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# The impacts of data deviations between MRIO models on material footprints

## A comparison of EXIOBASE, Eora, and ICIO

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### Abstract

In various international policy processes such as the UN Sustainable Development Goals, an urgent demand for robust consumption-based indicators of material flows, or material footprints (MFs), has emerged over the past years. Yet, MFs for national economies diverge when calculated with different Global Multiregional Input–Output (GMRIO) databases, constituting a significant barrier to a broad policy uptake of these indicators. The objective of this paper is to quantify the impact of data deviations between GMRIO databases on the resulting MF. We use two methods, structural decomposition analysis and structural production layer decomposition, and apply them for a pairwise assessment of three GMRIO databases, EXIOBASE, Eora, and the OECD Inter-Country Input–Output (ICIO) database, using an identical set of material extensions. Although all three GMRIO databases accord for the directionality of footprint results, that is, whether a countries' final demand depends on net imports of raw materials from abroad or is a net exporter, they sometimes show significant differences in level and composition of material flows. Decomposing the effects from the Leontief matrices (economic structures), we observe that a few sectors at the very first stages of the supply chain, that is, raw material extraction and basic processing, explain 60% of the total deviations stemming from the technology matrices. We conclude that further development of methods to align results from GMRIOs, in particular for material-intensive sectors and supply chains, should be an important research priority. This will be vital to strengthen the uptake of demand-based material flow indicators in the resource policy context.

### KEYWORDS

material footprint, multiregional input–output databases, raw material equivalents, resource policy, structural decomposition analysis, structural production layer decomposition

## 1 | INTRODUCTION

In an increasingly globalized world, supply chains of primary materials, goods, and services span across countries and continents, disconnecting the location of production from the place of final demand. Thus, foreign consumption increasingly drives a range of local environmental and social problems in countries that extract primary materials or manufacture products (Wiedmann & Lenzen, 2018). Within industrial ecology, the analysis of these global "teleconnections" has become an important research field and several special issues in this journal have recently been devoted to this topic (see Hubacek, Feng, Chen, & Kagawa, 2016; Tukker, Wood, & Giljum, 2018).

Assessing these distant connections requires the application of supply chain–wide indicators with a global coverage. For the category of raw materials, the indicator "raw material consumption (RMC)" has been introduced. The RMC comprises material extractions that enter the economy and are directly and indirectly required to satisfy domestic final demand in a specific country, independently of the geographical location of material extraction. In line with many other studies (e.g., Giljum, Bruckner, & Martinez, 2015; Wiedmann et al., 2015), we use the term "material footprint" (MF) in this paper when referring to the RMC indicator. In the past few years, this indicator has been employed to assess raw materials embodied in internationally traded products and the life cycle–wide environmental pressure of consumption of single countries (Kovanda & Weinzettel,

2013; López, Arce, Morenate, & Zafrilla, 2017; Schaffartzik, Eisenmenger, Krausmann, & Weisz, 2014; Wang et al., 2014), world regions such as the EU (Giljum et al., 2016; Schoer, Weinzettel, Kovanda, Giegrich, & Lauwigi, 2012), as well as for performing comparative international studies (Bruckner, Giljum, Lutz, & Wiebe, 2012; Giljum, Bruckner, et al., 2015; Pothen, 2017; Schandl et al., 2017; Tian, Wu, Geng, Bleischwitz, & Chen, 2017; Wiedmann et al., 2015).

Various international policy processes, most prominently the UN Sustainable Development Goals (SDGs), require robust indicators for resource efficiency of production and consumption (see SDG target 8.4) to inform about the success of policies that aim to improve the overall resource efficiency of national economies and thereby reduce environmental pressures and impacts of economic activities. MF indicators have been selected by the Inter-Agency Expert Group (IAEG) to monitor progress for SDG targets 8.4 and 12.2 (United Nations, 2017). They are also used to inform the resource efficiency initiative of the Group of 7 (G7, 2015), and the Organisation for Economic Co-operation and Development's (OECD's) process toward reporting demand-based indicators for material flows in the context of the "Green Growth" initiative (OECD, 2017). A major obstacle to broad uptake of the MF indicator by the policy community is remaining uncertainties about methodological maturity and data reliability. This has led the IAEG to classify the footprint indicator as tier 3 in the SDG indicator classification that refers to such indicators where a global methodological standard is in development, hampering countries' ability to report.

Three alternative methodological approaches are used to calculate the MF indicator. Methods based on various forms of environmentally extended input–output analysis (IOA), methods applying material intensity coefficients derived from process analyses and life cycle assessment (LCA), as well as hybrid approaches combining elements of both IOA and LCA (Lutter, Giljum, & Bruckner, 2016; Schoer, Wood, Arto, & Weinzettel, 2013; Wiesen & Wirges, 2017). The development of Global Multiregional Input–Output (GMRIO) databases with high country and sector detail, such as Eora and EXIOBASE, has provided a particular boost for various footprint assessments on the global level in recent years (Giljum, Bruckner, & Lutter, 2018; Tukker et al., 2016; Tukker, Giljum, & Wood, 2018; Wiedmann, 2016; Wiedmann & Lenzen, 2018).

A solid understanding of the reliability and uncertainty of demand-based indicators is necessary when applying the models in the context of policies addressing consumption activities in relation to the environmental pressures and impacts that occur along the supply chains. For the carbon footprint indicator, a number of studies have compared various GMRIO databases and have identified the main factors causing the observed differences in the indicator results (Arto, Rueda-Cantuche, & Peters, 2014; Moran & Wood, 2014; Owen, Steen-Olsen, Barrett, Wiedmann, & Lenzen, 2014; Owen, Wood, Barrett, & Evans, 2016; Wieland, Giljum, Bruckner, Wood, & Owen, 2018). Previous research on national-level MFs has illustrated that indicator values diverge when using different GMRIO databases (Eisenmenger et al., 2016; Giljum, Bruckner, et al., 2015; Giljum et al., 2015, 2017). Some studies have also pointed to the importance of the first processing stages as a key determining factor for a high accuracy of the overall MF results (Galli, Weinzettel, Cranston, & Ercin, 2013; Schoer et al., 2012).

