Economic Systems Research, 2014
http://dx.doi.org/10.1080/09535314.2014.987731

REGIONAL AND SECTORAL DISAGGREGATION OF MULTI-REGIONAL INPUT–OUTPUT TABLES – A FLEXIBLE ALGORITHM

LEONIE WENZ[a,b,c*], SVEN NORMAN WILLNER[a,b],
ALEXANDER RADEBACH[a,c,d], ROBERT BIERKANDT[a,b],
JAN CHRISTOPH STECKEL[a,c,d] and ANDERS LEVERMANN[a,b]

[a]*Potsdam Institute for Climate Impact Research, Potsdam, Germany;* [b]*Institute of Physics, Potsdam University, Potsdam, Germany;* [c]*Mercator Research Institute on Global Commons and Climate Change, Berlin, Germany;* [d]*Economics of Climate Change, Technical University, Berlin, Germany*

(*Received 23 June 2014; accepted 11 November 2014*)

A common shortcoming of available multi-regional input–output (MRIO) data sets is their lack of regional and sectoral detail required for many research questions (e.g. in the field of disaster impact analysis). We present a simple algorithm to refine MRIO tables regionally and/or sectorally. By the use of proxy data, each MRIO flow in question is disaggregated into the corresponding sub-flows. This downscaling procedure is complemented by an adjustment rule ensuring that the sub-flows match the superordinate flow in sum. The approximation improves along several iteration steps. The algorithm unfolds its strength through the flexible combination of multiple, possibly incomplete proxy data sources. It is also flexible in a sense that any target sector and region resolution can be chosen. As an exemplary case we apply the algorithm to a regional and sectoral refinement of the Eora MRIO database.

Keywords: Disaggregation; Disaster impact analysis; Global supply chains; Life cycle assessment; Regionalization

1. INTRODUCTION

Large-scale economic structures have changed considerably over the last decades: in the course of globalization, international supply and value-added chains have become increasingly integrated and complex (Wiedmann et al., 2011a). While it is as crucial as it is difficult to collect detailed quantitative information on this complex network, the process inevitably gives rise to a large variety of formerly unforeseen cause–consequence relations. The individual links of the global supply chains are at risk from external perturbations, which may be of economic, social, political or ecological origin. In the context of global climate change, Levermann (2014) emphasizes the consequences of increasingly integrated economic networks for the vulnerability of world markets to single extreme weather events. Particular impacts loom even more as climate model simulations predict extreme events to become more intense and (most likely) more frequent in the future

*Corresponding author. E-mail: leonie.wenz@pik-potsdam.de

(Rahmstorf and Coumou, 2011; IPCC, 2012; IPCC, 2014). Given the growing environmental pressures, direct and indirect transnational impacts of natural and man-made disasters on global commodity flows supplying industrial, public and private demand need to be examined.

The problem of assessing the vulnerability of economic systems including higher order effects has been addressed by different frameworks. An overview of methodologies which analyze the direct and indirect economic losses of disasters based on (multi-regional) input–output (I–O) data is given in Okuyama and Santos (2014). These methodologies can mainly be classified into three approaches: (1) I–O models (as in Hallegatte, 2008, 2014; Jonkeren and Giannopoulos, 2014), (2) social accounting matrices (SAM, as in Okuyama and Sahin, 2009) and (3) computable general equilibrium (CGE) models (as in Haddad and Okuyama, 2012; Haddad and Teixeira, 2013).

Multi-regional input–output (MRIO) tables are systematically assembled and harmonized by projects like the Eora MRIO database (Lenzen et al., 2012), the Global Trade Analysis Project (GTAP, Narayanan et al., 2012) or the World Input-Output Database (WIOD, Dietzenbacher et al., 2013).[1] Even though these databases are covering a considerably large number of regions, they do not go deeper than the country level. Specifically, but not exclusively for large countries such as China or the USA, economic activities differ substantially across their subregions (e.g. Su et al., 2010). Thus, a high regional resolution is required for disaster impact analysis. The same argument holds for the sectoral dimension of disaster-induced supply-change cascades. In this regard, Wiedmann et al. (2011a) state that “most current initiatives do not provide for maximum sector disaggregation but opt for a compromise between the number of sectors and countries”.

The problem of coarse sector resolution is also well known in I–O-based life cycle assessment (LCA; e.g. Suh and Nakamura, 2007). LCA modeling frameworks aim at assessing the whole life cycle of a good or service, for example, with respect to emissions. Basically, there are two different approaches: a bottom-up process analysis and a top-down I–O analysis. While I–O LCA often lacks suffiently detailed data, process LCA cannot always provide for system completeness (Rebitzer et al., 2004). Bullard et al. (1978) introduced the notion of ‘hybrid analysis’ by proposing a framework that combines process and I–O analysis to overcome the limitations of both. This has entailed a large number of follow-up studies (Moriguchi et al., 1993; Suh and Huppes, 2002; Stromman and Hertwich, 2004; Suh, 2004).

In the context of environmental I–O analysis, Lenzen (2011) highlights the sectoral ‘aggregation bias’ to be problematic. Since in particular environmentally sensitive sectors are frequently aggregated in I–O data, he strongly advocates a disaggregation even if it is based on a small amount of proxy information only.

Hence, not only the analysis of cascading effects induced by disaster impacts but also many other research questions require a high resolution along the regional and sectoral dimension.[2] However, as data incompleteness typically is a major challenge for compiling

[1] In some cases, the MRIO tables are replaced by more precise supply-use tables, which are capable of capturing the full diversity of different commodities that different industries may consume and produce instead of assuming a one-to-one relationship of commodities and industries.

[2] Even beyond standard I–O analysis there is a need for MRIO data sets with increased sectoral resolution, for example, in the field of studies of structural change and growth processes (Radebach et al., 2014).

MRIO tables,[3] it is particularly difficult to provide MRIO data at high regional and sectoral detail. Some economic information is available at very high detail, though, for instance global export data (e.g. Base pour l'Analyse du Commerce International with +5,000 sectors for +200 countries (Gaulier and Zignago, 2009)) or specific national I–O data (e.g. US Bureau of Economic Analysis (BEA) annual I–O data (2014)).

A recent approach has been undertaken by Lenzen et al. (2014). They propose compiling an MRIO table designed for each specific research question by aggregating root data of very high resolution. Since this table only requires a certain level of detail, they yield computationally manageable matrices. However, the application of this method depends on the completeness of the root data.

In the past, attempts of sectoral disaggregation often did not focus on the actual economic flows but on the technical coefficient matrix $\mathbf{A}$ or the Leontief Inverse $\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1}$, where $\mathbf{I}$ denotes the unit matrix of (environmental) I–O models. Wolsky (1984) proposes a routine for constructing a sectorally refined I–O model from an available model using information that was aggregated when this available model was built. This approach requires information that is generally not available. Stating that a useful disaggregation method should rely on data less costly to obtain than those needed for the direct estimation of relevant data, Gillen and Guccione (1990) present an algorithm to estimate a refined technical coefficient matrix $\mathbf{A}$ from information on final demand, gross output, and input and output prices. Lindner et al. (2012) point out that the unknown coefficients of the Leontief Inverse of an I–O model are not unique. They suggest constructing a probability distribution based on a random-walk algorithm to explore all coefficient combinations.

Wiedmann et al. (2011b) apply a pro-rata disaggregation to split the electricity industry when analyzing the indirect emissions of wind power in the UK. The same approach is used by Liu et al. (2012) to demonstrate the heterogeneous emission intensities of Taiwanese electricity subsectors.

Aleexeva-Talebi et al. (2012) deal with sectoral disaggregation in a CGE modeling framework. For the disaggregation of energy-intensive and trade-exposed sectors in the GTAP database, they extract subsectors from the aggregate sector by proceeding additional data on production, imports and exports as well as intermediate and final demand.

In terms of disaggregation in the regional dimension, Flegg's Location Quotient (FLQ) was developed to deduce regional flows from national I–O data using additional region-specific information (e.g. Flegg et al., 1995; Kowalewksi, 2013). Furthermore, the Regional Input–Output Modeling System (RIMS) commercially provided by BEA produces macro-economic multipliers for regional projections of economic impacts in the USA.

