Creating global scenarios of environmental impacts with structural economic models

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Chapter 3

Effect of aggregation and disaggregation on embodied material use of products in input-output analysis[1]

Abstract

Consumption based material footprints calculated with multi-regional Input-Output (mrIO) analysis are influenced by the sectoral, spatial and material aggregation used in the mrIO tables and the lack of disaggregation can be a source of uncertainty. This study investigates the effect of the resolution of mrIO databases on consumption based material footprints. The effect of aggregation was investigated by making different input-output tables with different spatial, product and material category resolution and comparing the calculated material footprints. Our results indicate that the material footprints of countries calculated with the different spatial and product aggregations are in general in the order of a few percentage with outliers in the order of 25% difference. The use of IO models with a low product category resolution (e.g. 60 product categories) to calculate the embodied material use of individual products will likely result in estimations of the total embodied material that are for some product categories inaccurate. The effect of having aggregated material categories as extensions to the mrIO is more influential on the material footprint of countries, the difference can be in the order of 30% when aggregating the original 46 material categories into 16 material categories. This result strongly suggests that the material data used for to create the extensions for the IO framework should be collected at the highest resolution that is practically feasible.

3.1 Introduction

Multi-regional IO systems are currently recognized as constituting a state-of-the art system for the calculation of economy-wide environmental impacts of consumption, including carbon, water, land and material footprints (Bruckner et al., 2012; Tukker et al., 2014; Eisenmenger et al., 2015; Bouwmeester, 2014; Wiedmann et al., 2014). Different multi-

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regional IO systems (mrIOs) exist, and they differ in their level of resolution with respect to material categories, products/industries and countries/regions (Tukker & Dietzenbacher, 2013). Much of this work on consumption-based accounts with mrIOs has focused on the carbon footprints of countries and products (Hoekstra, 2010; Ahmad & Wyckoff, 2003; Hertwich & Peters, 2009; Davis & Caldeira, 2010), and increasing attention is devoted to factors causing uncertainty in such footprint estimates (e.g. Peters et al., 2012; Wilting, 2012; Lenzen et al., 2010; Moran & Wood, 2014; Stadler et al., 2014). Currently, efforts are being made to use similar approaches to estimate footprint type indicators of material usage for policy applications (EC, 2011; OECD, 2011). An important example of such efforts is the ongoing work of the United Nations Environment Program International Resources Panel (UNEP IRP)[1] and OECD (2008) to develop a harmonized resource extraction database covering almost all countries in the world. In this context, the question is what factors are relevant when creating robust estimates of material footprints. Since the UNEP IRP effort will harmonize much of the primary extraction data, the question we focus on in this paper is: what is the impact of data resolution and aggregation on estimates of material footprints using mrIOs? We focus on this specific question within three particular domains: (1) the resolution of information on material extracted from the environment; (2) the resolution of product groups tracked in the input-output system; (3) the geographic resolution. By investigating these aspects, we have sought to identify a reasonable level of resolution for mrIO work in order to get representative results, and to identify the areas that are most critical to provide detail on when either creating or utilizing mrIO data.

Tukker & Dietzenbacher (2013) provided an overview of the latest developments in mrIOs. Previous work has shown that the resolution in an input-output table (IOT) affects the results obtained. As early as in 1949, Leontief discussed the influence of aggregation (Leontief, 1949). Hatanaka (1952) and McManus (1956) showed that aggregated input-output tables are very likely to yield outputs that differ from that of the original table. The impact of the resolution of IOTs and mrIOTs on footprints of countries and products has until now mainly been investigated for CO_2 or greenhouse gas emissions (e.g. Su & Ang, 2010; Su et al., 2010;

[1] See the website of the UNEP IRP (http://www.unep.org/resourcepanel/) for completed work and ongoing research.

Lenzen, 2011; Bouwmeester & Oosterhaven, 2013; Steen-Olsen et al., 2014). The conclusion of this work is that a greater level of sector and country resolution generally improves the accuracy of carbon footprints estimates. Bouwmeester & Oosterhaven (2013) concluded that the effect of sectoral aggregation is much larger for water footprints than for CO_2 emissions, highlighting the need for a separate investigation of the influence of aggregation on material footprints. Wood et al. (2015) compared multipliers and impacts embodied in the trade of labour and carbon dioxide, finding significantly enough variation to warrant further research into disaggregation. Lenzen (2011) empirically analysed the question, again for carbon dioxide, finding a clear indication that disaggregation is always preferred to aggregation. Steen-Olsen et al. (2014) concluded that more work is necessary to investigate the relationship between the level of resolution of IOTs and multipliers for other environmental extensions, such as materials. Huysman et al. (2014) looked at the need for disaggregated material extraction data in order to characterize the material footprint by means of a secondary indicator (exergy in this case). Linking pressure indicators such as material extraction to impact indicators that require a characterization of resource use will create a further argument for material disaggregation, which we acknowledge, but do not analyse here.

Work on understanding the uncertainty in material footprint calculations with mrIO is still in its early stages. Eisenmenger et al. (2015) and Giljum et al. (2014) presented comparisons of the material footprint for Austria, the EU-27, the US and China, calculated using different mrIOs: WIOD (Dietzenbacher et al., 2013; Timmer, 2012), Eora (Lenzen et al., 2013), GTAP (Narayanan et al., 2012), OECD-GRAM (Bruckner et al., 2012) and EXIOBASE (Wood et al., 2015). The material footprints calculated with these mrIOs ranged from 29 to 33 tons per capita for Austria (Eisenmenger et al., 2015), and from 10 to 11 billion tons for the EU-27, 7.5 to 12.5 billion tons for the US, and 7 to 19 billion tons for China (Giljum et al., 2014). It is likely that this range of outcomes is principally due to basic differences in, for example, the material extraction data used (an issue that will be solved by the aforementioned work of the UNEP IRP). However, as was found for carbon footprints, some of the differences can be attributed to differences in resolution, at the level of countries, industry and products, and material categories, as used in the different mrIOs[1].

Until now the effect of resolution in mrIOs on the material footprint has not been studied in detail. The specific novelty of the present study is its focus on material footprints and the effect of using more or less detail in material categories. As indicated above, the effect of material category resolution is especially interesting for the ongoing discussions at UNEP regarding the set-up of a world-wide material accounting database. While the incorporation of this database in a detailed mrIO can definitively be an argument for a high level of detail, issues such as copyrights or the demand for less detailed data by the majority of users argue for the use of less detailed material extraction data. This paper aims to specifically offer guidance on the effects of having higher or lower resolution in the material data.