However, so far an assessment of the impact of deviations in the GMRIO databases on MFs has been lacking, which is a gap that is addressed in this paper. With our analysis, we aim at identifying the critical sectors in the GMRIO systems that lead to disproportionate differences in MFs, as opposed to the carbon footprint differences that have already been analyzed extensively in the literature. To do so, we apply structural decomposition analysis (SDA) and structural production layer decomposition (SPLD) methods. SDA allows quantifying the differences in footprints caused by the main data blocks of the GMRIO data system, such as the Leontief inverse matrix or final demand. By decomposing the Leontief inverse matrix, SPLD then enables zooming into the technology matrix to identify differences in those interindustry inputs that have the highest influence on MFs. Therefore, we are able to identify domains of the GMRIO databases where further improvement of data is necessary to develop methods and models that increase the alignment of MF results.

The rest of the paper is structured as follows. Section 2 introduces the data sources and the applied methods. Section 3 contains the results, starting with an overview of MF deviations between the selected GMRIO databases and then illustrating the SDA and SPLD results for specific countries and groups of raw materials. Section 4 discusses the results from the perspective of future options to improve the robustness of GMRIO-based MF calculations. Section 5 concludes the article.

## 2 | DATA AND METHODS

### 2.1 | GMRIO databases and material extraction data

The comparison of MF indicators performed in this paper employs three GMRIO frameworks: EXIOBASE, Eora, and—for the first time in the context of MF publications—the OECD Inter-Country Input–Output (ICIO) database. Table 1 provides an overview of the main properties of the GMRIO databases. An extensive description and comparative assessment of the data sources and construction principles for the three GMRIO databases can be found in chapter 1 in Supporting Information S1.

EXIOBASE was developed in several European research projects and was particularly designed for environment-related applications (Wood et al., 2015). EXIOBASE version 3 distinguishes 200 products (and 163 industries) for all covered countries and regions, of which 33 products (and 25 industries) refer to extraction of biotic and abiotic raw materials (Stadler et al., 2018). Data are published as a multiregional input–output (IO) table. EXIOBASE models all EU-28 countries and their 16 most important trading partners plus five aggregated "Rest-of-the-World (RoW)" regions. The Eora database is the most detailed GMRIO database currently available and comprises data for 189 individual countries

**TABLE 1** Main properties of the EXIOBASE, Eora, and OECD ICIO MRIO data bases

Category	EXIOBASE	Eora	OECD ICIO
Type	MRIOT	Combined MRSUT/MRIOT	MRIOT
Countries/regions	44 countries plus five Rest-of-the-World regions	189 countries	61 countries plus one Rest-of-the-World region
Total number of sectors	163 industries/200 products	26 to ~500 industries/products	34 industries
Material extraction sectors	25 industries/33 products	3–63 industries/products	2 industries
Time series	1995–2011	1990–2013	1995, 2000, 2005, and 2008–2011

MRIOT = multiregional input–output table; MRSUT = multiregional supply-use table.

(Lenzen, Moran, Kanemoto, & Geschke, 2013). The sector detail for each country in the multiregional IO table ranges between 25 (for many developing countries) and more than 500 sectors (in some industrialized countries), thereof 2–63 material extraction sectors. The final GMRIO table has a mixed structure that varies from country to country, where some regions are represented by supply-use and others by IO tables. OECD's ICIO database (OECD, 2015b) comprises 61 countries. Intersectoral trade flows are modeled for 34 industries, of which only two refer to extractive industries. The final GMRIO database is published in the form of symmetric IO tables. OECD ICIO can be regarded as the most “authoritative” GMRIO database currently available with regard to the acceptance by national institutions, such as national statistical offices (Tukker et al., 2018).

It is important to note that all three GMRIO models apply the industry-technology assumption to construct the IO tables from the underlying supply-use tables. However, the three databases employ various strategies for balancing the GMRIO system, which can significantly alter the original data, in order to achieve coherence at the global level. There is different priority given to various parts of the data by GMRIO model developers, for example, whether national accounts data or trade data are used as the main constraint in the balancing procedures (Moran & Wood, 2014; Wood, Hawkins, Hertwich, & Tukker, 2014).

In this paper, two different aggregation levels are applied. The models in full detail are used when analyzing absolute MFs. However, the SDA and SPLD techniques, as described below, can only be applied when the matrices of the GMRIO databases are of identical size and structure. The three multiregional input–output tables were therefore aggregated into a “common classification (CC)” comprising 40 countries plus a “RoW” region and 17 industries following the example of earlier studies (see Owen et al., 2014; Steen-Olsen et al. 2014). The full list of countries/regions and industries in the CC can be found in chapter 2 in Supporting Information S1. The concordance matrices for the three models are added as an Excel file in Supporting Information S2. Note that when GMRIO models are applied under the CC, a subscription  $_{cc}$  is added to the model name.

In the case of the full models, material extraction data are allocated to the number of primary sectors available in the various GMRIO databases (see Table 1). Under the CC, material extraction is allocated to only two sectors (“agriculture” and “mining”) in all cases, as the ICIO database provides the main constraint.

