

FABIO — The Construction of the Food and Agriculture Biomass Input–Output Model

Martin Bruckner,^{*,†} Richard Wood,[‡] Daniel Moran,[‡] Nikolas Kuschnig,[†] Hanspeter
Wieland,[†] Victor Maus,^{†,¶} and Jan Börner^{§,||}

[†]*Institute for Ecological Economics, Vienna University of Economics and Business, 1020
Vienna, Austria*

[‡]*Industrial Ecology Programme, NTNU Trondheim, 7491 Trondheim, Norway*

[¶]*Ecosystems Services and Management, International Institute for Applied Systems
Analysis, 2361 Laxenburg, Austria*

[§]*Institute for Food and Resource Economics, University of Bonn, 53115 Bonn, Germany*

^{||}*Center for Development Research, University of Bonn, 53113 Bonn, Germany*

E-mail: martin.bruckner@wu.ac.at

Abstract

Harvested biomass is linked to final consumption by networks of processes and actors that convert and distribute food and non-food goods. Achieving a sustainable resource metabolism of the economy is an overarching challenge which manifests itself in a number of the UN Sustainable Development Goals. Modeling the physical dimensions of biomass conversion and distribution networks is essential to understanding the characteristics, drivers and dynamics of the socio-economic biomass metabolism. In this paper, we present the Food and Agriculture Biomass Input–Output model (FABIO), a set of multi-regional supply, use and input–output tables in physical units, that document the complex flows of agricultural and food products in the global economy. The

11 model assembles FAOSTAT statistics reporting crop production, trade, and utilization
12 in physical units, supplemented by data on technical and metabolic conversion efficien-
13 cies, into a consistent, balanced, input–output framework. FABIO covers 191 countries
14 and 130 agriculture, food and forestry products from 1986 to 2013. The physical supply-
15 use tables offered by FABIO provide a comprehensive, transparent and flexible structure
16 for organizing data representing flows of materials within metabolic networks. They
17 allow tracing biomass flows and embodied environmental pressures along global supply
18 chains at an unprecedented level of product and country detail and can help to answer
19 a range of questions regarding environment, agriculture, and trade. Here we apply
20 FABIO to the case of cropland footprints and show the evolution of consumption-based
21 cropland demand in China, the EU, and the US for plant-based and livestock-based
22 food and non-food products.

23 **Introduction**

24 In the context of the Paris Agreement, the UN Sustainable Development Goals (SDGs) and
25 related resource efficiency and circular economy agendas, the increasing displacement of en-
26 vironmental impacts from primary production through global trade has become a prominent
27 issue in international policy debates.¹ Traceability tools are needed to support both stake-
28 holders and policy makers in monitoring and governing global trade-flows and their undesired
29 impacts.²

30 Traceability tools should provide results, which are trustworthy, comprehensive, and
31 detailed enough to be able to guide policy response. We argue in this paper that current
32 global supply chain databases, in the form of multi-region input–output (MRIO) models,
33 are often inadequate a) to account for the specific environmental impacts associated to a
34 large range of different agricultural products, and b) to capture the physical basis of the
35 food system. Farming, grazing, and forestry activities are central in many sustainability
36 challenges across health, water, energy, and biodiversity. Gaining an accurate picture of the

37 physical metabolism of these goods through the global economy, i.e. the networks of processes
38 and actors that convert and distribute food and non-food goods (metabolic networks), is
39 arguably a prerequisite for addressing biomass goods in the context of sustainability goals.

40 Material flow analysis (MFA)³ has developed into an important framework to study
41 metabolic networks and support the governance of societal transitions. MFA aims at quan-
42 tifying the biophysical dimension of socio-economic activities⁴ and identifying options to
43 reduce their negative environmental impacts, such as global warming.⁵ Physical supply-use
44 tables (PSUT) provide a comprehensive, transparent and flexible structure for organizing
45 data on material flows within metabolic networks. The groundwork for PSUTs was laid by
46 Kneese et al.⁶ and their application of the material balance approach to economic analysis.
47 In the meantime, pilot PSUTs and physical input–output tables (PIOT) have been presented
48 for a number of countries and regions, including the European Union, Austria, Germany,
49 Finland, Italy, the Netherlands, Japan, and China.^{7–10} PSUTs are the basis for compiling
50 PIOTs and provide a detailed description of the physical flows between the natural and the
51 socio-economic system.

52 Bio-based inputs, such as crops and timber, are supplied by the natural environment
53 and mostly introduced into the economic system by the agriculture and forestry sectors.
54 Processing industries, such as paper and food industries, use and transform these inputs
55 of natural resources to generate products for intermediate or final consumption. Residuals
56 are generated by both, industries and households, and are either treated further within the
57 economy or released back to the environment.

58 In recent years, environmentally-extended multi-regional input–output (EE-MRIO) ap-
59 proaches have been widely used to study physical flows of materials induced by production
60 and consumption activities in the global economy. Despite the significant progress,¹¹ the ro-
61 bustness of MRIO-based calculations of global physical biomass flows has been questioned.
62 Three main problematic areas have been identified.^{12–15} First, the monetary structure of the
63 economy does not always represent the quantities of physical product flows correctly. Due

64 to price variations of product flows between different customers, the assumption of propor-
65 tionality between monetary and physical flows can lead to over- or underestimations.^{16,17}
66 Second, the limited detail of monetary input–output tables results in a grouping of products
67 with differing material and environmental properties and use structures into homogeneous
68 sectors.¹³ Third, there exist mismatches between agricultural and forestry statistics reported
69 in physical units on the one hand, and macro-economic production statistics in monetary
70 units on the other hand, for example due to different system boundaries.¹⁸

71 In order to reduce uncertainties arising from the above mentioned limitations of input–
72 output models, a number of studies have suggested moving from sector-level economic data
73 towards a more detailed physical data basis. For example, Ewing et al.¹⁹ developed physi-
74 cal use accounts for agricultural products which model the first stage of agricultural supply
75 chains in physical instead of monetary units and allocate crops to the first users reflecting
76 detailed international trade and type of the first use provided by FAOSTAT. This approach
77 was further developed by Weinzettel and Wood²⁰ and applied to calculate footprints for bio-
78 diversity,²¹ scarce water use,²² and net primary production.²³ A similar approach is applied
79 by Croft et al.²⁴, but going one step further for selected processed products such as vegetable
80 oils. Liang et al.¹⁰ presented a 30-sector, mixed-unit PIOT for China to investigate material
81 flows by aggregated product groups.

82 All these hybrid IO models rely on monetary IO data to track biomass products from the
83 first (or second) use stage to the final consumers. A growing number of researchers worldwide,
84 however, argue that describing the structure of material conversion and distribution networks
85 in physical terms, i.e., by means of detailed PSUTs, provides a beneficial basis for the
86 analysis of material flows in metabolic networks.^{25,26} While Kastner et al.²⁷ developed a
87 trade accounting approach that tracks crops embodied in international trade purely based
88 on physical data, they convert all products into primary crop equivalents. The same is
89 the case for the Trase.earth project,²⁸ which does not use an input–output framework but
90 instead is collecting detailed data on production and trade of critical commodities, such as

91 soy and palm oil, pursuing a bottom-up approach to providing detail on key countries and
92 commodities. A system of physical supply-use or input–output tables instead transparently
93 describes all intermediate uses and conversion processes, thereby retaining flow information
94 at each step of the supply chain.

95 In this paper, we present the Food and Agriculture Biomass Input Output model (FABIO),
96 a global set of trade-linked PSUTs and PIOTs capturing detailed supply chain information
97 for 130 raw and processed agricultural and forestry products covering 191 countries and one
98 rest of world region from 1986 to 2013. By using agricultural statistics from FAOSTAT, we
99 obtain a considerably higher level of product and process detail compared to any available
100 MRIO database and, moreover, cover supply chains in physical units, thereby alleviating the
101 uncertainties introduced by the homogeneity, proportionality and consistency assumptions
102 applied in IO analysis.

103 We demonstrate this physical MRIO model applying it to the case of the cropland foot-
104 print of China, the EU-28, and the US. We reveal differences in trends and composition of
105 cropland footprints and import shares over a period of nearly three decades, and highlight
106 the role of allocation when tracing physical flows along processing steps.

107 **Overview of the FABIO model**

108 Figure 1 illustrates the approach used to build FABIO. The procedure is described in detail in
109 the following sections. First, we give a detailed overview of all data sources used to construct
110 FABIO. In Section 3.2 we then describe how we deal with data gaps and inconsistencies. After
111 that we elucidate how supply and use tables are built based on the available data. Finally,
112 we show how national PSUTs are trade-linked and converted into a symmetric multi-regional
113 PIOT.