Here, we present a disaggregation algorithm that is simple, generally applicable and computationally efficient.[4] Its main idea is to combine raw data of multiple data sources to yield a compromise between data accuracy and data availability. The algorithm basically is an iteration of the following two steps: first, a given large-scale MRIO flow is refined sectorally and/or regionally on the sub-level by the use of suitable refinement proxies reflecting the sub-flows' contributions to the superordinate flow. These proxies can, for

[3] Approaches to deal with this problem are, among others, the RAS (Stone and Brown, 1962), the cRAS (constrained RAS, Lenzen et al., 2006) and the GRIT (Generation of Regional Input-Output Tables) algorithm (Bayne and West, 1989).

[4] Available as open source at http://github.com/swillner/disaggregation.

example, be based on gross domestic product (GDP), exports and imports. It is central to the method that they are not required to be homogeneous. Second, all sub-flows that were approximated at a low level of precision are adjusted with respect to the flows of a higher level of precision in order to match the superordinate flow in sum.

This approach, which will be detailed in Section 2, has some advantages compared to other more comprehensive approaches. Since it does not approximate a technical coefficient matrix or a Leontief Inverse but simply enlarges an existing MRIO table, it can be used for all kind of research foci. Furthermore, it can make use of different kinds of proxy data that are available. This multi-sourcing approach enables the combination of different proxies for input and output flows. If a proxy is available that is considered to be better suited for the approximation of a certain flow, all related flows are automatically adjusted accordingly. The enlarged MRIO table can thus become more and more accurate. Since harmonizing or inverting procedures are not required, there are neither artificially produced flows nor major computational constraints. The algorithm keeps the data assembling and computing effort minimal.

Despite these advantages it is important to note that the algorithm provides approximations which will generally deviate from the 'real' values. The accuracy of an approximated sub-flow depends on three aspects. First, it is determined by the reliability of the refinement proxy and of the underlying base table, which cannot be assessed by the algorithm. Second, it depends on how strongly the proxy constrains the sub-flow. Third, due to the adjustment step of the algorithm, it may be increased if many of the sub-flows that are derived from the same superordinate flow are approximated by more precise proxy data.

The paper is organized as follows: a description of the algorithm for disaggregating MRIO tables is given in Section 2. Subsequently, we investigate its performance by exemplifying a sectoral and a regional disaggregation procedure in Section 3. More precisely, we firstly extend the 26 US sectors given by the Eora MRIO database for 2011 to 71 sectors using GDP and export data by BEA. Then, we compare the enlarged MRIO table to existing data at this scale. Secondly, we refine the Eora 2011 MRIO table by subdividing the USA into its 51 states (incl. the District of Colombia) where we deduce the respective input and output sub-flows from subregional GDP and subregional GDP-by-industry data provided by BEA. We contrast these approximations with data provided by the Economic Research Service of the US Department of Agriculture (USDA; USDA-ERS, 2014). Then, we shortly describe the large-scale application of our algorithm within the *zeean* community data platform (www.zeean.net). We conclude with an overview on strengths and limitations of our approach in Section 4.

2. THE REFINEMENT ALGORITHM

The general concept of the refinement algorithm is the following: starting from a given MRIO table the flows to be disaggregated have to be defined as well as the final subregions and/or subsectors, that is, the target classification. Then, a set of proxies in a hierarchical order (by suitability) has to be chosen that can be used for approximating the flows at the sub-level. All these values are the input of the algorithm. In a first step, the algorithm disaggregates the initial flows into the correspondent sub-flows by equal distribution or by proxy data if the same type of proxy is given for all sub-flows. This first approximation of sub-flows is then improved by iterating over the hierarchy of proxies. Each iteration step consists of two sub-steps. First the approximation is improved for those sub-flows for which a proxy is given at the current level of hierarchy (the *approximation* part of the algorithm). Second, the remaining sub-flows are adjusted to match the initial flow in sum (the *adjustment* part of the algorithm).

In the following subsections, we describe the algorithm in detail. After providing all necessary definitions in Section 2.1, we propose a hierarchy of refinement proxies required as input for the algorithm in Section 2.2. In Section 2.3, we describe the algorithm, and in Section 2.4, we conclude by presenting a method to roughly assess the quality of its outcome.

2.1. Definitions

Let $\mathbf{Z}$ be an MRIO table, the base table, whose regional and sectoral detail shall be increased. Let r be the region to be disaggregated into n subregions. The latter are denoted by the set $R_r = \{r_\lambda\}_{\lambda=1,\ldots,n}$. Let i be the sector to be disaggregated into m subsectors represented by the set $I_i = \{i_\mu\}_{\mu=1,\ldots,m}$. Note that both sets R_r and I_i can consist of one element only. Further, sector i can be disaggregated in region r only or in several or in all regions represented in $\mathbf{Z}$. The set of subsectors I_i may even vary between different regions.

The algorithm is applied to each flow of the original MRIO table that refers to region r or sector i, that is, to each flow that is going to (incoming) or coming from (outgoing) the region and/or sector in question. Exemplarily, we demonstrate its functionality for an outgoing flow, denoted by $Z_{ir\to js}$, where j is an arbitrary target sector and s an arbitrary target region and i and r are the sector and region from which the flow originates. Incoming flows $Z_{js\to ir}$ can be dealt with analogously when altering the algorithm inputs accordingly. Intraregional flows $Z_{ir\to jr}$ or intra-sectoral flows $Z_{ir\to is}$ are disaggregated by applying the algorithm to the incoming and outgoing side, respectively.

The algorithm disaggregates the flow $Z_{ir\to js}$ into $m \cdot n$ sub-flows $Z_{i_\mu r_\lambda \to js}$ by splitting it into smaller values that sum up to the initial value. These values, that is, the amount to which each sub-flow $Z_{i_\mu r_\lambda \to js}$ contributes to $Z_{ir\to js}$, are determined by proxy data. A set of 'refinement proxies' must thus be provided as an input for the algorithm. More precisely, at least one refinement proxy $v^{(d)}_{ir\to js}(\lambda, \mu)$ is required for each sub-flow. Ideally, the actual sub-flow itself can be given as an input. If this is not possible, a proxy should be used that reflects the importance of the sub-flow for the aggregate flow as precisely as possible. For different sub-flows, the corresponding refinement proxy may be derived from different data sources and the set of all proxies does not have to be homogeneous (resembling the multi-sourcing aspect of the algorithm). Depending on their associated proxy, some sub-flows might hence be approximated more precisely by the algorithm than others.

Before starting the algorithm, all proxies used for disaggregating the flow $Z_{ir\to js}$ have to be brought into a hierarchical order. This ranking should reflect how well each proxy is considered to be suited for the approximation procedure. In the following, we refer to a proxy's ranking level as its 'level of detail d' or its 'd-level'. The higher a proxy's d-level, the more impact it has on the final value of the corresponding sub-flow. This is due to the adjustment of the approximation along the hierarchical order of proxies.

We introduce a set E_d that comprises for each d-level all pairs of sub-flow indices (λ, μ) a proxy at that level is given for:

$$E_d := \{(\lambda, \mu) | v^{(d)}_{ir\to js}(\lambda,\ \mu) \text{ given}\}. \tag{1}$$

A sub-flow $Z^{(d,\,\text{approx.})}_{i_\mu r_\lambda \to js}$ is called ‘approximated’ at level d when a refinement proxy $v^{(d)}_{ir\to js}(\lambda,\mu)$ at this level is available. Otherwise the sub-flow is adjusted such that the sum of all sub-flows equals the initial aggregate flow (see Section 2.3 for more information on that part of the algorithm). We denote the outcome of the iteration corresponding to level d by $Z^{(d)}_{i_\mu r_\lambda \to js}$.

2.2. Refinement Proxies

Table 1 proposes a hierarchy of proxies for disaggregating an outgoing flow $Z_{ir\to js}$. This hierarchy is motivated by the following consideration: a sub-flow $Z_{i_\mu r_\lambda \to js}$ of this flow is characterized by the six indices $i, i_\mu,\ r, r_\lambda,\ j, s$. The more indices a proxy comprises, the more rigorously the sub-flow is constrained and the better the approximation quality will be. In general, a high d-level is to represent a high approximation quality under the chosen assessment.

