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Gigatons of greenhouse gas emission increase from global food consumption and driving forces

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Abstract

Greenhouse gas (GHG) emissions related to food consumption complement production-based or territorial accounts by capturing carbon leaked through trade. Here, we evaluate global consumption-based food emissions between 2000 and 2019 and underlying drivers using a physical trade flow approach and structural decomposition analysis. In 2019, emissions throughout food supply chains reached 30±9% of anthropogenic GHG emissions, largely triggered by beef and dairy consumption in rapidly developing countries - while per capita emissions in developed countries with a high percentage of animal-based food declined. Emissions outsourced through international food trade dominated by beef and oil crops increased by ~1 Gt CO₂-eq, mainly driven by increased imports by developing countries. Population growth and per capita demand increase were key drivers to global emission increase (+30% and +19%, respectively) while decreasing emission intensity from land-use activities was the major factor to offset emission growth (-39%). Climate change mitigation may depend on incentivizing consumer and producer choices to reduce emission-intensive food products.

39 Introduction

40 The agrifood system drives global land use, agricultural and other beyond-farm
41 activities, and contributes to about one-third of global anthropogenic greenhouse gas
42 (GHG) emissions¹⁻³. The United Nations projects that an additional 70 percent of the
43 current food demand will be needed to feed the world's estimated population of 9.1
44 billion by 2050⁴. Population growth, expansion of food production, and an increase in
45 animal-based diets are likely to further increase emissions and squeeze the global
46 carbon budget^{5,6}. Thus, mitigating emissions at every stage of food supply chains from
47 production to consumption is crucial to limit global warming⁶⁻⁸.

48 Production-based emissions (PBE) or territorial emissions are based on emissions
49 from production (including exports) within a region⁹. Previous studies^{1,2,10,11} have
50 quantified global GHG emissions from food production based on global food-related
51 emission inventories (e.g., FAOSTAT, EDGAR-Food). However, food products are
52 increasingly traded internationally through global supply chains, and geographically
53 distant consumer demand may lead to emission outsourcing to producers¹²⁻¹⁴.
54 Consumption-based emission (CBE) accounting allocates emissions from producers
55 to final consumers irrespective of the place of production^{15,16}. CBE is complementary
56 to PBE and allows allocating responsibility and informs emission mitigation from a
57 consumer perspective. CBE helps to understand to what extent final consumers trigger
58 emissions along the entire global supply chain, allows quantification of virtual flows in
59 trade outsourced to other countries, and provides information for additional policy tools
60 for emission mitigation with a focus on consumption^{17,18}. Therefore, a detailed
61 assessment of global consumption-based GHG emissions throughout food supply
62 chains with a breakdown into the detailed process- and product-levels are needed to
63 reveal the distant emission drivers and to facilitate emission mitigation from a
64 consumer perspective. However, such consumption-based assessments are
65 hampered due to the complexity and variety of processes in which different food
66 products are cultivated, processed, and traded through multiple intermediate
67 regions^{19,20} as well as the required degree of data consistency and granularity in terms
68 of processes and products of the global agrifood system.

69 A number of studies used bottom-up life-cycle assessment (LCA) to investigate
70 emissions of specific food products during their lifecycle²¹. However, these results are
71 not comparable because of differences in scope^{21,22} and oftentimes ignoring
72 differences in emissions from different origins along global food supply chains²⁰. With
73 the international, time-series input-output databases at high sectoral detail, multi-
74 regional input-output (MRIO) analysis is now widely used for tracing consumption-
75 based emissions²³. MRIO is applied to quantify emissions induced by food
76 consumption based on input-output relations (in monetary values) along supply
77 chains^{19,24}. This approach has been frequently criticized due to its highly aggregated
78 sectors lacking product details²⁵⁻²⁷. For example, soybean, together with other oilseed
79 crops such as palm oil and rapeseed, are aggregated in the same oil crop sector,
80 ignoring important finer-scale differences in terms of land use, input requirements, and

81 associated emissions. PTF based on physical product flows provides a more detailed
82 analysis of trade flows for agricultural products based on higher sectoral and product
83 resolution²³. Some PTF bilateral trade approaches use the difference between
84 production, imports, and exports to calculate GHG emissions from food
85 consumption^{11,28,29} but without consideration of re-export via longer international supply
86 chains. The improved PTF developed by Kastner et al. provides a framework with
87 detailed data to link consumption and associated impacts to the origins of cultivated
88 crops or livestock (on-farm stages) beyond bilateral trade^{25,26}.

89 Here, we analyze the trend of consumption-based food GHG emissions of 153
90 products (both animal- and plant-based food) in 181 countries or areas for the years
91 2000, 2005, 2010, 2015, and 2019. Using the PTF approach by Kastner et al.²⁵ and
92 detailed trade data from FAOSTAT³⁰, we reallocate production-based GHG emissions
93 (CO₂, CH₄, and N₂O)³¹ from agricultural land use and land use change (LULUC),
94 agricultural production, and beyond-farm processes (excluding emissions from
95 household and end-of-life)^{1,2,32} throughout the supply chains of 153 products to final
96 consumers. All emissions are in CO₂ equivalents (CO₂-eq) using 100-year global
97 warming potentials of CH₄ and N₂O used in the IPCC 5th Assessment Report (AR5).
98 We quantify emissions embodied in food domestic supply and trade (i.e., imports and
99 exports) between countries involving re-exports. Finally, structural decomposition
100 analysis is applied to identify the contributions of five driving factors from production to
101 consumption to variations in consumption-based emissions - namely emission intensity,
102 trade structure, domestic supply ratio, per capita consumption, and population. Our
103 study uses the most recent data to attribute emissions across the entire food supply
104 chains at a global scale to final consumers with a consistent and detailed breakdown
105 of processes and products. This allows us to indicate how to reduce food emissions
106 from production to consumption through policy applications for the entire supply chain
107 and final consumers.