We place this research question in a broader context by calculating both material and carbon footprints, and comparing the results regarding the variance of the calculated material footprints with the calculated carbon footprints of countries and products/industries. The carbon footprints serve as a reference with which the material footprints are compared. Is the effect of resolution on the material footprint smaller or larger than on the carbon footprint? The carbon footprint is a useful reference because of the wealth of other studies examining the effect of resolution on carbon footprints. In addition, greenhouse gas emissions are also emitted by many sectors of the economy, in contrast to material extraction, which is by and large concentrated in the agriculture, forestry and mining sectors, leading to much higher concentrations in supply chains.

This study used the recently published version 2 of EXIOBASE (Wood et al., 2015; Tukker et al., 2014). The available multi-regional supply-use tables (mrSUTs) at the highest level of

[1] As summarized by e.g. Tukker et al. (2013), not only the mrIO approach but also various other approaches, including coefficient approaches, can be used to estimate (material) footprints of countries. A coefficient approach for the material footprint looks at the weight of an imported product according to trade data, and then uses life cycle inventory data to estimate the primary material extraction needed to produce that product (cf. Eurostat, 2012b). Comparison of mrIO and coefficient approaches is beyond the scope of this paper – see Schoer et al. 2013.

detail were used as the starting material. Subsequently, this set of mrSUTs was transformed to four different mrIOs, each representing a scenario. These scenarios allowed us to investigate the effect of (1) reduced product resolution, (2) reduced spatial resolution, and (3) reduced material category resolution. The basic comparison between the scenarios regards the total material and carbon footprints of countries/regions and the embodied material use and carbon emissions of products per million Euro of the product. In specific cases, the result was broken down into different material categories for further explanation and interpretation.

3.2 Material and methods

Most of the studies mentioned in the introduction investigated the effect of aggregation of the IOT. However, since the work of Stone and co-workers (UN, 1968) it is generally accepted that the best route to arrive at an IOT is to compile data in the form of a supply-use table (SUT) first. This SUT is then transformed into an IOT for analytical purposes. The purpose of examining the influence of aggregation is to assess the implications of having less detailed data available. Since the basic data for an IOT is given in the form of a SUT, the investigation preferably starts by aggregating the SUT and transforming the aggregated SUT into an IOT. As is shown below, aggregation at the level of an SUT usually results in an aggregated IOT that is different from an IOT created by aggregating the IOT in the same way.

Various SUT to IOT transformation models exist, see for instance Miller & Blair (2009) and Eurostat (2008), but the most commonly used model for product-by-product tables uses transformation according to the industry technology assumption (PxP-ita), which is also recommended by the UN (1993). The PxP-ita IOT always gives positive values and can work with rectangular SUTs like those used in this study. We therefore used the PxP-ita model in this research to transform the SUT into a symmetric product-by-product table.

The basic data used to construct all four scenarios consists of mrSUTs exported from EXIOBASE version 2.2.0[1]. This set of tables represents the EXIOBASE mrSUT data at their highest level of detail for 48 countries/regions, 200 product categories, 163 industry sectors

[1] EXIOBASE version 2 can be downloaded free of charge from www.exiobase.eu.

and 46 different material categories. See the Supporting Information for a full specification of these classifications. Also included in the set are the three major greenhouse gases (CO_2, CH_4 and N_2O). These were used to calculate consumption-based carbon footprints of countries as well as carbon footprints of individual products, and served as a reference with which the material footprint can be compared.

The total material footprint is based on the sum weight of all the individual material categories (only the “used extraction” categories were taken into account. The “unused extraction” data have not been used). The carbon footprint was calculated based on the global warming potentials of CO_2, CH_4 and N_2O with a 100-year time frame (GWP_{100}). These values are given in the Supporting Information.

The construction of the four different scenarios is described below, while a graphical overview is provided in Figure 3.1.

Default scenario. This is the scenario at the highest level of detail, where the mrSUT is transformed into a product-by-product IO system according to the industry technology assumption (PxP-ita), distinguishing 48 countries/regions, 200 products per country/region and 46 different materials. The algorithms for the transformation of the mrSUT into an mrIOT can be found, for instance, in Eurostat (2008) and Miller & Blair (2009).

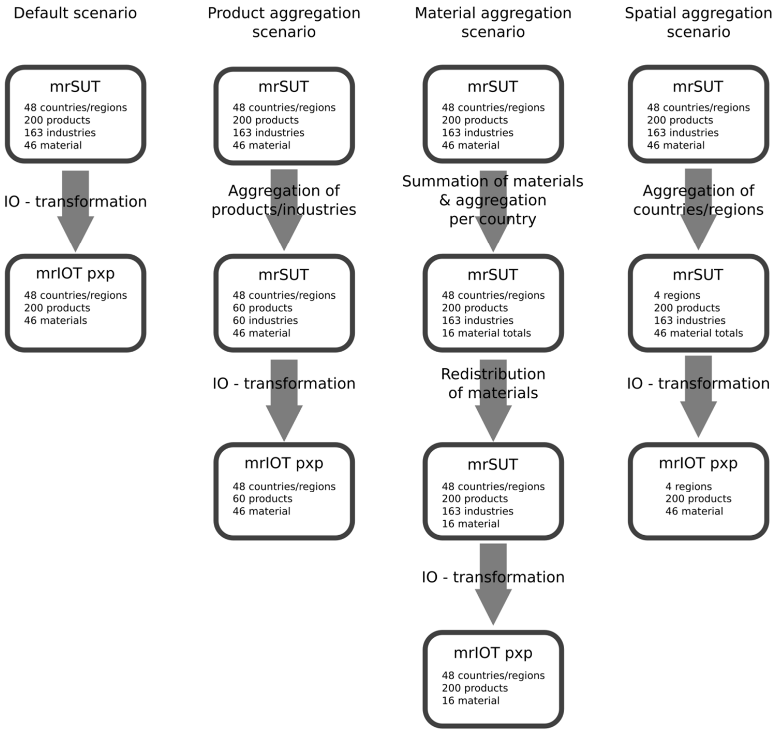

Figure 3.1: Overview of transformation steps used to create the different scenarios.

