

1 **Accounting for raw material embedded in imports**
2 **by multi-regional input-output modelling and life**
3 **cycle assessment, using Finland as a study case**

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15

16 **Abstract**

17 The two main methods used to estimate raw material embedded in
18 imports are life cycle assessment (LCA) and multi-regional input-
19 output (MRIO) models. The key advantage of LCA is its higher
20 product resolution but it relies on global or regional averages, which
21 could bias results. Our outcomes suggest that this obstacle could be
22 avoided for primary goods if domestic process data are collected, since
23 the necessary raw materials are mostly extracted from the environment
24 of the direct trade partner. Conversely, for many other products,

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25 intermediate inputs are produced following a wide range of blueprints
26 and cross multiple borders, which makes it challenging to determine
27 how and where raw materials needed for their production originate.
28 For these products, a method to combine the superior coverage of
29 MRIO with the product resolution of LCA is evaluated here, using
30 imports to Finland as a study case. The analysis provides insights on
31 how to identify critical supply chains and illustrates a relatively
32 simple, replicable solution that can be used in other regions or
33 environmental accounts. Nevertheless, the existing resolution of
34 MRIO models and dissimilarities in classifications between the two
35 tools could constitute a new source of errors if not properly handled.

36

37 **Keywords**

38 material flow accounting, raw material equivalents, material footprint

39 **1. Introduction**

40 In analyses of the metabolism of socioeconomic systems, all materials
41 required by the economy are ideally taken into account on the basis of
42 mass conservation. To this end, a set of indicators has been developed
43 within the framework of material flow accounting (MFA), so that present
44 and past trends can be analysed and policy targets for a more sustainable
45 future can be set (e.g. OECD, 2011; UNEP, 2011; European Commission,
46 2011). Standard practice in MFA suggests that all raw material extracted
47 within the boundaries of the system called ‘domestic extraction’ (DE) and
48 material flows associated with trade need to be accounted for
49 (EUROSTAT, 2013; OECD, 2008). Accounting for DE is relatively
50 straightforward, using official statistics, while there are two distinct ways
51 of incorporating the material flows of traded products in MFA that can
52 give different results regarding the raw material requirements of a given
53 system. On one hand, indicators such as direct material input and domestic
54 material consumption consider only mass of imports and exports (‘direct’
55 imports and exports, using MFA terminology). In particular, the direct
56 material input is obtained by adding together the direct imports to the DE,
57 whereas the domestic material consumption is direct material input minus
58 direct exports. On the other hand, broader-scope indicators, such as raw
59 material input and raw material consumption, are based on the concept of
60 ‘raw material equivalents’ (RME) of imports and exports, which refer to
61 all raw material extracted and used for production of traded products. Thus
62 in the RME approach, all upstream raw materials involved in the
63 production of imports and exports are considered, regardless of the mass
64 that finally crosses the border. Indicators based on direct imports and

65 exports are easier to calculate, but it is acknowledged that they are not able
66 to capture appropriately the existence of dislocation of material-intensive
67 industries and, consequently, burden shifting of raw material extraction
68 among countries. Moreover, evidence of increasing dependence on non-
69 domestic raw material in most rich economies highlights the urgency of
70 including RME-based indicators in resource efficiency policies (Giljum et
71 al., 2014a; Wiedmann et al., 2013). Accordingly, the RME approach
72 appears preferable for assessing the material basis of socioeconomic
73 systems.

74 However, estimation of RME is challenging because, in contrast to the
75 survey estimation of direct flows, it involves modelling the technology of
76 industries and countries involved in complex supply chains (from
77 extraction to final production) using diverse data sources and strong
78 assumptions, which can have a marked impact on the outcomes. Two
79 broad methods can be distinguished in RME calculations: Life cycle
80 assessment (LCA) and input-output (IO) models. LCA adopts a bottom-
81 up perspective, modelling coefficients of RME for particular products
82 employing process data collected using technical information on (ideally)
83 all upstream production processes in the supply chain. These coefficients
84 are usually first estimated for representative individual products and later
85 adapted or employed for all trade products. In contrast, IO models adopt a
86 top-down approach whereby coefficients of RME are modelled at macro
87 level for broad product groups or industries. This is done by linking
88 physical data about biomass harvested by agriculture and forestry and
89 minerals extracted by mining companies with monetary data about
90 transactions among economic sectors and final consumers, so that raw

91 materials flows can be tracked along supply chains, from extraction to
92 final use. The most promising IO models are multi-regional IO (MRIO)
93 models, which have the highest geographical coverage, since world
94 economies are interconnected via trade and domestic transactions.
95 Furthermore, there is increasing interest in combining approaches in order
96 to take advantage of their main features, in the so-called hybrid or life
97 cycle assessment input-output (LCA-IO) approach.

98 In this paper, we focus on the issue of the (limited) regional coverage
99 of LCA compared with MRIO models. We begin by assuming that existing
100 LCA-based approaches oversimplify the diversity in technology in
101 exporting regions, which has the potential to bias results (Dittrich et al.,
102 2012), since they are often based on global or regional averages. To this
103 end, we first explore the extent to which including specific process data
104 from exporting nations can improve accuracy, especially for products
105 originating from long, complex supply chains. We then introduce and
106 assess a method making use of the higher degree of detail in the bottom-
107 up perspective and also expanding the system boundaries to full coverage
108 of the world using MRIO.

109

110 **2. Life cycle assessment vs. multi-regional input-output models in** 111 **estimation of raw material equivalents**

112 Material flow accounting has become one of the key tools in industrial
113 ecology and ecological economics since its development by Ayres and
114 Kneese (1969), as reviewed by Ayres and Ayres (1998), Daniels and
115 Moore (2002), Daniels (2002) and Fischer-Kowalski et al. (2011). Since
116 the early days of MFA, the relevance of the RME concept has been

117 acknowledged and significant efforts supported by international policy
 118 bodies are underway to improve the estimation methods. Below, use of
 119 LCA, MRIO and mixed models in RME estimation is compared, focusing
 120 on methodological differences relevant for the present analysis.

121 In the LCA-based approach (also process-based or coefficient
 122 approach), RME coefficients (also ‘cradle-to-product’ or life cycle
 123 inventory coefficients) are estimated based on process data for individual
 124 products. This approach considers all exchanges between social and
 125 natural spheres that occur during the product life cycle, as summarised by
 126 the general expression:

$$\mathbf{r} = \boldsymbol{\alpha}' \mathbf{N} \mathbf{m} \quad (1)$$

127 where lower case letters are vertical vectors, ' denotes transposition, \mathbf{r} is
 128 RME of imports, $\boldsymbol{\alpha}$ is a vector of process-based coefficients expressed in
 129 kg of RME per kg or euro imported, \mathbf{N} is an aggregation matrix with
 130 dimensions number of coefficients by number of imported products with
 131 elements 1 and 0 appropriately placed, and \mathbf{m} is the vector of imports. In
 132 the literature, RME estimated in this way are also termed ‘ecological
 133 rucksack’ (Dittrich et al., 2012).

134 Input-output models were introduced to describe technological
 135 dependencies between industries and product flows within the economy
 136 (Leontief, 1936). An essential feature of these models is the ‘Leontief
 137 inverse’, which consists of direct and indirect inputs required per unit of
 138 final demand of each economic sector or product group. To analyse
 139 environmental burden flows, information regarding how much raw
 140 material is extracted per euro of economic output is included, so

141 biophysical requirements by industry and final user can be obtained. The
 142 MRIO model is summarised by the general expression:

$$\mathbf{r} = \mathbf{e}' \mathbf{L} \mathbf{N} \mathbf{m} = \mathbf{p}' \mathbf{N} \mathbf{m} \quad (2)$$

143 where $\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1}$ is the Leontief inverse (\mathbf{I} being the identity matrix
 144 and \mathbf{A} the matrix of technical coefficients) and \mathbf{e}' is the vector of sectoral
 145 coefficients of material input (for further details of IO modelling, see
 146 Miller and Blair, 2009; European Commission et al., 2014). Elements of the
 147 row vector \mathbf{p} represent the raw material multipliers or RME coefficients.

