Towards accepted procedures for calculating international consumption-based carbon accounts

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ABSTRACT
Since the early 1990s, global trade has doubled, with a corresponding increase in emissions embodied in trade. Standard accounting of emissions counts the ‘territorial’ emissions that occur within a country, but there has also been discussion about the need for ‘consumption-based’ carbon accounting (CBCA) that counts the carbon emissions required to produce the goods and services consumed in a country (in short: the Country Carbon Footprint (CCF)). Global multi-regional input-output (GMRIO) databases form the method of choice to calculate carbon footprints. Due to the need to combine different data sources to construct GMRIOs, and incompleteness and inconsistencies in data sources, estimations and balancing procedures have to be applied. Such construction procedures are not uniform. This leads to hesitation over using CCF results in policy formulation. The empirical analysis reviewed in this paper synthesizes the few simple measures that can already lead to robust CCF results, even with different GMRIO models. The single most important point is to use harmonized territorial carbon emissions in different GMRIO models. Then, differences between databases for most countries are less than 10% between GMRIOs, and considerably lower than 10% for large countries with a high GDP compared to imports. When investigating the trends in CCF as opposed to the absolute value, the differences become even smaller. Hence, harmonizing data already used in classical production-based accounts and related policy making appears to be the most relevant factor also for CBCA and calculating CCFs.

Key policy insights

• Country Carbon Footprints (CCFs) are best calculated with Global Multi Regional Input Output (GMRIO) databases.
• Compared to territorial carbon accounting, the additional use of GMRIOs for calculating CCFs in principle leads to higher uncertainties.
• However, trends in CCFs – that is, relative change over time – calculated with different GMRIOs are already very robust.
• Harmonizing territorial emissions across GMRIOs is the single most important factor that reduces uncertainty in CCFs, followed by the use of an official national Environmentally Extended Input-Output model for the country for which a CCF is calculated.
• Working towards an internationally accepted GMRIO, such as the OECD’s inter-country input-output (ICIO) table, is recommended.
Since the early 1990s, global trade has doubled, with a corresponding increase in emissions embodied in trade. Current estimates show a growth from around 21% to 26% of total global emissions embodied in trade over the period 1995–2006, before declining to around 24% in 2015 (Wood, Grubb, et al., 2020). This has had large implications for the accounting of carbon emissions. Current practice within the Intergovernmental Panel on Climate Change (IPCC) is to account for carbon emissions that occur within a country – the so-called ‘territorial’ approach. There has, however, been discussion about the need to also have ‘consumption-based’ carbon accounting (CBCA) or a ‘carbon footprint’ approach that counts the emissions required to produce the goods and services consumed in a country (Munksgaard, Pedersen, & Wier, 2000; Peters, 2008). Such accounting implies that we would need to decouple our emissions not only from domestic industrial production, but also from the goods and services underpinning our consumption and lifestyles. Figure 1 below shows that, relative to Gross Domestic Product (GDP), carbon emissions emitted on EU territory have decreased (production perspective) relative to 1990 levels. However, from a consumption perspective, in 2007, emissions were higher than in 1990, and the subsequent reduction in consumption-based emissions corresponds to a period of net-zero economic growth. At the same time, net imports of carbon have grown from less than 10% to over 20% of total consumption based accounts for the EU (Wood, Neuhoff, Moran, Simas, & Stadler, 2020). If Europe and other developed nations are serious in decoupling their lifestyles from global emissions, there is a clear case for accounting emissions on a consumption basis. Further, as policy is being developed alongside these measures (Grubb, Crawford-Brown, Neuhoff, & Shanes, 2020), there is a clear need for robustness in the footprint accounts and calculations.

**Figure 1.** Evolution of EU carbon emissions, 1960–2015. Instead of time on the x-axis, GDP/capita is used to show increasing affluence (economic growth). Upwards sloping figures then show increasing emission per unit of economic growth, whilst downward sloping figures show decreasing emissions per unit of economic growth (i.e. relative decoupling). Own calculations based on data presented in Wood, Grubb, et al. (2020).
The method of choice to calculate carbon- and other environmental footprints of nations, industries and product groups is currently based on the use of global multi-regional input-output (GMRIo) models. The most important advantages of such models include the inherent comprehensive coverage of the economic system. Truncation errors and cut-offs that are present in Life Cycle Assessment (LCA) based approaches for calculating environmental footprints cannot occur (Lenzen, 2001; Pomponi & Lenzen, 2018; Suh et al., 2004). Further, GMRIos ensure an inherent consistency between all global territorial carbon emissions and the total global carbon footprint (Tukker, Giljum, & Wood, 2018b).

Investments in GMRIos have led to the development of a number of databases suitable for calculating consumption-based carbon accounts for recent years (Tukker & Dietzenbacher, 2013). As explained in the extended editorial of this Special issue, and highlighted in more detail in Box 1, this includes the WIOD, Eora, GTAP, EXIOBASE and OECD-ICIO databases (Tukker & Dietzenbacher, 2013; Tukker, Pollitt, & Henselmans, 2020).

