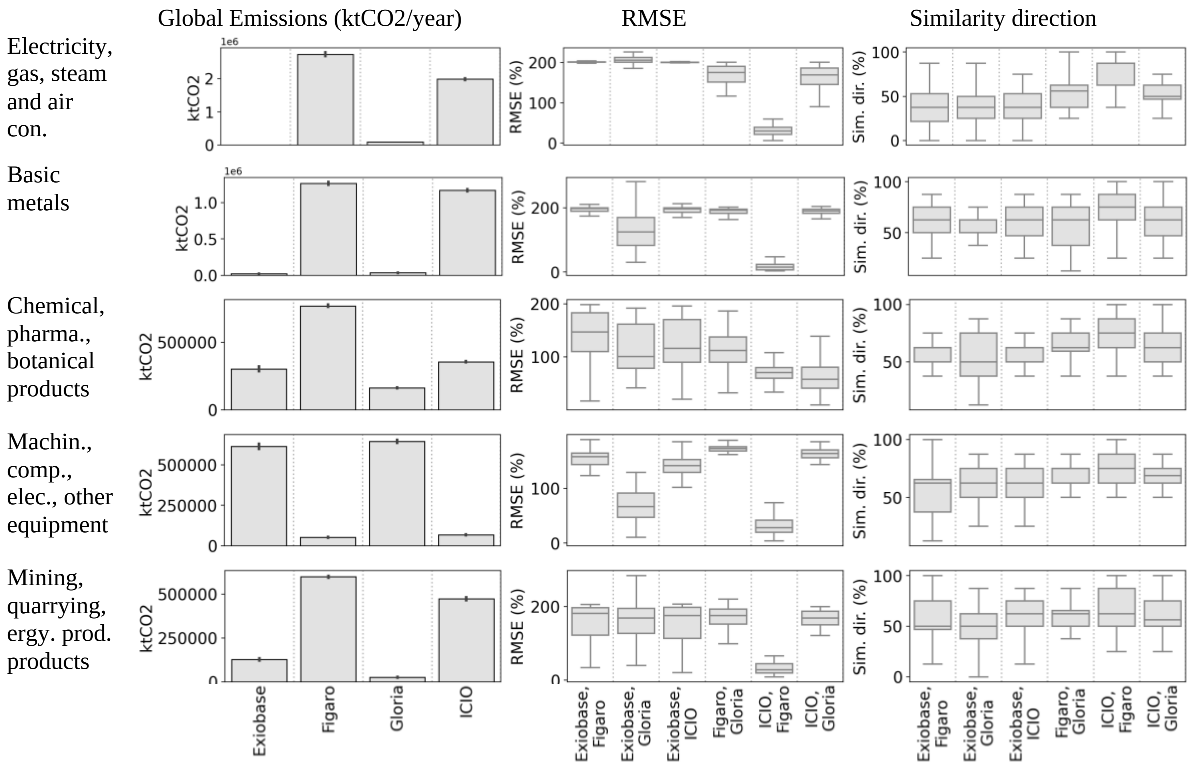

Figure 6. Imported global emissions, RMSE as a percentage of mean emission, and similarity in direction of change (bottom) by sector.

** Note: Total emissions are shown as a global sum, while RMSE and Similarity direction results show country level results. Errorbar in global emissions shows +/-1 standard deviation from the mean.

Discussion

Total CBEs at the country level are comparable between all MRIOs. Thus, the choice of using EXIOBASE, FIGARO, GLORIA, or ICIO to calculate a country's total CBEs, does not influence results strongly. Choice of data may therefore depend on data availability for the country in question. However, differences get stronger with more disaggregation; estimates differ more strongly for imports than total emissions, and at a sectoral level over a country aggregate. Moreover, we find no evidence, that the direction in trend of emission changes over time is comparable across the MRIO datasets, even when absolute differences in estimates are high. Thus, selecting the right dataset for a particular use case is crucial when looking beyond total emission estimates.

4.1. Creating national MRIO tables

When using these datasets to create national MRIO tables, understanding the differences in imports is especially important. As domestic data is supplemented with national accounts (Tukker et al., 2018) in these cases, reducing uncertainty in import data is a priority. For imported data, two clear groupings emerge. FIGARO and ICIO show more similarity than other pairings, and EXIOBASE and GLORIA show more similarity than other pairings. Which dataset will be best, however, depends on a few factors.