114 **Comparison with other MRIOs**

115 The resulting FABIO database offers PSUTs and PIOTs with an unprecedented level of detail
116 for agriculture and food products. In most standard IO tables, such as those provided by
117 EUROSTAT, and also in the WIOD, ICIO, and Eora MRIO databases, these products are
118 represented using 1-10 aggregate categories, while FABIO features 127 distinct products (see
119 Table S.1). GTAP and EXIOBASE distinguish 21 and 27 agriculture and food products,
120 respectively. We note that Eora offers more detail for some countries, the UK representing an
121 extreme case with 80 agriculture and food products and 1022 products in total. Furthermore,
122 FABIO provides more detail than most other MRIOs also regarding country detail and time
123 coverage. Most importantly, it documents product flows in physical instead of monetary
124 units. However, other parts of the economy are not represented, which implies limitations
125 for the tracking of non-food commodities such as biofuels, wood, and fibers. These caveats
126 are further elaborated in the Discussion Section.

127 **Open science**

128 All data sets and R scripts are available to the research community under the GNU Gen-
129 eral Public License (GPL-v3) license via GitHub ([https://github.com/martinbruckner/](https://github.com/martinbruckner/fabio)
130 `fabio`) and the open science platform Zenodo,²⁹ which is fully compliant with the FAIR guid-
131 ing principles³⁰ for the provision and management of open data in scientific research. We
132 hope that openness, transparency and sharing of code contributes to further advancements
133 and invite researchers to test and scrutinize our codes and results.

134 **Methods and data**

135 In this section, we explain which data sources were used and how they were processed to
136 build multi-regional PSUTs and PIOTs for agriculture, fish, forestry, and food products.

137 **Data sources**

138 Most of the data used for constructing the FABIO supply and use tables are provided by
139 FAOSTAT, the Statistical Services of the Food and Agriculture Organization of the United
140 Nations.³¹ To build FABIO we used data from the following FAOSTAT domains:

- 141 • Production, Crops
- 142 • Production, Crops processed
- 143 • Production, Live animals
- 144 • Production, Livestock primary
- 145 • Production, Livestock processed
- 146 • Trade, Crops and livestock products
- 147 • Trade, Live animals
- 148 • Trade, Detailed trade matrix
- 149 • Commodity balances, Crops primary equivalent
- 150 • Commodity balances, Livestock and fish primary equivalent
- 151 • Forestry production and trade
- 152 • Forestry trade flows

153 Additionally, fodder crop production data (previously part of the aggregated item “Crops
154 Primary (List)” in the *Production* domain) are required, but are no longer available from the
155 FAOSTAT website. These data were often estimated, and as we understood FAO has become
156 hesitant to publish such estimated data. However, we decided it was valid to continue using
157 these estimates as (a) some estimate is better than estimating the amount of fodder crops
158 at zero and (b) due to the way FABIO is constructed these estimates will be aligned and
159 constrained with other datasets to inform the final FABIO model result. In order to replicate
160 FABIO, it is necessary to request these data from FAOSTAT.

161 Global statistics on capture and aquaculture fish production were retrieved from FAO's
162 fishery division.³² UN Comtrade, the international trade statistics database of the United
163 Nations Statistics Division³³, provides bilateral trade data. We use the Comtrade database
164 for data on bilateral fish and ethanol trade from 1988 to 1994. Data for all other years are
165 sourced from BACI, a reconciled and harmonized version of the UN Comtrade database,
166 which is available for 1995 to 2017.³⁴ The trade data are balanced as described below.

167 Production data for ethanol from agricultural sources are reported by FAOSTAT under
168 the name *Alcohol, non-food*. However, large data gaps induced us to use production data on
169 ethanol and biogasoline from both EIA³⁵ and IEA³⁶.

170 The data structures of all data sets were harmonized, particularly regarding their country
171 and commodity classification. We defined 130 commodities, 121 processes and 191 countries
172 plus one rest of world region to be covered in FABIO. The final classifications are given in
173 the Supporting Information (SI) (see Table S.2, Table S.3, and Table S.4).

174 The Commodity Balance Sheets (CBS), available from FAOSTAT, are the core of the
175 FABIO PSUTs. The CBS provide detailed and comprehensive supply and use data for pri-
176 mary and processed agricultural commodities in terms of physical quantities by matching
177 supply (domestic production, imports, and stock removals) with utilization (food, feed, pro-
178 cessing, seed, waste, other uses, and exports). Other uses “refer to quantities of commodities
179 used for non-food purposes, e.g. oil for soap. [...] In addition, this variable covers pet
180 food.”³¹ Changes in moisture content, which may occur for many products between extrac-
181 tion and use, are neglected. The CBS database structure is designed to cover each country's
182 entire agricultural and food processing sector.³⁷ About 200 different primary and processed
183 crop and livestock commodities can be linked to form a consistent commodity tree structure
184 using technical conversion factors.³⁸

185 While particularly the use accounts are an indispensable source of information for the
186 development of PSUTs, an unavoidable limitation of these data is that for many cases crops
187 and derived products are combined into a single CBS by converting products into primary

188 equivalents. For example, the CBS for *wheat and products* comprises also trade and con-
189 sumption of bread and pasta measured in wheat equivalents. Disaggregating primary from
190 processed products, thus, represents an option for future refinements. However, we do not
191 expect differentiating primary and processed products to have a significant influence on the
192 results when using FABIO as a footprinting tool,²⁰ but it would be of relevance when linking
193 FABIO to data from economic accounts.

194 As other domains of FAOSTAT (e.g. *Trade* and *Production*) give the actual weight of
195 products, units had to be converted into primary equivalents where applicable. This was
196 done using country specific technical conversion factors (TCF) for 66 products and global
197 average TCF for 404 products, which for example give the kg of wheat required to produce
198 an average kg of bread.³⁸

199 Trade data for crops and crop products, livestock and livestock products, timber, and
200 fish are organized in different data domains of the FAO. We therefore harmonized their
201 data structures and integrated them into one bilateral trade database (BTD). To reconcile
202 discrepancies, i.e. the case that A's reported exports to B disagree with B's reported imports
203 from A, only import data were used. We assumed that the importer will rather know
204 the correct origin of a traded commodity, than the exporter the correct final destination.
205 Moreover, import statistics use to be more complete as customs have comprehensible interest
206 in thorough data collection for tax purposes. In the case of missing records for a country we
207 obtained missing trade data from "mirror" statistics, i.e. trade partners' data.

208 **Estimating missing values**

209 Data gaps are a common problem in any heavily data-dependent research work. We used
210 several approaches to estimate missing data.

211 Commodity balances

212 The CBS database does not cover some of the commodities included in the FABIO model,
213 i.e. live animals, fodder crops (grasses, forages and silage from cropland), grazing (grasses
214 and hay from grasslands), and timber. Therefore, commodity balances had to be built based
215 on alternative sources. We estimated grazing production based on³⁹. Production data for
216 all other missing commodities as well as trade data for live animals and timber are available
217 from FAOSTAT. Fodder crops and grasses are assumed not to be traded internationally. Low
218 prices and the consequent disproportionate transportation costs support this assumption.
219 For simplicity, stock changes, seed use and waste were assumed to be zero. Domestic use of
220 live animals is at large assigned to food processing (i.e. animal slaughtering), fodder crops
221 and grazing to feed use, and timber to other uses.

222 The CBS and bilateral trade data for *Alcohol, non-food* were updated with production
223 data from IEA and EIA (using the highest value respectively) and trade data from Com-
224 trade/BACI.

225 For some countries, not included in the CBS domain (namely: Singapore, Qatar, Demo-
226 cratic Republic of the Congo, Bahrain, Syrian Arab Republic, Papua New Guinea, Burundi,
227 Libya, Somalia, Eritrea, Timor-Leste, and Puerto Rico), all commodity balances were esti-
228 mated based on available production, seed use and trade data. FAO has stopped reporting
229 the seed use in the production domain of FAOSTAT. Thus for future updates seed-production
230 ratios reported in past years or for other countries will be taken. While production for seed
231 is important, it is not especially large in physical terms. On average globally, 1.4% of crop
232 production is used for seed in the following year, though this ranges between as much as
233 5.7% for pulses to 0.01% for vegetables. Processing requirements, e.g. the rapeseed used
234 for rapeseed oil production or the sugar cane used for sugar production, were estimated for
235 each commodity based on production data for the derived products and the country specific
236 TCF. If we then found data gaps for co-products, e.g. molasses from sugar production, we
237 imputed these data using again the respective TCF.

238 In the CBS, a certain commodity might be reported for a country most of the time, but
 239 with a few years missing. While production and trade data are available from other data
 240 domains of FAOSTAT throughout the time series, the use structure of the commodities is
 241 only provided by the CBS. In their absence, we performed linear inter- and extrapolation
 242 of the respective use structures. In total, for the case of the year 2013, 15,234 commodity
 243 balances were reported for the 191 countries included in FABIO, and 4271 were estimated
 244 (see Table S.5 and Table S.6), representing less than 0.5 % of the covered global product
 245 supply.