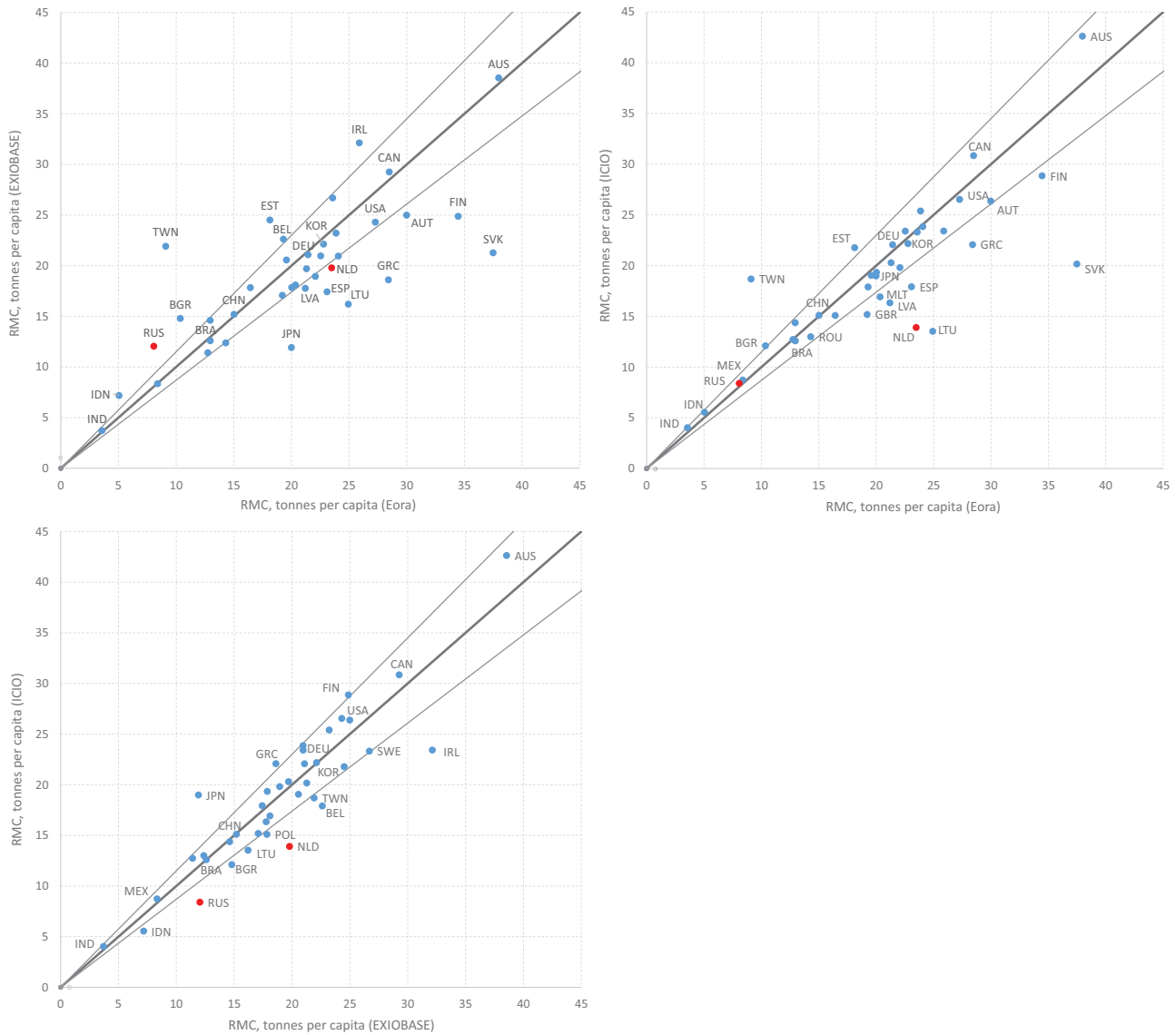
The large influence of differences in the environmental satellite data included in various GMRIO databases on footprint results has been stressed by other studies (e.g., Owen et al., 2014). To ensure that observed variations in indicator results can be assigned solely to differences in monetary elements of the GMRIO systems, we apply one harmonized data set for global domestic material extraction across all models. This data set was compiled for UN Environment's International Resource Panel (see <http://www.resourcepanel.org/global-material-flows-database>), covering 44 material extraction categories for all countries worldwide (Schandl et al., 2017; UNEP, 2016). The analysis underlying this paper was performed for one year only, that is, 2010.

## 2.2 | SDA and SPLD methods

We select two complementary methods, SDA and SPLD, that allow quantifying the contributions of differences in the underlying raw data of the GMRIO models to differences in the absolute MF indicator. Both methods are briefly summarized below; detailed descriptions can be found in chapter 3 in Supporting Information S1.

SDA is a decomposition method based on IO models that allows breaking down the changes in some variable into the changes in its determinants. By that means, it can help to reveal the drivers behind the changes of indicators (Dietzenbacher & Los, 1998). In recent years, SDA has been widely applied to the case of environmental indicators, most notably to the issue of energy use and greenhouse gas emissions (Lenzen, 2016). A few studies have also investigated the drivers for changes in MFs applying an SDA approach (Munoz & Hubacek, 2008; Plank, Eisenmenger, Schaffartzik, & Wiedenhofer, 2018; Wang et al., 2014; Weinzettel & Kovanda, 2011; Wenzlik, Eisenmenger, & Schaffartzik, 2015). In this paper, we do not use SDA to understand the drivers of change between two points in time, but assess the drivers of MF variations calculated by a pair of two GMRIO databases for the same year (see Owen et al., 2014 for a similar study on the carbon footprint). Applying SDA allows illustrating the impact of data differences in the blocks of the Leontief matrix (L), aggregated final demand (Y), and total output (x).

Additionally, we apply the SPLD method that has recently been introduced by Wieland et al. (2018). At its core, SPLD structurally decomposes a set of PLD (production layer decomposition) results. The central idea of SPLD is thus a structural decomposition that uses the transaction matrix instead of the Leontief inverse matrix, as usually done in SDA. For the decomposition exercise, the SPLD calculus uses the interindustry transaction matrix and the resulting technology matrices (A-matrices) of various orders, thus reflecting the different production layers. SPLD thereby enables



**FIGURE 1** Comparison of material footprints per capita, three model pairs, 2010

Note: We exclude Luxembourg from the figure, as the material footprint is significantly higher than that of all other countries, that is, beyond 70 tons per capita in some of the models, mainly driven by the very high GDP per capita levels. Further, we do not show the value of the group of “Rest-of-the-World,” as this group contains countries with highly varying material use profiles.

differentiating between effects stemming from data differences of specific elements or parts in the A-matrix, for example, trade blocks versus domestic blocks and intermediate flows between different industries. Thereby, the most significant elements in the technology matrix, which cause differences in the MF indicator calculated with different GMRIO models, can be identified.