Product aggregation scenario. This scenario investigates the effect of working with a reduced product resolution on the calculated material and carbon footprints. First, the mrSUTs at the highest level of detail are aggregated into a mrSUT with a 60 products by 60 industry sectors dimension. This reduced resolution mrSUT is then transformed into a PxP-ita mrIO. The detailed product and industry classification can be found in the Supporting Information. The 60 product groups represent the product resolution at NACE rev 1.1 level 3 (EC, 2002) which is the level of detail of the SUTs supplied by Eurostat[1] for the years 2000 – 2006 (more recent years are available in a NACE rev 2 classification). This scenario thus typically represents a study in which mrIOs are constructed without further disaggregation of standard available SUTs.

[1] Available at epp.eurostat.ec.europa.eu, accessed 29 September 2014.

Spatial aggregation scenario. This is a scenario in which the original 48 countries and regions are aggregated into 4 large world regions, i.e. European Union (EU), high income countries (HI), fast developing countries (BX) and a rest-of-the-world region (WW). The definitions of these regions can be found in the Supporting Information. Comparing this scenario with the default scenario shows to what extent spatial aggregation may affect the overall material footprint calculations. For products, there exists a hierarchical classification in which product groups are defined at different levels of aggregation. These aggregated product groups combine more or less similar products. Such a standard hierarchical classification does not exist for countries. We decided to at least distinguish the European Union as an area of interest, and defined the other regions based on their current economic development, constrained by the countries distinguished at the lowest level of detail in EXIOBASE. The implications of this choice are examined below when discussing the results of the spatial aggregation scenario.

Material aggregation scenario. This is a scenario that assumes that the material extraction data are available at an aggregation level of 16 different categories, rather than at the default level of 46 categories. The 16 material categories[1] represent the two-digit level of the material categories defined in Eurostat's economy-wide material flow accounts (EW-MFA) guide (Eurostat, 2012a). The correspondence between the two-digit EW-MFA material categories and the 46 EXIOBASE material categories is given in the Supporting Information.

The multi-regional material extensions table was not simply aggregated into 16 material categories before the transformation into an mrIO system. Such an operation would not change anything relative to the default scenario when calculating the total material footprint of countries or products. Instead, the aggregation of the material categories was carried out in such way that it mimicked the difficulties that arise when attributing the extraction of specific material categories to specific industry sectors when the material categories are much more

[1] The official EW-MFA classification at the two-digit level distinguishes 17 categories. However, two of these categories (A.3.2 - Chalk and dolomite and A.3.6 - Limestone and gypsum) fall into a single EXIOBASE material category (Non-Metallic Minerals - Limestone, gypsum, chalk, dolomite), see Supporting Information. Therefore, the two EW-MFA categories are treated as one.

aggregated. In the course of the construction of EXIOBASE, total domestic extraction of the 46 material categories could quite easily be attributed to the production of specific products. For instance, domestic extraction of rice can be attributed to rice output, iron ore to mined iron output etc. When all agricultural products are lumped together into a single "crop extraction" category, simplistic assumptions have to be made about the distribution of this crop extraction over the different agricultural products, if no further information is available. This scenario assumes that the distribution of material categories that can be attributed to more than one product category is proportional to the monetary value of these product outputs.

The material aggregation was done in the following steps. The material extensions table per country that is available in the SUT system in the form of material category use per industry sector was first used to calculate the total material extraction in a country for 46 material categories. Subsequently, these totals were aggregated into the 16 EW-MFA categories. Each of the aggregate material categories was then allocated to the production of one or more products using an allocation matrix which is described in detail in the Supporting Information. The allocation matrix and supply table of a country were then used to redistribute the total material extraction over the different product outputs and were subsequently transformed into a new material extensions table at the 16-category level for the mrSUT. This mrSUT was then transformed into a PxP-ita mrIO at the level of 48 regions, 200 products and 16 material categories. A full mathematical description, including an example of the material aggregation, allocation and redistribution operation can be found in the Supporting Information.

The four different scenarios resulted in a set of four different mrIOs. These mrIOs were used to calculate the material and carbon footprints of countries. We also calculated the materials and carbon emissions embodied in the individual product groups, expressed in thousands of tons per million Euro and kg CO_2 equivalents per million Euro, respectively. Subsequently we calculated the percentage change going from the default scenario to one of the other scenarios with reduced. A change of 50% means that the scenario resulted in a footprint that is half as much higher than that of the default scenario resolution e.g. from 56 to 84 kg CO_2/million Euro. A change of -50% means that the scenario resulted in a footprint half as low as that of the default scenario, e.g. going from 46 to 23 kg CO_2/million Euro. Notice that calculating the percentage change means a transformation of scale, where the highest negative change possible is -100% and the highest positive change is unlimited (in theory).

The distribution of differences obtained from the calculations was described with the usual statistical metrics such as the median, as well as the 1st and 3rd quartiles. The standardized unitless measure of kurtosis was also calculated, which is important to detect if the differences resulting from the aggregation have a larger influence on the material footprint than on the carbon footprint and vice versa. Kurtosis is a measure reflecting the degree to which a distribution is peaked, or more specifically, it provides information regarding the height of a distribution relative to its standard deviation (Sheskin, 2007). Distributions may be divided into three categories: mesokurtic, leptokurtic and platykurtic. The mesokurtic distribution can be represented by a normal distribution and has a kurtosis of approximately 0. A leptokurtic distribution has a higher degree of peakedness compared to the mesokurtic distribution, and its kurtosis is much larger than 0. The platykurtic distribution is much more spread out than the mesokurtic distribution, and its kurtosis is much less than 0, and we may expect a high probability of extreme values (Sheskin, 2007).

Note that to ensure a fair comparison between carbon footprint and material footprint, and in order to focus on the influence of resolution, the direct GHG emissions associated with the consumption phase of products (also called household emissions) were not taken into account. There are two reasons for not doing so in this study. Firstly, domestic extraction of materials only occurs at the level of industry sectors, not at the household level. Secondly, it is not very simple to allocate the total GHG emissions of households to the final consumption of a product. The calculation of the carbon footprint of products thus represents only the emissions occurring within industries. As a consequence, the carbon footprints of countries presented in this paper should not be interpreted as comprehensive, and they are not comparable to results presented elsewhere.

3.3 Results

In the following tables and figures we present the results of the analyses carried out, which are then discussed in more detail. Table 3.1 presents an overview of the percentage changes of the material and carbon footprints of countries resulting from aggregation. The calculated material and carbon footprints of all the individual countries are given in the Supporting Information. Table 3.2 provides an overview of the percentage changes of the material and carbon footprints of products/industries. Box-and-whisker plots of the same results are shown in Figure 3.2, while the corresponding histograms are given in the Supporting Information.