**Box 1. Available GMRIo databases used for consumption-based accounting**

**EXIOBASE.** EXIOBASE was constructed with a focus on activities that are relevant from an environmental standpoint, has 163/200 industry/product categories respectively, and contains environmental extensions for energy, air emissions, water use, land use, material extraction and biodiversity impacts. This is given for 44 countries and five rest-of-world regions for the years 1995–2016 (Stadler et al., 2018; Tukker et al., 2009; Wood et al., 2015). Energy accounts are based on data from the IEA's energy balances, which are converted to the residential principle by means of auxiliary transport models and Eurostat's bridge tables (Usubiaga & Acosta-Fernández, 2015). To allocate IEA activities and products to EXIOBASE sectors/final use categories and products, correspondence tables have been created. Emissions related to combustion are calculated by multiplying emission relevant energy use data with emission factors obtained from the TNO Emission Assessment Model. The last update of emissions accounts to 2016 is described in Wood, Neuhoff, et al. (2020).

**Eora.** Eora is a global, high resolution GMRIo database, covering 187 individual countries with a total sectoral detail of 15,909 sectors, spanning a time series of 21 years. The Eora energy accounts are built on national energy data wherever available. Nevertheless, these cases only represent a small fraction of the countries represented in the model. In all other cases energy data from the IEA and from the US Energy Information Administration (EIA) are used. There is no special handling done to convert the energy data from the primary source into the residential principle for either the national energy data, the IEA data or the EIA data. The greenhouse gas (GHG) emission accounts are based on data from the Emissions Database for Global Atmospheric Research (EDGAR) database and allocated according to industry output. This holds for both energy-related and non-energy related emissions. As in the case of energy related emissions, the data from the emission inventory is not converted into the residential principle before allocating it to sectors, and as in the energy case, national and international data are also used as constraints in a constrained optimization approach (Lenzen, Kanemoto, Moran, & Geschke, 2012; Lenzen, Moran, Kanemoto, & Geschke, 2013). Eora has been updated to 2015.

**WIOD.** The World Input-Output Database (WIOD) is a free access database and covers 40 countries and a single rest-of-world region, with a sectoral detail of 35 different industries (Dietzenbacher, Los, Stehrer, Timmer, & de Vries, 2013). It is based on raw data from national statistical institutes (NSIs) and UN COMTRADE, and covers the period 1995–2011. The main source for the energy reported in the WIOD database is the energy balances provided by the IEA (IEA, 2011a, 2011b), except in cases in which equivalent data from NSIs was available. Different auxiliary datasets are used to convert the energy balances into energy accounts (Genty, Arto, & Neuwahl, 2012). Emissions datasets for EU countries were retrieved from Eurostat. In this context, it should be noted that not all EU Member states bridge the gap between the territory and residential principles when reporting air emission accounts, hence where necessary a scaling factor is applied. For non-EU countries, international air emissions inventories from the United Nations Framework Convention on Climate Change (UNFCCC), EDGAR and Convention on Long-Range Transboundary Air Pollution (CLRTAP) are used (Genty et al., 2012).
In some cases, the differences observed have to do with straightforward differences in the accounting approach. Some studies use an Emissions Embodied in Bilateral Trade (EEBT) approach rather than a true MRIO approach. EEBT assumes that all embodied emissions in the imports of country B from A are caused by country A (and hence parallels the full economic value of these exports). The MRIO approach looks at the global value chains of such imports (see for further discussion Kanemoto, Lenzen, Peters, Moran, and Geschke (2012)). Further, production- and consumption-based accounting are two extremes along a continuum (Tukker et al., 2020). Accounting principles that share responsibilities along value chains (e.g. based on income or value added) can be expected to lead to differences in allocated responsibilities of carbon emissions.

Even when such methodological differences in allocation principles are avoided, carbon footprints calculated with different GMRIOS vary (Arto, Rueda-Cantuche, & Peters, 2014; Dawkins, Moran, Palm, Wood, & Björk, 2019; Owen, 2017; Owen, Steen-Olsen, Barrett, Wiedmann, & Lenzen, 2014; Steen-Olsen, Owen, Hertwich, & Lenzen, 2014; Wieland, Giljum, Bruckner, Owen, & Wood, 2018). This, in turn, leads to policy makers being hesitant to use the results of consumption-based accounting in policy design.

At the same time, production-based accounts based on standard inventories of territorial emissions have uncertainties too. Several studies suggest that, at least at the national level, and considering stochastic uncorrelated error, uncertainty does not significantly increase from a production-based account to a consumption-based one (Karstensen, Peters, & Andrew, 2015; Lenzen, Wood, & Wiedmann, 2010; Moran & Wood, 2014). The level of disagreement between results is common for production-based accounts as well and the main source of difference between models has been shown to be due to the choice of data for the production-based emission inventory across the models (Owen et al., 2014). Furthermore, for setting policy targets, it may be sufficient to design metrics that focus on the rate of change of emissions over time, rather than the absolute deviation between different model results. This, then, leads to the question of whether the

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**OECD-ICIO.** The OECD inter-country input-output (ICIO) table was first constructed during the joint OECD WTO project on Trade in Value Added (TiVA) (OECD-WTO, 2012; OECD., 2013a, 2013b, 2015). The updated 2015 version is a symmetric input-output table covering 34 industries in 61 countries and the rest of the world for the years 1995–2011 (OECD ICIO, 2015). Production-based CO₂ emissions by ICIO industries are directly estimated from the IEA CO₂ from fuel combustion data (IEA, 2015a). This data in turn is based on IEA energy balances (IEA, 2015b) and the default methods and emission factors from the 1996 IPCC Guidelines (IPCC, 2006). For most CO₂ flows, a straight forward allocation to the ICIO industries is possible. In cases where one CO₂ flow corresponds to multiple ICIO industries, emissions are allocated using weights of industry output. Emissions from unallocated autoproducers, other energy industry own use and emissions by transport are allocated to industries using emissions by fuel type information from the Energy Balances. Emissions from road transport are distributed across all industries and final demand categories. Currently, the OECD-ICIO provides tables from 2005 to 2015.