108 **Results**

109 **Emissions driven by global and national food consumption**

110 In 2019, food consumption in the five highest emitting countries, China (2.0 Gt CO₂-
111 eq), India (1.3 Gt), Indonesia (1.1 Gt), Brazil (1.0 Gt) and the USA (1.0 Gt), were
112 responsible for more than 40% of global food supply chain emissions (16.0 (95%
113 confidence interval 11.4-20.7) Gt CO₂-eq) which cover most of the emissions of the
114 global agrifood system^{2,3} ((Insert Fig. 1, details of uncertainty ranges see Suppl. Table
115 1). Annual global GHG emissions associated with food increased by 14% (i.e., 2 Gt
116 CO₂-eq) from 2000 to 2019, which largely owes to consumption rise in populous
117 countries, with China contributing 46%, India 24%, and Pakistan 11% to emission
118 growth.

119 The substantial increase in consumption of animal-based products contributed to ~95%
120 of the global emission rise, reaching almost half of the total food emissions³, with 7.9
121 (5.9-10.1) Gt CO₂-eq in 2019. We find that many countries have dominated animal-

122 based emissions, represented by Australia (82%), the USA (66%), and South Asian
123 countries including India (63%). The share of animal-based emissions in total
124 emissions continued increasing in most developing countries/regions (e.g., Brazil, East
125 Asia) but remained stable in affluent countries. Beef and dairy contributed 32% and
126 46% of the increase in global animal-based emissions and reached 3.4 Gt CO₂-eq and
127 2.8 Gt CO₂-eq respectively in 2019 (Suppl. Fig. 1, details of the uncertainty ranges see
128 Suppl. Table 2). Top emitters of beef consumption included Brazil (437 Mt CO₂-eq), the
129 USA (409 Mt), and Argentina (118 Mt) in 2000 but later included Brazil (409 Mt), China
130 (402 Mt), and the USA (365 Mt). Increased consumption of beef led to 28% of China's
131 growth of animal-based emissions. Beef's contribution is similar to pork which
132 dominates China's meat market. Emissions from beef consumption constitute 64% of
133 animal-based emissions in Brazil, and over 50% occurred in the Rest of Latin America
134 and the Caribbean (LAC), the USA, Japan, and Southeast Asia. Emissions from India's
135 dairy consumption increased considerably by 1.2 times, reaching 78% of national
136 animal-based emissions as well as over 1/5 of global dairy emissions in 2019. Dairy
137 consumption in Russia, Oceania, and European countries also contributed to over half
138 of national animal-based emissions.

139 The consumption of grains and oil crops is responsible for 43% (3.4 Gt CO₂-eq in 2019)
140 and 23% (1.9 Gt CO₂-eq) of global plant-based emissions, respectively (Suppl. Fig. 2,
141 details of uncertainty ranges see Suppl. Table 2). Rice contributes to over half of the
142 global grain-related emissions (1.7 Gt CO₂-eq), with Indonesia (20%), China (18%),
143 and India (10%) being the top three contributors. Soybean (0.6 Gt CO₂-eq) and palm
144 oil (0.9 Gt CO₂-eq) have the largest shares in global emissions from oil crops with 30%
145 and 46%, respectively. Brazil's demand for soy-related food products generated the
146 largest percentage of the world's soybean-related emissions (45%) in 2000, but it was
147 replaced by China (32%) after 20 years. Indonesia, the world's leading consumer of
148 palm oil, has the largest emissions from palm oil (35% of the global total in 2019),
149 followed by Southeast Asia (13%), Western Europe (10%), and China (9%).

150

151 *(Insert Fig. 1 here)*

152

153 There are apparent inequalities in per capita emissions induced by food consumption
154 worldwide, but the disparities have been gradually declining ((Insert Fig. 2 here)).
155 Consistent with the scope of production-based estimates^{1,2,33}, global average per
156 capita emissions from food supply chains have increased from 1.8 (95% CI 1.6-3.1) to
157 2.1 (1.5-2.7) t CO₂-eq during the study period (details of uncertainty ranges see Suppl.
158 Table 5). Australia has the highest average animal-based emissions (4.9 t CO₂-
159 eq/person in 2019) from consumption, followed by Brazil (3.0 t/person), Canada (2.5
160 t/person), and the USA (2.1 t/person) (Suppl. Fig. 3, details of uncertainty ranges see
161 Suppl. Table 6). Although developed countries emit more animal-based emissions per
162 capita (1.7 t CO₂-eq/person) than the global average, differences exist between these
163 affluent countries. For example, people in Australia, Canada, and the USA have higher

164 per capita animal-based emissions than Western Europeans (1.4 t CO₂-eq/person)
165 mainly due to higher red meat consumption. Indonesia (3.9 t CO₂-eq/person in 2019),
166 Oceania (2.6 t/person), and Brazil (2.0 t/person) have the highest level of plant-based
167 emissions per capita despite a downward trend (Suppl. Fig. 4). Canada (1.8 t CO₂-
168 eq/person) and European countries (1.3 t CO₂-eq/person) have larger average plant-
169 based emissions than other developed countries, mainly due to large demand for oil
170 crops (e.g., palm oil) and stimulants (e.g., coffee). Although below the global average
171 of animal- (1.0 t CO₂-eq/person in 2019) and plant-based emissions (1.1 t/person), per
172 capita GHG emissions of the top two most populous countries, China (1.4 t/person)
173 and India (1.0 t/person), increased by 64% and 19%, respectively.

174

175

(Insert Fig. 2 here)

176

177 **International trade has reshaped food emission patterns**

178 Fig. 3 and Suppl. Fig. 5 show the countries with the largest amounts of emissions
179 embodied in food imports and exports, and their ratio of domestic emissions to
180 consumption-based emissions in 2019. Emissions from most major exporters are
181 dominated by two categories – oil crops and beef. Indonesia (307 Mt CO₂-eq in 2019)
182 and Brazil (196 Mt CO₂-eq) are the world's largest exporters of embodied emissions
183 from oil crops, dominated by palm oil and soybean, respectively. Indonesia's export of
184 oil crop emissions almost tripled during the study period, while Brazil's emissions
185 increased by 18%. Australia (200 Mt CO₂-eq in 2019) and Brazil (144 Mt CO₂-eq)
186 export the largest amounts of beef-related emissions, followed by India (44 Mt CO₂-eq)
187 and the USA (30 Mt CO₂-eq). We found that major net exporters, excluding Malaysia
188 which highly relies on meat imports (from India, Australia, etc.), create over 70% of
189 their food emissions within their national boundaries. As the world's largest net exporter,
190 Brazil's emission exports reached the highest level in the mid-term of the study period
191 (720 Mt CO₂-eq in 2010) and declined (to 581 Mt CO₂-eq in 2019) in the later period.