Table 3.1: Statistical measures describing the differences (expressed in percentages) observed between the material and carbon footprints of countries, under different assumptions about the resolution in the Supply-Use table.

Metric	**Effect of spatial aggregation**		**Effect of product aggregation**		**Effect of material aggregation**
	Material FP	**Carbon FP**	**Material FP**	**Carbon FP**	**Material FP**
Count	4	4	48	48	48
Min	-2.67	-0.25	-28.7	-10.1	-18.6
Max	2.10	0.56	13.7	46.7	30.7
Median	-0.40	0.27	2.88	0.65	2.08
25% quartile	-2.14	0.08	0.43	-1.57	-0.65
75% quartile	1.39	0.39	5.03	1.75	5.67
interquartile range	3.52	0.31	4.60	3.31	6.32
In range -25% to 25%	100	100	98	98	98
Kurtosis	-4.8	1.2	5.02	28.81	6.07

3.3.1 Product aggregation scenario

Calculating the carbon footprint of countries with the product aggregation scenario leads in most cases to less than 10% increase or decrease of the calculated carbon footprint. The exception is Luxembourg, with a 47% higher carbon footprint (see Table 3.1). The influence of reduced product resolution on the material footprint of countries ranges from -29% to +14% (see also Figure 3.3). Examination of the effect of the reduced product resolution for individual products (Table 3.2) shows that for some product groups, it is as large as +1151% for the material footprint and +692% for the carbon footprint. Thus, in the most extreme case the footprint calculated with 60 product groups is about a factor 10 higher for a specific product group than that calculated with an IO model using 200 product groups. Notwithstanding these extreme cases, the change is less than 25% for 90% and 93% of the product groups for the material and carbon footprints, respectively. The kurtosis value indicates that the distributions are leptokurtic.

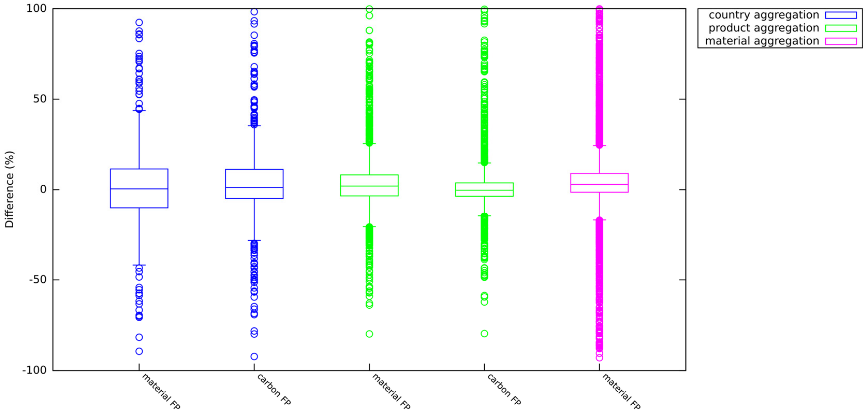

Figure 3.2: Box-and-whisker plots of the differences between the embodied material use and carbon footprints of products calculated under the different scenarios. The box indicates the interquartile range; the lower whisker is defined by the 1st quartile - 1.5 x IQR; the upper whisker is defined by the 3rd quartile + 1.5 x IQR; the median is indicated by the bar within the box. Outliers are indicated by the ○ symbol. Outliers with a difference larger than 100% are not shown.

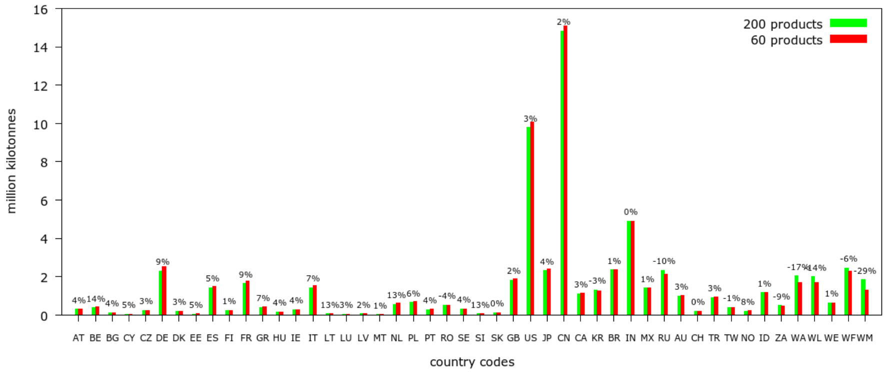

Figure 3.3: Product aggregation scenario: effect of reducing the product resolution from 200 to 60 products on the material footprint of countries. The percentage at the top is the percentage change between the default scenario (green bar) and the product aggregation scenario (red bar).

Table 3.2: Statistical measures describing the differences (expressed in percentage change with respect to scenario 1) observed between the material and carbon footprints of products under different assumptions.

Metric	Effect of spatial aggregation		Effect of product aggregation		Effect of material aggregation
	Material FP	Carbon FP	Material FP	Carbon FP	Material FP
Count	682	682	2644	2644	6677
Min	-89.4	-92.2	-79.8	-79.7	-93
Max	3560	1267	1151	692	22213
Median	0.4	1.3	2.0	-0.3	2.9
25% quartile	-10.0	-4.9	-3.4	-3.6	-1.4
75% quartile	11.4	11.3	8.2	3.8	9.0
Interquartile range	21.5	16.2	11.6	7.4	10.4
In range -25% to 25%	78%	80%	90%	93%	86%
Kurtosis	472	130	467	221	693

The data indicate that reduced product resolution has a greater influence on the material footprint than on the carbon footprint, as is shown by the interquartile range and the number of observations within the -25% to +25% interval. The difference in the distributions of material and carbon footprints was tested with the non-parametric Friedman test, which revealed that there is a significant difference ($X^2(2) = 101$, $p = 0.000$) between the mean ranks of the two distributions (Siegel and Castellan, 1988), see Table 3.3.