First, the MRIO tables include different countries. FIGARO (46 countries/regions), ICIO (67 countries/regions), and EXIOBASE (49 countries/regions) include notably fewer countries than GLORIA (164 countries/regions). Thus, GLORIA is more useful for many countries and users wanting to analyse countries typically underrepresented in MRIO data. However, as the makers of ICIO and FIGARO have more access to countries' national accounts, these datasets may be best for countries included in them. Moreover, as national MRIO tables may aggregate countries and regions from these MRIO tables (e.g. Owen and Kilian, 2024), having a high level of country disaggregation may not be necessary for makers of national MRIO tables. Despite this, information in key trading partners is also important. Where one table includes a key trade partner, which other datasets miss, this dataset may provide more accurate results for a country.

Promisingly, countries with more open economies, who often have higher imports, show lower levels of errors in absolute differences between the MRIO tables. This means that using any of these different datasets provides similar estimates for many of these countries. Countries where errors in imported emissions are higher also tend to have fewer imports overall, meaning that this uncertainty has a smaller effect on the footprint overall.

4.2. Analysing change over time vs absolute emissions

Analysing change over time or absolute emissions carry different data uncertainties. We find that for some countries, the four MRIOs provide more similar results when analysing the changing trend over time, while for other countries the MRIOs are more comparable when looking at absolute differences in emission estimates. Thus, the interpretation of emission estimates should depend on the country. We find smaller countries with more open economies to have more similar absolute estimates. This means that for smaller countries who trade a lot, analysing emission estimates as values with some uncertainty may be better than analysing change over time. For countries with less open economies, on the other hand, we find a slight increase in similarity of trend. For these countries, therefore, analysing whether emissions increase or decrease over time, may add less uncertainty than analysing the estimates in absolute terms. The type of analysis performed, is therefore country-dependent and should be informed by how much data uncertainty is present in different methods of interpreting estimates.

4.3. Sectoral disaggregation

At a sectoral level, we find larger differences between datasets than at a country-level. Higher levels of uncertainty at sectoral levels are frequently reported in MRIO uncertainty analysis (Karstensen et al., 2015; Rodrigues et al., 2018), and thus make sectoral analysis more difficult. It should be noted that GLORIA (120 sectors) and EXIOBASE (163 sectors) have a much higher level of sectoral disaggregation than FIGARO (64 sectors) and ICIO (sectors). For instance, GLORIA and EXIOBASE allow for analysing various agricultural products, while ICIO and FIGARO group these together. Nonetheless, for the countries studies in this analysis only FIGARO and ICIO produce similar results at a sectoral level. Moreover, for the most polluting sectors, GLORIA and EXIOBASE, and FIGARO and ICIO have large differences in their global emission estimates. For countries importing a lot of their electricity and gas emissions, EXIOBASE should not be used.

4.4. Limitations

Limitations arise from the different levels of aggregation in the databases. Databases need to be aggregated to report on matching countries and sectors. Here, we aggregate sectors and countries after the footprint calculation, but results may have varied if aggregation was conducted prior to the analysis. This is done to match results more closely to those of future users who may not aggregate the databases or may do this differently. Results are therefore more universally applicable. However, the impact of this on results may present a limitation of this research.

In addition, while the RMSE analysis is a frequently used tool to quantify differences and errors, the similarity difference calculation is novel. We use this, due to its potential policy relevance; policy makers may be more interested in the direction of change than in the actual emission estimate. Evaluating our results in this way, therefore, considers the practical implications of this research. However, this quantifier also means that small differences may be classed as not similar in direction, despite only seeing small changes. Future work may consider leaving a small percentage change to be classed as no change in emissions. However, in the current research this is compensated for by also reporting proportional RMSE values.

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Appendices

Appendix A. Aggregation of sectors, countries and final demand categories.