### 3 | RESULTS

We start this section with an analysis of the deviations between the aggregated MF indicators calculated with the three GMRIO databases in full detail. We then select two illustrative example countries with high deviations in the MF results for further investigation applying SDA and SPLD using the CC versions of the GMRIO models. The final section lifts the analysis back to the level of all investigated countries, drawing general conclusions from the SPLD on the most important sectors and regions in the technology matrix causing the deviations in the MF results.

#### 3.1 | Aggregated MFs

Figure 1 provides a pairwise comparison of the MFs per capita calculated with the EXIOBASE, Eora, and ICIO models in full detail for the year 2010, with the same population data from the World Bank being taken for all three models. For illustrative purposes, we define a discrepancy

range of 15% between the model results. The thick gray line (45°) indicates equality of results. For countries located off-diagonal but between the two thin gray lines, the footprint results of the two compared models deviate by a maximum of 15%. Country codes are provided for all countries outside the discrepancy range and for selected major countries within the corridor. Results for all countries can be found in chapter 4 in Supporting Information S1.

Of all investigated countries, 46% (18 countries) are located within the discrepancy range of 15% across the three model pairs. This group comprises a number of European countries of different sizes and economic structures, such as Germany, France, Denmark, Czech Republic, and Hungary, other OECD countries including the United States, Canada, Korea, and Australia, but also emerging economies, notably China, India, and Brazil.

However, for several other countries, deviations in the MF calculated with different models are remarkable. For example, EXIOBASE suggests a MF for Taiwan in 2010 of 21.9 tons per capita, whereas Eora's result is only 9.1 tons per capita. In contrast, Eora's result for Slovakia is much higher compared to EXIOBASE (37.5 tons versus 21.3 tons). For the Netherlands, ICIO delivers 13.9 tons per capita, and Eora delivers 23.5 tons per capita. For Russia, the results generated with Eora and ICIO are comparable (8.0 and 8.4 tons), while EXIOBASE's result is around 50% larger (12 tons per capita).

Across the three GMRIO databases and for the vast majority of countries, results are directionally similar regarding the question, whether a country has a positive or negative raw material trade balance (RTB), that is, whether a country's final demand depends on net imports from other countries or serves as net exporter of raw materials embodied in international trade. While the United States, Japan, South Korea, and several European countries are identified as the main net importing countries, Australia and the BRIICS countries (Brazil, Russia, India, Indonesia, China, and South Africa) are the main net exporting countries in all three GMRIO databases (see Supporting Information S1, chapter 5 for the respective RTB figure).

When applying the CC to the specific models, the MF indicator on the country level differs from the assessments applying the GMRIO models with full sector and country detail. The number of countries within the deviation corridor is lower, with only 15 countries showing discrepancies of 15% or less across all three model pairs (see Supporting Information S1, chapter 6 for detailed figures). The impact of the aggregation from the full detail to the CC on a country's MF is illustrated in detail in chapter 4 in Supporting Information S1. With 1.5%, the average percentage deviation across all countries is lowest in ICIO, which could be expected, given that the sector classification in ICIO (34 industries) is closest to the one in the CC (17 sectors). In Eora, the average deviation is 7.7% and in EXIOBASE, the average deviation is 8.3%. The impact of the aggregation is very small in some countries, for example, Korea with a maximum change of 3% across the three models, Spain with 4.5%, or China with 5%. However, for other countries, the MF results change notably. Representatives of this group of countries are the United States (a maximum change of 20% across the three models), Russia (34%), the Netherlands (66%), and Belgium (71%).

As this paper focuses on the investigation of the differences in the interindustry matrices and their impacts on the MF indicators, the issue of deviations stemming from different aggregation levels is not further analyzed in detail (for studies investigating the aggregation effect in MF indicators, see de Koning et al., 2015; Piñero et al., 2015). However, we will comment on the aggregation issue in Section 4, after the SDA and SPLD results have been presented.

### 3.2 | Illustrative examples of SDA and SPLD results

For illustrating the results of the SDA and SPLD assessments, we selected two example countries for detailed investigations: the Netherlands and Russia. Both countries have significant model deviations with regard to the resulting MF, when calculated both with the full and the CC models (see above); at the same time, both represent countries of a significant economic output and of assumed adequate data quality. Further, they differ with regard to the extent that domestic versus foreign material extractions contribute to the MF. In the following, we present the results for the Netherlands. The detailed assessment for Russia can be found in chapter 7 in Supporting Information S1. In addition to the contribution to differences in the aggregate MF indicator, the comparisons are also disaggregated according to renewable (i.e., biomass) and non-renewable (i.e., fossil fuels, minerals, and metal ores) materials.

We first illustrate the SDA results for the MF per capita for the Netherlands (Figure 2). Performing an SDA allows identifying the main factors in the GMRIO models that cause the observed deviations. With 15.6 and 17.6 tons per capita for the EXIOBASE<sub>cc</sub>-Eora<sub>cc</sub> and ICIO<sub>cc</sub>-Eora<sub>cc</sub> pairs, differences in the Leontief inverse matrix (L-effect) cause the highest deviations in MFs. In the EXIOBASE<sub>cc</sub>-ICIO<sub>cc</sub> pair, the Y-effect reflecting differences in data on final demand is most significant. The x-effect is smallest in all three model pairs. Results are comparable to those found for the case of Russia (see Figure S1 1-3 in Supporting Information S1).