**GCP-GTAP MRIO.** The Global Carbon Project publishes final results for territorial and consumption accounts for over 114 countries. Emission estimates from 1990 onwards are updated every year with a 2 year lag for territorial accounts and a 3 year lag for consumption accounts (Le Quéré et al., 2015). The Global Carbon Project results stem mainly from the GTAP8 database (Narayanan, Badri, & McDougall, 2015), but has been modified in order to estimate time series of emission estimates (Peters, Davis, & Andrew, 2012a). The emissions are benchmarked to published databases (CIDIAC and Edgar for example) to give the temporal dimension.
differences in the rate of change of carbon footprints between Global MRIOs (GMRIOS) are less pronounced than the absolute differences in carbon footprints.

In this paper, we review the most important studies that have analysed differences in the carbon footprints of nations between GMRIOS, and factors contributing to those differences. We focus on literature as published particularly in *Economic Systems Research*, the *Journal of Economic Structures*, and *Environmental Science and Technology*. We restrict ourselves to assessments and comparisons of carbon footprints at the national level with GMRIOS (as opposed to studies into uncertainties of the carbon footprints of a single country or sector footprints). Analyses at the national level are much more forgiving than comparative analyses on product group level, since aggregation to the national level tends to iron out negative and positive differences at product group level (due to properties of the underlying theory of error propagation (Heijungs & Lenzen, 2014; Imbeault-Tétreault, Jolliet, Deschênes, & Rosenbaum, 2013)). Given this focus at the country level, in this paper we use the term Country Carbon Footprints (CCFs) instead of the more generic Consumption based Carbon Accounting (CBCA). We break down analysis in this review into three sections:

1. We first review the differences in CCF reported by studies that have compared different GMRIOS. We analyse both absolute differences, but also if relative change in time between GMRIOS differs.
2. We then review the factors reported in the literature that contribute to such differences, and how important they tend to be.
3. We then make suggestions to help improve the robustness of CCF in the future, from both a cross-sectoral and temporal perspective.

### 2. Empirically observed differences in footprints

#### 2.1. Introduction

With the exception of GTAP, all the GMRIOS presented here were released for the first time in the period of roughly 2010–2012. Since then, various studies have been performed analyzing the differences in CCFs as calculated with the different databases. We start this review in the next sections with a straightforward comparison of differences in the CCFs calculated with GMRIOS in different studies, as well as the differences in the rate of change of CCFs.

#### 2.2. Differences in absolute CCFs

Table 1 shows a direct comparison of CCFs between databases. Comparisons are done for different years (2002 or 2007) and different classifications. Most studies compare the CCFs across databases in their original classifications, while Rodrigues, Moran, Wood, and Behrens (2018) use a common classification of 22 regions and 17 sectors. Also, the numbers reported differ: Moran and Wood calculate the deviation for each country from the multi-model mean, while Arto et al. (2014) and Owen et al. (2014) look at the maximum difference in CCF for the same country between models, expressed as a percentage of the multi-model mean. Rodrigues et al. (2018) calculate a coefficient of variation informed by differences in the original (aggregated) databases, which can be expected to give lower numbers compared to an absolute difference.

**Table 1. Direct comparison of Country Carbon Footprints (CCFs).**

| Reference | Databases compared | Year compared, sector and country classification | Approach in brief | Conclusion in brief |
|-----------|--------------------|-----------------------------------------------|------------------|--------------------|

https://www.tandfonline.com/doi/epub/10.1080/14693062.2020.1722605?needAccess=true
We see that the deviations can be substantial. Moran and Wood (2014) found no less than 13 countries where the difference in CCF for an individual country between models could be 45% or more. Owen et al. (2014) found deviations of 30% or more for eight countries, that is, 20% of the 40 countries in common across the databases they included. Arto et al. (2014) found lower deviations, but only compared GTAP with WIOD, so could have missed any additional deviations that could occur by also taking Eora into account (as Owen et al. (2014) did).

Table 1 also does not provide a clear pattern of which countries may be most vulnerable to large deviations. Relatively small economies seem a little overrepresented in the last column of Table 1. Yet, Table 1 also shows large economies like Russia, Spain, Brazil and Japan with high deviations. The only constant factor seems to be Luxembourg, which shows high deviations in all studies. Luxembourg is not visible in the study of Rodrigues et al. (2018) due to their high country aggregation.

### 2.3. Differences in trends in CCFs

As well as viewing the absolute difference between GMRI0 footprint calculations, results can be normalized to a base year in order to assess the trend or change in footprints/emission values from year to year, as is undertaken in Wood, Moran, Rodrigues, and Stadler (2019).