TABLE 1. Refinement proxies for an outgoing flow together with their detail ranking as applied in this study and the associated approximation procedure.

Level $d=$	Refinement proxy $v^{(d)}_{ir\to js}(\lambda,\mu) :=$	Approximation $Z^{(d,\,\text{approx.})}_{i_\mu r_\lambda \to js} :=$
0	Equal distribution: $\lvert I_i\rvert \cdot \lvert R_r\rvert$	$\frac{Z_{ir\to js}}{\lvert I_i\rvert\cdot\lvert R_r\rvert}$
1	Population of subregion: POP_{r_λ}	$\left(\sum_{\lambda'=1}^{n} Z^{(d-1)}_{i_\mu r_{\lambda'}\to js}\right)\cdot\frac{\text{POP}_{r_\lambda}}{\text{POP}_r}$
2	Subregional GDP: GDP_{r_λ}	$\left(\sum_{\lambda'=1}^{n} Z^{(d-1)}_{i_\mu r_{\lambda'}\to js}\right)\cdot\frac{\text{GDP}_{r_\lambda}}{\text{GDP}_r}$
3	Regional GDP-by-sub-industry: $\text{GDP}_{i_\mu r}$	$\left(\sum_{\mu'=1}^{m} Z^{(d-1)}_{i_{\mu'} r_\lambda\to js}\right)\cdot\frac{\text{GDP}_{i_\mu r}}{\text{GDP}_{ir}}$
4	Subregional GDP-by-sub-industry: $\text{GDP}_{i_\mu r_\lambda}$	$Z_{ir\to js}\cdot\frac{\text{GDP}_{i_\mu r_\lambda}}{\text{GDP}_{ir}}$
5	Import of subsector by region: $Z_{i_\mu\to s}$	$\left(\sum_{\mu'=1}^{m} Z^{(d-1)}_{i_{\mu'} r_\lambda\to js}\right)\cdot\frac{Z_{i_\mu\to s}}{\sum_{r'}\sum_{j'} Z_{ir'\to j's}}$
6	Export from subregional subsector $Z_{i_\mu r_\lambda\to}$	$Z_{ir\to js}\cdot\frac{Z_{i_\mu r_\lambda\to}}{\sum_{j'}\sum_{s'} Z_{ir\to j's'}}$
7	Import of subsector by regional sector: $Z_{i_\mu\to js}$	$\left(\sum_{\mu'=1}^{m} Z^{(d-1)}_{i_{\mu'} r_\lambda\to js}\right)\cdot\frac{Z_{i_\mu\to js}}{\sum_{r'} Z_{ir'\to js}}$
8	Export from subregional subsector to region: $Z_{i_\mu r_\lambda\to s}$	$Z_{ir\to js}\cdot\frac{Z_{i_\mu r_\lambda\to s}}{\sum_{j'} Z_{ir\to j's}}$
9	$d = 5, 7, 8$ together: $Z_{i_\mu\to js}$, $Z_{i_\mu r_\lambda\to s}$ and $Z_{i_\mu\to s}$	$Z_{i_\mu\to js}\cdot\frac{Z_{i_\mu r_\lambda\to s}}{Z_{i_\mu\to s}}$ (Peters et al., 2011)
10	Exact flow: $Z_{i_\mu r_\lambda\to js}$	$Z_{i_\mu r_\lambda\to js}$

Notes: Column 2 gives potential refinement proxies for disaggregating an outgoing flow regionally and sectorally. Column 3 shows the corresponding approximation as it is performed by the algorithm. Up to level $d = 4$, the approximation is based on weights. From level $d = 5$ on, flows are used.

At level $d = 0$, the refinement proxy has to be chosen such that it is given for all sub-flows. Since no flows of a precedent level are available, an adjustment is not possible and all sub-flows must be approximated. The simplest approach is to distribute the superordinate flow equally to all sub-flows:

$$Z^{(0,\text{ approx.})}_{i_\mu r_\lambda \to js} = \frac{Z_{ir\to js}}{|R_r| \cdot |I_i|}; \tag{2}$$

where $|R_r| = n$ denotes the number of subregions and $|I_i| = m$ the number of subsectors. The corresponding refinement proxy that is always available reads

$$v^{(0)}_{ir\to js}(\lambda, \mu) = |R_r| \cdot |I_i|. \tag{3}$$

As this kind of proxy is already determined by the choice of refinement, it is merely no real proxy but the first canonical way of refinement. It can always be chosen if no proper proxy is available.

Regionally, the population density of a subregion compared to that of the superordinate region could be taken as a more precise refinement proxy ($d = 1$). Further, data on the GDP constitute a quite easily accessible but more precise refinement proxy. The GDP of a country as a measure of its overall economic activity represents the total value of final goods and services produced within this country in a given period of time. It is often not only provided for countries but also for smaller administrative units. In this case, the quotient of GDP of subregion r_λ and GDP of region r can be regarded as a measure for the economic importance of subregion r_λ within region r and thus be used for the approximation procedure:

$$Z^{(2,\text{ approx.})}_{i_\mu r_\lambda \to js} = \left(\sum_{\lambda'=1}^{n} Z^{(1)}_{i_\mu r_{\lambda'} \to js}\right) \cdot \frac{\mathrm{GDP}_{r_\lambda}}{\mathrm{GDP}_r}. \tag{4}$$

Since this proxy is only useful for a regional disaggregation, the subsectoral information $\sum_{\lambda'=1}^{n} Z^{(1)}_{i_\mu r_{\lambda'} \to js}$ of level $d = 1$ is kept.

On the downside, the application of regional GDP data implies that the economic structure of region r is transferred to all its subregions $r_\lambda \in R_r$. This is disputable as different geographical conditions suggest an inhomogeneous distribution pattern of sectors. While some subregions have a high agricultural output, others specialized on manufacturing sectors. It is therefore desirable to refine this approach by taking sectoral information into account as well. Some statistical agencies provide GDP data that are resolved sector-wise. If such data for subsectors or for subsectors per subregion are available, the approximation can be improved using quotients $\mathrm{GDP}_{i_\mu r}/\mathrm{GDP}_{ir}$ ($d = 3$) and $\mathrm{GDP}_{i_\mu r_\lambda}/\mathrm{GDP}_{ir}$ ($d = 4$), respectively. As sector classifications may differ from one country to another, it is possible that GDP is given for other industries than those represented in the MRIO table or those desired for the subsector level. In this case, a sector mapping is required.

So far, no refinement proxy has included information on the target region s and the target sector j. In order to address trade-specific patterns, export and import data could be considered. For instance, these could be import of subsector by region ($Z_{i_\mu \to s}, d = 5$), export of subregional subsector to all other regions ($Z_{i_\mu r_\lambda \to}, d = 6$), import of subsector by regional sector ($Z_{i_\mu \to js}, d = 7$) and export from sub-regional subsector to a region ($Z_{i_\mu r_\lambda \to s}, d = 8$).

Here, exports are ranked higher than imports because an outgoing flow is to be disaggregated. For the disaggregation of an incoming flow, this hierarchy has to be altered accordingly.

Importantly, there is no need to translate these flows into weights as it was necessary up to list level $d = 4$, but they can directly be used for an approximation as shown in Table 1.

If three different export and import flows are available, the following formula proposed by Peters et al. (2011) can be applied:

$$Z^{(9,\ \text{approx.})}_{i_\mu r_\lambda \to js} = Z_{i_\mu \to js} \cdot \frac{Z_{i_\mu r_\lambda \to s}}{Z_{i_\mu \to s}}. \tag{5}$$

If the actual sub-flow itself is given, it is ranked at the highest d-level ($d = 10$).

For an incoming flow similar proxies can be chosen. With respect to intraregional flows, national I–O tables, which are available for certain countries at a high level of sectoral detail, can be integrated into an MRIO table as follows: the intraregional flows are simply adopted, whereas import and export flows are approximated by the algorithm.