In the next step, we applied the SPLD method, which allows for decomposing the Leontief inverse matrix and zooming into this part of the GMRIO data system. The results of the SPLD assessment are contained in a matrix that illustrates the contribution of data deviations in each cell in the multiregional technology (or A) matrix to differences in the overall MF indicator. For illustrative purposes, we aggregated the results matrix from two perspectives; first from a geographical point of view, representing all sectors in each of the countries. In this view, trade flows are on the off-diagonal cells with the supplying countries in the rows and the receiving countries in columns; second, from an industry point of view, aggregating all countries for each of the industries.



**FIGURE 2** MF per capita of the Netherlands, 2010, SDA of three GMRIO pairs

As the example pair for further investigations applying the SPLD technique, we select the  $ICIO_{cc}$ - $Eora_{cc}$  pair with the highest L-effect in the SDA. The SPLD graphs for the other two model pairs are included in chapter 8 in Supporting Information S1.

Figure 3a reveals the geographical distribution of impacts on the Netherlands MF stemming from a comparison of the domestic and trade blocks in the multiregional A-matrices of the  $ICIO_{cc}$  and  $Eora_{cc}$  models. The cells on the diagonal matrix represent the domestic IO tables of all countries considered in the CC, whereas the off-diagonal cells relate to imports and exports between different pairs of countries. The bubbles indicate the absolute data deviations between the domestic and trade blocks of the A-matrices of  $EXIOBASE_{cc}$  and  $Eora_{cc}$  as well as the magnitude of their contribution to the differences in the Netherlands MF stemming from the technology matrix. Note that the sum of the A-effect matrices presented here converge toward the total L-effect as more and more production layers are decomposed (see chapter 3 in Supporting Information S1 for additional information on the SPLD technique).

In contrast to Russia, where differences mostly root in the domestic data of Russia itself (see Figure S1 1–4 in Supporting Information S1), Figure 3a illustrates that for the Netherlands, a large number of import blocks in the aggregated interindustry matrix contribute to the deviations in the MF. The high dependency of domestic final demand on imports from abroad is visible in the bubbles in the column marked “Netherlands (NL)”. This indicates that data deviations in the respective trade blocks, for example, imports from Belgium, Germany, France, Canada, and, very notably, from the large “RoW” region to the Netherlands, have significant impacts on the MF results. Together, the direct trade blocks add up to 64% of all deviations stemming from the A-matrix.

In addition, further upstream deviations in domestic tables of several other countries also play a role, including the tables of Belgium, Germany, the United States, India, Russia, and the RoW region. In order to align the  $ICIO_{cc}$ - and  $Eora_{cc}$ -based MF results for the Netherlands as a country, which is highly intertwined with the global economy, a much larger number of countries needs to be put in focus compared to the case of Russia (see Supporting Information S1, chapter 7).

Figure 3b illustrates the sector perspective on the Netherlands MF deviations in the  $ICIO_{cc}$ - $Eora_{cc}$  pair, covering all global supply chains serving Netherlands' domestic final demand. Overall, 83% of all deviations related to the A-matrix can be attributed to the non-renewable MF and only 17% to the renewable MF.

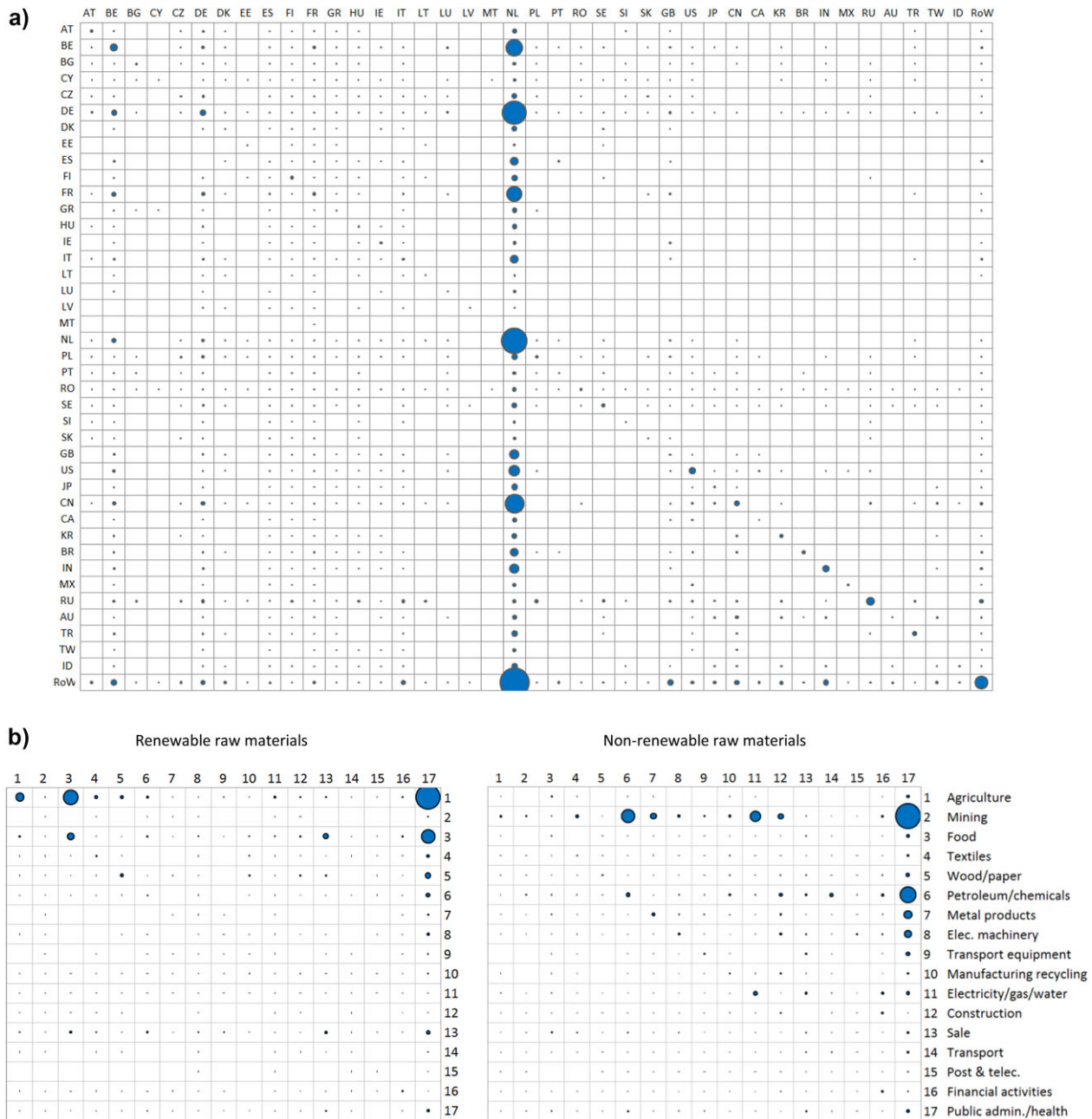
The sources for deviations in the biomass footprint of the Netherlands are mainly related to the deliveries of the agricultural (including forestry) sector to food (15% of total A-matrix deviations in the biomass footprint) and—very notably—to public administration (39%). To a lower extent, also the supply chain of food products, that is, deliveries of food to sale (2%) and to public administration (13%), plays a role.