Table 3.3: Friedman test statistics to detect if the effect of aggregation for the material footprint is different from the effect of aggregation on the carbon footprint.

	material footprint versus carbon footprint	
	effect of spatial aggregation	effect of product aggregation
N	682	2644
Chi-square	9.859	101
df	1	1
Significance	0.002 **	0.000 **

** $p < 0.01$

A list was made of the 20 product groups showing the largest effect of product aggregation on the material footprint. Ten of these 20 products are summarized as “p14, Other mining and quarrying products”, which is an aggregation of the products “stone”, “sand and clay” and "chemical and fertilizer minerals, salt and other mining and quarrying products n.e.c.". Other composite products that occur multiple times in the top 20 are "p01, agricultural products" and "p16, tobacco products". It appears that the effect of product aggregation is strongest for agricultural products and other mining and quarrying products, indicating that the embodied material use for sub-categories in these product groups is highly variable, and that the product groups where the actual material extraction takes place are most affected. The result for p16, tobacco products, whilst perhaps not significantly affecting macro-level results, is an interesting illustration of the nature of the aggregation effects. P16 is basically the manufacturing of tobacco products, and involves no direct material extraction from the environment itself, but instead involves inputs from the agricultural sector. The fact that the manufacturing process purchases a very specific agricultural product (tobacco) rather than a range of produce, and that tobacco is somewhat a-typical compared to the rest of the agricultural sector (very high value to embodied weight ratio), causes it to show such high variability.

The patterns in the differences were further analysed by creating a "heatmap", which shows the difference between the default and product aggregation scenarios for each country and each product group by means of a colour code. The most affected product groups show up in bright red or dark blue. The overall impression from Figure 3.4 is that white and nearly white colours dominate, which underlines the conclusion that for most product groups the differences resulting from product aggregation are small. Product groups p01, p14, and p16 show up as columns dominated by red. Interestingly, in product groups p21 - p26, the colours for the group of manufactured products indicate a moderate influence on the calculated material footprint.

It is known from earlier work (e.g. Tukker et al., 2014) that p45, construction work, is the product with the largest total embodied material use, with sand & gravel having the highest share. It is therefore interesting to see how the product aggregation has affected this key sector. Notice that the construction sector itself was not aggregated in our product aggregation scenario, but all the effects seen for this product result from the aggregation of products used as input for construction work. Figure 3.4 shows that the embodied material use of construction work in almost all countries decreases upon aggregation. This can be explained by the fact that the original sand and clay mining sector, which has the highest material extraction multiplier in terms of kg/Euro, is aggregated with other mining sectors that have a lower material extraction multiplier.

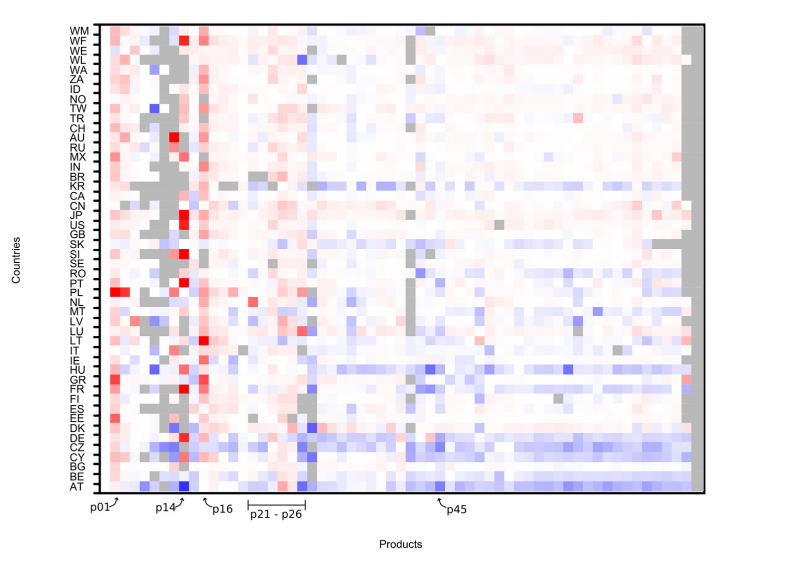

Figure 3.4: Heatmap showing the difference in embodied material use per country and per product for the product aggregation scenario, in the form of color codes. The differences are expressed as percentages. Dark blue means a difference of -100%. Dark red means a difference > 250%. The columns for product groups p01, agricultural products, p14, other mining and quarrying products, and p16, tobacco products, are dominated by red colors. p45 is construction work. Grey color means not available.

In addition, we prepared a list of the 20 product groups showing the largest effect of product aggregation on the carbon footprint. Six out of these 20 products are aggregated in “p26, other non-metallic products”, while a further five are in “p11, crude petroleum and natural gas services”. However, it is not obvious from the ranking of the product groups that the sectors with the highest emissions are most affected by the aggregation, as was observed for the material footprint.

3.3.2 Spatial aggregation scenario

Table 3.1 and Figure 3.1

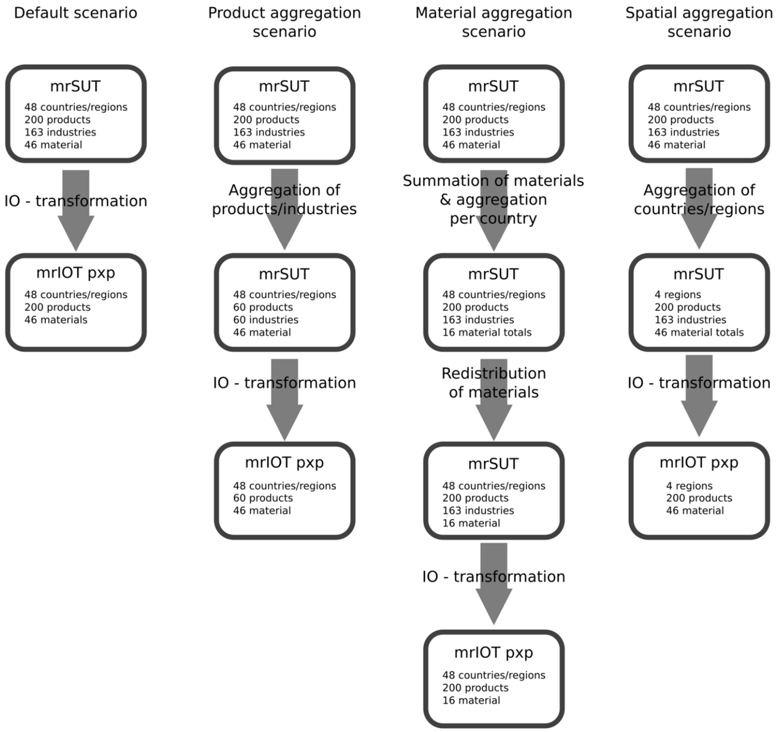

Figure 3.1 illustrate that the influence of reducing the spatial resolution on the calculated regional footprints is limited. The maximum differences for the footprints of the four regions are about 2% for the material footprint and less than 1% for the carbon footprint. If we focus on the embodied material use and embodied carbon emissions in individual product groups, the calculated embodied material use of products shows larger variation than the embodied carbon emissions, as is shown by the interquartile range. For the carbon footprint, 50% of the observed differences are in the range of -5% to +11%, while for the material footprint this is -10% to + 11%. We may conclude that the effect of reducing the spatial resolution is somewhat larger for the material than for the carbon footprint. The difference between the two distributions is significant ($X^2(2) = 9.859$, $p = 0.002$) according to the Friedman test (Table 3.3). The maximum percentage change observed when aggregating into 4 regions is 3560%