192 Overtaking US and Japan, China is by far the world's largest importer of embodied
193 emissions (585 Mt CO₂-eq in 2019). China's imports of embodied emissions are
194 dominated by oil crops (46%) and pork (16%), and both import volumes have
195 quadrupled mainly due to an increase in China's domestic demand for palm oil (+4.6
196 times), soybean oil (+1.8 times), and soybean cake for pig feed (+4.5 times). Beef
197 makes up the largest component of embodied emission imports from the USA (39% in
198 2019), Japan (42%), Russia (51%), and South Korea (43%), while oil crops (mainly
199 palm oil, soy) account for a large share in imports of embodied emissions by India
200 (88%) and the Netherlands (51%). Over this period, ~30% of consumption-based food
201 emissions in developed countries were generated overseas. This ratio in developed
202 countries with only a weak degree of self-sufficiency, such as Japan, South Korea, and
203 European countries, reached over 60%. In contrast, developing countries generated
204 91% of food-related emissions within national boundaries in 2000, although this ratio
205 declined to 85% in 2019.

206

207

(Insert Fig. 3 here)

208

209 We observe that the patterns of emissions embodied in international trade of food have
210 changed gradually, in which developing countries, especially China, are playing an
211 increasingly important role (Fig. 4). Between 2000 and 2019, the share of emissions
212 embodied in international trade to total consumption-based food emissions increased
213 from 14% to 19%. In 2019, 16% of animal-based and 21% of plant-based food
214 emissions were embodied in trade. Over this period, imports of embodied emissions
215 of developed countries kept constant (~1.1 Gt CO₂-eq), but its share in global trade
216 declined from 56% to 39%. In 2000, the USA, Japan, and Western European countries,
217 which are the world's richest countries, dominated international trade with their imports
218 contributing to nearly half of the total food-related emissions embodied in global trade.
219 By 2019 this share has dropped to 31%, while China has become the largest importer
220 of embodied emissions (22%). For example, the largest embodied emission flows to
221 China, i.e., imports from Brazil (319 Mt CO₂-eq) and Indonesia (69 Mt CO₂-eq),
222 increased around fourfold, respectively, while flows from Brazil (-62%) and Indonesia
223 (-33%) to Western Europe, which were the largest in the beginning, decreased.
224 However, emission transfers within Europe have intensified, such as flows between
225 Western European countries (+53%). Animal-based and plant-based emissions
226 embodied in food exports to developing countries have increased by 84% and 1.5
227 times. Increased food demand in developing countries creates a substantial increase
228 in emission outsourcing to major food exporting countries, including Indonesia (+71%),
229 Brazil (+65%), Australia (+34%), Canada (+42%), and the USA (+43%).

230

231

(Insert Fig. 4 here)

232

233 **Drivers of emissions of the global food system**

234 We apply structural decomposition analysis (SDA) to investigate the contributions of
235 different driving factors across the entire food supply chains to the variations of food-
236 consumption emissions globally and in different regions and countries (Fig. 5 and
237 Suppl. Table 7). Population growth was a significant contributor to emission rise in most
238 countries/regions (except Japan and Russia), which increased global total emissions
239 by 30% during the study period. The greatest emission increase driven by population
240 was in South Asia (+71%), Sub-Saharan Africa (SSA) (+64%), Near East and North
241 Africa (NENA) (+59%), and India (+42%). Above countries/regions have a high
242 population growth rate (over 30%) (Suppl. Table 8), with SSA being the highest (71%).
243 The rising per capita consumption level was another important driver of the global
244 emission increase (+19%) over the period. Per capita consumption drove up food
245 emissions in almost all developing countries, ranging from a modest +9% in LAC to
246 +61% in China. Except for Indonesia and SSA (over 90% are plant-based) where

247 farmland expansion leading to extensive land-use change, over 50% of per capita
248 consumption-related emission increases in developing countries are generated by
249 growing demand for animal-based food, such as China (+60%), India (+87%), NENA
250 (+77%) and LAC (nearly 100%) (Suppl. Table 7). However, declining demand for
251 animal-based food led to the decline of embodied emissions in Australia (-38%), Japan
252 (-7%), the USA (-6%), and Canada (-9%). These countries' per capita consumption of
253 red meat, such as beef (-53%, -22%, -13%, and -7%, respectively), have declined over
254 this period (Suppl. Fig. 6).

255 Despite the upward trend of global food emissions by other drivers, emission intensity,
256 measured by the amount of emissions per unit of weight of food product, was the
257 dominant factor offsetting parts of emission growth, decreasing global emissions by
258 37%, avoiding additional 5.2 Gt CO₂-eq emission globally. Emission intensity includes
259 three components, i.e., the intensity of LULUC, agricultural production, and beyond-
260 farm activities. The effect of substantially declining emission intensity from LULUC
261 activities was responsible for over 5.4 Gt CO₂-eq global emission decline (-39%) with
262 other factors held constant and had a prominent effect on emissions in countries with
263 extensive land use activities, such as Brazil (-90%), SSA (mainly South and Central
264 African regions) (-57%) and Indonesia (-46%) (Suppl. Table 7). However, the driving
265 effects of emission intensity related to agricultural production and beyond-farm
266 processes slightly increased the world's emissions by 149 Mt CO₂-eq (+1%) and 63 Mt
267 CO₂-eq (+0.5%), respectively. Our decomposition results show that a sharp drop in
268 Brazil's emissions (by ~1 Gt CO₂-eq) during the period from 2010-2015 is attributed to
269 the contribution of decreasing LULUC emission intensity. The root cause of the
270 decrease in LULUC emission intensity is shrinking LULUC activities (largely
271 deforestation) and associated emissions. After a series of measures³⁴, such as the
272 Forest code³⁵ and Amazon Soy Moratorium³⁶, for legally limiting deforestation activities
273 in Amazon, Brazil's deforestation rate reached a historically low level in 2010-2015,
274 with a reduction of 50-80% compared with 2004³⁷ but this trend has significantly
275 changed under the following political leadership³⁸.