148 Therefore, assuming that in both cases the imports are the same,
 149 differences in RME estimates across methods should derive from
 150 differences between components α and \mathbf{p} . The pros and cons of each
 151 method have been explored previously and it has been concluded that both
 152 have their advantages and drawbacks and that there is currently no optimal
 153 method (Eisenmenger et al., 2016; Lutter et al., 2016; Schoer et al., 2013).

154 In the context of the present study, a key shortcoming of LCA-based
 155 coefficients is that they are estimated most commonly as representative
 156 regional or world averages (which might refer to a particular moment in
 157 time or an average), whereas MRIO models can capture more conveniently
 158 differences in resource use between countries (Wiedmann et al., 2011).
 159 That is to say, it can be assumed that multipliers \mathbf{p} in MRIO models
 160 represent divergences in technology between nations. However, MRIO
 161 models can be strongly affected by sector or country resolution. These
 162 aggregation errors may appear depending on how products/countries are
 163 grouped in the model because averaged inputs need to be considered,
 164 which could cause distortions that are passed on via the Leontief inverse

165 to multipliers (de Koning et al., 2015; Piñero et al., 2015). Disaggregation
166 of official or basic data could be performed to alleviate this problem, but
167 at the expense of higher uncertainty. In addition, more country resolution
168 does not necessarily mean more accurate outcomes, particularly if based
169 on poor underlying data (Schoer et al., 2013). In contrast, the main
170 advantage of LCA is its high resolution and product coverage (Dittrich et
171 al., 2012), since calculations can be as detailed as the highest product
172 resolution offered by customs statistics offices (or in other words, matrix
173 \mathbf{N} in equation 1 can be suppressed if α is sufficiently detailed). However,
174 this does not mean that process-based coefficients are free from
175 aggregation problems, it being common practice to work with aggregated
176 data (Majeau-Bettez et al., 2011). Furthermore, due to time and resource
177 constraints and to make the model operative, aggregation is frequently
178 applied in RME estimation based on LCA, which involves certain
179 uncertainties as a result of the use of averages for heterogeneous product
180 groups (e.g. the same coefficient may be employed for all types of
181 imported printers, whether a small device intended for home use or
182 professional printing equipment). Moreover, these aggregation problems
183 persist even at the most disaggregated levels of custom statistics (Dittrich
184 et al., 2012) (e.g. because there are multiple models even within the group
185 of printers for home use, with predictably different raw material basis).

186 Other shortcomings of LCA are that it can be severely affected by
187 boundary setting for the system, e.g. truncation errors can arise as a result
188 of excluding high-order upstream production stages (Lenzen, 2000). In
189 addition, fewer data are available for finished products or services than for
190 raw materials and semi-manufactured goods, because the former involve

191 much complex supply chains and material composition mixes (Dittrich et
192 al., 2012). This extra degree of complexity in downstream production
193 stages is also acknowledged in studies focusing on particular materials,
194 such as aluminium (Cullen and Allwood, 2013), copper (Graedel et al.,
195 2002) or iron (Wang et al., 2007). In contrast, in MRIO models an
196 approximation to such complexity in composition mixes is achieved and
197 the cut-off error is minimised by multiplier estimation itself.

198 Both LCA (Dittrich et al., 2012) and MRIO models (Arto et al., 2012;
199 Bruckner et al., 2012; Giljum et al., 2014a; Tukker et al., 2014; Wiedmann
200 et al., 2013) have been used to estimate RME embodied in trade products.
201 Although possible, combinations between high geographical coverage
202 MRIO models and process-based coefficients have not been developed so
203 far in MFA studies. However, some mixed models combining features of
204 national or EU IO models and LCA data already exist, for example for the
205 European Union (Schoer et al., 2012b), Czech Republic (Kovanda et al.,
206 2010), Austria (Schaffartzik et al., 2014) and Italy (Marra Campanale and
207 Femia, 2013). These mixed or hybrid models are described in the early
208 works of Moriguchi et al. (1993), Joshi (2000), Treloar (1997), Suh et al.
209 (2004), Suh (2004) and Suh and Heijungs (2007). In the remainder of this
210 paper such models are referred to using the acronym LCA-IO, because the
211 term hybrid is also applied to mixed units (physical and monetary) in IO
212 models. In the literature, mixed model approaches are also referred as LCI-
213 IO or LC-IO, from life cycle inventory or life cycle, respectively.

214 All approaches model the same reality (i.e. upstream raw material
215 requirements of traded products) and hence the results should be similar.
216 In reality, there are a number of methodological differences which might

217 explain differences in the outcomes. To date, only a few studies have
218 compared existing methods. An evaluation of a LCA-IO method and a
219 MRIO model focusing on the EU found that discrepancies at more
220 aggregated levels remain within 5-10% for RME of imports, although they
221 are significantly higher for broad groups of materials (Schoer et al., 2013).
222 This gap is reduced when further steps are taken to attenuate
223 methodological differences. Another comparison between three MRIO
224 models and one LCA-IO method found that RME of trade products deviate
225 markedly across models, especially when considering disaggregated
226 material groups (Giljum et al., 2015). In addition, strong deviations
227 between economic sectors or product groups have been reported, whereby
228 the more disaggregated the comparison, the higher the discrepancies.
229 Using Austria as a case study, six methods have been compared and
230 discrepancies of around 30-40% in aggregated RME-based indicators have
231 been reported (Eisenmenger et al., 2016). In that study, the sign of the
232 physical trade balance (RME of imports minus RME of exports) changed
233 for some raw material categories depending on the approach, which
234 implies some vagueness about whether Austria plays the role of net
235 importer or net exporter of environmental loads in the international arena.
236 Although the studies by Schoer et al. (2013) and Giljum et al. (2015)
237 highlight that deviations at more aggregated level are manageable and that
238 uncertainty does not compromise current policy applications of RME-
239 based estimates, dissimilarities reported for some countries correspond
240 with the results for Austria and call for a more profound understanding of
241 existing methodological differences.

242 Overall, there are a number of other differences (such as monetary
243 versus mass units, time window in the functional unit, how capital stocks
244 are modelled etc.) that can explain discrepancies in outcomes and which
245 should also be considered in the choice of approach. In order to improve
246 estimation of RME, in this study we attempted to incorporate the superior
247 coverage of supply chains by MRIO models into more detailed LCA-based
248 approaches. Due to the differences between these two tools and the
249 particularities of the models and databases employed, many obstacles had
250 to be overcome, using rough assumptions in some cases and ad-hoc
251 correspondences between products and materials in others. In this manner,
252 the benefits and risks of combining LCA and MRIO methods for RME
253 estimation in a systematic manner were analysed.

254

255 **3. Material & Methods**

256 Three models were used in the analysis: the Envimat Imports model,
257 the Eurostat RME tool and the Exiobase MRIO model. The Envimat
258 Imports model (Koskela et al., 2013, 2011; Seppälä et al., 2011) was
259 chosen to represent the LCA approach, since RME of all imported goods
260 are modelled using process-based coefficients and only services are
261 estimated using the IO technique. The Eurostat RME tool (Eurostat, 2015;
262 Schoer et al., 2012a) was selected because is the most popular LCA-IO
263 model for RME estimation. Although different MRIO models exist, with
264 different product and country coverage (Tukker and Dietzenbacher, 2013),
265 in this study Exiobase was chosen because of its high detail in extractive
266 sectors and its focus on the EU (Tukker et al., 2014; Wood et al., 2015).
267 Main features of each of these models are explained in the subsection

268 Model specifications. Full product and material classifications,
269 correspondence tables, model specifications and complementary
270 mathematical descriptions and results are available in Supporting
271 Information.

272 The results are described in two sections. Section 4.1 (Raw material
273 flows in international supply chains) examines the question of how much
274 domestic raw material extraction occurs in direct trade partners compared
275 with extraction in third countries. For the sake of replicability, this analysis
276 was performed using only Exiobase data (for the year 2007). Section 4.2
277 (Country-specific information from the Exiobase MRIO model in LCA-
278 based approaches) attempts to refine original RME coefficients from the
279 Envimat (LCA) and Eurostat (LCA-IO) models by accounting for
280 country/regional variations in the embodiments. Finland was chosen as a
281 study case for this purpose and 2010 data as the base, because those are
282 the most recent IO data available for Finland. Further explanations and
283 mathematical details are presented in the subsection The Method.