246 **Bilateral trade**

247 The BTD was reconciled to receive a bilateral trade matrix b_c^{rs} in the format countries-by-
 248 countries ($r \times s$) for each commodity c and year as described in Section "Data sources". The
 249 dataset, as provided by FAOSTAT, reveals significant gaps and discrepancies with the total
 250 import and export quantities reported in the CBS. We followed a multi-step approach to
 251 estimate a comprehensive set of bilateral trade data, which is in accordance with the CBS:

- 252 • We first derive a BTD estimate by spreading exports for each commodity over all
 253 countries worldwide according to their import shares. The elements of B' for a specific
 254 crop c and a country pair r, s are derived by $b_c'^{rs} = imp_c^r / imp_c \cdot exp_c^s$
- 255 • We repeat this procedure, but spreading imports for each commodity over all countries
 256 worldwide according to their export shares: $b_c''^{rs} = exp_c^s / exp_c \cdot imp_c^r$
- 257 • We derive the average of the two estimates \bar{b}_c^{rs} and proceed.
- 258 • We calculate the difference between the total exports of crop c from country r docu-
 259 mented in the BTD and those reported in the CBS dataset.
- 260 • We populate the gaps in \mathbf{B} , i.e. those fields that are N/A , with the corresponding values
 261 from $\bar{\mathbf{B}}$ up-/down-scaling them to meet the target export sum for each commodity and
 262 each exporting country as reported in the CBS.

263 • We balance the resulting bilateral trade matrices one product at a time using the RAS
264 biproportional balancing technique⁴⁰ to ensure the original total imports and total
265 exports are matched.

266 The resulting bilateral trade matrix is fully consistent with the import and export totals
267 given by the CBS per country and commodity. In order to give an idea of the potential
268 uncertainties, we show the discrepancies between the different FAO datasets, which are
269 overcome with the help of the RAS method, in Table S.7 in the SI.

270 **Building the supply tables**

271 Populating the supply table is straightforward, as production data is available from FAO-
272 STAT and can be attributed to a specific process. First, we identify the processes, supplying
273 more than one output, i.e. joint products or by-products. We find a reasonable list of
274 multi-output processes such as the crushing of oilseeds, the production of sugar, alcoholic
275 beverages, and livestock products (see Table S.9). We insert the compiled production data
276 for each process-item combination into a supply table. Ten livestock commodities are sup-
277 plied by multiple processes. Production values of those have to be divided between the
278 respective processes:

279 • Milk and butter from 5 different animal groups are aggregated into one CBS item. At
280 the same time, FAOSTAT reports detailed production data for fresh milk by animal
281 type (e.g. cattle, goats, camels). These are used to split the aggregates over the
282 supplying animal sectors in FABIO.

283 • The same is true for meat, hides and skins, where the CBS provide less detail than the
284 FAO's production statistics. We use the latter to allocate meat supply to the detailed
285 slaughtering processes.

286 • Slaughtering by-products such as edible offal, animal fats, and meat meal are split

287 among the animal categories according to their respective share in overall meat pro-
288 duction.

289 We obtain one supply table \mathbf{S} with i commodities by p processes for each country and
290 year.

291 **Building the use tables**

292 The Commodity Balance Sheets distinguish the following uses: exports, food, feed, process-
293 ing, seed, waste, and other uses. Moreover, we invert the supply item *stock removals*, thereby
294 converting it into the additional use item *stock additions*.

295 Waste can be treated in a physical accounting framework in different ways.⁴¹ On-farm
296 waste of biomass can be regarded as an output flow that would either be returned to the
297 environment or serve as an input to other processes. Such an accounting perspective enables
298 assessing the actual physical flows within metabolic networks.⁴² Alternatively, waste flows
299 can be allocated to the process where the waste occurs, thus considering losses synonymous
300 to an own use. As opposed to the tracking of actual physical flows in option one, the second
301 option allows for the tracking of embodied flows, which is required for consumption-based (or
302 footprint) accounting.⁴³ In this first version of FABIO, we decided to implement the latter
303 option, but plan to release an alternate version with waste streams reported as out-flows as
304 well.

305 Seed is considered an own use of the process which later harvests a crop. Exports, stock
306 additions, food, and other uses are considered final demand categories. Exports will later
307 be spread over the receiving countries, while food, stock additions and other uses together
308 comprise the final demand categories of FABIO.

309 In the following, we describe the allocation of feed and processing use.

310 **Allocation of processing use**

311 Processing uses are allocated to the respective processes distinguishing between several cases.

312 **Single-process commodities:** Commodities that are only processed by one single pro-
 313 cess include oil crops (processed in the respective oil extraction processes), hops (used in
 314 beer production), seed cotton (separated into cotton lint and cotton seed in the cotton pro-
 315 duction process), and live animals (processed by the respective slaughtering sectors). Given
 316 processing quantities are directly allocated to the respective processes.

317 **Multi-purpose crops:** Crops that are used by several processes are allocated by esti-
 318 mating the input requirements to each process based on technical conversion factors giving
 319 the conversion efficiencies for food processing. The use of product i in process p is deter-
 320 mined by $u_i^p = \sum_j (s_j^p \cdot \phi_{ij}^p)$, where s_j^p is the supply of product j by process p and ϕ_{ij}^p is
 321 the conversion efficiency from product i to product j in process p . For example, $\phi_{ij}^p = 0.5$
 322 indicates, that process p converts each ton of product i into 0.5 tons of product j . This
 323 approach is used to estimate the use of sugar crops in sugar production, rice in ricebran oil
 324 extraction, maize in maize germ oil extraction, and grapes in wine production.

325 **Ethanol feedstock:** For Brazil and the US, responsible for over 85 % of the global
 326 ethanol production in 2014,³⁶ the feedstock composition is known. Brazil uses sugar cane,
 327 while the ethanol industry of the US is mainly based on maize, with less than 2 % coming
 328 from sorghum, barley, cheese whey, sugar cane, wheat, and food and wood wastes.⁴⁴ For all
 329 other countries, i.e. less than 15 % of global ethanol production, feedstocks are estimated
 330 based on the availability of useful feedstock crops and their respective conversion rates.

331 **Alcoholic beverages:** Crops are allocated to the processes which supply alcoholic bev-
 332 erages by solving an optimization problem. We have given the national production of beer
 333 and other alcoholic beverages s_j , the total available feedstock supply u_i which was not allo-
 334 cated already to other processes, and the conversion efficiencies ϕ_{ij} , e.g., from barley to beer.
 335 With these inputs, we solve the following constrained least-squares optimization problem:

$$\min \sum \left(\left(\frac{\mathbf{s} - \tilde{\mathbf{s}}}{\bar{\phi}} \right)^2 + (\mathbf{u} - \tilde{\mathbf{u}})^2 \right),$$

336 where

$$\tilde{s}_j = \sum_{i=1}^n (\tilde{u}_{ij} \cdot \phi_{ij}),$$

337 s.t.

$$\sum_{j=1}^m \tilde{u}_{ij} = u_i \pm 0.1,$$

338 and receive a table of crop use per alcoholic beverage and country, which we insert into the
339 use table.

340 Allocation of feed use

341 The quantities of each crop used as animal feed are reported by FAOSTAT. This feed supply
342 is allocated to the 14 animal husbandry sectors specified in FABIO (Table S.3) according to
343 their feed intake requirements. The procedure is explained in the following three steps:

- 344 • **Feed supply:** Retrieve detailed data on feed supply from FAO in fresh weight, and
345 convert them into dry matter (DM).
- 346 • **Feed demand:** Calculate feed demand of 14 livestock groups in tons of DM.
 - 347 – **Cattle, buffaloes, pigs, poultry, sheep and goats:** Bouwman et al.³⁹ pub-
348 lished estimates on the feed demand in kg DM per kg product (e.g. milk, beef,
349 fat) for 1970, 1995 and 2030, differentiating specific dietary requirements and feed
350 composition (i.e. feed crops, grass, animal products, residues, and scavenging) for
351 livestock in 17 world regions. We interpolate the given feed conversion rates to get
352 year-specific values and multiply them with the reported production quantities of
353 animal products to get the total feed requirements per product. For this step, it
354 was important to consider trade with live animals in order to correctly assign feed
355 demand to the country, where the animals were raised.
 - 356 – **Horses, asses, mules, camels, other camelids, rabbits and hares, other**
357 **rodents, other live animals:** Krausmann et al.⁴⁵ provide average feed demand

358 coefficients for the above listed animal groups in kg DM per head, which are mul-
359 tiplied with the reported livestock numbers to calculate total feed requirements.

360 • **Match supply and demand:** We then balance the generated feed requirements per
361 country to match the reported feed supply by proportional up- or downscaling. Finally,
362 we convert the quantities into the fresh weight of every single feed crop.