2.3. Algorithm

The algorithm is defined as follows (see Box 1 for pseudo-code and Figure 1 for a schematic illustration): it starts by disaggregating the flows in question of the initial MRIO table into the correspondent sub-flows. This is carried out by equal distribution ($d = 0$ in Table 1) or by the use of proxies ($d > 0$) if the same proxy type is available for all sub-flows. Subsequently, the algorithm iterates over all remaining levels d. At each level it checks for each subsector–subregion index pair $(\lambda,\ \mu)$ whether a refinement proxy $v^{(d)}_{ir\to js}(\lambda, \mu)$ is given, that is, if $(\lambda, \mu) \in E_d$. If this is the case, the corresponding sub-flow $Z^{(d)}_{i_\mu r_\lambda \to js}$ is set

$$Z^{(d)}_{i_\mu r_\lambda \to js} = Z^{(d,\,\text{approx.})}_{i_\mu r_\lambda \to js}; \tag{6}$$

where $Z^{(d,\,\text{approx.})}_{i_\mu r_\lambda \to js}$ is deduced from $Z_{ir\to js}$ by the use of $v^{(d)}_{ir\to js}(\lambda, \mu)$ as shown in Table 1. For all index pairs $(\lambda,\ \mu)$ that have no refinement proxy at this level, an adjustment procedure is applied: the difference between the superordinate flow $Z_{ir\to js}$ and the sum of all flows approximated at this level is distributed among the remaining flows considering their size at the precedent level:

$$Z^{(d)}_{i_\mu r_\lambda \to js} = \left(Z_{ir\to js} - \sum_{(\lambda',\,\mu')\in E_d} Z^{(d)}_{i_{\mu'} r_{\lambda'} \to js} \right) \cdot \frac{Z^{(d-1)}_{i_\mu r_\lambda \to js}}{\sum_{(\lambda',\,\mu')\notin E_d} Z^{(d-1)}_{i_{\mu'} r_{\lambda'} \to js}}. \tag{7}$$

This component of the algorithm does not refer to the balancing of row and column totals of MRIO tables and is hence not to be confused with such methods. The original MRIO balance of row and column totals is preserved by the algorithm at the aggregate level. Only if flows instead of weights are used for the approximation procedure (i.e. list level $d \geq 5$ in Table 1), the set of all approximated sub-flows does not necessarily sum up to the superordinate flow. This is especially problematic if it exceeds the superordinate flow. In this case, it has to be decided whether the superordinate flow or the approximated flows

Algorithm

To disaggregate a flow $Z_{ir\to js}$ with respect to i and r

$q =$ maximum level

For $d = 0$:

For each $\lambda \in [1, \ldots, n], \mu \in [1, \ldots, m]$:

Approximate: $Z^{(0)}_{i_\mu r_\lambda \to js} = Z^{(0,\text{approx.})}_{i_\mu r_\lambda \to js}$

For each $d \in [1, q]$:

$E_d := \{(\lambda, \mu) | v^{(d)}_{ir\to js}(\lambda, \mu)\text{given}\}$

For each $(\lambda, \mu) \in E_d$:

Approximate: $Z^{(d)}_{i_\mu r_\lambda \to js} = Z^{(d,\text{approx.})}_{i_\mu r_\lambda \to js}$

For each $(\lambda, \mu) \notin E_d$:

Adjust: $Z^{(d)}_{i_\mu r_\lambda \to js} = \left(Z_{ir\to js} - \sum_{(\lambda',\mu')\in E_d} Z^{(d)}_{i_{\mu'} r_{\lambda'} \to js}\right) \cdot \frac{Z^{(d-1)}_{i_\mu r_\lambda \to js}}{\sum_{(\lambda',\mu')\notin E_d} Z^{(d-1)}_{i_{\mu'} r_{\lambda'} \to js}}$

$Z_{i_\mu r_\lambda \to js} := Z^{(q)}_{i_\mu r_\lambda \to js}$

BOX 1. Algorithm to refine an outgoing flow. An approximation is performed if a suitable proxy at the respective d-level is available. Otherwise the flow of the $(d-1)$-level is adjusted according to those flows that could be approximated. At level $d = 0$ all sub-flows have to be approximated, for example, by distributing the superordinate flow equally among them.

are altered. The decision can, for example, be based on plausibility checks or confidence intervals. Here, we propose to leave the superordinate flow unchanged unless all sub-flows have been derived by the formula of Peters et al. ($d = 9$ in Table 1) or unless all the sub-flows themselves have been given ($d = 10$). Then, a rebalancing of the original aggregate matrix has to be considered. In all other cases, the approximated flows are mistrusted and the difference is distributed equally among them.

After having iterated all levels, each sub-flow $Z_{i_\mu r_\lambda \to js}$ is transcribed to the corresponding approximated or adjusted flow of the highest d-level.

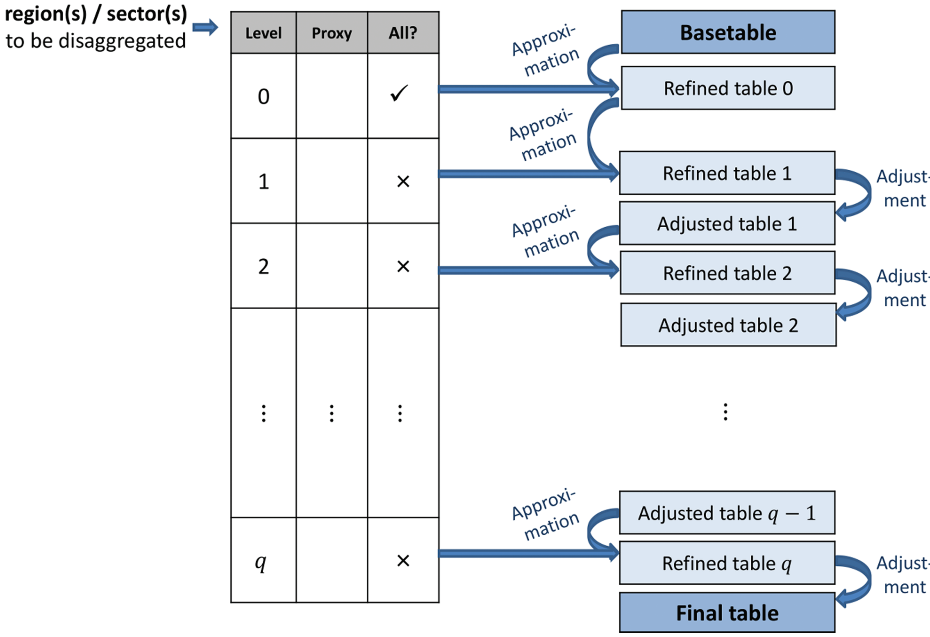
As mentioned at the beginning of this section, the algorithm can be applied analogously to incoming flows or flows to final demand if the refinement proxies and their associated d-levels are altered accordingly. With respect to intra-sectoral and intraregional flows $Z_{ir\to ir}$, the algorithm requires proxies for the incoming and outgoing side. Here, we do not provide for a disaggregation of value-added data. By the use of appropriate proxies, the algorithm can also be applied to value-added data. It then has to be complemented by a balancing procedure in order to guarantee equilibrium of total input and total output not only at the superordinate but also at the sub-level.

After having applied the algorithm to each flow of the initial transaction matrix that refers to region r and/or sector i, these are replaced by their corresponding subregions and subsectors.

2.4. Quality of Outcome

Since the application of the algorithm will generally not result in a perfectly accurate data set, that is, a data set perfectly reflecting real-world flows, the approximated and adjusted

FIGURE 1. Schematic illustration of the refinement algorithm.