Number of countries matching across all four MRIO tables	Number of additional countries			
	EXIOBASE	ICIO	FIGARO	GLORIA
43	6	24	3	121

	Sector analysed	EXIOBASE	ICIO	FIGARO	GLORIA
Sectors	Agriculture, hunting, forestry	18	1	2	21
	Fishing and aquaculture	1	1	1	2
	Mining and quarrying, energy producing products	15	3	1	17
	Food products, beverages and tobacco	12	1	1	16
	Textiles, textile products, leather and footwear	3	1	1	2
	Wood and products of wood and cork	2	1	1	1
	Paper products and printing	4	1	2	2
	Coke and refined petroleum products	2	1	1	2
	Chemical, pharmaceuticals and botanical products	4	2	2	7
	Rubber and plastics products	3	1	1	2
	Other non-metallic mineral products	5	1	1	4
	Basic metals	12	1	1	8
	Fabricated metal products	2	1	1	1
	Machinery, computer, electronic, optical equipment	4	3	3	3
	Motor vehicles, trailers and semi-trailers	1	1	1	1
	Other transport equipment	1	1	1	1
	Manufacturing nec; repair, installation of machinery	4	1	2	2
	Electricity, gas, steam and air conditioning supply	16	1	1	2
	Water supply; sewerage, waste management	23	1	2	3
	Construction	2	1	1	2
	Wholesale and retail trade; repair of motor vehicles	4	1	3	1
	Land transport and transport via pipelines	3	1	1	3
	Water transport	2	1	1	1
	Air transport	1	1	1	1
	Accommodation and food service activities	1	1	1	1
	IT, information, postal, communication services	2	4	6	4
	Financial and insurance activities	3	1	3	1
	Real estate activities	1	1	1	1
	Admin., professional, supporting transport services	4	3	10	3
	Public admin., defence; compulsory social security	1	1	1	1
	Education	1	1	1	1
	Human health and social work activities	1	1	2	1
	Other service activities	3	2	5	2
	Activities of households as employers	1	1	1	1
	Activities of extraterritorial organisations and bodies	1	0	1	0
	Private households	0	0	1	0
Final demand	Gross Fixed Capital Formation	1	1	1	1
	Governments	1	1	1	1
	Households	1	1	1	1
	Changes in Inventories and Valuables	2	1	2	1
	Non-profits serving households	1	1	1	1
	Other	1	1	3	1

Appendix B. Populations and emissions per capita for countries analysed.

	Population[3]	Mean $ktCO_2$[4]	tCO_2/capita
Australia	26,177,414	403,082	15.40
USA	338,289,857	4,584,639	13.55
Luxembourg	647,599	8,197	12.66
Canada	38,454,327	450,320	11.71
Estonia	1,326,062	14,567	10.99
South Korea	51,815,810	568,552	10.97
Norway	5,434,319	59,474	10.94
Japan	123,951,692	1,262,156	10.18
Switzerland	8,740,472	88,207	10.09
Finland	5,540,746	54,792	9.89
Denmark	5,882,262	53,470	9.09
Germany	83,369,843	732,177	8.78
Ireland	5,023,109	44,113	8.78
Greece	10,384,971	89,991	8.67
Belgium	11,655,930	100,471	8.62
Netherlands	17,564,014	149,127	8.49
Czechia	10,493,986	83,417	7.95
Russia	144,713,314	1,106,644	7.65
Austria	8,939,617	68,206	7.63
Malta	533,286	3,996	7.49
Cyprus	1,251,489	9,105	7.28
UK	67,508,936	472,099	6.99
Sweden	10,549,347	67,446	6.39
Italy	59,037,474	361,779	6.13
Slovenia	2,119,844	12,926	6.10
Poland	39,857,146	241,591	6.06
China	1,425,887,337	8,276,968	5.80
France	64,626,628	361,888	5.60
Latvia	1,850,651	10,130	5.47
Slovakia	5,643,453	30,752	5.45
Lithuania	2,750,055	14,719	5.35
Spain	47,558,630	233,585	4.91
Bulgaria	6,781,953	31,581	4.66
South Africa	59,893,886	269,996	4.51
Portugal	10,270,865	46,084	4.49
Croatia	4,030,358	16,688	4.14
Turkey	85,341,241	351,828	4.12
Hungary	9,967,308	37,695	3.78
Romania	19,659,267	66,815	3.40
Mexico	127,504,126	403,561	3.17
Brazil	215,313,498	437,822	2.03
Indonesia	275,501,339	455,491	1.65
RoW	3,166,702,468	5,034,371	1.59
India	1,417,173,173	1,827,836	1.29

[3] Mid-year population data for 2022 from https://population.un.org/dataportal/home
[4] This is an average from 2010-2018