363 Trade-linking

364 Once the supply and use tables for all countries are filled, they are linked into multi-regional
365 supply and use tables. The multi-regional supply table \mathbf{S} with the dimensions $\{r, i\} \times \{s, p\}$
366 contains zeros at the trade blocks (where $r \neq s$) and is filled with the domestic supply tables
367 where $r = s$.

368 The national use tables are trade-linked by spreading the use of a product i in a process
369 p in country s over the source countries r of that product: $u_{ip}^{rs} = u_{ip}^s \cdot h_i^{rs}$, where $h_i^{rs} = s_i^{rs}/s_i^s$
370 and s_i^{rs} is the total supply of product i in country s sourced from country r . Finally, we
371 receive a matrix \mathbf{U} with the dimensions $\{r, i\} \times \{s, p\}$.

372 Constructing symmetric IO table

373 The transformation from supply-use tables into symmetric input–output tables requires as-
374 sumptions on how to deal with multiple-output processes, i.e. a process supplying more
375 than one product such as, e.g., soybean crushing delivering soybean oil and cake. The issue
376 of how to allocate process inputs to outputs is discussed both in the fields of input–output
377 economics and life cycle analysis, with clear parallels in the allocation approaches.^{46,47} When
378 applying the widely used industry technology assumption for the transformation of rectan-
379 gular process-by-product SUTs into symmetric product-by-product IOTs, process inputs are
380 allocated to its respective outputs according to the supply shares documented in the supply
381 table. For example, in the case of soybean crushing, the input quantities of soybeans are

382 allocated to the outputs of oil and cake. We do this by deriving the product mix matrix or
383 transformation matrix $\mathbf{T} = \hat{\mathbf{g}}^{-1}\mathbf{S}$, where $\hat{\mathbf{g}}$ is a diagonalized vector with the row sums of \mathbf{S} ,
384 and multiplying the use and the transformation matrix $\mathbf{Z} = \mathbf{UT}$.

385 Assuming PSUTs in weight units, this allocates inputs according to the relative weight
386 of the outputs. In order to facilitate analyses of the economic drivers of resource flows, we
387 derive also a version that uses the relative economic value for the allocation. We therefore
388 convert the supply tables into monetary values (based on price information from FAOSTAT
389 and IEA) before deriving the transformation matrix as explained above. Thereby, we switch
390 from mass to value allocation, i.e. allocating the inputs of each process to its outputs in
391 relation to their value rather than their weight.

392 This allows us to test the effects that the different allocation decisions have on the
393 resulting PIOTs. This is particularly relevant for products from processes that produce
394 outputs with highly varying value-weight ratios. It should be noted that, in accordance with
395 the requirements of a specific research question, allocation could be performed also according
396 to supply shares in other units, for example based on the carbon, nitrogen, phosphorous or
397 protein content.

398 Results

399 Heatmaps of the resulting physical MRIO table for 2013 can be found in the SI. We extend
400 the FABIO model by cropland use data sourced from FAOSTAT³¹ and calculate exemplary
401 cropland footprint results for China, the EU-28, and the US, distinguishing plant-based and
402 livestock-based products for food and non-food uses from 1986 to 2013. We apply both ver-
403 sions of FABIO, i.e. using mass and value allocation. Figure 2 presents the results derived
404 with the FABIO model based on mass allocation (in the upper part), the difference between
405 mass and value allocation (in the middle part), and the share of imports in the overall foot-
406 print (in the lower part) based on mass allocation. The figure reveals characteristic patterns

407 and distinct trends for these three major agricultural producer and consumer regions. While
408 animal source foods take the highest but declining share in the EU and the US cropland
409 footprint, their place is still only second after plant-based food in China, albeit showing a
410 rapid increase throughout the time series. Other uses, i.e. mainly industrial non-food uses,
411 are particularly increasing in China and the US. In the EU, we see a shift from animal-based
412 to plant-based non-food products. The middle part of Figure 2 illustrates the impact of
413 using mass or value allocation for by-products in the construction of FABIO on the crop-
414 land footprints. While the overall footprint only changes slightly, the composition changes
415 significantly. In China and the EU, livestock products have a smaller footprint when using
416 value allocation. This is mainly due to the lower price of soybean cake (used as animal feed)
417 as compared to soybean oil. Accordingly, non-food uses of crop products such as soybean
418 oil receive a higher share of the land inputs. In contrast, the products from the livestock
419 sector used by non-food industries, for instance hides and skins, are usually cheaper than
420 those intended for human consumption. China constitutes an exception, as prices of animal
421 hides are driven by the high demand of industries and often exceed meat prices, thus shift-
422 ing more of the inputs to hides when switching from mass to value allocation. The relative
423 impact of allocation choice is significant, with a maximum of 59% of the total impact of the
424 food-livestock product group, 63% of the other uses of livestock products, and 38% of the
425 other uses of crops being affected by choice of allocation. The evolution of import shares,
426 shown at the bottom of Figure 2, reveals an increasing reliance on imports for China's use
427 of livestock products and crops for other uses. The EU, at the same time, reduced import
428 dependence for most product groups, albeit starting from high levels. The US import share
429 of crop products for other uses declined by roughly half, while increasing slightly for the
430 other product groups.

431 For a first comparison of our results with other land footprint studies, we amend the
432 comparison of net-trade flows of embodied cropland for China in 2004 presented in Hubacek
433 and Feng⁴⁸, including numbers from Qiang et al.⁴⁹, Kastner et al.¹⁷, Meyfroidt et al.⁵⁰,

434 Weinzettel et al.⁵¹, and Yu et al.⁵², with results generated with FABIO (see Figure 3).

435 FABIO is evidently very much in line with other physical accounting methods, although
436 applying the IO method. We could determine net-imports of 21 Mha cropland, both with
437 mass and value allocation. This, however, could change when further tracing the supply
438 chains of non-food uses (e.g. the further export of derived cotton/leather products such as
439 clothing and furniture). Currently, FABIO does not cover non-food manufacturing industries
440 (see Discussion Section). In total, 27 Mha of cropland were embodied in other uses of
441 agricultural products in Chinese industries in 2004. Many of these might produce for export
442 markets, thus reducing China's net-imports. Yet, net-exports of 17 Mha as shown by Yu
443 et al.⁵² couldn't be reached, even if China exported all of its manufacturing products. A
444 detailed model comparison is beyond the scope of this article and is being prepared separately.

445 Discussion

446 Limitations and next steps

447 Estimating feed production and demand

448 Achieving accurate estimates of feed production and demand is extremely challenging. On
449 the production side, crops grown for feed are reported inconsistently, or not at all, to FAO. In
450 some cases a crop is grown for feed and reported, in other cases a crop is used for both human
451 consumption and animal feed (e.g. cereal grains are used for food and the straw used for
452 feed), and in other cases crops may be grown for feed but not reported. On the consumption
453 side, there are no international statistics on the total herd feed consumption from roughage
454 (incl. grazed biomass) versus concentrate feed. Cattle and sheep can vary widely in their
455 feed demands, in the extreme by perhaps up to an order of magnitude (compare a small
456 undernourished street cow in urban India, foraging opportunistically with little provided
457 feed, to a prizewinning Austrian dairy cow). FABIO attempts to use the best available data

458 with global coverage^{39,45} and reconcile feed production and feed demand estimates into a
459 mass-balance consistent model, but nevertheless it must be kept in mind that estimates of
460 feed demand remain a source of uncertainty in the results.

461 **Model uncertainty**

462 The global PSUT provided by FABIO is an underdetermined system, i.e. not all data
463 elements in the result are explicitly informed by input data. As described above in the
464 Methods, some elements are inferred by disaggregating or pro-rating more aggregate totals.
465 Thus, every element of the global PSUT output is best understood not as a “true” value
466 but rather as an estimate which is subject to some degree of uncertainty. We expect lower
467 uncertainty for crops and derived products such as vegetable oils, as for these parts of
468 FABIO we could draw on extensive FAOSTAT data with only minor needs for estimates or
469 assumptions. The uncertainty for animal feed, particularly grasses, is presumably higher, as
470 this module of FABIO is widely based on incomplete data, hence requiring comprehensive
471 estimation algorithms. The number of commodity balances reported and estimated for each
472 country and for each commodity for 2013 are given in Table S.5 and Table S.6 in the SI.
473 Formalizing or estimating this uncertainty remains an open task for future versions of the
474 model. For example, standard deviation can be used with Monte Carlo methods to estimate
475 the variance of model results.^{53,54}

476 **Linear dependency**

477 The high similarity in the feed input composition among monogastric as well as among
478 ruminant animals results in some degree of linear dependency between the columns of the
479 input–output table \mathbf{Z} , thus impeding invertibility. The Leontief inverse therefore can be
480 approximated using the power series expansion, i.e. $\mathbf{L} = \mathbf{I} + \mathbf{A} + \mathbf{A}^2 + \mathbf{A}^3 + \dots + \mathbf{A}^\infty$, where
481 \mathbf{I} is the identity matrix and \mathbf{A} is the technology matrix, which is generated by the equation
482 $\mathbf{A} = \mathbf{Z}\hat{\mathbf{x}}^{-1}$, where $\hat{\mathbf{x}}$ is the diagonalized vector of total production output. Alternatively, the

483 matrix becomes invertible by making an incremental change (e.g. $-1e-10$) to those values
484 at the main diagonal of the Leontief matrix $\mathbf{I} - \mathbf{A}$ which are exactly equal to one. For the
485 results presented here, we used the latter approach.