Whilst the absolute value is the most general indicator available, significant policy importance is attached to the trend – whether we are seeing improvements or not over time (or relative to a base year), and whether we are seeing large growths in net emission transfers between regions. Wood, Moran, et al. (2019) undertake the exercise of normalizing the five main GMRI0 models discussed in Box 1. Using a common base year of 2007, they calculate both raw and normalized GMRI0 model results for a range of regions and individual countries. In addition, they measure the level of variance before and after normalization using a measure of relative standard deviation (noting the small number of data points).
Figure 2 below shows the change from absolute value to normalized results based on calculating rates of change to a common base year (2007) for the EU; on the left panel are the differences in results from five GMRIO models for the EU, whilst on the right panel, results for 2007 are normalized (by benchmarking the different rates of change from the different GMRIO models to a common 2007 value). Normalized accounts differ by less than 2% across years with good data availability (1995–2011).

Hence, uncertainty in the calculation of consumption-based emissions of big country blocks such as the EU is reduced to very low levels if results are normalized to a common value for a common base year. At the country level, the same pattern is observed, here with result variance averaged over the time period 1995–2011 (Figure 3, derived from Wood, Moran, et al. (2019)).

Figure 2. Variation in production and consumption accounts for 5 different GMRIO models. Left panel shows raw results. Right panel shows results normalized to a common 2007 value. On the right panel, relative standard error across the models is plotted on the right axis. Figure based on design and data from Wood, Moran, et al. (2019), but plotted for the EU.

Figure 3. Variance across production- and consumption-based accounts by region and country for original model values, and when looking at growth rates (trends) from a 2007 reference year. Average is taken over the time period 1995–2011. Relative standard deviation is calculated by the standard deviation divided by the multi-model mean. Derived from Wood, Moran, et al. (2019).

3. Factors contributing to differences in CCFs

3.1. Introduction

Studies have used a variety of techniques and hypotheses to analyse the factors that contribute the most to differences in CCFs, especially absolute ones, as calculated with different GMRIOs.
A first point is that GMRIOs have quite different levels of aggregation. Further, comparative studies often convert GMRIOs into a common country and sector classification, which is usually much more aggregated than the original one (e.g. Owen et al., 2014; Rodrigues et al., 2018). This leads to the question of how important aggregations might be, as discussed below.

We then look at studies singling out specific factors, such as the use of the territorial versus residential principle (section 3.3), and the use of original official data provided by statistical offices rather than those found in GMRIOs for small countries (section 3.4). Further, we review studies that, using a variety of methods, try to identify the data blocks, sectors, and countries that contribute the most to deviations of CCFs (section 3.5). Section 3.6 synthesizes these results.

3.2. Aggregation bias

The subject of aggregation bias has been explored extensively for the input-output field (e.g. see Holzman (1953) for early coverage). Whilst early studies were focused on making tables computable (and hence small), as computational power advanced, later work focused on the benefits of disaggregated tables compared to aggregated tables (e.g. see Lenzen, 2011). Here, we focus specifically on the literature undertaken for GMRIOs, firstly for sectoral and then spatial aggregation.

Table 2 reviews findings of various studies that report on how CCFs would change if the sector (and, in some cases, country) resolution of an original database were changed. The aggregations are reported for different databases, different years, and also reflect totally different levels of aggregation given the original level of detail of databases. WIOD is already highly aggregated (35 sectors), and so, in this case, a further aggregation to the common classification developed by Owen et al. (2014) and Steen-Olsen et al. (2014) of 17 sectors would probably have less impact than aggregating EXIOBASE (129 sectors/products in version 1 and 200 products in versions 2 and 3) to the same level. This probably explains why Owen et al. (2014) found that only GTAP and Eora, and not WIOD, showed an aggregation bias of 10% or more for some countries. Overall, Table 2 gives the impression that aggregation, in general, is not a critical factor, particularly if drastic aggregation of detailed databases like EXIOBASE or Eora to 10 or 17 sectors is avoided. In such cases, aggregation errors tend to be below 10%, with an occasional exception (e.g. Cambodia in Peters & Solli, 2010 (GTAP), Russia in Bouwmeester & Oosterhaven, 2013 (EXIOBASE 1) or Luxembourg in de Koning et al., 2015 (EXIOBASE 2)). However, drastic sector reduction to e.g. 10 sectors leads to a significant chance of aggregation bias. Several studies for individual countries confirm this. Illustrations include Lenzen, Pade, and Munksgaard (2004) who reduced a Danish table from 118 to 10 sectors, and Wyckoff and Roop (1994) who reduced a US table from 33 to six sectors. Similarly, when emissions embodied in imports or exports are analysed instead of total national carbon footprints, the aggregation error can again be significant (Wood, Hawkins, Hertwich, & Tukker, 2014).

Table 2. Relevance of aggregation bias. (Table view)

| Reference | Databases and emissions included | Year compared, sector and country classification | Approach in brief | Conclusion in brief |
|-----------|---------------------------------|-----------------------------------------------|------------------|---------------------|
| Peters and Solli (2010 p. 49) | GTAP6 | 2004, Aggregation from 59 to 8 sectors and 129–5–10 regions | Direct comparison of CCF expressed as percentage difference | KHM (17%), AUS (9%), lower for other industrial countries |
| Bouwmeester and Oosterhaven (2013) | EXIOBASE1, CO2 | 2000, aggregation from 129 to 59 and 10 sectors | Direct comparison of CCF expressed as percentage difference | 129->59 sectors: RUS (24%), MEX (6%), all others < 5% 129->10 sectors: RUS (36%), NOR (30%), LUX (20%) and BGR (20%), others < 20% |
In addition to the effect of sector aggregation error, spatial aggregation error occurs when large global regions are represented as a single region before the calculation of footprint accounts. Bouwmeester and Oosterhaven (2013) aggregated trading partners of individual countries to four or one global rest-of-world region, finding that spatial aggregation errors can be managed if done in an appropriate way. Andrew, Peters, and Lennox (2009) performed a sensitivity analysis using a range of aggregation levels, finding that results for the USA were at a maximum of about 4%, and quickly converged to a less than 1% difference. Across all countries, most changes in footprints fell in the +/-1% range. When investigating the impact of the rest-of-world aggregation, Stadler, Steen-Olsen, and Wood (2014) found impacts generally well below 5%. In contrast, a number of studies have found significant bias when looking at the effect of regional aggregation in China. As China is now the largest global region, and as it has a significant portion of the economy focused on export commodities, the regional aggregation error can be significant (Su & Ang, 2015).