284 At this point, two issues regarding MFA principles require
285 clarification. First, in this study only the ‘Used’ fraction of raw material
286 extraction is considered, i.e. only materials entering the economy via
287 prices are studied. Other materials removed but not bought or sold, such
288 as mining overburden or fishing by-catch (‘Unused’ raw materials), are
289 excluded. The reason is to keep calculations simple, since the method
290 developed would be similar in both cases. Second, estimation of RME of
291 imports for a country depends on whether or not intermediate imports for
292 production of exporting products are included in the calculations. If the
293 goal is to measure environmental pressure exerted by a given domestic

294 final demand, then these loads are usually reallocated to those end-user
295 countries receiving those exports (this approach is applied e.g. by Giljum
296 et al. (2015b) and in the cited studies using MRIO models). However, in
297 the present study, all imports as recorded by customs offices were
298 included, because making a distinction would involve extra effort and
299 probably detract from the focus of the analysis.

300

301 3.1. Model specifications

302 In the Envimat Imports model (hereafter 'Envimat'), basic data in
303 physical and monetary units are obtained mostly from foreign trade
304 statistics compiled at combined nomenclature (CN) eight-digit product
305 resolution and then converted to the Envimat classification system for
306 products (ETTL), which distinguishes around 490 goods and is derived
307 from the classification of products by activity (CPA) 2008. In addition, a
308 hierarchical classification of 85 types of raw materials is made in the
309 Envimat resource classification. Furthermore, process-based coefficients
310 are calculated for goods on a mass basis, i.e. kg RME per kg of goods
311 imported, while for services kg RME per euro imported is used. Most of
312 these coefficients represent world average values, although in some cases
313 they refer to European averages or to particular countries (e.g. natural gas
314 from Russia). Basic data are mainly retrieved from the life cycle inventory
315 database Ecoinvent version 3.0 (Wernet et al., 2016) and, for some
316 products, a direct correspondence with data available in Ecoinvent and
317 ETTL products can be drawn. For other products input data from technical
318 and academic literature is used to build streamlined LCA systems (full
319 description in Supporting Information).

320 The Eurostat RME tool (Eurostat, thereafter) comprises 166 product
321 groups and 52 raw material categories, since standard MFA classification
322 is further disaggregated for metals, through the so-called ‘metal model’.
323 Basic calculation was carried out using an IO table for the EU27 region,
324 in which monetary flows of fossil fuels, metal concentrates and base
325 metals are replaced by physical flows (fossil raw materials in oil
326 equivalent tons and metals in tons). In addition, for some raw materials
327 and basic products (metals, oil and gas), LCA data is utilised. For other
328 imported products, manufacturing and services, the so-called ‘domestic
329 technology assumption’ is followed, i.e. the technology for import
330 production was assumed to be the same as in the importer region (EU27
331 in this case). The model is based on CPA 2002 and coefficients represent
332 EU import average values.

333 Exiobase is a MRIO database that includes data for 200 products and
334 48 countries or world regions, more precisely 27 EU countries, 16 non-EU
335 countries and five regions. Single countries considered (43) cover 90% of
336 global gross domestic product (GDP). In short, the database harmonises
337 official IO tables and material extraction data using auxiliary information
338 from international agencies, such as the Food and Agriculture
339 Organization (FAO) and International Energy Agency (IEA). The product
340 classification uses the CPA 2002 scheme with high resolution for
341 extractive products (33 product groups) and data currently available are
342 for the years 2000 and 2007. Publicly available data are in various formats,
343 but for this study ‘product by product’ tables were chosen for two reasons:
344 i) errors dependent on the version chosen are reported to be small (Marin

345 et al., 2012) and ii) the product by product approach gives easier
346 correspondence between models and trade data.

347 Lastly, it should be stressed that the emphasis in this study was on
348 goods and therefore services were excluded from the calculations, so a
349 fixed amount of RME associated with imported services was included in
350 all models. The reason is twofold: i) customs data for services are more
351 incomplete and ii) services are less relevant than goods as raw material
352 extraction drivers. For instance, in 2010, imported services reached almost
353 17 050 million euros according to IO data from Statistics Finland, whereas
354 imported services included in customs data were a mere 182 million euros.
355 Unfortunately, the former data do not specify country of origin of service
356 companies. In addition, it has been pointed out that services only
357 accounted for 3.4% of total RME embodied in Finnish imports in 2005
358 (Seppälä et al., 2011).

359

360 3.2. The Method

361 Raw materials extracted and used for production of same type of
362 product differ between countries, i.e. producing a watch in Switzerland
363 and in China differs in raw material terms, since technology and
364 production blueprints vary from country to country (in the Supporting
365 Information, dispersion statistics for multipliers of the full Exiobase are
366 presented). Customs statistics usually report where goods are dispatched,
367 so assuming that those traded products are entirely or mostly produced in
368 the dispatching country, which is typically the case for primary products,
369 allows process data including technology particularities of those countries
370 to be gathered and RME coefficients to be estimated. In the Envimat and

371 Eurostat models, this approach is followed for some products. However,
 372 production of more sophisticated products often takes place in more than
 373 one country, so raw material extraction might happen in country A, further
 374 processing in countries B and C, and final export to Finland by country D.
 375 Therefore, to study the fraction of RME of imports from a particular
 376 product and country that has been extracted domestically or elsewhere,
 377 multipliers of full Exiobase were aggregated according to this criterion.

378 As mentioned previously, there is extensive literature on combining
 379 LCA and IO approaches. Such studies have, at their core, the definition of
 380 system boundaries, consideration of possible miscounting or double
 381 counting and the importance of sectoral, regional and time frame details,
 382 depending on the object of the study. In the present study, a method for
 383 including MRIO information from Exiobase in the Envimat and Eurostat
 384 models was developed. The method is based on a correction matrix **C**
 385 dimension number of countries by number of products, the elements of
 386 which are the ratio between full Exiobase multipliers and those from an
 387 averaged Exiobase version that describes world or EU average values, re-
 388 arranged in country by product form. Thus c_{ij} informs for product j about
 389 deviations of country i in relation to the regional average under
 390 consideration (i.e. if $c_{ij} > 1$, RME for product j coming from country i are
 391 above average, while if $c_{ij} < 1$, the opposite occurs). Using algebra, matrix
 392 **C** can be estimated as:

$$\mathbf{C} = \mathbf{P}\hat{\mathbf{p}}_A^{-1} \quad (3)$$

393 where **P** is a multiplier matrix whose elements are disposed in country by
 394 product form (i.e. p_{ij} is the RME coefficient for product j from country i)

395 and $\hat{\mathbf{p}}_A$ indicates the diagonal matrix of \mathbf{p}_A , which is the vector describing
 396 average multipliers for products.

397 Matrix \mathbf{W} , which describes coefficients corrected including MRIO
 398 information in country by product form, can then be calculated as:

$$\mathbf{W} = \mathbf{C}\hat{\boldsymbol{\alpha}} \quad (4)$$

399 where w_{ij} describes the ‘MRIO-refined’ RME coefficient for product j
 400 imported from country i .

401 After refining original RME coefficients, RME embedded in imports
 402 can be estimated considering technological differences among countries:
 403 if matrix \mathbf{M} is an imports matrix re-arranged in country by product form,
 404 then matrix \mathbf{R}^* can be obtained using the Hadamard product denoted by
 405 \circ as:

$$\mathbf{R}^* = \mathbf{W} \circ \mathbf{M} \quad (5)$$

406 where r_{ij}^* informs about RME embedded in imports of product j from
 407 country i .

408 Finally, to obtain RME after correction by product \mathbf{r}_p^* , \mathbf{R}^* can be pre-
 409 multiplied by a row vector of ones, i.e. $\mathbf{r}_p^* = \mathbf{i}'\mathbf{R}^*$. Similarly, raw material
 410 embedded after correction by country \mathbf{r}_c^* can be calculated following \mathbf{r}_c^*
 411 $= \mathbf{R}^* \mathbf{i}$.