486 **Industrial uses**

487 The final demand category *other uses* of FABIO comprises all industrial non-food uses. Fur-
488 ther trade and final consumption of these products cannot be traced based on FAO data,
489 therefore these supply chains are truncated at the place where a commodity enters a non-
490 food industry. As shown by Bruckner et al.⁵⁵, non-food products are responsible for about
491 one quarter of the EU's cropland footprint, a share which was constantly rising over the
492 past 20 years. These trends are confirmed by the results shown in this article for China,
493 the EU, and the US (see Figure 2). We find that crop-based non-food products are the
494 only product category consistently showing increases throughout the three regions. This
495 emphasizes the relevance and importance of correctly accounting for trade and consumption
496 of non-food products such as biofuels, cosmetics, textiles and leather products. The trun-
497 cation of non-food supply chains could be avoided by integrating FABIO with a monetary
498 MRIO into a hybrid IO system in order to track flows of non-food products along monetary
499 supply chains.^{20,24} Currently FABIO, as well as other biophysical accounting approaches,⁵⁶
500 considers other uses a final consumption category. Yet, hybridization of FABIO is an obvious
501 development option.

502 **SEEA compatibility**

503 In its current version, FABIO is not fully compliant with the SEEA guidelines for physi-
504 cal flow accounts for agriculture, forestry and fisheries.⁵⁷ First, natural inputs (e.g. carbon
505 dioxide, soil minerals, water), technical inputs (e.g. fertilizers, fuels, pesticides), and resid-
506 uals (food waste, oxygen, water vapor, unused biomass, not incorporated technical inputs)
507 are not fully captured by the PSUTs. Moreover, the commodity balances are reported in

508 primary equivalents, aggregating agricultural and food products. Primary and secondary
509 products can thus in many cases not be distinguished. This is a substantial limitation, as it
510 means that FABIO's classification is not compatible with that of national accounts and it
511 is therefore difficult to connect with economic modeling approaches using a standard indus-
512 try classification such as ISIC or NACE. While production and trade data are available for
513 agricultural and food products separately, use information is only obtainable in aggregate
514 form. This could be overcome applying additional assumptions and some standard estima-
515 tion procedures for input-output tables such as RAS or maximum entropy modeling.⁵⁸ For
516 the first version of FABIO, we decided to stick as far as possible to the data as reported
517 by FAOSTAT, thus not further splitting commodity balances into primary and secondary
518 products.

519 **Transparency and flexibility**

520 PSUTs represent a highly transparent and flexible way of organizing physical flow data
521 strictly following a mass balancing principle. SUTs were introduced into economic accounting
522 in order to give a transparent framework for reporting economic transactions without the
523 need for assumptions. They give an integrated framework for checking the consistency
524 and completeness of data, and report transactions in natural units (products as inputs and
525 outputs, industries as activities that transform products). From SUT data, a variety of
526 assumptions can be made in order to utilize the data for various analytical purposes.⁴⁶

527 **Allocation**

528 The critical aspect here for environmental footprint or life-cycle type approaches is when
529 co-production (joint products/by-products) occurs such that inputs into one activity are
530 used to produce more than one output. Either disaggregation of co-production must occur,
531 or some form of assumption (based on weight, value, the protein or energy content, etc.)
532 must be applied to allocate the inputs into the co-production process to the respective

533 product outputs.^{43,59} This is the step that transforms a SUT to an IOT where inputs are
534 uniquely represented in relation to the production and further use of products. The current
535 version of the FABIO database comprises two sets of IO tables based on value and mass
536 allocation. While value allocation, and the resultant footprints, pursue an economic logic,
537 when assigning responsibility for inputs to the output product, mass allocation represents a
538 biophysical logic, splitting inputs based on the physical outputs independent of their value
539 for the economic system.

540 The choice of unit used in the allocation has a large effect on results. We compared both
541 physical and economic allocation for transformation of PSUT to IOT, and found significant
542 differences for livestock products and “other uses” of crops. These product groups are based
543 on processes with highly differing prices of co-products. The choice of allocation procedure
544 for these co-products can thus easily have a large impact on net-trade results. While we
545 found only minor differences in net-trade for China, the US, and the EU as a whole (see
546 Figure 2), calculations for Germany revealed even a change in the direction of net-trade
547 flows. We found that Germany was a net-exporter of 0.42 Mha in the year 2013 when using
548 mass allocation. This result, however, changed to net-imports of 0.31 Mha when applying
549 value allocation.

550 It is important to note that the allocation procedure discussed here solely focuses on
551 the allocation of inputs to co-produced products (the step to form an IOT). The further
552 allocation according to subsequent usage of the product (performed during the Leontief
553 inverse) fully follows a physical logic in our approach (i.e. the IOT is in physical terms). For
554 example, the land use impacts of wheat production are allocated to the subsequent users
555 of wheat based on the kg of wheat used, and not its dollar value. In contrast, monetary
556 IOTs would allocate wheat to users according to the users’ payments, irrespective of actual
557 physical flows.

558 **Drivers**

559 Moreover, in contrast to other biophysical accounting approaches such as presented by Kast-
560 ner et al.⁵⁶ and Tramberend et al.⁶⁰, any data analysis methods applicable to matrix struc-
561 tures can be applied to FABIO. Structural decomposition analysis, for example, can be used
562 to identify the drivers of changes in the global agriculture and land use system.

563 FABIO exposes the detailed composition and origin of renewable raw materials and re-
564 lated land embodied in a wide range of final products. Applying decomposition methods
565 reveals the main driving factors, such as technology or feed mix, supply structure or affluence,
566 responsible for changes in biomass consumption and related supply chains in different world
567 regions over the past three decades. Such an assessment will deliver an important empirical
568 basis for identifying potential future trade-offs arising from the increased competition for
569 global biomass and for designing actions by business and policy makers to reduce competing
570 demands.

571 **Economic modeling**

572 FABIO can be used as a stand-alone tool to perform footprint and scenario analyses in
573 the tradition of Leontief-style IO analysis. However, these analyses assume that physical
574 shares in production inputs are constant, e.g. that beef producers in one country use a
575 fixed amount of soy cake from another country per ton of produced beef. Economic models,
576 such as CGE and econometric models, can be combined with FABIO in order to introduce
577 dynamic changes, such as altered bilateral trade shares based on relative price changes. At
578 the same time, FABIO can strengthen existing economic simulation models by contributing
579 additional product and country detail.

Acknowledgments

This project has received funding from the German Federal Ministry of Education and Research (STRIVE project), the NRW Bioeconomy Science Center (Econ-BioSC project), and the European Research Council (ERC) under the European Union’s Horizon 2020 research and innovation program (FINEPRINT project, grant agreement No. 725525).

Supporting Information

A. Heatmaps of the physical input–output table for 2013

B. A tabular comparison of available MRIO databases with FABIO

C. Auxiliary tables containing information on classifications, data gaps and discrepancies

References

- (1) Kehoe, L.; Reis, T.; Virah-Sawmy, M.; Balmford, A.; Kuemmerle, T.; 604 signatories, 590 Make EU trade with Brazil sustainable. *Science* **2019**, *364*, 341–341. 591
- (2) Lambin, E. F.; Gibbs, H. K.; Heilmayr, R.; Carlson, K. M.; Fleck, L. C.; Garrett, R. D.; 592 le Polain de Waroux, Y.; McDermott, C. L.; McLaughlin, D.; Newton, P.; Nolte, C.; 593 Pacheco, P.; Rausch, L. L.; Streck, C.; Thorlakson, T.; Walker, N. F. The role of supply- 594 chain initiatives in reducing deforestation. *Nature Climate Change* **2018**, *8*, 109–116. 595
- (3) Haberl, H.; Fischer-Kowalski, M.; Krausmann, F.; Weisz, H.; Winiwarter, V. Progress 596 towards sustainability? What the conceptual framework of material and energy flow 597 accounting (MEFA) can offer. *Land Use Policy* **2004**, *21*, 199–213. 598
- (4) Fischer-Kowalski, M.; Krausmann, F.; Giljum, S.; Lutter, S.; Mayer, A.; Bringezu, S.; 599 Moriguchi, Y.; Schütz, H.; Schandl, H.; Weisz, H. Methodology and Indicators of 600