| Reference          | Databases and emissions included | Year compared, sector and country classification | Approach in brief | Conclusion in brief                                                                 |
|--------------------|----------------------------------|-------------------------------------------------|-------------------|--------------------------------------------------------------------------------------|
| Arto et al. (2014) | GTAP, WIOD, CO2                 | 2007, aggregation from 57 (GTAP)/35(WIOD) and 129 (GTAP)/40 regions to 24 sectors and 40 countries | Direct comparison of CCF expressed as Relative Percentage Difference | GTAP: <5% except RUS (5.3%) and AUS (7.5%), average 0.4% WIOD: <5%, average 0.2% |
| Wood et al. (2014) | EXIOBASE1                       | 2000, Aggregation from 129 to 59 sectors.        | Comparison of both multipliers at the sector level as well as emissions embodied in exports expressed as percentage difference | Small trade exposed countries up to 50% difference (exports). Large countries ~5% |
| Moran and Wood (2014) | Eora, EXIOBASE2, WIOD, OPEN EU | 2002, Eora aggregated to 26 sectors and EXIOBASE from 163 to 15 sectors | No extended analysis, other than the remark that aggregation of the US and China had little impact | Eora: BEL (19%), ESP (17%), LUX, SVK (14%), BGR (12%), TUR (11), EST, LVA, FIN (10%) GTAP: AUS (10%). All other countries and databases lower. |
| Owen et al. (2014)  | WIOD, Eora, GTAP                | 2007, Aggregation to 17 sectors and 40 regions   | Direct comparison of CCF expressed as percentage difference | - |
| Stadler et al. (2014) | WIOD, Eora, GTAP            | 2007, Aggregation to 17 sectors and 40 regions   | Report only the changes due to aggregation to 17 sectors, not country footprints | Most changes less than 5% for GHG, SWE, CHE, LUX outliers. For employment, changes usually less than 10%, for land use, much higher effects. |
| Stadler et al. (2014) | EXIOBASE                      | 2007 | Compare footprints of countries with one rest of world region versus five. | - |
| de Koning et al. (2015) | EXIOBASE2, all GHG          | 2007, aggregation from 200 to 60 products       | Direct comparison of CCF expressed as percentage difference | LUX: 47%, CYP: 11%, DNK: 6%, SVN: 7%, CHE: 10%, all others <5% |
2010). The largest effect can be found in differentiating processing and normal exports (Chen et al., 2019; Su, Ang, & Low, 2013; Yang et al., 2015).

This paper focuses on carbon footprints only. For footprint indicators where the stressor is more concentrated in terms of sectors than CO2, such as material extraction or water extraction, aggregation can lead to significantly higher biases (e.g. Bouwmeester & Oosterhaven, 2013, for water; de Koning et al., 2015, for materials, Stadler et al., 2014 for land).

3.3. Residential versus territorial principle

The use of the territorial, rather than residential, principle has been identified as a major reason for differences in CCFs across studies (Peters et al., 2012b; Tukker et al., 2018a). We found only one study analyzing this issue for a large number of countries with a GMRIO. Usubiaga and Acosta-Fernández (2015) used EXIOBASE3 for 2010 to analyse how CCFs change if the territorial instead of the residential principle were used. This becomes an issue since the GMRIOs do not all consistently follow the same principle. Eora and GTAP, for instance, do not implement the residential principle entirely. But even between databases that account according to the residential principle, differences can be observed. Many GMRIOs base their carbon emissions to some degree on combusted energy and this data is often obtained from official energy balances (like the IEA energy balances). Such balances follow the territorial principle. Two major challenges need to be addressed to convert them to the residential principle. First, bunker fuels are reported as supply, meaning that there is only information about how much bunker fuel a country supplies to world bunkers (aviation and shipping) for a certain year, but there is no record of how much of these world bunkers a country uses (and hence how much it emits by combusting them). Different databases handle this differently; some approximate the use by the supply and hence just use the supply values, others try to use different auxiliary datasets to estimate the use. This results in differences of carbon emissions allocated to a country. Second, fuel for road transport might be bought by residents of other countries (fuel tourism). There is no detailed data on this for countries affected by it and hence different GMRIOs deal with it differently, from not at all, to using auxiliary datasets like monetary expenditure on fuel by tourists, for example. Usubiaga and Acosta-Fernández (2015) found that, in most cases, these challenges result in limited deviations. Large deviations, however, were found for small countries that have a large shipping fleet (e.g. GRC, NOR, CYP, DNK), have large bunkers that provide fuel used for international shipping or air transport activities (e.g. NDL, BEL), or where fuel tourism plays an important role (LUX). For these countries, differences can be substantial – between 30% and 70% – and hence CCF results obtained for these countries using different databases can vary substantially (see Table 3). Some studies even neglect bunker fuels altogether. Obviously, neglecting bunker fuels entirely is not acceptable and a residential principle is to be applied. In a true consumption-based approach, transport emissions then have to be allocated to the users of the goods transported (Hu, Wood, Tukker, Boonman, & de Boer, 2019).