412 Hereafter, the MRIO-corrected versions of the Envimat and Eurostat
 413 models are referred to as ‘Envimat-MRIO’ and ‘Eurostat-MRIO’,
 414 respectively. For the Envimat-MRIO version, refinements refer mainly to
 415 global averages, although EU values are also employed for some products.
 416 Conversely, country-specific coefficients are not corrected. For the

417 Eurostat-MRIO version, EU averages are mostly utilised, except for
418 minerals and fossil fuels, for which world averages are used. Both
419 corrections are based on values from Exiobase for 2007, and therefore it
420 is assumed that variations between countries within a particular year are
421 not greatly affected by price changes.

422 In addition, RME of imports using original versions of Envimat and
423 Eurostat are presented. The calculation is straightforward: imports from
424 customs statistics in CN eight-digit resolution in mass (Envimat) or mixed
425 units (Eurostat) are appropriately converted using correspondence tables
426 and multiplied by a set of RME coefficients.

427

428 **4. Results & Discussion**

429 In this section, we first present results for countries with the lowest and
430 highest domestic (vs. foreign) extraction, and their shares by product
431 group and by type of extraction. These results provide insights and rules
432 for types of extraction and justify the integration performed in the
433 Envimat-MRIO and Eurostat-MRIO models for some products and
434 countries.

435

436 4.1 Raw material flows in international supply chains

437 Tables 1 and 2 list exporting countries with the lowest and the highest
438 percentage domestic extraction, respectively, per euro imported to Finland
439 in 2007 (aggregated regions excluded). As Table 1 shows, small countries
440 with high population/GDP density tend to have low domestic extraction in
441 their exports. On the other hand, countries endowed with significant
442 amounts of natural resources (usually also large in area and population

443 size) show high domestic extraction. An interesting exception is Denmark,
444 for which a high score was obtained. This score is better explained by
445 Figure 1, in which percentage domestic extraction in RME and country
446 falls into broad groups of raw materials (biomass, metals, fossil fuels and
447 other minerals). The dot size indicates RME by country in absolute values
448 for 2007. The x-axis follows the Exiobase ordering of countries, with the
449 EU countries displayed from left to centre and other economies to the
450 right. It can be seen that the high domestic extraction of Denmark is due
451 to other mineral products exported to Finland, broken or crushed stones
452 and chalk mainly, as reflected in publicly available custom statistics.
453 Overall, Figure 1 informs modellers about when to use LCA based on
454 national data or MRIO combined models in RME estimation. It can be
455 observed that, in general, EU countries have low domestic extraction of
456 metals and fossil fuels in their exports (with the exception of Sweden for
457 metals and Estonia for fossil fuels). Therefore, in these cases, modelling
458 RME via LCA would involve an extra degree of complexity, particularly
459 for some key trade partners such as Germany and Belgium. In contrast, for
460 other products, most of the raw materials come from the direct partner. In
461 addition to Sweden and Estonia, this is the case for Russia for fossil fuels,
462 for China, India and Spain for other minerals and for Brazil for biomass
463 embodied in agricultural and forestry products. Therefore, it could be
464 argued that, for these countries, performing a LCA based on national data
465 would potentially improve RME estimates with less effort than in previous
466 examples.

467

468 **Tables 1 and 2.**

469 **Figure 1.**

470

471 Table 3 depicts the percentage of domestic extraction by industry
472 embodied in imports. It can be seen that extractive sectors (agriculture,
473 forestry and mining), along with electricity and food production, show
474 high domestic extraction per euro imported in direct partner countries. The
475 relative importance of the extractive sector means that, overall, almost
476 73% of all raw materials embedded in Finnish imports in 2007 were
477 extracted from the environment of direct trade partners. Regarding
478 manufacturing, there are a wide range of domestic extraction forms,
479 although most sectors have an approximately equal share. Accordingly, if
480 only sectors C1 to C10 are considered, total DE in direct partners drops to
481 53%. In Figure 2, the percentage of domestic extraction in RME by
482 industry is plotted by raw material type. As can be seen from the diagram,
483 the domestic share of metals seems lowest for most products (between 8%
484 and 42%), while other minerals and biomass show a wider dispersion of
485 shares across products. Moreover, considering their volume and low
486 domestic extraction share, LCA modelling of products belonging to C7
487 (Basic metals and fabricated metal products) seems particularly
488 problematic.

489 Both pieces of information, on industry and country of origin, help
490 modellers in identifying possible sources of bias and also open the way for
491 improvement of MFA indicators, since it is clear that for large countries
492 with highly developed extractive profiles, the LCA-based approach has
493 the potential to refine the calculations. Furthermore, similar procedures
494 can be applied for simple supply chains, i.e. for those trading schemes

495 involving a reduced number of countries and industries. To that end, our
496 combined approach could be complemented with existing techniques,
497 such as production layer decomposition (see e.g. Giljum et al. (2016),
498 where the underlying logic is equivalent to that applied in this study) or
499 structural path analysis (see e.g. Lenzen, 2007), which could bring more
500 detail, regarding the importing countries and sectors across the whole
501 supply chains. On the other hand, the existence of highly complex supply
502 chains and process data constraints at country level for many products
503 exemplifies the limitations of process-based approaches and the
504 importance of integrating precision from LCA with global coverage from
505 MRIO, as described in the following section.

506

507 **Tables 3 and 4.**

508 **Figure 2.**

509

510 4.2 Country-specific information from the Exiobase MRIO model
511 in LCA-based approaches

512 In Figure 3, the original Envimat and Eurostat models are compared
513 with the versions extended with MRIO information. Direct imports
514 obtained from official statistics are also shown, as a dashed line. Total
515 direct imports were 57.1 Mt, while raw materials embedded in Finnish
516 imports amounted to 233.9 Mt (original Envimat), 268.7 Mt (Envimat-
517 MRIO), 144.2 Mt (original Eurostat) or 212.9 Mt (Eurostat-MRIO). The
518 significant differences between direct imports and RME estimates support
519 the idea that the latter concept is important, particularly for metals and
520 other minerals and, to a lesser extent, for fossil fuels. However, it is worth

521 mentioning that these global estimates sometimes mask other differences
522 that are less evident in aggregations. Moreover, there are marked
523 differences in RME figures depending on the method chosen, calling for a
524 deeper understanding on this matter, as mentioned in previous studies.
525 Tables showing most important differences between coefficients by
526 product group and country (see Supporting Information) were used for
527 describing the deviations in the following.

528

529 **Figure 3.**

530

531 In Figure 4, the comparison between original Envimat and Envimat-
532 MRIO is disaggregated for broad groups of products. It can be seen that
533 the two most important deviations at this level arise in metals and other
534 minerals. For metals, the almost non-existent difference between both
535 models shown in Figure 3 is revealed to be an offset effect: Envimat-
536 MRIO tends to increase material embedded in extractive products but
537 decrease that in metal products (Sector C7 in Figure 4). In Table 4, changes
538 in multipliers and the most important deviations for metals and other
539 minerals between the two model versions are shown. As can be seen,
540 increases in extractive products occur mainly in ‘Iron ores’ and ‘Copper
541 ores and concentrates’, whose coefficients notably increase in Envimat-
542 MRIO. Regarding iron ores, 97.7% of exports to Finland in 2010 were
543 from its neighbour Sweden. In the Supporting Information, the ratio of DE
544 per euro imported is shown for all countries and products (based on 2007
545 data). For iron ores from Sweden, 99% of raw materials required were
546 extracted from the Swedish environment and in that case process-based