- 601 Economy-wide Material Flow Accounting. *Journal of Industrial Ecology* **2011**, *15*, 855–
602 876.
- 603 (5) Binder, C. R.; Hinkel, J.; Bots, P. W.; Pahl-Wostl, C. Comparison of frameworks for
604 analyzing social-ecological systems. *Ecology and Society* **2013**, *18*, 26.
- 605 (6) Kneese, A. V.; Ayres, R. U.; d’Arge, R. *Economics and the environment: a material*
606 *balance approach*; John Hopkins Press: Baltimore and London, 1970.
- 607 (7) Bösch, M.; Jochem, D.; Weimar, H.; Dieter, M. Physical input-output accounting of
608 the wood and paper flow in Germany. *Resources, Conservation and Recycling* **2015**,
609 *94*, 99–109.
- 610 (8) Giljum, S.; Hubacek, K. In *Handbook of input-output economics for industrial ecology*;
611 Suh, S., Ed.; Springer: Dordrecht, The Netherlands, 2009; pp 61–75.
- 612 (9) Hoekstra, R.; van den Bergh, J. C. J. M. Constructing physical input-output tables
613 for environmental modeling and accounting: Framework and illustrations. *Ecological*
614 *Economics* **2006**, *59*, 375–393.
- 615 (10) Liang, S.; Wang, Y.; Zhang, T.; Yang, Z. Structural analysis of material flows in China
616 based on physical and monetary input-output models. *Journal of Cleaner Production*
617 **2017**, 209–217.
- 618 (11) Tukker, A.; Koning, A.; Owen, A.; Lutter, S.; Bruckner, M.; Giljum, S.; Stadler, K.;
619 Wood, R.; Hoekstra, R. Towards Robust, Authoritative Assessments of Environmental
620 Impacts Embodied in Trade: Current State and Recommendations. *Journal of Indus-*
621 *trial Ecology* **2018**, *22*, 585–598.
- 622 (12) Bruckner, M.; Giljum, S.; Lutz, C.; Wiebe, K. S. Materials embodied in international
623 trade - Global material extraction and consumption between 1995 and 2005. *Global*
624 *Environmental Change* **2012**, *22*, 568–576.

- 625 (13) Koning, A. d.; Bruckner, M.; Lutter, S.; Wood, R.; Stadler, K.; Tukker, A. Effect of
626 aggregation and disaggregation on embodied material use of products in input–output
627 analysis. *Ecological Economics* **2015**, *116*, 289–299.
- 628 (14) Majeau-Bettez, G.; Pauliuk, S.; Wood, R.; Bouman, E. A.; Strømman, A. H. Balance
629 issues in input-output analysis: A comment on physical inhomogeneity, aggregation
630 bias, and coproduction. *Ecological Economics* **2016**, *126*, 188–197.
- 631 (15) Schoer, K.; Weinzettel, J.; Kovanda, J.; Giegrich, J.; Lauwigi, C. Raw Material Con-
632 sumption of the European Union-Concept, Calculation Method, and Results. *Environ-*
633 *mental Science & Technology* **2012**, *46*, 8903–8909.
- 634 (16) Bruckner, M.; Fischer, G.; Tramberend, S.; Giljum, S. Measuring telecouplings in the
635 global land system: A review and comparative evaluation of land footprint accounting
636 methods. *Ecological Economics* **2015**, *114*, 11–21.
- 637 (17) Kastner, T.; Schaffartzik, A.; Eisenmenger, N.; Erb, K.-H.; Haberl, H.; Krausmann, F.
638 Cropland area embodied in international trade: Contradictory results from different
639 approaches. *Ecological Economics* **2014**, *104*, 140–144.
- 640 (18) Schaffartzik, A.; Haberl, H.; Kastner, T.; Wiedenhofer, D.; Eisenmenger, N.; Erb, K.-H.
641 Trading Land: A Review of Approaches to Accounting for Upstream Land Require-
642 ments of Traded Products. *Journal of Industrial Ecology* **2015**, *19*, 703–714.
- 643 (19) Ewing, B. R.; Hawkins, T. R.; Wiedmann, T. O.; Galli, A.; Ertug Ercin, A.;
644 Weinzettel, J.; Steen-Olsen, K. Integrating ecological and water footprint accounting
645 in a multi-regional input-output framework. *Ecological Indicators* **2012**, *23*, 1–8.
- 646 (20) Weinzettel, J.; Wood, R. Environmental Footprints of Agriculture Embodied in Inter-
647 national Trade: Sensitivity of Harvested Area Footprint of Chinese Exports. *Ecological*
648 *Economics* **2018**, *145*, 323 – 330.

- 649 (21) Weinzettel, J.; Vačkář, D.; Medková, H. Human footprint in biodiversity hotspots.
650 *Frontiers in Ecology and the Environment* **2018**, *16*, 447–452.
- 651 (22) Weinzettel, J.; Pfister, S. International trade of global scarce water use in agriculture:
652 Modeling on watershed level with monthly resolution. *Ecological economics* **2019**, *159*,
653 301–311.
- 654 (23) Weinzettel, J.; Vačkář, D.; Medková, H. Potential net primary production footprint
655 of agriculture: A global trade analysis. *Journal of Industrial Ecology* **2019**,
- 656 (24) Croft, S. A.; West, C. D.; Green, J. M. Capturing the heterogeneity of sub-national
657 production in global trade flows. *Journal of Cleaner Production* **2018**, *203*, 1106–1118.
- 658 (25) Heun, M. K.; Owen, A.; Brockway, P. E. A physical supply-use table framework for
659 energy analysis on the energy conversion chain. *Applied Energy* **2018**, *226*, 1134–1162.
- 660 (26) Kovanda, J. Use of Physical Supply and Use Tables for Calculation of Economy-Wide
661 Material Flow Indicators. *Journal of Industrial Ecology* **2018**, *153*, 63.
- 662 (27) Kastner, T.; Kastner, M.; Nonhebel, S. Tracing distant environmental impacts of agri-
663 cultural products from a consumer perspective. *Ecological Economics* **2011**, *70*, 1032–
664 1040.
- 665 (28) Godar, J.; Persson, U. M.; Tizado, E. J.; Meyfroidt, P. Towards more accurate and
666 policy relevant footprint analyses: Tracing fine-scale socio-environmental impacts of
667 production to consumption. *Ecological Economics* **2015**, *112*, 25–35.
- 668 (29) Bruckner, M. Food and Agriculture Biomass Input–Output (FABIO) database, Version
669 1.0. *Zenodo* **2019**, available at <http://dx.doi.org/10.5281/zenodo.2577067>.
- 670 (30) Wilkinson, M. D.; Dumontier, M.; Aalbersberg, I. J.; Appleton, G.; Axton, M.;
671 Baak, A.; Blomberg, N.; Boiten, J.-W.; da Silva Santos, Luiz Bonino.; Bourne, P. E.;
672 Bouwman, J.; Brookes, A. J.; Clark, T.; Crosas, M.; Dillo, I.; Dumon, O.; Edmunds, S.;

- 673 Evelo, C. T.; Finkers, R.; Gonzalez-Beltran, A.; Gray, A. J.; Groth, P.; Goble, C.;
674 Grethe, J. S.; Heringa, J.; 't Hoen, P. A.; Hooft, R.; Kuhn, T.; Kok, R.; Kok, J.;
675 Lusher, S. J.; Martone, M. E.; Mons, A.; Packer, A. L.; Persson, B.; Rocca-Serra, P.;
676 Roos, M.; van Schaik, R.; Sansone, S.-A.; Schultes, E.; Sengstag, T.; Slater, T.;
677 Strawn, G.; Swertz, M. A.; Thompson, M.; van der Lei, J.; van Mulligen, E.; Vel-
678 terop, J.; Waagmeester, A.; Wittenburg, P.; Wolstencroft, K.; Zhao, J.; Mons, B. The
679 FAIR Guiding Principles for scientific data management and stewardship. *Scientific*
680 *Data* **2016**, *3*, 160018.
- 681 (31) FAOSTAT, Food and Agriculture Organization of the United Nations. FAOSTAT
682 Statistics Database. 2019; <http://www.fao.org/faostat/>.
- 683 (32) FAO, Fishery Statistical Collections - Global Production. 2019; [http://www.fao.org/](http://www.fao.org/fishery/statistics/global-production/en)
684 [fishery/statistics/global-production/en](http://www.fao.org/fishery/statistics/global-production/en).
- 685 (33) United Nations Statistics Division, UN Comtrade: International Trade Statistics
686 Database. 2019; <https://comtrade.un.org/>.
- 687 (34) Gaulier, G.; Zignago, S. *BACI: International Trade Database at the Product-Level. The*
688 *1994-2007 Version*; Working Papers 2010-23, 2010.
- 689 (35) EIA, International Energy Portal. 2019; [https://www.eia.gov/beta/](https://www.eia.gov/beta/international/)
690 [international/](https://www.eia.gov/beta/international/).
- 691 (36) IEA, World - Renewable and Waste Energy Supply (Ktoe): IEA Renewables Informa-
692 tion Statistics (database). 2019; <http://dx.doi.org/10.1787/data-00550-en>.
- 693 (37) FAO, *FOOD BALANCE SHEETS. A handbook*; Electronic Book, 2001.
- 694 (38) FAO, *Technical conversion factors for agricultural commodities*; Report, 2003.
- 695 (39) Bouwman, L.; Goldewijk, K. K.; Van Der Hoek, K. W.; Beusen, A. H. W.; Van Vu-
696 uren, D. P.; Willems, J.; Rufino, M. C.; Stehfest, E. Exploring global changes in ni-