Table 3. Residential versus territorial principle. (Table view)

| Reference | Databases used | Year, sector and country classification | Approach in brief | Conclusion in brief |
|-----------|----------------|----------------------------------------|-------------------|---------------------|
| Usubiaga and Acosta-Fernández (2015) | EXIOBASE3 | 2010, 163 sectors, 48 regions | Creating a bridge table that links the territorial carbon emissions to residential carbon emissions (less land, water and air transport of non residents plus the same items for residents abroad) | MLT (−70%), GRC (+70%), NOR (+60%), CYP (+50%), DNK (+30%) LUX (−30%), BEL (−20%), NLD (−20%), IRL (+20%) |

3.4. Correction of transit trade

https://www.tandfonline.com/doi/epub/10.1080/14693062.2020.1722605?needAccess=true
Other researchers have argued that, for small economies, the construction process of GMRIOS may result in noticeable adjustments in national tables. Small countries may therefore have significant transit trade that cannot always be derived from published statistics. Researchers from the Netherlands (Edens et al., 2015) and Belgium (Hambÿe, Hertvedt, & Michel, 2018) hence used specific data from National Statistical Institutes (NSIs) to represent their country in WIOD. The ‘rest of WIOD’ was then adjusted to create a balanced global table, often also using confidential information to deal properly with transit trade. This resulted in a lower CCF for Belgium for some years of 15%. For the Netherlands, the adjustment of the CCF was limited to 6% (see Table 4).

Table 4. Use of national tables with a focus on the correction of transit trade. (Table view)

| Reference      | Databases used | Year, sector and country classification | Approach in brief                                                                 | Conclusion in brief                                                                 |
|----------------|----------------|-----------------------------------------|-----------------------------------------------------------------------------------|------------------------------------------------------------------------------------|
| Edens et al. (2015) | WIOD, Netherlands national SUT | 2003, 2009, 35 sectors and 40 regions (WIOD), 100s of products (Dutch SUT, confidential) | Netherlands in EXIOBASE2 is replaced by an official Dutch table. Then the GMRIO is rebalanced while keeping Dutch data constant. | Difference of 6% in 2003 and 4% in 2009, largely attributed to a better handling of transit trade in the Dutch data. |
| Hambÿe et al. (2018) | WIOD, Belgian national SUT | 1995–2007, 35 sectors and 40 regions (WIOD), 35 sectors (Belgian SUT; better detail available but not public) | Belgium in the WIOD table is replaced by an official Belgian table. Then the GMRIO is rebalanced while keeping Belgian data constant. | No difference in CCF from 1995–2002. Difference rising to 15% between 2004 and 2007, largely attributed to a better handling of transit trade in the Belgian SUT |

3.5. General analyses of factors causing differences in CCFs

We identified six studies that tried to undertake a comprehensive analysis of elements in GMRIOS contributing most to deviations in CCFs between GMRIOS. Approaches to identifying the most important factors varied from harmonizing certain data sets (e.g. emissions), to applying techniques such as structural path analysis and structural decomposition analysis, to calculation of uncertainty reduction by harmonizing specific elements in GMRIOS.

Moran and Wood (2014) focused on the influence of eliminating the differences between environmental extensions, by using the same CO₂ emissions per sector for each GMRIO. This appeared to reduce the deviations in CCFs significantly, roughly by half. The idea that harmonization of emission data is the most important factor in reducing uncertainty in CCFs is supported by all studies looking into this issue mentioned in Table 5. We further see that the studies in Table 5 agree that differences in the domestic blocks are in general more important than differences in the import and export blocks to explain differences in CCFs (e.g. Owen et al., 2014; Wieland et al., 2018). This is in line with Wilting (2012), whose study focused on the Netherlands. He used the 57 sector GTAP 6 database aggregated to 13 regions (the Netherlands plus 12 other regions). He applied a Monte Carlo simulation to analyse which elements would influence the Dutch CCF most. Over 70% of the 5,000 elements that contributed the most to changes in the Dutch CCF belonged to domestic blocks. Owen et al. (2014) further identified another straightforward reason why footprints of countries differ: if the final demand and/or GDP of a country expressed as a percentage of global GDP differs across databases, this obviously also has implications for the share of global carbon emissions allocated to that country in a consumption-based accounting approach.