The importance of data deviations regarding public administration is also visible in the bubble chart on non-renewable raw materials. Highest deviations in the non-renewable part of the MF are caused by deliveries of the mining sector to the petroleum and chemicals sector (10% of total A-matrix effects on the abiotic MF), the electricity/gas/water sector (6%), as well as to public administration (32%). Also deliveries of petroleum and chemicals to public administration (13%) impact on the deviations. Across all types of raw materials, it can be concluded that data deviations in the sectors downstream the supply chains, that is, manufacturing and service sectors only contribute minor to deviations in MF results.

### 3.3 | Overview of country results

We performed the SDA and SPLD assessments for all countries in the CC. The results of the SDA are illustrated in detail in Figure 4.

The analysis reveals that across the three model pairs, no clear pattern can be extracted regarding a specific importance of one of the three effects (L-effect, Y-effect, and x-effect) in contributing to the overall differences in MFs. In the  $Eora_{cc}$ - $EXIOBASE_{cc}$  pair, the L-effect is responsible for 37% of the deviations across all countries and thus more important than the two other effects (33% and 30%, respectively). For the  $EXIOBASE_{cc}$ - $ICIO_{cc}$  pair, it is the Y-effect (36%) compared to 33% and 31%, respectively, for the L- and x-effects. For the  $Eora_{cc}$ - $ICIO_{cc}$  pair, the x-effect is strongest (45%, compared to 32% and 23%, respectively, for the L- and Y-effects).



**FIGURE 3** SPLD results for the MF of the Netherlands, country perspective (a), sector perspective (b), ICIO<sub>cc</sub>-Eora<sub>cc</sub> pair, 2010  
 Note: The size of the bubbles is scaled for each graph separately in order to best illustrate the deviation patterns for each specific aggregation and material group. Bubble sizes across figures can therefore not be directly compared.

In order to provide an overview across all investigated countries and to identify general patterns from the SPLD, Figure 5 presents the aggregated results for the sector perspective across all investigated countries in the three model pairs for the cases of renewable and non-renewable raw materials. The pie charts below the sector illustrations provide an aggregated information, whether the domestic or foreign part of the interindustry matrix contributes more prominently to the deviation of the respective MF indicator.

Figure 5 illustrates that the patterns described for the two country examples above can be generalized, when analyzing the aggregated view across all countries. On average across the model pairs, the two raw material extraction sectors of agriculture and mining together explain 60% of all A matrix-related deviations. In contrast, data deviations further down the supply chains, that is, in sectors producing manufacturing products and in service sectors, have a much smaller impact. This result has important implications for reducing uncertainties with regard to GMRIO-based MF calculations (see Section 4).

Regarding renewable raw materials, the supply structure of the agricultural sector is responsible for 60% of the biomass footprint deviation stemming from the A-matrix across the three model pairs. The food sector explains another 18%. Interindustry relations of all other sectors combined are thus responsible for only 22%. For the agriculture sector, its own use as well as its supply structures to a range of receiving sectors are