276 Over this period, changes in the trade structure increased global emissions by 8% (1.1
277 Gt CO₂-eq) through increasing exported products from regions and countries with
278 emission-intensive production, while a decline in food consumption from domestic
279 supply in importing regions and countries reduced global emissions by 5% (0.7 Gt CO₂-
280 eq). In 2000-2015, food importers became increasingly dependent on exports of
281 emission-intensive products from agricultural suppliers including Brazil and Indonesia.
282 As a result, international food trade accelerated global emissions. However,
283 international trade tends to reduce emissions of global food consumption after 2015
284 with the improvement of production productivity in exporting countries.

285

286 *(Insert Fig. 5 here)*

287

288 **Discussion and conclusions**

289 Our study attributes production-based emissions^{2,3,32} to final consumers at a product
290 level using physical trade flows which provides complementary information to PBE,
291 thus allowing to investigate emissions and target mitigation efforts across the whole
292 food supply chain. Results show considerable differences regarding emission patterns
293 and effects of drivers between regions and countries, and we could classify them into
294 four groups according to these differences: (1) countries with high per capita food
295 emission levels and dominant livestock emissions (mainly from red meat) (North
296 America, Australia, LAC); (2) developed countries which heavily rely on imports and
297 outsource substantial amounts of food-related emissions (Japan and Europe); (3)
298 rapidly developing countries with substantial emission increase driven by rapid
299 population growth or improved living standards (China, South Asia, NENA); (4)
300 countries with emission-intensive production, mainly with extensive land-use change
301 activities (Brazil, Indonesia, and South and Central African regions). Discussions on
302 comparison with other studies of global food emissions are provided in the
303 Supplementary Discussion.

304 Our results show considerable differences in food consumption and associated
305 emissions across countries. Residents in the first group of countries have an animal-
306 dominated (especially beef) diet and larger associated emissions compared with other
307 groups, while the third group is generating increasing consumption of beef and dairy
308 due to the demand for improving living standards and diet diversity. As for the same
309 protein content, red meat, especially beef, generates more emissions than poultry, fish,
310 and plant-based protein products³⁹. Thus, the growth of the global population and rising
311 per capita demand for emission-intensive food are likely to boost emissions further.
312 Diet shifts, including reducing excessive intake of red meat or improving shares of
313 plant-based protein, will not only reduce emissions but avoid health risks such as
314 obesity and cardiovascular disease⁴⁰. However, widespread and lasting diet shifts (e.g.,
315 the EAT-Lancet diet⁴¹) are very difficult to achieve within a narrow timeframe. Therefore,
316 incentives that encourage consumers to reduce red meat or buy products with higher
317 environmental dividends through eco-labeling, adding taxes or subsidies reflecting
318 some of the environmental costs in product prices, and education on actual food
319 emissions could help to reduce food emissions^{7,39}.

320 International food trade policies incorporating environmental externalities which are
321 less covered in production-side policies are urgently needed to avoid possible
322 emission leakage and realize emission reduction across supply chains. Emissions
323 outsourced through international food trade increased by ~1 Gt CO₂-eq over the study
324 period, accelerating global emission increase and unequal distribution. Countries in
325 the second and third groups have considerably lower PBE² than CBE by outsourcing
326 their domestic food emissions through imports from agricultural suppliers such as
327 Brazil, Indonesia, and Oceania. Emissions embodied in these food imports vary
328 considerably depending on the originating countries, while the world's main food
329 suppliers are not regions with the highest efficiency. For example, the total emission

330 intensity of production per kilogram of beef in Western European countries (range from
331 15-17 kg CO₂-eq) is far less than in Brazil (44-46 kg CO₂-eq) (Suppl. Fig. 7), but the
332 latter is the largest beef exporter for European countries⁴². Countries with high
333 efficiency for domestic production import emission-intensive products from regions
334 with a large scale of LULUC activities or low agricultural efficiency will tend to increase
335 emissions of the global food system. Although the magnitude of food emissions
336 embodied in global trade is considerable, proposals for measures to avoid carbon
337 leakage such as the EU's proposed Carbon Border Adjustment Mechanism⁴³ have
338 rarely been extended to include agricultural or food-related emissions. Key emission-
339 intensive products which dominate international food trade (e.g., beef from Australia,
340 beef and soybean from Brazil, palm oil from Indonesia) could be targets of such
341 taxation policies. Our data and model with information at the product level can help
342 quantify the size of the necessary adjustment.

343 A series of trade policies are accelerating emissions through increasing food imports
344 from countries/regions with emission-intensive production. For instance, the EU's
345 Green Deal encourages less intensive agriculture in Europe and increasing imports of
346 agricultural products from countries such as Brazil, the USA, Indonesia, and Malaysia⁴⁴.
347 Another example that leads to emissions increase through trade is the US-China trade
348 war, which led China to import more soybean from Mercosur countries to reduce its
349 dependence on the USA⁴⁵. Above imports from major suppliers induced by demand
350 led to a surge in deforestation and associated emissions. However, trade between
351 diverse international partners provides opportunities to ameliorate emissions by
352 allowing consumers to choose products from places with less emission-intensive
353 production. Long-term commitments are needed to comprehensively assess
354 emissions embodied in the entire supply chain for trade-offs between domestic
355 production and imports from multiple origins, thereby minimizing global impacts.