547 estimation based on national figures would clearly be advisable. In the
548 case of copper, 49.2% of imports to Finland in 2010 came from Peru and
549 Chile, both categorised in Exiobase as ‘Rest of America and Caribbean’.
550 In this case too, almost 100% of materials were extracted domestically and
551 a LCA-based estimation considering Peruvian and Chilean technological
552 particularities would be desirable. The reason why the increases described
553 are offset at the macro level can be seen in Table 4. Because Envimat has
554 higher resolution, refinements of metal products in Table 4 were
555 performed using multipliers for three corresponding Exiobase products:
556 ‘Basic iron and steel and of ferro-alloys and first products thereof’, ‘Other
557 non-ferrous metal products’ and ‘Copper products’. In the Supporting
558 Information, it can be seen that percentages of metal DE for these three
559 products can vary significantly between countries. Focusing on key
560 Finnish trade partners in Table 4, for basic iron and steel products
561 Exiobase delivers 1% metal DE for German products, whereas it increases
562 to 47% for Swedish products. For copper and other non-ferrous metal
563 products, the percentage of metal DE embedded varies from almost 0%
564 for Spanish nickel products to almost 100% for Russian, Brazilian and
565 ‘Rest of Africa’ products. Considering that Spanish nickel mining and the
566 content of iron from German mines in basic iron and steel products are
567 both negligible, performing a process-based estimation would involve
568 substantial extra effort. Nevertheless, since their mineral intermediate
569 inputs coming from third countries can be followed using MRIO, the
570 method developed in this study could be utilised. In contrast, for copper
571 products coming from Russia, nickel products from Brazil and cobalt
572 products from the Democratic Republic of Congo (which is the other main

573 non-ferrous metal product coming from Africa), LCA-based data
574 estimation would be desirable. For Swedish iron and steel products, an
575 intermediate solution might be best.

576 For other minerals, it is revealed in Figure 4 that the increases in the
577 MRIO version occur mainly in the sectors mining and quarrying and C5
578 (Other chemical products). The rise in mining is because of ‘Clays and
579 kaolin’ products, mostly coming from India and the United Kingdom.
580 Consulting publicly available disaggregated customs data reveals that the
581 reason for the high score for India is from exports to Finland of ‘Bentonite’
582 (6.1 million kg imported in 2010). Including MRIO information greatly
583 increases the original coefficient for clays and kaolin for India (see Table
584 4), explained by existing high analogous differences between world
585 average and Indian values using Exiobase. This enormous difference could
586 be an error in Exiobase original data and might be related to the difficulties
587 in data gathering in India reported by the database’s developers (Giljum et
588 al., 2014b). However, it serves to illustrate how the existence of outliers
589 or unexpectedly high values can cause errors in the refined method
590 proposed in this study. In addition, Finland imports a high volume of
591 kaolin (927.6 million kg in 2010), as an input for the paper industry, from
592 three countries: UK (36%), US (33%) and Brazil (29%). The Envimat
593 original coefficient for clays and kaolin increases to 37.6 kg/kg for the UK
594 in Envimat-MRIO, while it increases only slightly or decreases for the
595 other two key trade partners, which leads to a significant RME allocation
596 to imports from the UK (-12140.4 Mkg bias). These examples exemplify
597 the two possible causes of re-allocation in the method proposed: high
598 multiplier dissimilarities between original and MRIO versions (India), and

599 less significant variations for substantial import flows (UK). Lastly, most
600 notable deviations in other chemical products occur in imports from
601 Norway of ‘Other inorganic basic chemicals’ and ‘Peptones, modelling
602 pastes, activated carbon, finishing agents, pickling preparations etc.’ (see
603 Table 4). The increase in both cases is caused by the differences between
604 multipliers in Exiobase for ‘Chemicals not elsewhere classified (nec.)’ and
605 salt DE comparing Norway and world-average values. For other inorganic
606 basic chemicals, customs data show that two products are mainly
607 responsible for this increase: ‘Calcium carbonate’ and ‘Sodium hydroxide
608 (caustic soda)’. Total imports of calcium carbonate to Finland in 2010
609 were 674.9 million kg, of which 99.3% came from Norway, whereas
610 imports of caustic soda were 149.7 million kg, of which 19.8% came from
611 Norway. Although alternative routes exist, calcium carbonate is mainly
612 produced from lime and carbon dioxide (European Commission, 2007).
613 Therefore including MRIO country-specific information could bias
614 allocation of salt DE, rather than refining outcomes. In contrast, caustic
615 soda is mostly produced by electrolysis from sodium chloride solution
616 with mercury, and it is clear that importing caustic soda implies significant
617 amounts of salt embedded, which is also one of the main contributors to
618 the overall environmental burden of the production process (Hong et al.,
619 2014). Similar considerations apply to the second group of products,
620 which mainly refer to finishing agents for the paper industry imported
621 from Norway.

622

623 **Figure 4.**624 **Table 4.**

625

626 For the Eurostat models, including MRIO information from Exiobase
627 also caused significant deviations in extractive and metal manufacturing
628 products. However, in this case, both estimates were higher in the
629 Eurostat-MRIO model. This situation is mainly explained by the
630 significant growth taking place in metal embedded in imports of ‘Other
631 non-ferrous metal products’ as can be observed in Table 5, which shows
632 the main deviations between original Eurostat and Eurostat-MRIO. This
633 happens because the correction is based on an EU average, whereas for
634 Envimat-MRIO a global average is used. This outcome shows that average
635 EU RME embedded per kg imported are significantly lower than global
636 and African values. However, two related issues need to be considered: i)
637 this refers to an ‘Other’ products category, where many diverse products
638 are included, and ii) it belongs to a ‘Rest of’ MRIO category. Other notable
639 increases in metal products occur in ‘Basic iron and steel products’ from
640 Russia and other partners. Thus, in comparison with the outcomes from
641 Envimat-MRIO, these results suggest that, if global values are used
642 (Envimat), RME tend to be overestimated, whereas if EU averages are
643 employed (Eurostat), they seem to be underestimated.

644 For other minerals, more than 50% of the higher quantities obtained
645 with Eurostat-MRIO compared with the original Eurostat model are due
646 to ‘Ceramic products and other non-metallic mineral products’ coming
647 from the United States (C6: Other non-metallic mineral products) in
648 Figure 4). According to customs statistics, this is mostly due to ‘Carbon
649 fibres and articles of carbon fibres, for non-electrical purposes’. However,
650 the refinement was performed considering multiplier dissimilarities for

651 disaggregated non-metallic DE of Exiobase's 'Other non-metallic mineral
652 products', in particular differences in DE of 'Building stones', which is
653 three orders of magnitude above the average for US multipliers according
654 to Exiobase. Therefore, it seems clear that product aggregation into a
655 single 'Other non-metallic mineral products' category, in combination
656 with the above-average building stones intensity in US multipliers, cause
657 inaccurate re-allocation of raw materials in Eurostat-MRIO. A high
658 domestic share of raw material extraction of other minerals for this product
659 in the US (around 80%, see Supporting Information) suggests that a
660 process-based estimation considering domestic particularities would be a
661 better choice.

662 In biomass flows, deviations are caused by increases in biomass
663 embedded in 'Animal and vegetable oils and fats', along with 'Fruit, nuts,
664 beverage and spice crops' (see Table 5). The increase for the former refers
665 mainly to imported palm crude oil from Malaysia, which comprised about
666 385 million kg in 2010, to which an extra load of raw material is allocated
667 based on multiplier differences for Exiobase's 'Products of vegetable oils
668 and fats'. However, since agricultural products typically involve shorter
669 supply chains (98% of biomass is domestically harvested for this product
670 in the Rest of Asia and Pacific region, see Supporting Information),
671 process data could be used to cross-check this outcome. A similar situation
672 arises for fruits, nuts etc. from Brazil and other Latin American countries.

673 Finally, for fossil fuels, the increase observed is mainly because
674 including MRIO information raises RME embedded for products coming
675 from Russia, in particular for 'Petroleum oils and oils obtained from
676 bituminous minerals' (explaining the growth observed in mining and

677 quarrying in Figure 5), and ‘Other basic chemicals’ and ‘Fertilizers and
678 nitrogen compounds’ (explaining the increase in other chemical products
679 in Figure 5). Therefore, in this case, the correction proposed increases the
680 raw material requirements of more fossil fuel-intensive Russian exports of
681 the petrochemical industry.