for the material footprint and 1267% for the carbon footprint, which is in the same order of magnitude as the maximum effect of the aggregation into 60 product groups.

Investigating the products that show the largest percentage change in embodied material extraction or embodied carbon emissions upon aggregation shows that no particular product seems to be specifically affected by the spatial aggregation, unlike the results obtained for the product aggregation scenario.

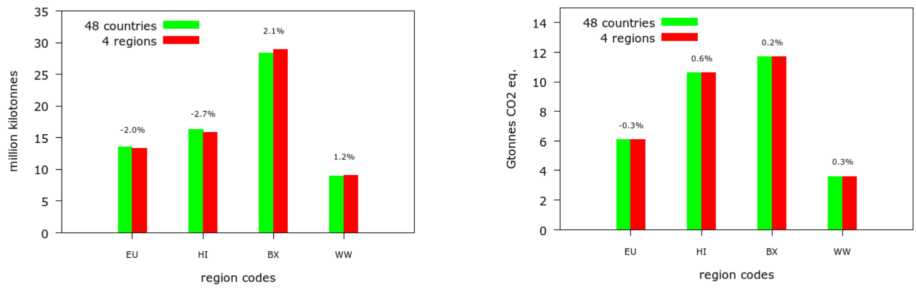

Figure 3.5: Spatial aggregation scenario: effect of spatial aggregation on the calculated carbon (right) and material footprints (left) of countries. The percentage change between the default scenario and the spatial aggregation scenario is given at the top of the bars.

The calculated carbon and material footprints are of course affected by the level of aggregation of the countries. Work by Stadler & Wood (2014) using the same data as our study and focusing on the product group of “wearing apparel: furs” showed that the material footprint of this product group was at most 25% smaller when considering an EU and aggregated world region. An aggregation into EU and main regions reduced the calculated material footprint by 5%. Stadler & Wood (2014) examined the effect of spatial aggregation on all products using different spatial aggregation scenarios, and found that the effect on the material footprint was much larger than on the carbon footprint, which corroborates our results.

3.3.3 Material aggregation scenario

The effect of aggregating the material categories from 46 to 16 categories on the material footprints of countries/regions ranges from -19% to +31% change, and is not significantly different from the effect of spatial aggregation or product aggregation, according to the Friedman test (see Table 3.4). At the level of individual product groups, the effect of material aggregation is significantly smaller than the effect of spatial aggregation, in the same order of magnitude as the effect of product aggregation (but significantly different); see Table 3.2 and Table 3.5. If we take the effect range of -25% to +25% change as an acceptable change, the effect of the material aggregation scenario is slightly larger.

Table 3.4: Friedman test statistics to detect if the percentage change in the calculated material footprint of countries due to material aggregation is different from the effect of spatial aggregation and product aggregation.

	material footprint of products effect of material aggregation versus that of	
	spatial aggregation	**product aggregation**
N	4	48
Chi-square	1.000	.750
df	1	1
Significance	.317	.386

** $p < 0.01$

If we look at the effect of material aggregation on the individual embodied materials in products (see Supporting Information), there is no effect at all for the categories of wood, fish, iron, marble, slate, clays & kaolin, salt, and chemical and fertilizer minerals. The effect on embodied sand & gravel in products is very small. The structure of the SUT and hence the IOT does not change in the material aggregation scenario, and some material categories are allocated to a single primary sector both in the EXIOBASE classification and in the corresponding EW-MFA 16-category classification. In such a case there will be no effect of the aggregation scenario on the embodied material use. This rule also applies to the sand & gravel category, yet we see a very small aggregation effect. This is the due to some of the manual tweaks that have been made to the original data, which were not applied in the aggregated material extensions[1]. The effect on the individual material categories is largest for

[1] In the original data, sand & gravel extraction was connected to the production of p14.2, sand and clay in all countries and regions except in India. In the aggregated material data, the sand & gravel extraction was connected to the production of p14.2 without exception.

crops, chalk & dolomite, limestone and gypsum and other non-metallic minerals, as shown in the Supporting Information.

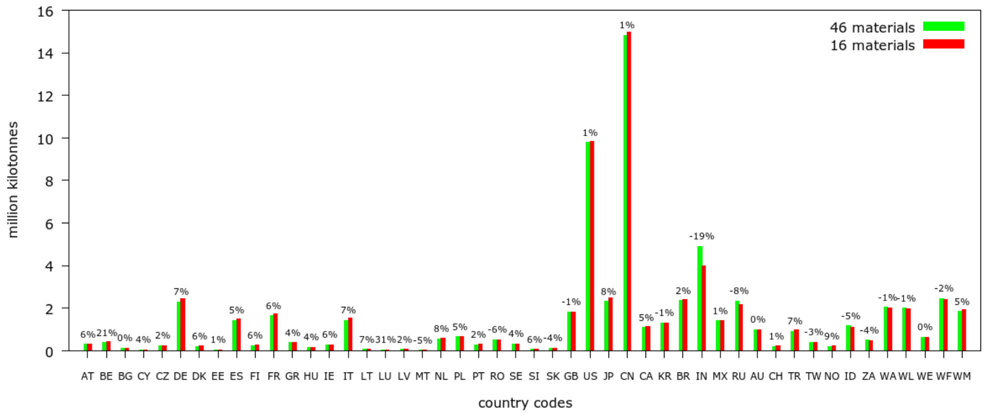

Figure 3.6: Effect of the aggregation of the 46 material categories into the 16 EW-MFA categories on the calculated material footprints of countries/regions. The percentage change between the default scenario and the material aggregation scenario is given at the top of the bars.