356 Furthermore, our study traces the origins and emission intensities of specific products
357 which ultimately flow to final consumers. Results show that reducing PBE through
358 agricultural intensification with technology improvement or lower levels of resource
359 inputs (reflected in lower emission intensity), especially for agricultural producers from
360 group four with abundant natural resources (e.g., forests, peatland)⁴⁶ which generated
361 vast amounts of emissions from widespread LULUC activities such as deforestation,
362 is vital for mitigating climate effects across food supply chains. Changes in consumer
363 behavior or trade policies (e.g., proposed legislation to eliminate deforestation by
364 European countries⁴⁷) in the second and third group of countries can trigger deeper
365 impacts via food supply chains and eventually improve production-side efficiency for
366 the fourth group⁴⁸. Altered levels and composition of food consumption (with less
367 emission-intensive products) could reduce land use change, relocate production to
368 places with fewer emissions, or incentivize food suppliers to decrease emission
369 intensity as well as avoid destructive environmental impacts (e.g., through the Amazon
370 Soy Moratorium^{36,49}). However, we find that the fourth group of countries themselves
371 have substantial consumption-based emissions due to the domestic demand for
372 emission-intensive products (e.g., oil crops). Raising awareness and legislation
373 nationally to reduce emissions from food production are needed across these countries,

374 otherwise the domestic leakage may offset part of the emission reduction brought by
375 supply chain measures⁴⁹.

376 **Methods**

377 **Food consumption accounting**

378 We apply the physical trade flow (PTF) approach proposed by Kastner et al.^{25,50} to
379 calculate the consumption of 153 food products (both primary and processed products)
380 (Suppl. Table 9, 10) based on the physical trade between 181 countries or areas in five
381 given years (2000/2005/2010/2015/2019) (Supplementary Methods 1.1). We use the
382 criteria proposed by the United Nations⁵¹ to define developed and developing countries
383 (Suppl. Table 3). Countries or areas are classified into 18 countries/regions for
384 comparison according to geographical locations (Suppl. Fig. 8, Suppl. Table 4). The
385 PTF approach by Kastner et al. allows tracing product flows through international
386 supply chains as well as final consumers to which products ultimately flow based on
387 domestic production and bilateral trade between countries. We use data from the
388 detailed trade matrix of products on FAOSTAT³⁰ to construct the matrix showing the
389 physical flows between countries. All data are in units of mass (metric tonnes). Detailed
390 data sources used for this study are shown in Supplementary Methods 1.2 and Suppl.
391 Table 11. We mainly use the reported import data by assuming that imports are more
392 reliable due to the strict custom records⁵². The PTF approach assumes that the
393 domestic production and imported products are proportionally distributed between
394 domestic supply and exports. Because of the limited shelf life of food and the relatively
395 small share of agricultural commodities used for food stocks, this study does not
396 include variations in stocks.

397 The PTF approach by Kastner et al. is suitable for linking consumption and associated
398 environmental impacts to crop cultivation or livestock raising (on-farm stages)²⁵ at a
399 product level²³. To investigate the GHG emissions of processed products generated
400 during on-farm processes, we transform the bilateral trade matrix of processed
401 products using the ratio of sources for primary products, which is developed based on
402 the proportion of domestic production and imports of primary products (Supplementary
403 Methods 2.2). We use conversion factors for agricultural commodities from FAO⁵³ to
404 convert the processed products into primary products, and some missing factors are
405 supplemented by using the factors from the GTAP Data Base with Nutritional
406 Accounts⁵⁴ (Supplementary Methods 2.2 and Suppl. Table 9). Therefore, we can obtain
407 the new production and bilateral trade matrix of the processed products in the form of
408 primary equivalents, which trace the sources of raw materials for processed product
409 production and the destination where these processed products are finally consumed
410 (Supplementary Methods 2.3). Here we simplify the calculation by ignoring the
411 difference between inputs during the production of processed products and assuming
412 all primary products used as raw materials are consumed in one place. Furthermore,
413 agricultural products for non-food use are excluded by using data of non-food use
414 commodities from the food balance sheet on FAOSTAT⁵⁵ (Supplementary Methods
415 2.5).

416 **Quantification of consumption-based food emissions**

417 By combining the emission intensity (the amount of emissions per unit weight of food
418 product) and the consumption matrix (see Suppl. Fig. 9 for the accounting framework),
419 the consumption-based emissions of each product are calculated as follows²⁵:

$$420 \quad E_i = \sum_j \frac{G_{ij}}{P_i} \cdot (I - A_i)^{-1} \cdot P_i \cdot \frac{DMC_i}{DMI_i} = \sum_j f_{ij} L_i P_i c_i \quad \text{Equation 1}$$

421 where E_i refers to the consumption-based GHG emission of product i . $f_{ij} = G_{ij}/P_i$
422 represents the vector of emission intensity of product i from food supply chain
423 process j , of which G_{ij} is total emissions generated from supply chain process j of
424 product i , P_i is the production vector of product i . c_i is the vector of share of DMC_i
425 in DMI_i , of which DMC_i (Domestic Material Consumption) is the amount of product i
426 consumed domestically, DMI_i (Domestic Material Input) represents total inputs of
427 product i in one country; DMI_i equals DMC_i plus exports of product i (or production
428 plus imports). $L_i = (I - A_i)^{-1}$ denotes the trade structure of product i , of which A_i is
429 the matrix of export shares in DMI_i , and I is the identity matrix with the same
430 dimension as matrix A_i (Supplementary Methods 2.1).

431 To obtain the emission intensity along supply chain processes, we distribute the annual
432 GHG emissions (including CO₂, CH₄, and N₂O) from LULUC, agricultural, and beyond-
433 farm activities to plant- and animal-based products using the similar approach
434 performed by Hong et al.¹⁰. CH₄ and N₂O are converted into CO₂ equivalents using the
435 100-year global warming potential values of 28 and 265 from IPCC AR5⁵⁶. National
436 emission data are obtained from the FAOSTAT Climate Change dataset³¹ (Suppl. Table
437 11), which provides data of country- and process-specific emissions from the food
438 system based on activity data and IPCC Tier 1 Methodology. Results of consumption-
439 based emissions of CO₂, CH₄, and N₂O are shown in Suppl. Fig. 10 and Suppl. Data
440 2. Detailed GHG categories and emission processes are shown in Suppl. Table 12.