682

683 **Figure 5.**

684 **Table 5.**

685

686 **5. Conclusions**

687 This study examined the theoretical connection between life cycle
688 assessment (LCA) and input-output (IO) methods. Although there has
689 been more than a decade of key development and application of these
690 tools, there is still a need to provide simple and effective rules for
691 improving the estimation of raw material equivalents (RME) embedded
692 in imports. In particular, this study examined domestic (vs. foreign)
693 extraction contents for countries and products, developed in order to help
694 modellers overcome limitations imposed by the use of averages in LCA-
695 based approaches. One of the conclusions that can be drawn is that
696 domestic process-based data are preferable for primary mining and
697 biomass products and for manufacturing products, which rely heavily on
698 natural resources from the domestic environments of direct trade
699 partners. This involves mixing physical and monetary flows and
700 coupling bottom-up with top-down methods. It also requires access to
701 detailed custom and LCA data for key trade partners and the

702 development of correspondences between product, country and material
703 classifications.

704 For products involved in longer trade chains, or for which domestic
705 LCA data are not available, a refined method providing a systematic way
706 of analysing the embodied contents of RME based on multi-regional IO
707 (MRIO) was developed. The results suggest that comparisons between
708 original (based on regional averages) and MRIO-refined models could
709 give valuable insights into iteratively correcting possible errors or biases.
710 However, there are also methodological limitations, due to different
711 products or raw material classifications and aggregation into
712 miscellaneous products or material groups (such as ‘Other’, ‘nec.’ or
713 ‘Rest of’ categories) that need to be handled carefully when applying our
714 method. Moreover, the products and regions that serve as reference in
715 MRIO models need to be chosen with care and should be the closest in
716 coverage to the original process-based coefficient being split. Depending
717 on data and resource availability, our approach is equally applicable to
718 more distant tiers of the supply chain (e.g. trade partners of direct trade
719 partners) and can be combined with existing IO tools for assessing chain
720 length and complexity.

721 Our method may be applicable in the study of exports to any other
722 country and, since the multipliers used for corrections are of a very
723 general nature, they are applicable to other regions or product specific
724 studies. For this reason, basic data for the refinements are offered for all
725 countries (except Finland) in the Supporting Information. Similar
726 comparisons have previously been made between top-down and bottom-
727 up approaches for other environmental accounting tasks, e.g. for water

728 flows in Feng et al. (2011) and for ecological footprint in Weinzettel et
729 al. (2014). Thus the methodological developments presented here are
730 also of interest outside the material flow accounting community.
731 However, more work is needed to explain the differences between
732 current databases and models and to support future developments that
733 make use of the detailed product resolutions from LCA and the higher
734 coverage of supply chains in MRIO models.

735

736 **Acknowledgments**

737 We are grateful to the anonymous reviewer for helpful comments.
738 Pablo Piñero acknowledges the University of Oulu Graduate School and
739 the AURORA Doctoral Programme for financial support for this
740 research. The authors also thank Tuomas Mattila and Mari Heikkinen for
741 their work in improving the Envimat model.

742

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Table 1. Domestic extraction by the ten lowest countries

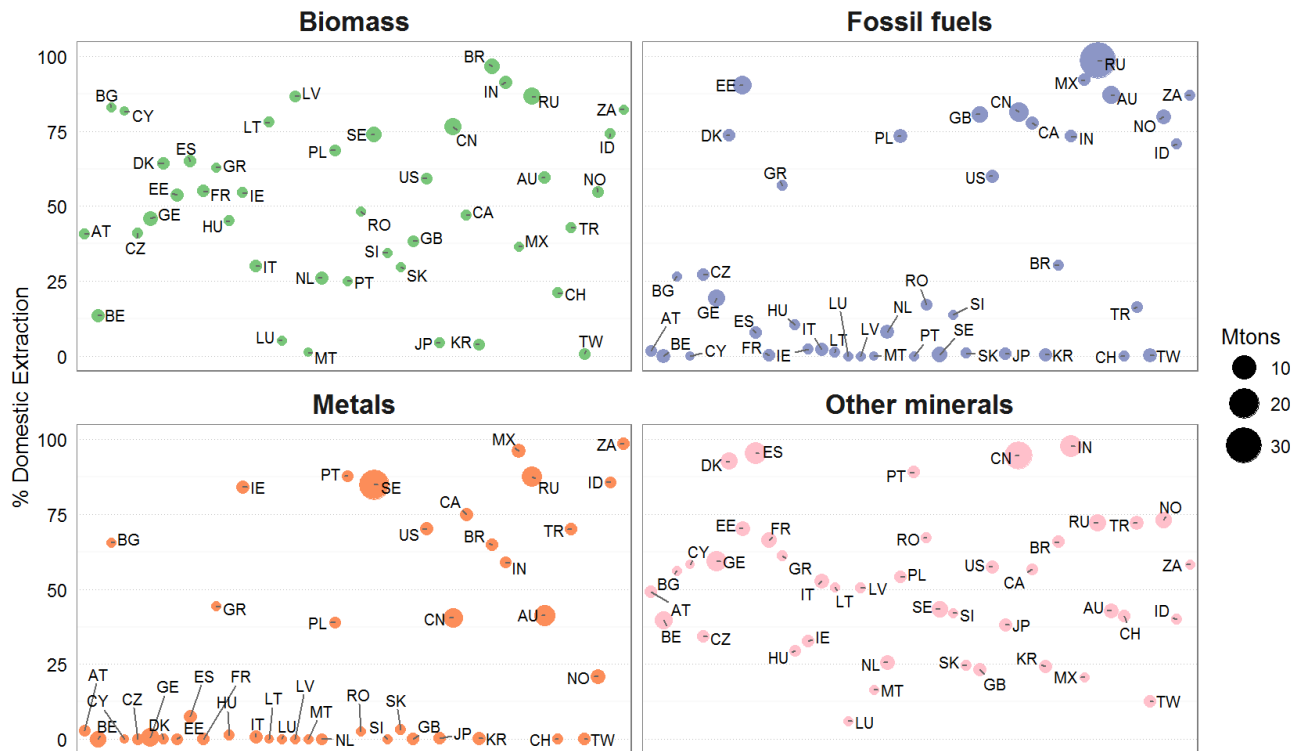
Code	Country	Domestic (%)	Other (%)
LU	Luxembourg	3	97
TW	Taiwan	3	97
MT	Malta	8	92
KR	South Korea	8	92
SK	Slovak Republic	13	87
JP	Japan	15	85
NL	Netherlands	19	81
BE	Belgium	19	81
HU	Hungary	22	78
SI	Slovenia	22	78

Code = country code used in Exiobase. **Country** = country name used in Exiobase. **Domestic** = % of Domestic extraction of exports to Finland. **Other** = % of extraction in other countries of exports to Finland.

Table 2. Domestic extraction by the ten highest countries

Code	Country	Domestic (%)	Other (%)
RU	Russian Federation	95	5
IN	India	94	6
ZA	South Africa	93	7
MX	Mexico	90	10
DK	Denmark	84	16
BR	Brazil	83	17
ES	Spain	83	17
CN	China	82	18
PT	Portugal	79	21
EE	Estonia	77	23

Code = country code used in Exiobase. **Country** = country name used in Exiobase. **Domestic** = % of Domestic extraction of exports to Finland. **Other** = % of extraction in other countries of exports to Finland.