Notes: The table comprises all proxies used as inputs for the algorithm. They are hierarchically ranked with q denoting the highest level. The last column indicates if the same proxy type is given for all sub-flows that correspond to a flow to be disaggregated. If this is the case, only the approximation step of the algorithm is performed at this level. If not, the approximation procedure is complemented by the adjustment step. The algorithm iterates over all levels. At level 0 it uses the associated proxies to refine the initial MRIO table. It then improves this table with the help of the proxies of level 1, etc. At level q a refined table has been constructed in which each sub-flow has been approximated by the best proxy information available.

flows of an extended MRIO table have to be considered with caution. Particularly, it is important to keep the highest d-level in mind at which a real approximation (instead of an adjustment) was performed. For this purpose, we propose the following quality measure that can be associated with each sub-flow:

$$Q_{i_\mu r_\lambda \to js} := \max\{0 \leqslant d \leqslant q : (\lambda, \mu) \in E_d\}. \quad (8)$$

It equals the highest d-level at which a proxy was available for that sub-flow. As the proxies are ranked according to their (assumed) suitability for approximation, flows with a high-quality measure $Q_{i_\mu r_\lambda \to js}$ are likely to approximate the 'real' sub-flow better than those with a smaller quality measure. This assessment clearly depends on the hierarchy of proxies chosen (as in Table 1) and has to be interpreted along the quality one assigns to the proxies of a particular level. Dependent on the kind of analysis that is performed based on the extended MRIO table, it might be reasonable to complement this first assessment by an additional analytical or numerical error analysis.

3. PERFORMANCE OF THE REFINEMENT ALGORITHM

In this section, we exemplify the performance of the refinement algorithm in two different setups. In Sections 3.1 and 3.2, the Eora MRIO database is extended sectorally and regionally, respectively, using data on GDP and exports provided by the US BEA (2014). The enlarged MRIO tables are then compared to existing data on similar flows. Subsequently, we present the large-scale application of the approach within the community data platform *zeean* in Section 3.3.

3.1. Example 1: Sectoral Disaggregation of the USA within the Eora MRIO Database

Here, we apply the algorithm to a sectoral disaggregation. Proceeding from an Eora MRIO table for 2011 (Lenzen et al., 2012) and neglecting all flows smaller than 1M USD (which in sum contribute less than 0.6% to the total flow volume), we enlarge the US sector resolution using data on GDP and exports. Our example focusses on the USA because data are available at a high sector detail to compare our results to.

Eora provides two MRIO tables for 2011: a homogeneous table covering annual monetary flows in USD for 26 sectors and final demand in 186 countries and an MRIO table with heterogeneous sector resolution. The latter comprises flows for 429 US sectors. Since this exercise is destined to simply illustrate the quality of the algorithm's outcome compared to existing data, we aggregate the 429 US sectors to 26. We then apply the algorithm to increase this sector resolution to 71 sectors. In addition, we aggregate the US flows of the heterogeneous Eora MRIO table to the same 71 sectors such that the US flows of both matrices are comparable.

As refinement proxies we first use sectorally resolved GDP data, that is, GDP-by-industry data published by BEA for 69 sectors for the year 2011 (BEA, Industry Data, 2011). A sectoral mapping is required that assigns a superordinate sector, that is, one of the 26 Eora sectors, to each of these 69 sectors. Since BEA provides no analogous category for four sectors ('Recycling', 'Private Households', 'Others', 'Re-Export & Re-Import') of the Eora base table, the corresponding flows are not disaggregated but simply transcribed to the extended MRIO table. To some sectors only one subsector can be assigned. These are not disaggregated either. Three BEA sectors ('Food and Beverage Stores', 'General Merchandise Stores', 'Other Retail') are on the contrary merged into one ('Retail Trade') for matters of comparison. In total, the US sector resolution of the enlarged MRIO table is 71. All sector mappings that were applied are provided as supplemental material.

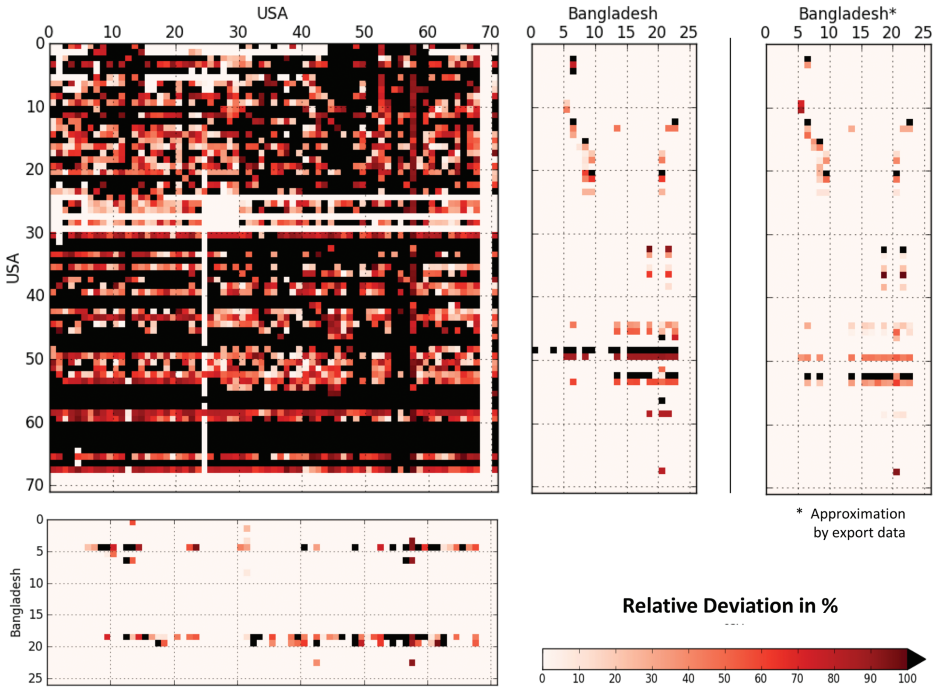
Using GDP-by-industry data as refinement proxies ($d = 3$), the algorithm approximates each sub-flow as follows:

$$Z^{(\mathrm{Algo})}_{i_\mu r \to js} = Z^{(3)}_{i_\mu r \to js} = Z^{(3,\,\mathrm{approx.})}_{i_\mu r \to js} = Z_{ir \to js} \cdot \frac{\mathrm{GDP}_{i_\mu r}}{\mathrm{GDP}_{ir}} \quad \forall i_\mu \in I_i. \tag{9}$$

Since a refinement proxy at level $d = 3$ is given for each sub-flow, the adjustment procedure is not applied and the quality measure is $Q_{i_\mu r \to js} = 3$ for all sub-flows.

We now compare the sub-flows generated by the algorithm to aggregated data of the heterogeneous Eora MRIO table. With regard to interregional outgoing flows, we calculate the relative deviation $\rho_{i_\mu r \to js}$ of each sub-flow $Z^{(\mathrm{Algo})}_{i_\mu r \to js}$ computed by the algorithm to its

FIGURE 2. Relative deviation of approximated flows from available data (in %).



Notes: The matrices show the relative deviation for each sub-flow within the USA as well as for each sub-flow between the USA and Bangladesh from its counter-part in the Eora MRIO table. Rows refer to output and columns to input flows. If both flows are smaller than 1M USD (per year), the relative deviation is set to 0%. It is cut off at 100%. Hatched areas denote non-zero deviations from zero values in the corresponding Eora table. Except for Bangladesh* all sub-flows are approximated by data on GDP-by-industry for 2011. Bangladesh* indicates an approximation by data on export for the same year.

counter-part $Z^{(\text{Eora})}_{i_\mu r \to js}$ given by Eora:

$$\rho_{i_\mu r \to js} = \frac{|Z^{(\text{Algo})}_{i_\mu r \to js} - Z^{(\text{Eora})}_{i_\mu r \to js}|}{Z^{(\text{Eora})}_{i_\mu r \to js}} \,. \tag{10}$$

For small flows $Z^{(\text{Algo})}_{i_\mu r \to js}$ and $Z^{(\text{Eora})}_{i_\mu r \to js}$ the relative deviation might be large even if the absolute difference is not. Thus, we set $\rho_{i_\mu r \to js}$ to zero if both values are smaller than 1M USD. If the Eora sub-flow is zero ($Z^{(\text{Eora})}_{i_\mu r \to js} = 0$) while the corresponding algorithm flow $Z^{(\text{Algo})}_{i_\mu r \to js}$ is larger than 1M USD, the relative deviation cannot be computed. The relative deviations for intraregional incoming and outgoing flows and the interregional incoming flows are calculated analogously.