Table 3.5: Friedman test statistics to detect if the percentage change in the calculated material footprint of products due to material aggregation is different from the effect of spatial aggregation and product aggregation.

	material footprint of products, effect of material aggregation versus	
	effect of spatial aggregation	**effect of product aggregation**
N	682	2644
Chi-square	42.375	233.660
df	1	1
Significance	.000 **	.000 **

** $p < 0.01$

Eight examples of the effect of the material aggregation on the embodied material composition of products are shown in Figure 3.7. Four examples (DE p40.11b, DE p40.11.f, US P26.d, US p27.5, see figure for explanation of codes) were chosen such that they included a high share of the embodied material categories of non-ferrous metals, calcium carbonate minerals and oil & gas. These are the material categories for which a large influence of the material aggregation scenario was observed. The other four examples (KR p14.3, SK p11.c, DE p11.c, ID p01.g) are the products showing the largest percentage change in embodied materials when the material categories are aggregated. The first four examples show that the composition of embodied materials of these four products is not much affected. In the most extreme case, a completely different embodied material composition is calculated, as illustrated by the last four cases.

We investigated if large percentage changes in the material footprint due to aggregation can be correlated with large percentage changes in the carbon footprint. This was done by creating scatterplots and calculating the Spearman rank correlation. Pearson's correlation coefficient was not calculated, as it is sensitive to outliers and assumes that the data are approximately normally distributed. The calculated Spearman correlation coefficients and two-tailed significance levels are given in Table 3.6. For spatial aggregation, a significant positive rank correlation was found between the changes in the material footprint and the carbon footprint. However, it is not possible to conclude directly that the percentage change in the footprints is correlated in these cases. A scatterplot of the rank-transformed data and the original data reveals that in both cases, the observed significant rank correlation is not an indication of correlation in general but is due to the nature of the data and the effect of rank transformation. We conclude that the percentage change observed in a material footprint is not correlated to the percentage change in the carbon footprint.

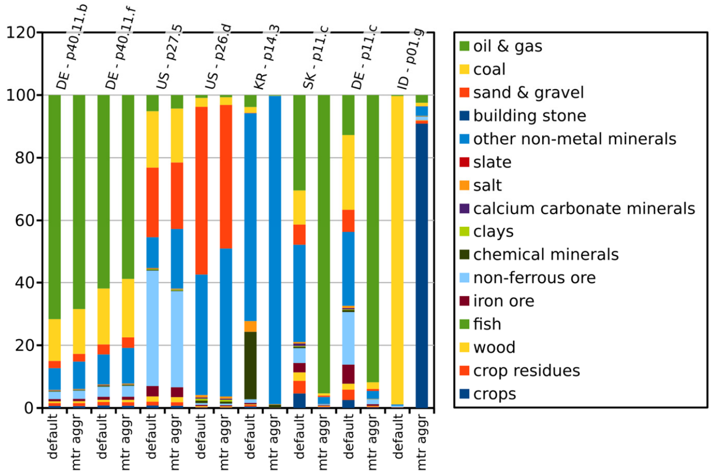

Figure 3.7: Some examples of the effect of aggregation of the 46 EXIOBASE material categories into the 16 EW-MFA categories on the embodied material composition of four different products. p40.11.b = Electricity by gas; p40.11.f = Electricity by petroleum and other oil derivatives; p26.d = Cement, lime and plaster; p27.5 = Foundry work services; p14.3 = Chemical and fertilizer minerals; p11.c = other hydrocarbons; p01.g = plant-based fibers; DE = Germany; US = United States of America; KR = South Korea; SK = Slovak Republic; ID = Indonesia.

Table 3.6: Measures of correlation between the percentage changes due to aggregation for the material footprint and carbon footprints of countries.

	Country footprint		**Product footprint**	
	Spearman rank correlation	**Significance (2 - tailed)**	**Spearman rank correlation**	**Significance (2 - tailed)**
Effect of spatial aggregation	-0.400	0.600	0.469**	0.000
Effect of product aggregation	-0.134	0.363	0.010	0.605

** $p < 0.01$

3.4 Discussion

Our findings show that aggregation of product groups from a high detail of 200 products to 60 product groups has a larger effect on the material footprint than on the carbon footprint. This is also true for our spatial aggregation scenario, where 48 regions are aggregated to 4 regions. This result can be explained by the fact that the variability of carbon emissions between sectors is smaller than the variability in material extraction. Carbon emissions occur in every sector, but material extraction is a very specific activity that occurs in the primary sectors only. When sectors are aggregated, it is likely that the sectors are more homogeneous in terms of the carbon emission multipliers than the material extraction multipliers.

No correlation was found between changes in embodied carbon emissions and embodied material use in products. Fossil fuel extraction is one of the material categories included in the total embodied material use indicator. Only for products where the embodied material use is dominated by fossil fuels that have been combusted can we expect an observable relation between the effects of aggregation on the embodied carbon emissions and the total embodied material use. This might be the case for the electricity sector.

The effect of product and spatial aggregation on the level of the mrSUT in this study, as well as in other studies investigating the effect of aggregation at the level of mrIOT, probably does not represent the full effect of having to work with aggregated (statistical) data. In our study, the aggregation of product groups and/or industry sectors was carried out at the level of the multi-regional SUT, after which this aggregated multi-regional SUT was transformed to an aggregated multi-regional IOT. We may call this approach half-way aggregation (see Figure 3.8). Many studies on the effect of aggregation have used an IO system as the starting point of their analysis (Hatanaka, 1952; Steen-Olsen et al., 2014; Su et al., 2010; Su & Ang, 2010) and aggregated the IO table, which means that the aggregation operation took place at a later stage. We call this approach late aggregation. Since we have access to the single-country SUTs in EXIOBASE, these single-country SUTs could also have been aggregated and used to construct a trade-linked mrSUT for further analysis. This route might be called early aggregation. Finally, the route in which the most detailed data are used to calculate indicators and the final indicators are aggregated to the desired resolution could be called final aggregation.