Table 5. Identification of main factors causing differences in CCFs. (Table view)
| Reference          | Databases compared | Year compared, sector and country classification | Approach in brief                                                                                                                                                                                                                                                                                                                                 | Conclusion in brief                                                                                                                                                                                                                      |
|-------------------|--------------------|-----------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Moran and Wood (2014) | Eora, Eora26, EXIOBASE, EXIOBASE15, Open EU, WIOD | 2002. Original (with both Eora and EXIOBASE to more aggregated forms) | Show CCF per GMRI0 as % deviation from the multi-model mean. Calculate maximum inter-model discrepancy in %. Do this also for harmonized extensions. Show standard deviation per CCF/GMRI0 using Monte Carlo analysis.                                                                 | Before harmonization: LUX, DNK, BEL, SVK, RUS, SLO, NED, CYP, ESP, HUN > 45% After harmonization of extensions LUX, SLO, GRE > 50% LVA, TWN, DEN, BEL, BUL, LTU > 30% Harmonization of extensions reduces differences in half |
| Arto et al. (2014)  | GTAP, WIOD         | 2007, 24 sectors and 40 countries            | Compare main components of the 2 models (intermediate use, final demand, total industry output, emissions by industry) with matrix difference statistics. Use Structural Decomposition Analysis to assess differences in structures of CCFs                                                                 | Countries: US, China, RUSa and India cause 50% of differences in CCF Sectors: electricity, refining and inland transport cause 50% of the differences in CF                                                                 |
| Owen et al. (2014), Owen (2017) | Eora, GTAP, WIOD | 2007, Aggregation to 17 sectors and 40 regions | Compare via SDA on a common classification of GMRI0s which elements contribute most to differences in CCFs                                                                                                                                                                                                                                   | Emission vector is the most important factor in the difference between Eora and GTAP and highly relevant in the other pairings. Difference in final demand and differences in structure of intermediate demand follow. Trade is least relevant. In terms of sectors, the electricity and transport sectors are the most relevant. |
| Owen et al. (2016) | Eora, GTAP, WIOD, EXIOBASE3 | 2007, Aggregation to 17 sectors and 40 regions | Apply structural path decomposition analysis to understand which elements in GMRI0s contribute most to differences in CCFs                                                                                                                                                                                                                     | The emission element is the most important factor in 63 out of the top 100 path deviations. None of the top 100 path differences crosses a border. Paths originating in China, India, US and Russia make up over 80% of the path differences in all GMRI0 pairings. Electricity, gas and water supply are major contributors to path differences and physical rather than monetary allocation can create major deviations. |
| Wieland et al. (2018) | Eora, EXIOBASE3, GTAP 9, WIOD | 2011, Aggregation to 17 sectors and 40 regions | Use a common data set for carbon emissions. Use structural production layer decomposition to identify sources of variation in CCFs                                                                                                                                                                                                     | Variations in domestic blocks are more important as variations in trade blocks. China, Russia and RoW have most influence on the EU CF (next to Germany, UK and Italy in the EU). Electricity in China is most relevant. |
Studies using structural path decomposition analysis (Owen, Wood, Barrett, & Evans, 2016) and production layer decomposition (Wieland et al., 2018), along with the study of Rodrigues et al. (2018), also allowed for the identification of countries and sectors that are most relevant in reducing uncertainty in CCFs. From a sector perspective, the electricity and transport sectors are important, whereas from a country perspective, China, the US, India and Russia are relevant. Owen et al. (2016) mentioned that the economic allocation principle usually implicit in GMRIOs can be particularly problematic in the electricity sector; a physical allocation of electricity use, rather than based on monetary transaction value, can have a major influence on how emissions related to electricity use are allocated to final demand.

4. Discussion: relative importance of factors creating differences in CCFs.

Section 2 showed that, when CCFs from e.g. WIOD, GTAP, EXIOBASE and Eora are compared, significant absolute differences occur. Moran and Wood (2014) found no less than 13 countries where the difference in CCF of an individual country between models could be 45% or more. At the same time, section 2 also showed that, if one is just interested in CCF trends, the relative change in CCF in each database when they are set to a common value in a specific base year, shows high consistency. An initial finding is, hence, that the current GMRIOs are already quite helpful if one wants to track relative changes in CCFs, for example compared to a reference year. However, to assess the absolute levels of CCFs, there are large differences between GMRIOs for some countries and uncertainty reduction is required. From the preceding sections some clear suggestions can be derived for GMRIO compilers on what the main factors leading to deviations in CCFs are, and how such deviations can be reduced. In this, we assume that analysis is based on a true MRIO approach (as opposed to e.g. EEBT or others).

Aggregation. GMRIOs have a quite different aggregation level, ranging from 35 sectors and products in WIOD to 160 sectors/200 products in EXIOBASE. If drastic aggregations (e.g. to just 10 or 17 sectors) are avoided, aggregation errors for most countries tend to be below 10%.

Residential principle. GTAP and Eora in part follow the territorial rather than the residential principle. Using the territorial instead of the preferred residential principle can lead to significant deviations of 20%–70%. These occur, however, mainly for relatively small countries with a major shipping fleet, important bunkers, or significant fuel tourism such as Luxembourg, Belgium, Netherlands, Greece, Norway, Malta and Cyprus.

Transit trade. Two studies sought to enhance the reliability of CCFs by using official national data and the use of more specific information on transit trade instead of a country representation in WIOD. They found adjustments of the CCF of just up to 15%. This was the case for the Netherlands and Belgium, and the authors were able to use confidential data to adjust properly for transit trade.
**Emission data.** Studies comparing GMRIOs and CCFs comprehensively found that harmonizing emission data could reduce uncertainty the most, being responsible for around half the deviations.