Figure 2 shows a matrix of the relative deviations for all sub-flows within the USA as well as matrices of the relative deviations for interregional incoming and outgoing flows (here, exemplarily between USA and Bangladesh).

As many of the flows between Bangladesh and the USA are rather small, the relative deviation is often set to zero. The relative deviation is also zero for flows of sectors that are not disaggregated. Flows within the USA are mostly larger and the relative deviation is set to zero less often. Here, many sub-flows given by the algorithm are rather different to those of the inhomogeneous Eora table and the relative deviation exceeds 100% in many cases.

Equation 9 implies that the ratio of the GDP-by-industry of a 71 subsector and the GDP-by-industry of its 26 superordinate sector is used to derive all outgoing flows of the subsector from those of the superordinate sector. For example, the 71-subsector 'Computer and electronic products' contributes about 44.8% to the GDP-by-industry of its superordinate sector 'Electrical and machinery'. The algorithm transfers this percentage to all its outgoing and incoming flows: if the base table denotes that the US sector 'Electrical and machinery' delivers (receives) y (in M USD) to (from) an arbitrary regional sector, the refined table will indicate that 'Computer and electronic products' delivers (receives) $0.448 \cdot y$ (in M USD) to (from) this site. The results of the disaggregation procedure could hence be further improved if proxies were used that distinguish between export, import and intraregional flows.

In a next step, we use export data ($d = 6$) that is also provided by BEA as proxies for the disaggregation of the interregional outgoing flows.

$$Z^{(\text{Algo})}_{i_\mu r \to js} = Z^{(6)}_{i_\mu r \to js} = Z^{(6,\text{ approx.})}_{i_\mu r \to js} = Z_{ir \to js} \cdot \frac{Z_{i_\mu r \to}}{Z_{ir \to}} \quad \forall i_\mu \in I_i. \tag{11}$$

Comparing the newly approximated flows $Z^{(\text{Algo})}_{i_\mu r \to js}$ to their corresponding Eora flows $Z^{(\text{Eora})}_{i_\mu r \to js}$, we now find a smaller relative deviation (calculated analogous to Equation 10) than for the approximation by GDP in many cases. Bangladesh* in Figure 2 shows the results for all outgoing flows from the USA to Bangladesh.

The quality of the algorithm's outcome has thus increased by the use of a higher ranked proxy. Still, the refinement proxy in Equation 11 only comprises information on the general export structure and did not explicitly refer to the target region or the target sector. The results could be further improved by the use of refinement proxies revealing trade patterns between the USA and Bangladesh.

This example allowed us to test the performance of our algorithm and to contrast its result to available data. Since the algorithm only requires basic operations, its performance was computationally not demanding. The comparison to available data at the same sector level showed that the approximated sub-flows can deviate significantly from their 'real' values if only few or rough proxy data (here data on GDP) are available. We further learned that the quality of these approximations improves if more detailed, that is, higher ranked, proxies are also used. One shortcoming of this example was that the second part of the algorithm, the adjustment step, was not required. We will address this technique in the second example.

3.2. Example 2: Multi-sourced Regionalization of the USA

After having performed a sectoral disaggregation, we focus on regionalizing the USA into its 50 states and the District of Colombia. Since the previous example did not illustrate the adjustment part of the algorithm, we now choose a performance design that provides for it.

As base table we use the homogeneous Eora MRIO table for 2011. We firstly approximate all (inter- and intraregional) outgoing flows from the agricultural sectors of the 51 US states by data on subregional GDP ($d = 2$) provided by BEA for 2011 (BEA, GDP by State, 2011). Secondly, we approximate the outgoing flows for some states with the help of their GDP-by-agriculture ($d = 4$) that is also made available by BEA (BEA, Regional Data, 2011). The outgoing flows of all other states are subject to the adjustment step. We compare the results of both algorithm procedures to data provided by the Economic Research Service of the USDA (USDA-ERS, 2014).

We start the refinement algorithm by entering the subregional GDP ($d = 2$) of each state as refinement proxy for its sub-flows. Let i^{agr} denote the agricultural sector. The algorithm then approximates the outgoing agricultural flows of each US state as follows:

$$Z_{i^{\text{agr}} r_\lambda \to js} = Z^{(2)}_{i^{\text{agr}} r_\lambda \to js} = Z^{(2,\ \text{approx.})}_{i^{\text{agr}} r_\lambda \to js} = Z_{i^{\text{agr}} r \to js} \cdot \frac{\text{GDP}_{r_\lambda}}{\text{GDP}_r} \qquad \forall r_\lambda \in R_r. \tag{12}$$

Since all refinement proxies are ranked at the same d-level, the adjustment step of the algorithm is not required and the quality measure $Q_{i^{\text{agr}} r_\lambda \to js} = 2$ is assigned to each flow.

Figure 3(i) shows the resulting total agricultural output for each state, that is, the sum $X_{i^{\text{agr}} r_\lambda} = \sum_s \sum_j Z_{i^{\text{agr}} r_\lambda \to js}$ of all its outgoing flows (except flows to final demand) from the agricultural sector.

We have already discussed the shortcomings of GDP as refinement proxy. If we compare Figure 3(i) to information provided by the USDA, these limitations are stressed. The USDA ranked all states except Alaska, Hawaii and the District of Colombia according to their farm output for the years 1960–2004 (USDA-ERS, US Agricultural Productivity, 2004). Comparing the information for 2004 to our results, we find the following: a state, like New York that contributes strongly to the overall GDP of the USA, is allocated a huge agricultural output. It is, however, only ranked at position 26 by USDA. States like Iowa and Kansas that are on the contrary ranked at positions 2 and 7 according to their agricultural output but have comparably small overall GDPs contribute less to the total agricultural output of the USA according to our approximation.

We address these inadequacies by complementing, exemplarily, the previous refinement proxies of Iowa, Kansas and New York by GDP-by-agriculture. Let the subset of these three states be R_r^{IKN}. The outgoing flows of the agricultural sectors in Kansas, Iowa and New York are then approximated as follows:

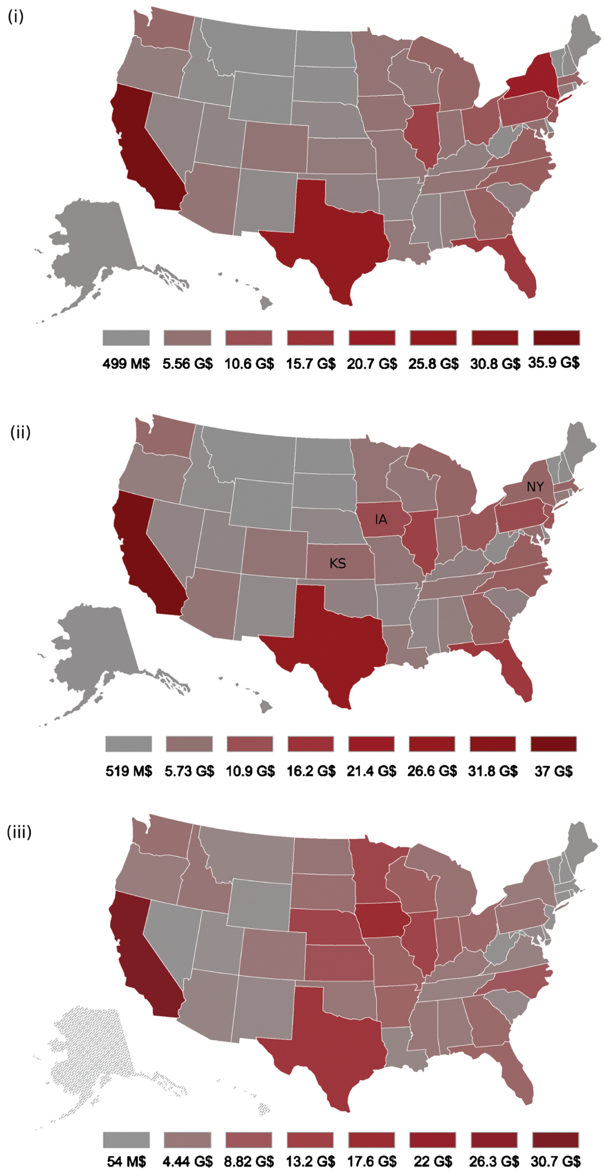
$$Z_{i^{\text{agr}} r_\lambda \to js} = Z^{(4)}_{i^{\text{agr}} r_\lambda \to js} = Z^{(4,\ \text{approx.})}_{i^{\text{agr}} r_\lambda \to js} = Z_{i^{\text{agr}} r \to js} \cdot \frac{\text{GDP}_{i^{\text{agr}} r_\lambda}}{\text{GDP}_{i^{\text{agr}} r}} \quad \text{for } r_\lambda \in R_r^{\text{IKN}}. \tag{13}$$