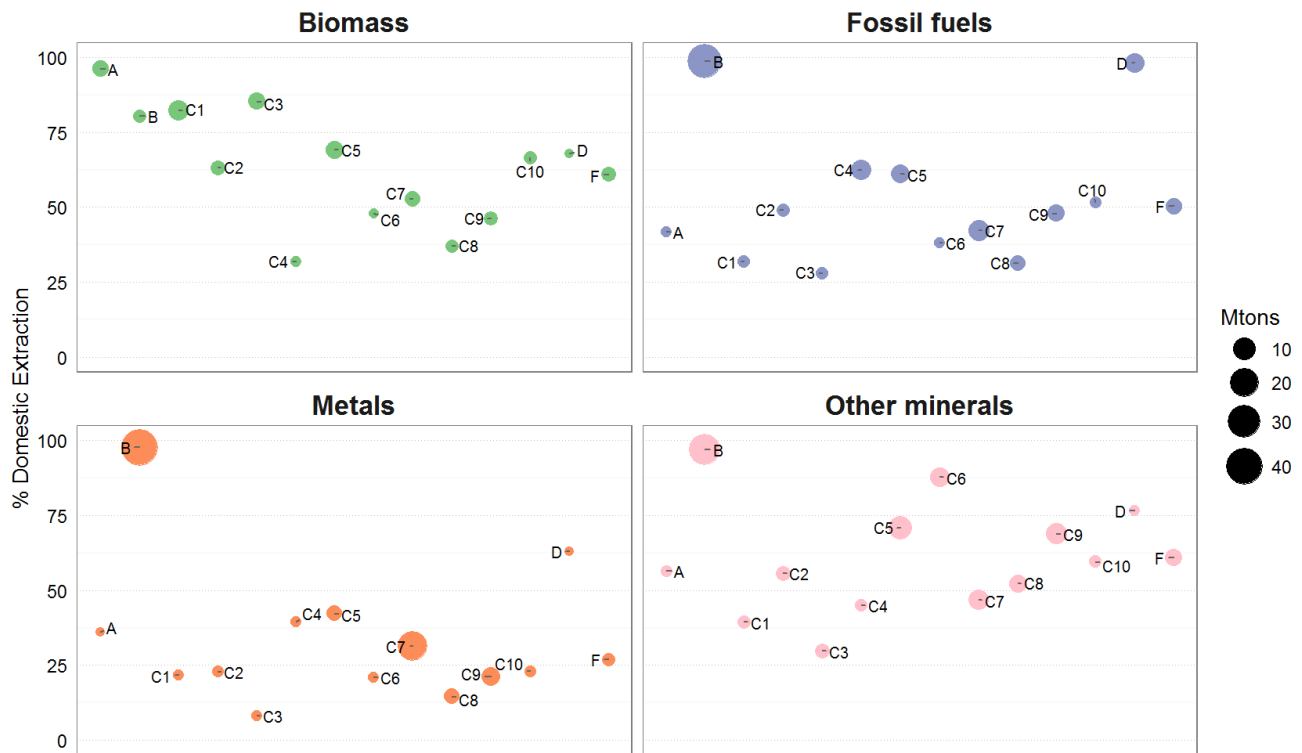
European Union Countries (left to centre): AT = Austria, BE = Belgium, BG = Bulgaria, CY = Cyprus, CZ = Czech Republic, GE = Germany, DK = Denmark, EE = Estonia, ES = Spain, FR = France, GR = Greece, HU = Hungary, IE = Ireland, IT = Italy, LT = Lithuania, LU = Luxembourg, LV = Latvia, MT = Malta, NL = Netherlands, PL = Poland, PT = Portugal, RO = Romania, SE = Sweden, SI = Slovenia, SK = Slovak Republic, GB = United Kingdom. Other countries (right): US = United States, JP = Japan, CN = China, CA = Canada, KR = South Korea, BR = Brazil, IN = India, MX = Mexico, RU = Russian Federation, AU = Australia, CH = Switzerland, TR = Turkey, TW = Taiwan, NO = Norway, ID = Indonesia, ZA = South Africa. Mtons denotes million tons of RME of imports by each raw material.

Figure 1. Percentage domestic extraction per euro imported to Finland in 2007, by country and raw material equivalents (RME) of imports.

Table 3. Percentage domestic extraction by product group

Code	Product group	Domestic (%)	Other (%)
A	Products of agriculture, forestry and fishing	87	13
B	Mining and quarrying	98	2
C1	Food, beverages and tobacco products	71	29
C2	Textile, clothing and leather products	54	46
C3	Wood, pulp and paper products	58	42
C4	Petroleum refining products	59	41
C5	Other chemical products	66	34
C6	Other non-metallic mineral products	82	18
C7	Basic metals and fabricated metal products	37	63
C8	Electrical and electronic products	50	50
C9	Machinery and transport equipment	37	63
C10	Other manufacturing products	55	45
D	Electricity and water supply	96	4
F	Services	54	46

Code = product group code developed for presenting results. **Product group** = product group name developed for presenting results. **Domestic** = % of domestic extraction of exports to Finland. **Other** = % of extraction in other countries of exports to Finland.



A = Products of agriculture, forestry and fishing, B = Mining and quarrying, C1 = Food, beverages and tobacco products, C2 = Textile, clothing and leather products, C3 = Wood, pulp and paper products, C4 = Petroleum refining products, C5 = Other chemical products, C6 = Other non-metallic mineral products, C7 = Basic metals and fabricated metal products, C8 = Electrical and electronic products, C9 = Machinery and transport equipment, C10 = Other manufacturing products, D = Electricity and water supply, F = Services. Mtons denotes million tons of RME of imports by each raw material.

Figure 2. Percentage domestic extraction per euro imported to Finland in 2007, by sector and raw material equivalents (RME) of imports.

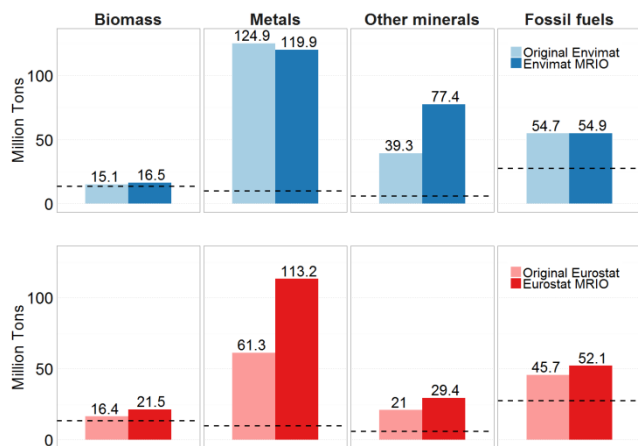
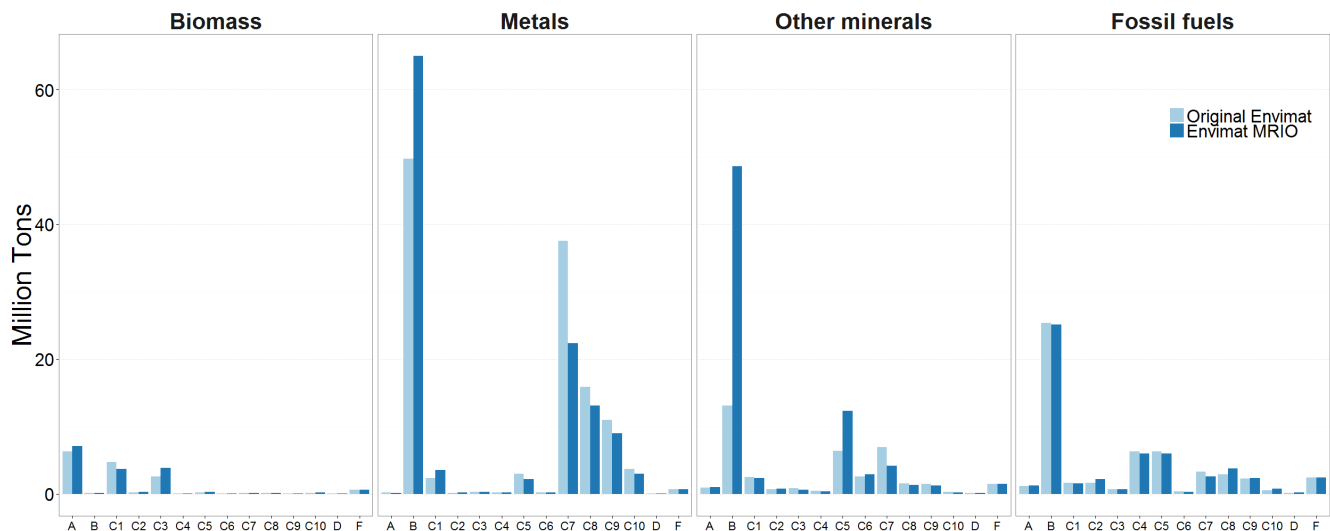


Figure 3. Raw material equivalents (RME) of imports to Finland in 2010, by material for original and multi-regional input-output (MRIO) refined models.