441 Allocation of LULUC emissions to food products

442 A top-down approach is applied to allocate production-based LULUC emissions due to
443 the expansion of cropland or pasture^{2,32} to primary products. LULUC emissions include:
444 (1) CO₂, CH₄, and N₂O from burning (of forests, savanna, humid tropical forests, and
445 organic soils), (2) CO₂ from net forest conversion, and (3) CO₂ and N₂O from the
446 drainage of organic soils. We assume that LULUC emissions are directly related to
447 land use areas for the production of primary products^{10,57,58} and distribute the annual
448 LULUC emissions to products according to harvested cropland areas or pasture areas
449 for feeding livestock in a given year. LULUC emission intensities are calculated using
450 the production and LULUC emissions of primary products (Supplementary Methods
451 3.1). All data of emission amounts³¹, land use areas⁵⁹, and production quantity⁶⁰ are
452 obtained from FAOSTAT^{2,3,32}. Legacy emissions cumulated in land due to LULUC
453 activities over time or absorbed emissions by land due to agriculture abandonment are
454 not incorporated. Based on the LULUC emission intensities of each product, we assign
455 LULUC emissions to final consumers using the PTF approach as *Equation 1*. Results
456 of consumption-based LULUC emissions in 181 countries are shown in Suppl. Fig. 11

457 and Suppl. Data 3.

458 Allocation of agricultural emissions to food products

459 Emissions from agricultural production for crops are: (1) N₂O from crop residues, (2)
460 CH₄ and N₂O from burning crop residues, (3) N₂O from synthetic fertilizer, (4) N₂O from
461 the use of synthetic fertilizer, (5) N₂O from manure applied to soils, (6) CH₄ from rice
462 cultivation and (7) CO₂, CH₄ and N₂O from energy use for crop cultivation^{2,3,32}. We
463 allocate production-based agricultural emissions³¹ to crops and calculate agricultural
464 emission intensities based on the production of crops from FAOSTAT⁶⁰
465 (Supplementary Methods 3.2). Emissions from crop residues⁶¹ are allocated by
466 Nitrogen contents and production of specific crops, while emissions from burning
467 residues⁶² are distributed by the amounts of burned biomass of crops. N₂O from
468 synthetic fertilizers is allocated to primary crops according to their fertilizer input
469 rate^{63,64} and harvested areas from FAOSTAT⁶⁰. Emissions from manure applied to soils
470 and rice cultivation³¹ are distributed by harvested areas of crops and rice production
471 quantity⁶⁰, respectively. In addition, we use the impact coefficient of food products
472 (emission per unit weight of the product)^{39,65} (Suppl. Table 13) to assign emissions of
473 energy use to products.

474 Emissions from the agricultural production of livestock (meat, dairy, and eggs) are
475 generated in five main processes: enteric fermentation, manure management, feed
476 production, manure left on pasture, and energy consumption. Country- and animal-
477 specific emissions from enteric fermentation (CH₄) of ruminant animals⁶⁶ and manure
478 management (CH₄ and N₂O)⁶⁷ based on Tier 1 level are obtained from FAOSTAT^{2,3,32},
479 and then allocated to livestock products using FAOSTAT statistics of production¹⁰.
480 FAOSTAT provides data on emissions generated in manure left on pasture (N₂O)⁶⁸ as
481 well. Emissions of manure left on pasture are allocated into livestock products
482 according to the pasture areas needed for feeding different animals, and then the
483 emission intensity is calculated based on production amounts of livestock products.

484 Emissions from feed crops are allocated to the livestock products that consume the
485 feed during production. Emissions from feed crops, including barley maize, wheat,
486 rapeseed cake, and soybean cake, for livestock production, are allocated to livestock
487 according to the feed conversion ratios (FCRs) specific to each product at the national
488 level⁶⁹⁻⁷². FCRs are calculated based on the national feed use quantities⁵⁵ and weight
489 factors of each livestock product^{69,71,72} (Supplementary Methods 2.4). Then we
490 calculate feed emissions per unit weight of animal-based products using the same
491 approaches as crops. Moreover, we use data on production and emissions generated
492 from the energy use of freshwater and marine products⁷³ to calculate the emission
493 intensity from fishery production.

494 Based on the emission intensity of crops and livestock during agricultural production,
495 we assign agricultural emissions to final consumers of 153 food products using the
496 PTF approach as *Equation 1*. Results of consumption-based agricultural emissions in
497 181 countries are shown in Suppl. Fig. 11 and Suppl. Data 3.

498 Allocation of beyond-farm emissions to food products

499 Bottom-up aggregation and top-down allocation approaches are combined to distribute
500 beyond-farm emissions to products. Emissions from beyond-farm processes include:
501 CO₂, CH₄, and N₂O from (1) processing, (2) packaging, (3) retail, (4) transport; (5) CO₂
502 and N₂O from fertilizer manufacturing; (6) CH₄ and N₂O from industrial wastewater
503 treatment related to food. The statistical data of total national emissions in the above
504 six processes are obtained from FAOSTAT^{2,3,32}. National emissions from food
505 processing, packaging, retail, and industrial wastewater treatment³¹ are downscaled to
506 the product level by using the impact coefficient of 153 products^{39,65} (Supplementary
507 Methods 3.3). Since the food-transport emissions are closely related to the transport
508 distance and freight volume, we use the monetary values between transport and food-
509 related sectors from the GTAP database⁷⁴ to distinguish emissions from domestic and
510 international transport. Therefore, emission intensities of specific products at different
511 distances (within or between countries) can be calculated using the impact coefficient
512 for food transport. In addition, emissions of fertilizer manufacturing are allocated
513 according to the same approach of distributing synthetic fertilizer-related emissions in
514 agricultural production. Beyond-farm emissions are attributed to final consumers using
515 the PTF approach shown in *Equation 1*. Results of consumption-based beyond-farm
516 emissions in 181 countries are shown in Suppl. Fig. 11 and Suppl. Data 3.