We assume that for all other states $r_\lambda \notin R_r^{\text{IKN}}$ a GDP-by-agriculture is not given. Hence, the corresponding outgoing sub-flows are adjusted:

$$Z_{i^{\text{agr}} r_\lambda \to js} = Z^{(4)}_{i^{\text{agr}} r_\lambda \to js} = \left(Z_{i^{\text{agr}} r \to js} - \sum_{\lambda' \in E_d} Z^{(4)}_{i^{\text{agr}} r_{\lambda'} \to js} \right) \cdot \frac{Z^{(3)}_{i^{\text{agr}} r_\lambda \to js}}{\sum_{\lambda' \notin E_d} Z^{(3)}_{i^{\text{agr}} r_{\lambda'} \to js}} \qquad \forall r_\lambda \notin R_r^{\text{IKN}}. \tag{14}$$

The algorithm distributes the difference between the initial aggregate flow and the sum of its sub-flows approximated at level $d = 4$ equally among all remaining sub-flows considering their value at the precedent level.

FIGURE 3. Total agricultural output of each US state.



Notes: For each state the maps show the sum of all outgoing flows from its agricultural sector. In (i) these flows are approximated by data on regional GDP for the year 2011. In (ii) the flows of Iowa, Kansas and New York are approximated by data on regional GDP-by-agriculture for 2011. All other agricultural flows are approximated by regional GDP data (2011) first and then adjusted. The last map (iii) shows data provided by the USDA on total farm outputs for the year 2004 (for Alaska, Hawaii and the District of Colombia the data are not provided).

The following quality measures can be assigned to the approximated and adjusted flows, respectively:

$$Q_{i^{\mathrm{agr}} r_\lambda \to js} = \begin{cases} 2 & \text{if } r_\lambda \notin R_r^{\mathrm{IKN}}, \\ 4 & \text{if } r_\lambda \in R_r^{\mathrm{IKN}}. \end{cases} \tag{15}$$

Figure 3(ii) shows the resulting total agricultural output of all states. In contrast to the first map, the agricultural outputs of Kansas and Iowa have increased, while their counter-part in New York has diminished.

Due to the adjustment step of the algorithm the outgoing flows of the agricultural sectors in all other states have also changed. However, since the adjustment procedure distributes differences across all remaining subregions consistently to their previous magnitude, their shares remain the same.

Apart from the rankings, the USDA provides data on the implicit quantities of farm outputs by state. Figure 3(iii) shows these data for 2004. Comparing all three maps, we find that (ii) approaches (iii) better than (i) does. There are, however, still large deviations. Particularly, the Mid-Western states have a much higher agricultural output (relative to the overall agricultural output of the USA) according to USDA data than they have in our first (Figure 3(i)) and second (Figure 3(ii)) approximations. Our results can further approach the data provided by USDA if agricultural GDP is used as a refinement proxy for each state.

3.3. Embedding of the Refinement Algorithm within the *zeean* Data Project

Even though the algorithm allows for a regional or sectoral disaggregation of an MRIO table based on few data, the precision of the approximated flows increases as more refinement proxies at a high d-level are available. In order to yield MRIO tables not only of high resolution but also of high data quality, we integrated the algorithm into the community data platform *zeean* (www.zeean.net). This platform has recently been launched to initiate a community effort to seek, collect and provide detailed information on economic interdependencies. Building on available data from the Eora MRIO database, *zeean* enables registered users to enlarge the database by entering further data on GDP, exports, imports and other economic flows. According to the principles of Wikipedia, this information is planned to be cross-checked and validated by other users. The idea is that, although many data are openly available, a community effort is required to assemble it.

By combining the *zeean* database and the refinement algorithm, we aim at facilitating the construction of MRIO tables at any sector and region detail. Given a target resolution of sectors and regions, the algorithm will use the most suitable refinement proxies available in the *zeean* database to construct an MRIO table accordingly.

4. CONCLUSIONS

We presented an algorithm to refine existing MRIO tables regionally and/or sectorally. The algorithm derives flows on the subregional and subsectoral level from those of the initial table by iterating the following two steps. First, all sub-flows within a specific region or sector are approximated with the help of refinement proxies. These proxies do not have to be homogeneous but can be deduced from different data like GDP, exports, imports and other economic indicators (multi-sourcing approach). Each proxy is assigned a level of detail, d, that reflects its information content with regard to the sub-flow to be approximated (Table 1). Secondly, all sub-flows that were calculated by the use of refinement proxies of a lower d-level are adjusted using those sub-flows that were approximated at a higher d-level. This step guarantees that the sub-flows match the superordinate flow in sum.

Our approach provides a framework to obtain an MRIO table at any sectoral and regional detail even when only few proxy data are available. The computational effort is low and no additional data processing is required. Due to the adjustment step of the algorithm, the refined table can easily be updated at a later point in time if a proxy is available that is assumed to be better suited for approximating one of the sub-flows. On the downside, the resulting MRIO sub-flows are error-prone. Their accuracy depends on the information content of the refinement proxies chosen for their and their surrounding sub-flows' approximations. It is also subject to the reliability of the proxy data and of the underlying base table, which cannot be judged by the algorithm. Depending on these factors, it should be thoroughly weighted whether a coarser but more reliable MRIO table is preferred or a less accurate but more detailed one.

For many purposes and research questions, particularly in the context of disaster impact analysis and I–O-based LCA, the algorithm may generate a sufficient and easily computable MRIO table at high regional and sectoral detail. The algorithm has been integrated into the community data platform *zeean* where it is used to yield economic flow data at a high level of region and sector detail departing from the Eora MRIO database.

Acknowledgments

We thank Christian Otto and Julius Zwirner for fruitful discussions.

FUNDING

This research was supported by the German Environmental Foundation and the Heinrich-Böll Foundation. It has received funding from the European Union Seventh Framework Programme *FP7/2007-2013* under *grant agreement* n° 603864. Funding from Deutsche Forschungsgemeinschaft (DFG, CRC 1026 'Sustainable Manfacturing') is gratefully acknowledged.

SUPPLEMENTAL DATA

Supplemental material for this article is available via the supplemental tab on the article's online page at http://dx.doi.org/10.1080/09535314.2014.987731

References

Aleexeva-Talebi, V., C. Böhringer, A. Löschel and S. Voigt. (2012) The Value-added of Sectoral Disaggregation: Implications on Competitive Consequences of Climate Change Policies. *Energy Economics*, 34, 127–142.

Bayne, B.A. and G.R. West. (1989) *GRIT – Generation of Regional Input–Output Tables: User's Reference Manual*. Canberra, Australia, Australian Regional Developments No. 15, Australian Government Publishing Service.