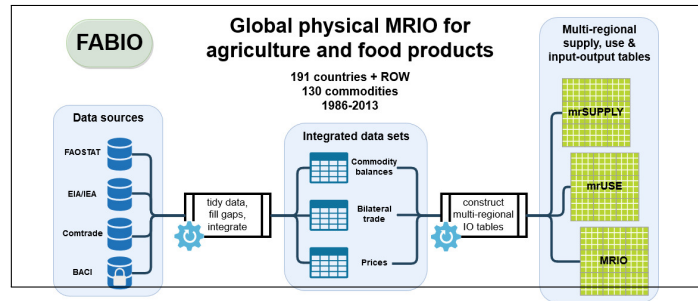
- 697 trogen and phosphorus cycles in agriculture induced by livestock production over the
698 1900–2050 period. *Proceedings of the National Academy of Sciences* **2013**, *110*, 20882–
699 20887.
- 700 (40) Stone, R.; Brown, A. *A Programme for Growth, vol. 1: A Computable Model of Eco-*
701 *nomie Growth*; Chapman and Hall: London, 1962.
- 702 (41) Giljum, S.; Hubacek, K. Alternative approaches of physical input-output analysis to
703 estimate primary material inputs of production and consumption activities. *Economic*
704 *Systems Research* **2004**, *16*, 301–310.
- 705 (42) Nakamura, S.; Nakajima, K.; Yoshizawa, Y.; Matsubae-Yokoyama, K.; Nagasaka, T.
706 Analyzing Polyvinyl Chloride in Japan With the Waste Input–Output Material Flow
707 Analysis Model. *Journal of Industrial Ecology* **2009**, *13*, 706–717.
- 708 (43) Weinzettel, J. Understanding Who is Responsible for Pollution: What Only the Market
709 can Tell Us—Comment on “An Ecological Economic Critique of the Use of Market
710 Information in Life Cycle Assessment Research”. *Journal of Industrial Ecology* **2012**,
711 *16*, 455–456.
- 712 (44) RFA, 2010 Ethanol Industry Outlook: Climate of Opportunity. 2010.
- 713 (45) Krausmann, F.; Erb, K.-H.; Gingrich, S.; Lauk, C.; Haberl, H. Global patterns of
714 socioeconomic biomass flows in the year 2000: A comprehensive assessment of supply,
715 consumption and constraints. *Ecological Economics* **2008**, *65*, 471–487.
- 716 (46) Majeau-Bettez, G.; Wood, R.; Strømman, A. H. Unified Theory of Allocations and
717 Constructs in Life Cycle Assessment and Input-Output Analysis. *Journal of Industrial*
718 *Ecology* **2014**, *18*, 747–770.
- 719 (47) Suh, S.; Weidema, B.; Schmidt, J. H.; Heijungs, R. Generalized Make and Use Frame-

- 720 work for Allocation in Life Cycle Assessment. *Journal of Industrial Ecology* **2010**, *14*,
721 335–353.
- 722 (48) Hubacek, K.; Feng, K. Comparing apples and oranges: Some confusion about using
723 and interpreting physical trade matrices versus multi-regional input–output analysis.
724 *Land Use Policy* **2016**, *50*, 194–201.
- 725 (49) Qiang, W.; Liu, A.; Cheng, S.; Kastner, T.; Xie, G. Agricultural trade and virtual land
726 use: The case of China’s crop trade. *Land Use Policy* **2013**, *33*, 141–150.
- 727 (50) Meyfroidt, P.; Rudel, T. K.; Lambin, E. F. Forest transitions, trade, and the global
728 displacement of land use. *Proceedings of the National Academy of Sciences of the United*
729 *States of America* **2010**, *107*, 20917–20922.
- 730 (51) Weinzettel, J.; Hertwich, E. G.; Peters, G. P.; Steen-Olsen, K.; Galli, A. Affluence
731 drives the global displacement of land use. *Global Environmental Change* **2013**, *23*,
732 433 – 438.
- 733 (52) Yu, Y.; Feng, K.; Hubacek, K. Tele-connecting local consumption to global land use.
734 *Global environmental change* **2013**, *23*, 1178–1186.
- 735 (53) Lenzen, M.; Wood, R.; Wiedmann, T. Uncertainty analysis for Multi-Region Input-
736 Output models - a case study of the UK’s carbon footprint. *Economic Systems Research*
737 **2010**, *22*, 43–63.
- 738 (54) Moran, D.; Wood, R. Convergence Between the Eora, WIOD, EXIOBASE, and
739 OpenEU’s Consumption-Based Carbon Accounts. *Economic Systems Research* **2014**,
740 *26*, 245–261.
- 741 (55) Bruckner, M.; Häyhä, T.; Giljum, S.; Maus, V. W.; Fischer, G.; Tramberend, S.;
742 Börner, J. Quantifying the global cropland footprint of the European Union’s non-food
743 bioeconomy. *Environmental Research Letters* **2019**, *14*, 045011.

- 744 (56) Kastner, T.; Erb, K.-H.; Haberl, H. Rapid growth in agricultural trade: effects on global
745 area efficiency and the role of management. *Environmental Research Letters* **2014**, *9*,
746 034015.
- 747 (57) FAO, *System of Environmental-Economic Accounting for Agriculture, Forestry and*
748 *Fisheries: SEEA AFF*; Report, 2018.
- 749 (58) Többen, J.; Wiebe, K. S.; Verones, F.; Wood, R.; Moran, D. D. A novel maximum en-
750 tropy approach to hybrid monetary-physical supply-chain modelling and its application
751 to biodiversity impacts of palm oil embodied in consumption. *Environmental Research*
752 *Letters* **2018**, *13*, 115002.
- 753 (59) Pelletier, N.; Ardente, F.; Brandão, M.; de Camillis, C.; Pennington, D. Rationales
754 for and limitations of preferred solutions for multi-functionality problems in LCA: is
755 increased consistency possible? *The International Journal of Life Cycle Assessment*
756 **2015**, *20*, 74–86.
- 757 (60) Tramberend, S.; Fischer, G.; Bruckner, M.; van Velthuisen, H. Our Common Cropland:
758 Quantifying Global Agricultural Land Use from a Consumption Perspective. *Ecological*
759 *Economics* **2019**, *157*, 332–341.