517 **Identification of driving factors**

518 To understand the driving forces behind emissions of food consumption, we employ
519 the Structural Decomposition Analysis (SDA), the widely adopted method in energy
520 and emission studies⁷⁵, to decompose the global and regional emissions of 153
521 products as:

$$522 \quad E = \sum_{i=1}^{153} \sum_j \frac{G_{ij}}{P_i} \cdot (I - A_i)^{-1} \cdot P_i \cdot \frac{DMC_i}{DMI_i} = \sum_{i=1}^{153} \sum_j f_{ij} \cdot L_i \cdot \frac{P_i}{DMI_i} \cdot \frac{DMC_i}{p} \cdot p = \sum_{i=1}^{153} \sum_j f_{ij} L_i R_i C_i p$$

523 *Equation 2*

524 where E refers to the consumption-related emissions of 153 products. The equation
525 includes five factors: emission intensity of product i in process j ($f_{ij} = G_{ij}/P_i$); trade
526 structure of product i (L_i) defined in *Equation 1*; domestic supply ratio of product i
527 ($R_i = P_i/DMI_i$), indicating the ratio of locally produced food to total food inputs;
528 per capita consumption of product i ($C_i = DMC_i/p$); population (p). The difference
529 between two time periods can be expressed as:

$$530 \quad \Delta E = E^t - E^0 = \sum_{i=1}^{153} \sum_j f_{ij}^t L_i^t R_i^t C_i^t p^t - \sum_{i=1}^{153} \sum_j f_{ij}^0 L_i^0 R_i^0 C_i^0 p^0 \quad \text{Equation 3}$$

531 Thus the changes in consumption-based emissions during 2000-2005, 2005-2010,
532 2010-2015, and 2015-2019 can be decomposed by five factors as:

$$533 \quad \Delta E = \sum_{i=1}^{153} \sum_j \Delta f_{ij} L_i R_i C_i p + \sum_{i=1}^{153} \sum_j f_{ij} \Delta L_i R_i C_i p + \sum_{i=1}^{153} \sum_j f_{ij} L_i \Delta R_i C_i p + \sum_{i=1}^{153} \sum_j f_{ij} L_i R_i \Delta C_i p +$$

$$534 \quad \sum_{i=1}^{153} \sum_j f_{ij} L_i R_i C_i \Delta p \quad \text{Equation 4}$$

535 where Δ represents changes in a factor from base year (0) to target year (t). Each of
536 five terms in *Equation 4* denotes the contributions to emission changes which are

537 triggered by one factor if other variables keep constant. The five factors in the SDA
 538 model can result in $5! = 120$ first-order decompositions, and here we use the solution
 539 named the average of two polar decompositions^{75,76} to approximate the average of all
 540 possible decompositions. The *Equation 4* are finally converted as:

$$\begin{aligned}
 541 \quad \Delta E = & \sum_{i=1}^{153} \sum_j 0.5(\Delta f_{ij} L_i^t R_i^t C_i^t p^t + \Delta f_{ij} L_i^0 R_i^0 C_i^0 p^0) + \sum_{i=1}^{153} \sum_j 0.5(f_{ij}^0 \Delta L_i R_i^t C_i^t p^t + f_{ij}^t \Delta L_i R_i^0 C_i^0 p^0) + \\
 542 \quad & \sum_{i=1}^{153} \sum_j 0.5(f_{ij}^0 L_i^0 \Delta R_i C_i^t p^t + f_{ij}^t L_i^t \Delta R_i C_i^0 p^0) + \sum_{i=1}^{153} \sum_j 0.5(f_{ij}^0 L_i^0 R_i^0 \Delta C_i p^t + f_{ij}^t L_i^t R_i^t \Delta C_i p^0) + \\
 543 \quad & \sum_{i=1}^{153} \sum_j 0.5(f_{ij}^0 L_i^0 R_i^0 C_i^0 \Delta p + f_{ij}^t L_i^t R_i^t C_i^t \Delta p) \quad \text{Equation 5}
 \end{aligned}$$

544 where ΔE represents changes in consumption-based emissions along supply chains
 545 of 153 products; Δf_{ij} captures the change of emission intensity of product i in supply
 546 chain process j ; ΔL_i measures the change in international trade structure of product
 547 i ; ΔR_i denotes the change in the ratio of locally produced product i to total inputs of
 548 product i ; ΔC_i identifies changes in per capita consumption of product i ; Δp
 549 measures changes in population.

550 **Uncertainty assessment**

551 Our results of global consumption-based emissions during different supply chain
 552 processes are generally consistent with global production-based food emission
 553 inventories from FAOSTAT^{2,3,32,77}. Similar to the uncertainty analysis performed by
 554 Tubiello et al.^{2,33,78} and Hong et al.¹⁰, we conduct a Monte Carlo approach (running
 555 10,000 simulations) to assess the uncertainty range of consumption-based emissions
 556 by simulating the varying activity data, emission factors and parameters for each
 557 process according to the default uncertainty ranges derived from the standard IPCC
 558 guidelines⁷⁹ and individual uncertainty ranges from previous studies (see Suppl. Table
 559 14). Uncertainty ranges of 95% confidence intervals of consumption-based food GHG
 560 emissions are adopted. Detailed uncertainty ranges of food emissions are provided in
 561 Suppl. Table 1, 2, 5, 6 and Suppl. Data 8, 9. We only consider the uncertainties
 562 generated in the production processes and do not include the uncertainties caused by
 563 trade because we cannot obtain the uncertainty ranges of original statistical data for
 564 reported imports of agricultural products^{11,19,28,80}. We recognize that the uncertainties
 565 of trade data in this study have an unknown magnitude.

566 **Limitations**

567 Our study has the following limitations and future work will focus on these aspects to
 568 provide a more accurate analysis of consumption-based food emissions.

569 First, the PFT approach by Kastner et al.²⁵ allows us to quantify re-exports to other
 570 countries based on conversion matrices but ignores the connections with other sectors
 571 within the economy compared to the MRIO-based approach. We do not choose
 572 physical MRIO because the FABIO²⁷ is outdated, and Exiobobase^{81,82} does not have
 573 as many countries and product detail as our database. The PTF approach we use is
 574 thus very suitable to capture relatively simple food supply chains but may ignore more
 575 complex processing and repacking steps in global supply chains and thus introduce
 576 some system boundary cut-off error²³. A more feasible design in the next step requires
 577 integration with models such as MRIO to investigate the entire supply chain
 578 considering the heterogeneity of production inputs and connections between food-

579 related and other sectors.