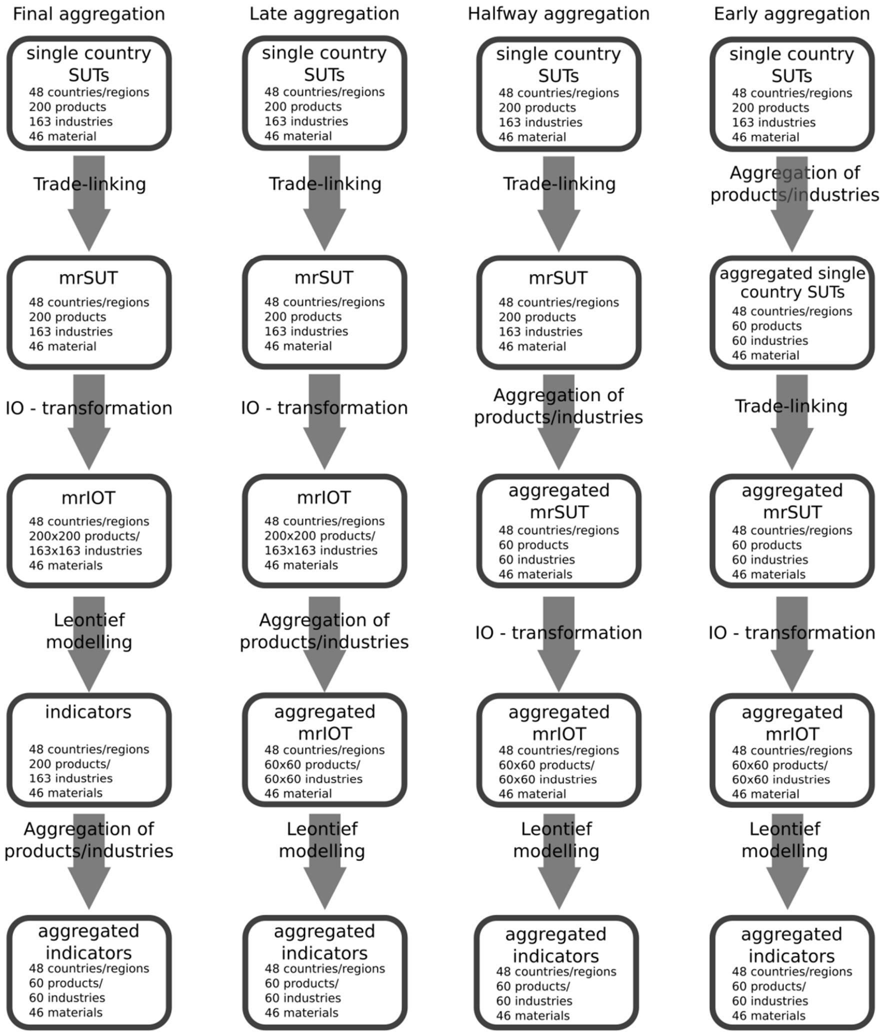

Figure 3.8: The four different routes towards aggregated environmental impact indicators calculated with a mrIO. By way of example, the default SUT available in EXIOBASE which distinguishes 200 products and 163 industry is aggregated to obtain aggregated environmental impact indicators distinguishing 60 products or 60 industry sectors.

Late aggregation for the PxP-ita model leads to different environmental impact indicator results than halfway aggregation, except in the case that only products are consolidated in aggregated groups (see Supporting Information for mathematical proof). In realistic cases, like those analysed in our different aggregation scenarios above, the aggregation concerns not only products but also industry sectors, so halfway aggregation results in an aggregated IO table that is different from a late-aggregated IO table. We know from the early work of Hatanaka (1952) that late aggregation and final aggregation also lead to differences. The cascade of effects from halfway aggregation to the final aggregated result is expected to be larger than the cascade of effects from late aggregation to final aggregated result.

Our results, showing the effect of aggregation on material and carbon footprint of countries and products, can therefore not be compared directly with those reported in studies of the effect of late aggregation. Moreover, our results probably underestimate the effect of aggregation, because in a "real-world" situation, where only aggregated SUTs of individual countries and materials can be collected and transformed into multi-regional SUT and IO systems, the early aggregation scenario would give the best description of the effect of having only aggregated data available. Trade linking (Bouwmeester, 2014) combines all the single-country SUTs into one multi-regional SUT system by combining trade data and the export/import data available in the single-country SUT systems, and reconciling all the differences between these disparate data sources. Having to work with aggregated data sources in this step will produce an aggregated mrSUT that is different from a halfway-aggregated mrSUT system and thus also from a late-aggregated mrIO system. The cascade of effects from early aggregation to final results will even be larger than the cascade of effects from halfway aggregation to final environmental impact indicator results. This means that the observed effects in the product aggregation and spatial aggregation scenarios underestimate the effects that would have been encountered if the primary data used to create the mrSUT had been aggregated.

3.5 Conclusions

This paper examined the impact of aggregation and disaggregation of material, product category/industry sector and country classifications in mrIOs on the calculation of the material footprint of countries and products. We found that the differences between the material footprint of a country as calculated with mrIO models that differ in product resolution and spatial aggregation are generally in the order of a few percent. However, outliers in the order of a 25% difference are possible. The effect of aggregating the original 46 material categories into 16 categories on the material footprint of countries can be in the order of 30% difference. This finding strongly suggests that the material data used to create the extensions for the IO framework should be collected at the highest resolution that is practically feasible. Since many of the original data sources used to compile material extension databases, like the International Energy Agency database (energy carriers), FAOSTAT (agricultural products) and the US Geological Survey (USGS; materials) are already at a high level of detail, we strongly recommend to stay as close as possible to the level of detail available in such original sources.

The effects of product aggregation, spatial aggregation and material category aggregation on the calculated total embodied material use of individual product groups is limited for many groups. For several individual product groups, however, the difference can be in the order of 100% or more. Particularly affected are primary sector products. The use of IO models with a low product category resolution (e.g. 60 product categories) to calculate the embodied material use of individual products will likely result in estimations of the total embodied material that are inherently inaccurate for some product categories. This limits the possibilities to use IOA in detailed MFA studies, if the IOA uses a relatively aggregated product resolution.

The effect of aggregation on the material footprints is larger than the effect on carbon footprints. This finding shows that it is important to specifically investigate the effect of aggregation on different indicators. An aggregation level that is acceptable for one environmental or economic indicator might be unacceptable for another indicator or purpose. When calculating footprints other than the carbon footprint, it is safest to do this at the highest level of detail and to aggregate results only at the very end.

The estimated effects of product category resolution and spatial resolution in this paper probably underestimate the effects that will be encountered when basic data to create the multi-regional SUTs are already aggregated, as in an early-aggregation scenario.

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