BEA. (2014) *US Bureau of Economic Analysis*. US Department of Commerce. www.bea.gov

BEA, GDP by State. (2011) *US Bureau of Economic Analysis*. Table 1: Real GDP by State, 2009–2012. Accessed April 2, 2014. www.bea.gov

BEA, Industry Data. (2011) *US Bureau of Economic Analysis*. Interactive Access to Industry Economic Accounts Data: GDP by Industry. Accessed March 24, 2014. www.bea.gov

BEA, Regional Data. (2011) *US Bureau of Economic Analysis*. Regional Data: GDP & Personal Income. Accessed April 2, 2014. www.bea.gov

Bullard, C.W., P.S. Penner and D.A. Pilati. (1978) Net Energy Analysis – A Handbook for Combining Process and Input–Output Analysis. *Resources and Energy*, 1, 267–313.
Dietzenbacher, E., B. Los, R. Stehrer, M. Timmer and G. de Vries. (2013) The Construction of World Input–Output Tables in the WIOD Project. *Economic Systems Research*, 25, 71–98.
Flegg, A.T., C.D. Webber and M.V. Elliott. (1995) On the Appropriate Use of Location Quotients in Generating Regional Input–Output Tables. *Regional Studies*, 29, 547–561.
Gaulier, G. and S. Zignago. (2009) BACI: International Trade Database at the Product-Level (Munich Personal RePEc Archive (MPRA), 31398).
Gillen, W.J. and A. Guccione. (1990) Disaggregating Input–Output Models; an Alternative to Wolsky's Method. *Economic Systems Research*, 2, 39–42.
Haddad, E.A. and Y. Okuyama. (2012) Spatial Propagation of the Economic Impacts of Bombing: The Case of the 2006 War in Lebanon (University of São Paulo (FEA-USP), 19).
Haddad, E.A. and E. Teixeira. (2013) Economic Impacts of Natural Disasters in Megacities: The Case of Floods in Sao Paulo, Brazil (ERSA Conference Papers (No.ersa13p409), European Regional Science Association).
Hallegatte, S. (2008) An Advanced Regional Input–Output Model and its Application to the Assessment of the Economic Costs of Katrina. *Risk Analysis*, 28, 779–799.
Hallegatte, S. (2014) Modeling the Role of Inventories and Heterogeneity in the Assessment of the Economic Costs of Natural Disasters. *Risk Analysis*, 34, 152–167. Accessed from Open Knowledge Repository.
IPCC. (2012) Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation. In: C.B. Field, V. Barros, T.F. Stocker, D. Qin, D.J. Dokken, K.L. Ebi, M.D. Mastrandrea, K.J. Mach, G.-K. Plattner, S.K. Allen, M. Tignor, and P.M. Midgley (eds.) *A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change*. New York, Cambridge University Press, 582 pp.
IPCC. (2014) Summary for Policymakers. In: C.B. Field, V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L. White (eds.) *Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge, Cambridge University Press, 1–32.
Jonkeren, O. and G. Giannopoulos. (2014) Analysing Critical Infrastructure Failure with a Resilience Inoperability Input–Output Model. *Economic Systems Research*, 26, 39–59.
Kowalewski, J. (2013) Regionalization of National Input–Output Tables: Empirical Evidence on the Use of the FLQ Formula (Regional Studies, ahead-of-print, 1–11).
Lenzen, M. (2011) Aggregation versus Disaggregation in Input–Output Analysis of the Environment. *Economic Systems Research*, 23, 73–89.
Lenzen, M., B. Gallego and R. Wood. (2006) A Flexible Approach to Matrix Balancing under Partial Information. *Journal of Applied Input–Output Analysis*, 11&12, 1–14.
Lenzen, M., K. Kanemoto, D. Moran and A. Geschke. (2012) Mapping the Structure of the World Economy. *Environmental Science and Technology*, 46, 8374–8381.
Lenzen, M., A. Geschke, T. Wiedmann, J. Lane, N. Anderson, T. Baynes, J. Boland, P. Daniels, C. Dey, J. Fry, M. Hadjikakou, S. Kenway, A. Malik, D. Moran, J. Murray, S. Nettleton, L. Poruschi, C. Reynolds, H. Rowley, J. Ugon, D. Webb and J. West. (2014) Compiling and Using Input–Output Frameworks through Collaborative Virtual Laboratories. *Science of the Total Environment*, 485, 241–251.
Levermann, A. (2014) Make Supply Chains Climate-Smart. *Nature*, 506, 27–29.
Lindner, S., J. Legault and D. Guan. (2012) Disaggregating Input–Output Models with Incomplete Information. *Economic Systems Research*, 24, 329–347.
Liu, C.-H., M. Lenzen and J. Murray. (2012) A Disaggregated Emissions Inventory for Taiwan with Uses in Hybrid Input–Output Life Cycle Assessment (IO-LCA). *Natural Resources Forum*, 36, 121–141.
Moriguchi, Y., Y. Kondo and H. Shimizu. (1993) Analysing the Life Cycle Impacts of Cars: The Case of CO_2. *Industry and Environment*, 16, 1–2.
Narayanan, B., A. Angel and R. McDougall. (2012). *Global Trade, Assistance, and Production: The GTAP 8 Data Base*. Center for Global Trade Analysis, Purdue University. www.gtap.agecon.purdue.edu/databases/v8/v8_doco.asp
Okuyama, Y. and S. Sahin. (2009) *Impact Estimation of Disasters: A Global Aggregate for 1960 to 2007*. World Bank. Accessed from Open Knowledge Repository: http://hdl.handle.net/10986/4157
Okuyama, Y. and J.R. Santos. (2014) Disaster Impact and Input–Output Analysis. *Economic Systems Research*, 26, 1–12.
Peters, G.P., R. Andrew and J. Lennox. (2011) Constructing an Environmentally Extended Multi-Regional Input–Output Table Using the GTAP Database. *Economic Systems Research*, 23, 131–152.
Radebach, A., H. Schult and J.C. Steckel. (2014) On the Importance of Manufacturing Sectors for Sustainable Economic Development and Growth (Paper presented at the 22nd International Input–Output Conference, Lisbon).
Rahmstorf, S. and D. Coumou. (2011) Increase of Extreme Events in a Warming World. *Proceedings of the National Academy of Sciences*, 108, 17905–17909.

Rebitzer, G., T. Ekvall, R. Frischknecht, D. Hunkler, G. Norris, T. Rydberg, W-P. Schmidt, S. Suh, B.P. Weidema and D.W. Pennington. (2004) Life Cycle Assessment Part 1: Framework, Goal and Scope Definition, Inventory Analysis and Applications. *Environment International*, 30, 701–720.

Stone, R. and A. Brown. (1962) *A Computable Model of Economic Growth*. London, Chapman and Hall.

Stromman, A.H. and E. Hertwich. (2004) Hybrid Life Cycle Assessment of Large Scale Hydrogen Production Facilities (Norwegian University of Science and Technology (NTNU), Industrial Ecology Programme (IndEcol), 3).

Su, B., H.-C. Huang, B.W. Ang and P. Zhou. (2010) Input–Output Analysis of CO2 Emissions Embedded in Trade: The Effects of Sector Aggregation. *Energy Economics*, 32, 166–175.

Suh, S. (2004) Functions, Commodities and Environmental Impacts in an Ecological-Economic Model. *Ecological Economics*, 48, 451–467.

Suh, S. and G. Huppes. (2002) Missing Inventory Estimation Tool Using Extended Input–Output Analysis. *The International Journal of Life Cycle Assessment*, 7, 134–140.

Suh, S. and S. Nakamura. (2007) Five Years in the Area of Input–Output and Hybrid LCA. *The International Journal of Life Cycle Assessment*, 12, 351–352.

USDA-ERS. (2014) *US Department of Agriculture: Economic Research Service*. www.ers.usda.gov

USDA-ERS, US Agricultural Productivity. (2004) *US Department of Agriculture: Economic Research Service*, Tables 20 and 23. Accessed May 8, 2014. www.ers.usda.gov

Wiedmann, T., H.C. Wilting, M. Lenzen, S. Lutter and V. Palm. (2011a) Quo Vadis MRIO? Methodological, Data and Institutional Requirements for Multi-Region Input–Output Analysis. *Ecological Economics*, 70, 1937–1945.

Wiedmann, T.O., S. Suh, K. Feng, M. Lenzen, A. Acquaye, K. Scott and J.R. Barrett. (2011b) Application of Hybrid Life Cycle Approaches to Emerging Energy Technologies – The Case of Wind Power in the UK. *Environmental Science and Technology*, 45, 5900–5907.

Wolsky, A. (1984) Disaggregating Input–Output Models. *The Review of Economics and Statistics*, 66, 283–291.