580 Second, we do not consider heterogeneity within countries. Countries present sub-
581 national differences in land-use, agricultural and other activities, and related emissions.
582 However, data in terms of production, trade, and emissions along the entire food supply
583 chain at the sub-national level is available for a few products and is limited to a range
584 of potential errors with inconsistent data sources. Therefore, we only focus on the
585 emissions from consumption and trade at a country level.

586 Third, our study focuses on upstream emissions along food supply chains before
587 household and excludes emissions from household consumption and end-of-life (i.e.,
588 waste management)^{1,2,32}. Above emissions beyond supply chains are difficult to
589 allocate to specific products given the limited data availability and are not part of the
590 international trade flows. Nonetheless, given the large magnitude of these emissions,
591 especially methane emissions from the decay of solid food waste in landfills and open
592 dumps², future studies which explore the mitigation of food emissions from consumers
593 will incorporate such emissions as an extension of findings.

594 Finally, the data available for this study have some limitations. Data of production for
595 some processed products have the problem of item aggregation in 2000 and 2005,
596 and we separate these products based on their shares in 2010. Meanwhile, because
597 of the lack of a standard distribution approach as well as harmonized food emission
598 coefficients at a product level, emissions from different processes are attributed to
599 specific products according to different approaches applied by previous studies which
600 may lead to biased results. Moreover, this study does not account for the legacy
601 emissions or carbon removals from land which are difficult to allocate to specific years
602 or products. With the improvement of data availability (e.g., the use of dynamic land-
603 use models), a more consistent and complete accounting framework of the food
604 system in the future will cover these emissions with breakdown into detailed products
605 at global, national, and sub-national levels.

606 **Data availability**

607 The LULUC, agricultural and beyond-farm emissions data are curated by the FAO and
608 freely available from FAOSTAT⁷⁷. Population data used in this study are obtained from
609 World Population Prospects of the United Nations⁸³. Data of monetary values for
610 transport and food-related sectors are obtained from GTAP database⁷⁴.
611 Supplementary methods, discussion, figures, tables and datasets used in the analysis
612 can be found in the Supplementary Information files. More detailed results are
613 available from the corresponding author on reasonable request.

614 **Code availability**

615 Code developed for data processing in MATLAB is available in the Supplementary
616 Information files.

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628 **Author contributions**

629 Y.L., Y.S., and K.H. designed the research. Y.L. performed the analysis with support
630 from Y.H., D.W., and Y.Z. on analytical approaches and visualization. Y.L. led the writing
631 with efforts from H.Z., Y.S., and K.H. Y.S. and K.H. supervised and coordinated the
632 overall research. All co-authors reviewed and commented on the manuscript.

633 **Competing interests**

634 The authors declare no competing interests.

635 **Figure legends/captions**

636 **Fig. 6: GHG emissions throughout global supply chains from consumption of food**
637 **products by country in 2000 and 2019.** The background map shows the level of consumption-
638 based emissions at the country scale. The pie chart shows the fraction of consumption-based
639 emissions of animal-based and plant-based food products, and the size represents the total
640 emissions for 18 countries/regions. AUS: Australia; BRA: Brazil; CAN: Canada; CHN: China;
641 ROEA: Rest of East Asia; EE: East Europe; IND: India; IDN: Indonesia; JPN: Japanese; ROLAC:
642 Rest of Latin America and the Caribbean; NENA: Near East and North Africa; ROO: Rest of
643 Oceania; RUS: Russia; ROSA: Rest of South Asia; ROSEA: Rest of Southeast Asia; SSA: Sub-
644 Saharan Africa; USA: United States of America; WE: Western Europe. Details for the division
645 and scope of 18 countries/regions are shown in Suppl. Table 3, 4. Base map layer: "World
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649
650 **Fig. 7: Per capita GHG emissions of food consumption by country in 2000 and 2019.** The
651 background map shows the level of per capita consumption-based emissions at the country
652 scale. The pie chart shows the fraction of average consumption-based emissions of animal-
653 based and plant-based food products per person, and the size represents per capita emissions
654 of 18 countries/regions. Abbreviations of 18 countries/regions and the source of base map are
655 shown in (Insert Fig. 1

656
657 **Fig. 8: GHG emissions embodied in domestic supply and international trade of food of**
658 **major countries in 2000, 2010, and 2019. (a)** Ratio of domestic GHG emissions to total
659 embodied emissions of food consumption by eighteen major countries. Domestic GHG
660 emissions refer to the emissions embodied in domestic food supply within a national territory
661 including emissions from all food products, animal-based, and plant-based food products (from
662 left to right). **(b)** GHG emissions embodied in food imports and exports of eighteen major
663 countries. The circles represent net imports or exports of emissions from food consumption.

664
665 **Fig. 9: Patterns of emission flows embodied in international trade of all types of (a),**
666 **animal-based (b), and plant-based (c) food products among and within 18**
667 **countries/regions in 2000 and 2019 (unit: Mt CO₂-eq).** Width of the lines represent the
668 volumes of emissions embodied in trade from exporter to importer, and the color is the same
669 as the exporter. Flows in the above Figure cover more than 90% of total emissions embodied
670 in international bilateral trade annually as small flows are not shown here. Number in brackets
671 represents the ratio of emissions embodied in trade to total consumption-based emissions.
672 Abbreviations of 18 countries/regions are shown in (Insert Fig. 1

673
674 **Fig. 10: Contributions of five driving factors to changes in GHG emissions from food**
675 **consumption of the global (a) and 18 countries/regions (b-s) between 2000 and 2019.** The
676 grey bars indicate total emissions. The colored bars represent the absolute contribution
677 (positive or negative) of different driving factors to the changes in global and national/regional

678 *emissions in every period.*

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