**Domestic and trade blocks.** The domestic blocks in general were found to be more important than the trade blocks. GMRIO compilers ideally should use balancing procedures that minimize changes in the structure of national tables. To do so, however, requires reconciling differences in national data because of inconsistencies between national data and trade data, which must be resolved in order to have a balanced global table. As such, most modern GMRIO compilers go beyond standard bi-proportional approaches of data balancing of only the final GMRIO table. In the reconciliation and balancing process, some compilers make implicit or explicit choices regarding which data sets they trust most, and hence which should not be included, or at least should be changed, in the reconciliation procedure. Other compilers explicitly include information on the reliability of specific data points in the reconciliation and balancing process – data points with high uncertainty are then allowed to change more as data points with low uncertainty in the objective function of an optimization function used in the balancing process (see for example (Dalgaard & Gysting, 2004; Geschke, Wood, Kanemoto, Lenzen, & Moran, 2014; Lenzen, Gallego, & Wood, 2009; Nagurney & Robinson, 1992; van der Ploeg, 1982, 1984, 1988; Wood et al., 2014)).

**Key countries and sectors.** From a sector perspective, the electricity and transport sectors are most important, whereas from a country perspective, China, the US, India and Russia are particularly relevant. A specific problem with the carbon intensive electricity sector is that GMRIOs allocate the use of electricity assuming equal prices among users, whereas in practice, prices differ. Physical allocation of electricity use can therefore have a major influence.

5. **Conclusions**

Our analysis shows that the current GMRIOs are already quite helpful if one wants to track relative changes in CCFs. Differences between GMRIOS in year on year changes for large economic blocks like the EU are very limited. This makes existing GMRIOS already very useful to track progress towards a CCF reduction target relative to a base year.

However, if one is interested in assessing the absolute levels of CCFs, the differences between GMRIOS can be significant and uncertainty reduction is required. Sections 3 and 4 make clear that emission data are probably the most important and most generic source of uncertainty. Further, we see that the residential principle can be important for specific countries, and that domestic blocks tend to contribute more to uncertainty than the trade blocks. Finally, not surprisingly, harmonization of carbon intensive sectors like electricity production and transport, particularly in high carbon emitting countries like China, the US, India and Russia, is important too. In comparison, the correct handling of transit trade and aggregation tends to be less important. In line with the conclusions of Tukker et al. (2018a), this leads to a clear way forward to generate more robust calculations of CCF.

First, countries that have official, national input-output tables could simply calculate carbon footprints by embedding such national tables in a GMRIO. This so-called single-country national accounts consistent (SNAC) footprinting approach was first developed by Edens et al. (2015). While section 3.4 concluded that the uncertainty reductions in the specific work of Edens et al. (2015) and Hambäj et al. (2018) were limited, it is important to note that both studies mainly addressed the uncertainty caused by transit trade. Using official, national input-output tables eliminates the following, high impact uncertainties:

1. Carbon emissions at the national level (often 50% or more of a CCF);
2. Proper application of the residential principle
3. Proper representation of the domestic block
4. Proper representation of sectors most contributing to uncertainty in CCFs, such as the electricity and transport sectors (as far as related to the national level).
An additional advantage is that the (usually relatively low) errors due to aggregation and transit trade can be avoided. The approach, however, has the disadvantage that only CCFs for single countries can be calculated, which will not be consistent globally, since for each country a specific national input-output table is used.

Second, GMRIO compilers could make an additional effort in terms of using harmonized carbon emission data. This would eliminate the single generic source of uncertainty. As is already the case for materials, where GMRIOs compilers can use the harmonized resource extraction database from the International Resources Panel, GMRIO compilers should agree to use a common emission database (e.g. based on the Global Carbon Project).

Finally, GMRIO compilers should ensure consistency in country GDPs, and use harmonization techniques that least influence the structure of the national table (see for instance Walmsley, Narayanan, Aguiar, and McDougall (2018)). As also suggested by Tukker et al. (2018a), one could consider using the ICIO developed by the OECD as a benchmark, being the only GMRIO developed by an international organization rather than researchers. While Tukker et al. (2018a,b) recommended further disaggregation of the ICIO for footprint analysis of e.g. land, water and materials, this is probably less relevant for carbon footprint studies, for which aggregation errors are not major.

Such a harmonized GMRIO, including a harmonized emission dataset, would, in combination with the aforementioned SNAC approach, enable the calculation of CCFs with a highly reduced uncertainty. Obviously, in an ideal situation, national statistical institutes would harmonize their national input-output tables and related trade data so that, also at a global scale, all national tables are consistent. This process has already started at European scale (e.g. Remond Tiedrez & Rueda-Cantuche, 2019).

It is important, however, to keep in mind that the current situation is already quite manageable: if harmonized emission data are used, then carbon footprints for large countries usually converge quite well across different GMRIOs, whereas for smaller countries, differences may be in the order of magnitude of 10% (Moran & Wood, 2014). CCF analyses are also helped by looking at rates of change rather than absolute values across databases; the variability in rate of change (e.g. a 5% growth in CCF from 2007) across models is much less than the variability in absolute values across current GMRIO databases used to calculated CBCAs in general and CCFs in specific. Our overall conclusion is, hence, that even at the current state of the art of GMRIOs, CCF can be calculated with uncertainty levels that can make a useful contribution to climate policies. Furthermore, the most important steps to reduce uncertainty seem relatively straightforward quick wins, rather than time consuming and costly undertakings. At the same time, further harmonization of national input-output tables and trade data in an official international context in the long term should ideally be pursued.

**Funding**

This work was supported by FP7 Environment [grant number 603386].

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