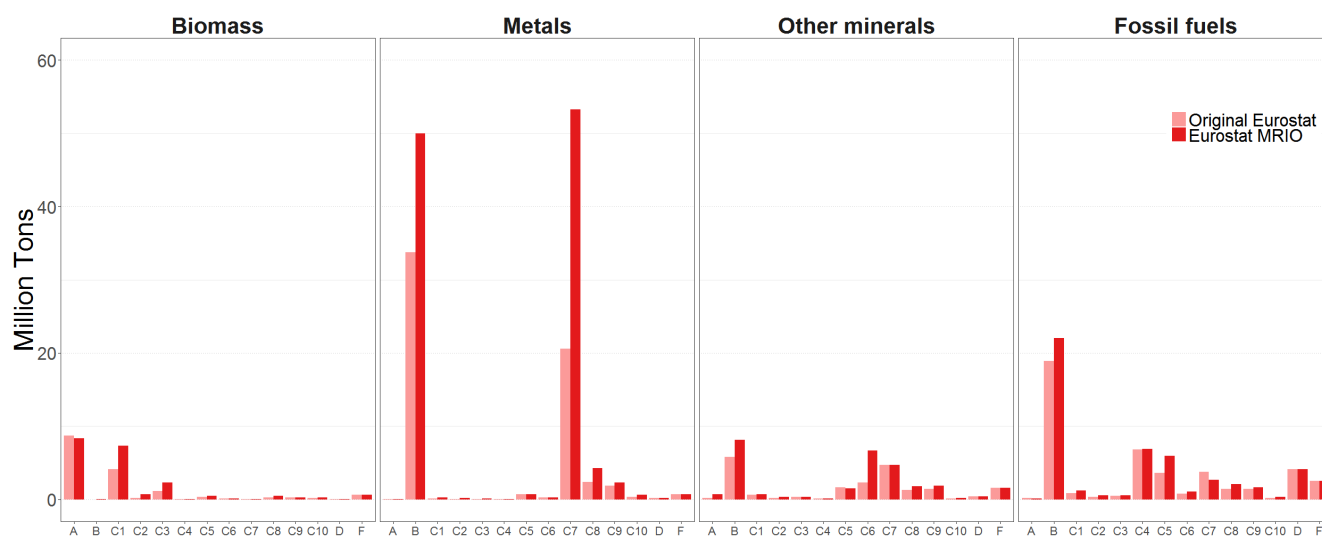
A = Products of agriculture, forestry and fishing, B = Mining and quarrying, C1 = Food, beverages and tobacco products, C2 = Textile, clothing and leather products, C3 = Wood, pulp and paper products, C4 = Petroleum refining products, C5 = Other chemical products, C6 = Other non-metallic mineral products, C7 = Basic metals and fabricated metal products, C8 = Electrical and electronic products, C9 = Machinery and transport equipment, C10 = Other manufacturing products, D = Electricity and water supply, F = Services. Mtons denotes million tons of RME of imports by each raw material.

Figure 4. Raw material equivalents (RME) of imports to Finland in 2010, by material and product groups for original Envimat and Envimat-multi-regional input-output (MRIO) models.

Table 4. Changes in multipliers and the most important deviations in metals and other minerals comparing original Envimat and Envimat-multi-regional input-output (MRIO) models

Product	Imports (Mkg)	Original Envimat (kg/kg)	Main partner (kg/kg)	Main partner bias (Mkg)	Total bias (Mkg)
Iron ores	3053	1.7	5.4 (SE)	-11007	-11301
Copper ores and concentrates	458	44.1	107.6 (WL)	-14307	-7378
Primary materials of iron and steel	1089	6.4	1.4 (SE)	4726	5154
Nickel, unwrought semi-finished products of nickel or nickel alloys	32	125.4	28.6 (ES)	1669	3027
Nickel mattes, nickel oxide sinters and other intermediate products of nickel metallurgy	34	125.4	47.3 (BR)	2156	1921
Flat rolled products of steel	548	4.9	1.2 (SE)	524	1478
Tubes, pipes, hollow profiles and related fittings, of steel	535	5.1	2.2 (GE)	746	1459
Other non-ferrous metals and articles thereof; cermet; ash and residues, etc.	33	110.9	164.7 (WF)	-1330	-1407
Semi-finished products of copper or copper alloys	45	108.8	56.1 (RU)	415	1399
Clays and kaolin	997	4.5	7303.4 (IN)	-18054	-30150
Other inorganic basic chemicals	1876	1.1	4.6 (NO)	-2874	-3846
Peptones, modelling pastes, activated carbon, finishing agents, pickling preparations etc.	282	2.7	13.2 (NO)	-2396	-2487

Product = product name used in Envimat. **Imports** = total imports to Finland in 2010, in million kg. **Original Envimat** = coefficient kg of material RME per kg imported for the broad raw material type under consideration. **Main partner** = coefficient kg of material RME per kg imported for the main deviations by country: SE = Sweden, WL = Rest of America, ES = Spain, BR = Brazil, GE = Germany, WF = Rest of Africa, RU = Russia, IN = India, NO = Norway. **Main partner bias** = most important deviation between partners, in million kg. **Total bias** = total bias by product, in million kg. Sign in bias denotes under- or over-estimation.



A = Products of agriculture, forestry and fishing, B = Mining and quarrying, C1 = Food, beverages and tobacco products, C2 = Textile, clothing and leather products, C3 = Wood, pulp and paper products, C4 = Petroleum refining products, C5 = Other chemical products, C6 = Other non-metallic mineral products, C7 = Basic metals and fabricated metal products, C8 = Electrical and electronic products, C9 = Machinery and transport equipment, C10 = Other manufacturing products, D = Electricity and water supply, F = Services. Mtons denotes million tons of RME of imports by each raw material.

Figure 5. Raw material equivalents (RME) of imports to Finland in 2010, by material and product groups for original Eurostat and Eurostat- multi-regional input-output (MRIO) models.

Table 5. Changes in multipliers and main deviations in biomass, metals, other minerals and fossil fuels comparing original Eurostat and Eurostat-multi-regional input-output (MRIO) models

Product	Imports (Mkg or Meuro)	Original Eurostat (kg/kg or kg/euro)	Main partner (kg/kg or kg/euro)	Main partner bias (Mkg)	Total bias (Mkg)
Animal and vegetable oils and fats (e)	416	2.0	7.7 (WA)	-1390	-1496
Fruit, nuts, beverage and spice crops (m)	301	1.0	6.6 (WL)	-477	-1283
Iron ores (m)	3053	1.2	3.9 (SE)	-7951	-8164
Copper ores and concentrates (m)	458	34.8	78.1 (WL)	-9751	-4427
Other non-ferrous metal products (m)	31	189.8	1162.7 (WF)	-24067	-28099
Basic iron and steel products (m)	3354	2.2	6.4 (RU)	-1348	-2474
Ceramic products and other non-metallic mineral products (e)	338	5.1	836.6 (US)	-4109	-4294
Petroleum oils and oils obtained from bituminous minerals (m)	11212	1.1	1.4 (RU)	-3174	-2888
Other basic chemicals (e)	2341	1.0	4.2 (RU)	-987	-1349
Fertilizers and nitrogen compounds (e)	228	1.5	6.7 (RU)	-862	-912

Product = product name used in Eurostat RME tool, (e) denotes economic flow and (m) mass flow. **Imports** = total imports to Finland in year 2010 in million kg or million euros. **Original Eurostat** = coefficient kg of material RME per kg or euro imported for the broad raw material type under consideration. **Main partner** = coefficient kg of material RME per kg or euro imported for the main deviations by country: WA = Rest of Asia and Pacific, WL = Rest of America, SE = Sweden, WF = Rest of Africa, RU = Russia, US = United States. **Main partner bias** = most important deviation among partners in million kg. **Total bias** = total bias by product in million kg. Sign in bias denotes under- or over-estimation.