760 Graphical TOC Entry

761



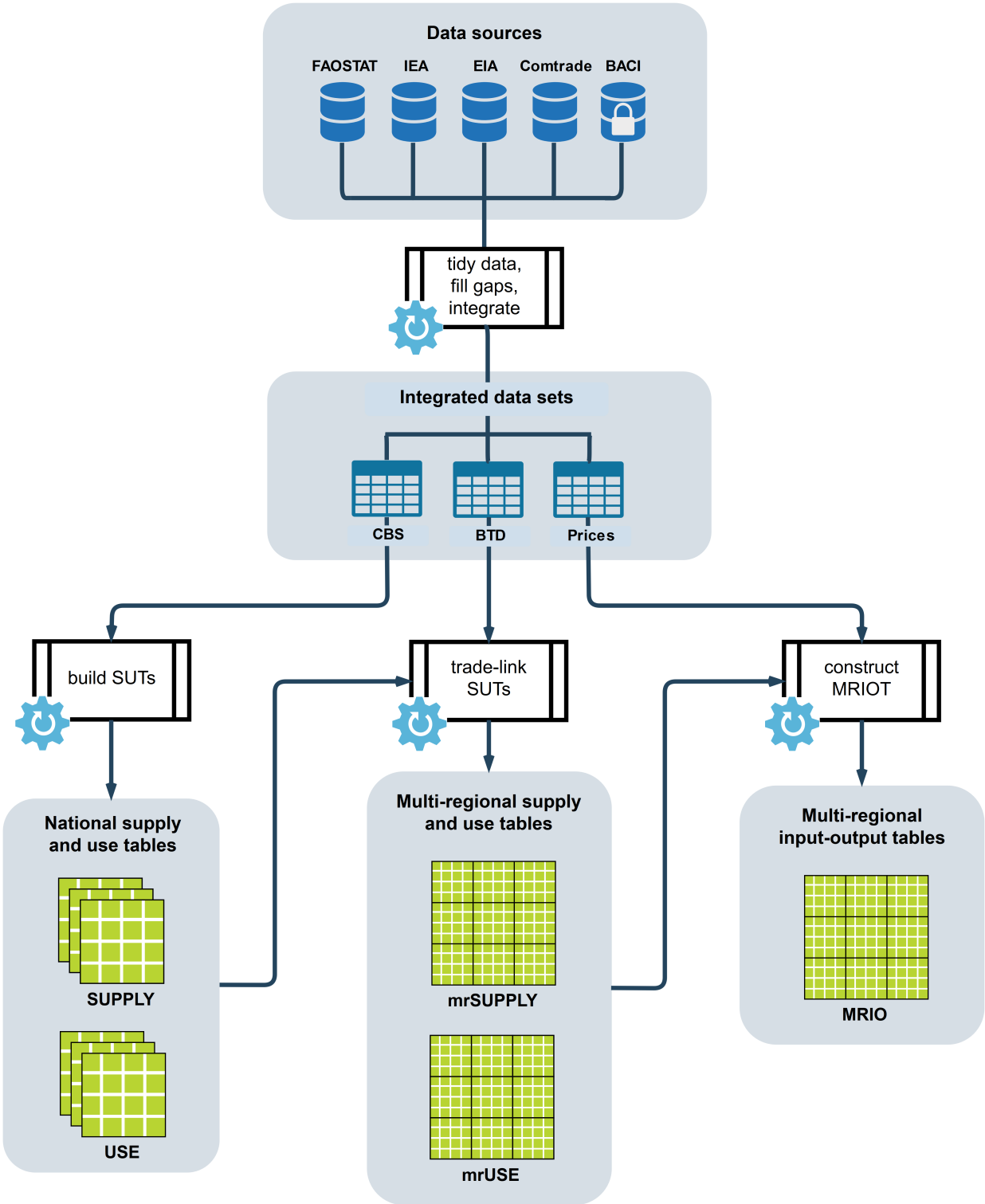


Figure 1: Flow chart illustrating the data sources and processing steps involved in building FABIO. (CBS = commodity balance sheets, BTD = bilateral trade data, SUT = supply-use table, MRIOT = multi-regional input-output table)

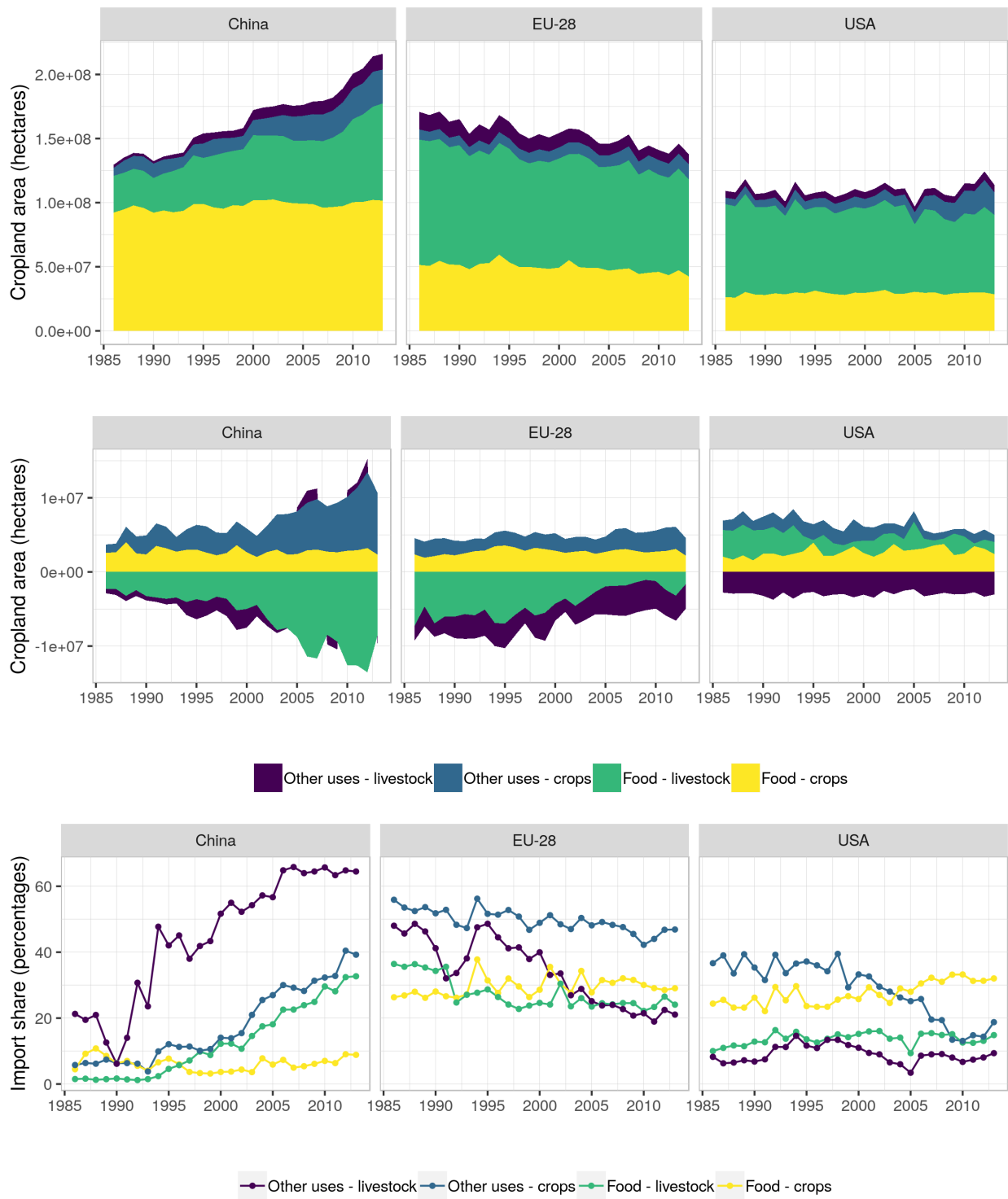


Figure 2: Plant and animal-based food and non-food cropland footprint of China, the EU-28, and the USA, 1986-2013; Top: overall footprint; center: difference due to allocation method (with positive values meaning higher footprints based on value allocation); bottom: share of imports in the footprint

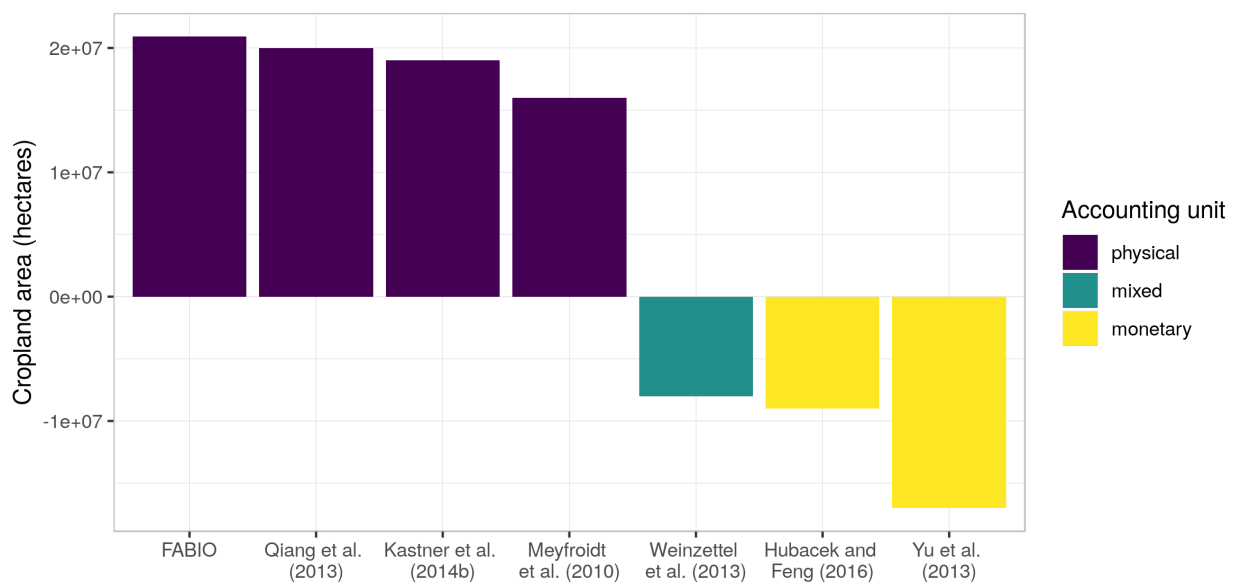


Figure 3: Comparison of China's net-trade with embodied cropland in 2004. Note: The results in Yu et al.⁵² are based on 2007 data, while all others are 2004 data.