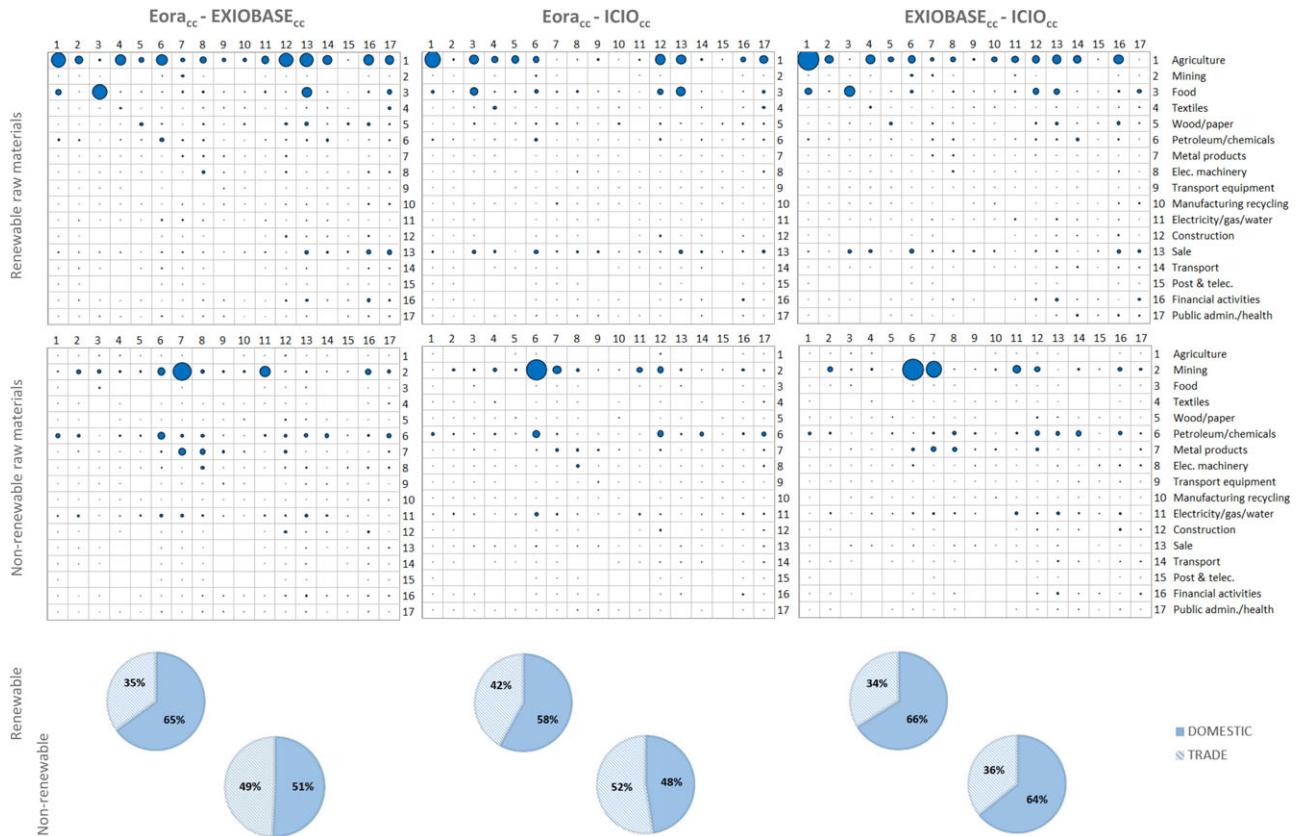


**FIGURE 4** SDA results for all countries in the common classification, 2010

highly influencing the results, including the deliveries to the food (4) and textiles (5) sectors, to sectors further processing non-renewable material (particularly, petroleum/chemicals, sector 6), and also to service sectors, most notably construction (12) and sale (13). In addition, the supply of processed biomass by the food sector contributes to the impact of the difference in A-matrices on the biomass footprint of countries, most pronounced for the sector's own use of food products as well as deliveries to the retailers in the sale sector. For some countries, other deliveries also play a role, such as the supply of biotic materials to construction, sale, or public administration.

With regard to non-renewable raw materials, the mining sectors' supply structure to all other sectors explains 59% of the differences in the abiotic MF resulting from the technology matrix across the three model pairs. Most notably, deviations in the deliveries of the mining sector to petroleum/chemicals (6) and metal products (7) show the strongest impacts. With much less importance follow the supply structures of the petroleum/chemicals (6) sector to a range of other manufacturing and service sectors. Data deviations in sector 6 contribute 16% across the three model pairs. All other sectors combined explain the remaining 25%.

The geographical perspective (pie charts at the bottom of Figure 5) reveals that regarding renewable raw materials, the domestic blocks generally play a more important role than the trade blocks (an average of 63% of all A-matrix effects across the three model pairs). Concerning non-renewable raw materials, the trade blocks contribute stronger to the deviations stemming from the A-matrix, 52% for the Eora<sub>cc</sub>-ICIO<sub>cc</sub> pair, 49% for Eora<sub>cc</sub>-EXIOBASE<sub>cc</sub>, but only 36% for EXIOBASE<sub>cc</sub>-ICIO<sub>cc</sub>. The higher importance of trade blocks regarding non-renewable raw materials could be expected, given that the extraction of fossil fuels and metal ores are concentrated in only a smaller number of countries, leading to high



**FIGURE 5** SPLD results for the sector perspective, aggregation of all countries, three model pairs, 2010

amounts of materials passing certain international supply chains. Small deviations in the trade data of fossil fuels and metal ores can thus translate into notable differences in the non-renewable part of the MF.

## 4 | DISCUSSION

In the context of increasing demand for robust resource use indicators by policy makers, our finding that per capita MF deviates only by 15% across all GMRIO databases for a large number of economically important countries is important for raising confidence in the indicator. This result is in line with earlier examinations of the carbon footprint. For example, Moran and Wood (2014) indicated a deviation of less than 10% for major economies, once the greenhouse gas emissions satellite has been harmonized. Further, we observed high congruence across GMRIO frameworks for the position a country occupies in international trade, that is, whether a country is a net exporter or net importer of raw materials. Still, the level of per capita MF assessed with different databases varies considerably for a number of countries.

Looking for the main causes of differences, our analysis illustrates that only small sections of the overall IO matrices are critical in determining the differences in MFs. Although the importance of primary sectors has been stressed in earlier studies (Ewing et al., 2012; Schoer et al., 2013), our analysis for the first time quantifies the numeric impact of these critical sectors and supply-chain sections. Following our results, further efforts of different groups constructing and hosting GMRIO data sets should therefore focus on primary sectors and their representation in GMRIO models, that is, on agriculture and forestry and the sectors receiving renewable raw materials for further processing, as well as the mining and quarrying sector and their interlinkages with the basic metal, petroleum, and chemical sectors.

The SDA and SPLD methods we applied required us to use a CC. National MFs therefore differ from those applying the GMRIO models with full sector and country detail. Thus, parts of the deviations between the GMRIO models directly result from this aggregation (see Owen et al., 2014). Earlier studies have argued that a higher level of detail in the material-intensive sectors is preferable to achieve robust MF results (see de Koning et al., 2015; Piñero et al., 2015). Our results illustrate that the deviations between models become larger, when the sector resolution is reduced. The number of countries located within the defined range of 15% decreased from 18 (out of 40) in the full detail to 15 in the aggregated CC. On average, across countries and the three model pairs, deviations increased by around 19% caused by the aggregation effect, from around 2.9 tons per capita to around 3.5 tons per capita. On the one hand, aggregation could decrease discrepancies by averaging effects. On the other hand, merging subsectors that are similar across models with regard to their product composition and supply structure with other sectors that have very different

characteristics could increase deviations in results. Although not the prime focus of this paper, our result confirms earlier findings arguing for a disaggregation of the material-intensive parts of the supply chain in order to decrease uncertainties in MF results.

The SDA and SPLD analyses based on a highly aggregated common sector classification allowed identifying areas of priority for further analyses and database developments. Although not testable with the analytical methods applied in this paper, we assume that the overall findings with regard to sector and supply-chain priorities to overcome differences in MFs also apply to the fully detailed GMRIO models. Also in the case of full model detail, material extraction is allocated only to primary extraction sectors, thus deviations in supply structures of those sectors will have a stronger effect on the resulting MFs compared to, for example, manufacturing or service sectors.

A full alignment of the existing GMRIO databases to a one-fits-all model is neither technically feasible nor desirable from a methodological and policy application point of view. The various databases and models serve different purposes and applications and thus together offer a diverse perspective on resource use issues. For instance, EXIOBASE aims at covering a large number of environmentally sensitive activities, while Eora's focus is on global coverage and the highest achievable level of sector detail. ICIO so far has been used mainly for the analysis of value added embodied in trade and of carbon footprints and has focused on a thorough representation of trade flows. A clear documentation of the main *construction procedures* and building blocks of GMRIO frameworks is essential to improve quality, comparability, and interpretability of the results; to reduce uncertainties; and to increase the applicability in policy contexts.

There exist a number of areas, where a harmonization of procedures could improve the quality of results (Moran & Wood, 2014, compare also the table with construction principles in chapter 1 in Supporting Information S1). These include

- main data sources and their classifications,
- reporting of meta data,
- methods to integrate source data into IO models, such as conversions into basic prices or of supply-use tables into IO tables,
- alignment of bilateral merchandise and trade in services statistics with national and global supply-use tables,
- agreed approaches for dealing with re-exports and re-imports,
- best-practice methods for developing the structure of the RoW region (see Stadler, Steen-Olsen, & Wood, 2014),
- methods to disaggregate environmentally sensitive sectors, and
- guidelines for the most suitable method of balancing the final table (Wiebe & Lenzen, 2016).

An effort addressing these issues and fostering the further development of data and methods would benefit from being facilitated by an international organization. In the past few years, the OECD has hosted three expert workshops on MF indicators (OECD, 2014, 2015a, 2018). The latest workshop held in September 2017 concluded that the necessary expertise to pursue a harmonization of core procedures existed across the various relevant institutions, which include research institutes, statistical offices, environmental authorities, and international organizations, but funding to realize such a process is lacking. To date, it is unclear whether OECD or another international organization can become the custodian of such a process or whether bottom-up efforts, such as, for instance, the global virtual multiregional input-output (MRIO) Laboratory (Lenzen et al., 2017) can replace the current lack of international coordination.

Finally, it is important to note that the thematic focus on raw materials of this paper leads to very specific conclusions regarding economic sectors and supply chains that should receive prime attention in reducing indicator uncertainties. The same analytical exercise could also be performed with regard to deviations of other footprint-type indicators, such as the carbon footprint (see Wieland et al., 2018 for a SPLD-based assessment of EU's carbon footprint). The priority areas for data alignment, that is, areas, where deviations of monetary data in the GMRIO system translate into major differences in the footprint indicators, will likely be very different for other environmental categories. This is due to the fact that other sectors and supply chains play a more important role than those highlighted for the case of material flows, for example, main greenhouse gas emitting sectors such as the electricity sector in the case of the carbon footprint (see Owen et al., 2014, 2016).

## 5 | CONCLUSIONS AND OUTLOOK

The core objective of this paper was to quantify the impact of data deviations in the multi-regional IO matrix of a number of commonly used GMRIO databases on the results for the MF. We found that across all analyzed countries and material groups, data differences in the primary material extraction sectors (i.e., agriculture, forestry, and mining) and in the subsequent processing sectors (such as food, petroleum, and chemicals; metal products; and construction) were responsible for most of the difference in MF indicators. If GMRIO databases report different monetary values for the deliveries of these sectors, both within the domestic economy and in trade with other countries, this results in significant differences in the MF indicator because of the large amount of materials embodied in the respective supply chains. In contrast, data differences in sectors, which receive materials at later stages in the supply chain, such as manufacturing or services, generally have only a minor impact on the demand-based material flow indicator. This pattern was observed for all selected countries, that is, developed countries and emerging economies alike.

For further research on MFs, we conclude that the material-intensive sectors and supply chains should be a priority in the further development of GMRIO models and databases that calculate MF indicators. In addition to further aligning construction procedures in monetary MRIO modeling, one future option is to exploit the growing body of global data sets in physical units, which allow tracing flows of primary materials in physical units (Bruckner, Giljum, Fischer, Tramberend, & Börner, 2018; Ewing et al., 2012). Future work could test whether detailed and reliable physical accounts for the first stages of processing can be established on the global level, allowing circumventing those sectors in the GMRIO databases that were identified as causing the highest deviations in MFs.

These development processes need to be pursued expeditiously in order to exploit the full potential of material flow accounting indicators as a useful and practical evidence base for an environmental policy approach that addresses the complexity and interconnectedness of the global economy and its relationship to environment and natural resources. This will help the research community to address the information needs of policy makers about the environmental effects of complex international supply chains and cause–effect relationships in an increasingly globalized world economy.

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## CONFLICT OF INTEREST

The authors declare no conflict of interest.

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## SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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