Changes in global food consumption increase GHG emissions despite efficiency gains along global supply chains

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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 CO_2-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.

Introduction

The agrifood system drives global land use, agricultural and other beyond-farm activities, and contributes to about one-third of global anthropogenic greenhouse gas (GHG) emissions[1-3]. The United Nations projects that an additional 70 percent of the current food demand will be needed to feed the world's estimated population of 9.1 billion by 2050[4]. Population growth, expansion of food production, and an increase in animal-based diets are likely to further increase emissions and squeeze the global carbon budget[5,6]. Thus, mitigating emissions at every stage of food supply chains from production to consumption is crucial to limit global warming[6-8].

Production-based emissions (PBE) or territorial emissions are based on emissions from production (including exports) within a region[9]. Previous studies[1,2,10,11] have quantified global GHG emissions from food production based on global food-related emission inventories (e.g., FAOSTAT, EDGAR-Food). However, food products are increasingly traded internationally through global supply chains, and geographically distant consumer demand may lead to emission outsourcing to producers[12-14]. Consumption-based emission (CBE) accounting allocates emissions from producers to final consumers irrespective of the place of production[15,16]. CBE is complementary to PBE and allows allocating responsibility and informs emission mitigation from a consumer perspective. CBE helps to understand to what extent final consumers trigger emissions along the entire global supply chain, allows quantification of virtual flows in trade outsourced to other countries, and provides information for additional policy tools for emission mitigation with a focus on consumption[17,18]. Therefore, a detailed assessment of global consumption-based GHG emissions throughout food supply chains with a breakdown into the detailed process- and product-levels are needed to reveal the distant emission drivers and to facilitate emission mitigation from a consumer perspective. However, such consumption-based assessments are hampered due to the complexity and variety of processes in which different food products are cultivated, processed, and traded through multiple intermediate regions[19,20] as well as the required degree of data consistency and granularity in terms of processes and products of the global agrifood system.

A number of studies used bottom-up life-cycle assessment (LCA) to investigate emissions of specific food products during their lifecycle[21]. However, these results are not comparable because of differences in scope[21,22] and oftentimes ignoring differences in emissions from different origins along global food supply chains[20]. With the international, time-series input-output databases at high sectoral detail, multi-regional input-output (MRIO) analysis is now widely used for tracing consumption-based emissions[23]. MRIO is applied to quantify emissions induced by food consumption based on input-output relations (in monetary values) along supply chains[19,24]. This approach has been frequently criticized due to its highly aggregated sectors lacking product details[25-27]. For example, soybean, together with other oilseed crops such as palm oil and rapeseed, are aggregated in the same oil crop sector, ignoring important finer-scale differences in terms of land use, input requirements, and associated emissions. PTF based on physical product flows provides a more detailed analysis of trade flows for agricultural products based on higher sectoral and product resolution[23]. Some PTF bilateral trade approaches use the difference between production, imports, and exports to calculate GHG emissions from food consumption[11,28,29] but without consideration of re-export via longer international supply chains. The improved PTF developed by Kastner et al. provides a framework with detailed data to link consumption and associated impacts to the origins of cultivated crops or livestock (on-farm stages) beyond bilateral trade[25,26].

Here, we analyze the trend of consumption-based food GHG emissions of 153 products (both animal- and plant-based food) in 181 countries or areas for the years 2000, 2005, 2010, 2015, and 2019. Using the PTF approach by Kastner et al.[25] and detailed trade data from FAOSTAT[30], we reallocate production-based GHG emissions (CO_2, CH_4, and N_2O)[31] from agricultural land use and land use change (LULUC), agricultural production, and beyond-farm processes (excluding emissions from household and end-of-life)[1,2,32] throughout the supply chains of 153 products to final consumers. All emissions are in CO_2 equivalents (CO_2-eq) using 100-year global warming potentials of CH_4 and N_2O used in the IPCC 5th Assessment Report (AR5). We quantify emissions embodied in food domestic supply and trade (i.e., imports and exports) between countries involving re-exports. Finally, structural decomposition analysis is applied to identify the contributions of five driving factors from production to consumption to variations in consumption-based emissions - namely emission intensity, trade structure, domestic supply ratio, per capita consumption, and population. Our study uses the most recent data to attribute emissions across the entire food supply chains at a global scale to final consumers with a consistent and detailed breakdown of processes and products. This allows us to indicate how to reduce food emissions from production to consumption through policy applications for the entire supply chain and final consumers.

Results

Emissions driven by global and national food consumption

In 2019, food consumption in the five highest emitting countries, China (2.0 Gt CO_2-eq), India (1.3 Gt), Indonesia (1.1 Gt), Brazil (1.0 Gt) and the USA (1.0 Gt), were responsible for more than 40% of global food supply chain emissions (16.0 (95% confidence interval 11.4-20.7) Gt CO_2-eq) which cover most of the emissions of the global agrifood system[2,3] ((Insert Fig. ***1***, details of uncertainty ranges see Suppl. Table 1). Annual global GHG emissions associated with food increased by 14% (i.e., 2 Gt CO_2-eq) from 2000 to 2019, which largely owes to consumption rise in populous countries, with China contributing 46%, India 24%, and Pakistan 11% to emission growth.

The substantial increase in consumption of animal-based products contributed to ~95% of the global emission rise, reaching almost half of the total food emissions[3], with 7.9 (5.9-10.1) Gt CO_2-eq in 2019. We find that many countries have dominated animal-based emissions, represented by Australia (82%), the USA (66%), and South Asian countries including India (63%). The share of animal-based emissions in total emissions continued increasing in most developing countries/regions (e.g., Brazil, East Asia) but remained stable in affluent countries. Beef and dairy contributed 32% and 46% of the increase in global animal-based emissions and reached 3.4 Gt CO_2-eq and 2.8 Gt CO_2-eq respectively in 2019 (Suppl. Fig. 1, details of the uncertainty ranges see Suppl. Table 2). Top emitters of beef consumption included Brazil (437 Mt CO_2-eq), the USA (409 Mt), and Argentina (118 Mt) in 2000 but later included Brazil (409 Mt), China (402 Mt), and the USA (365 Mt). Increased consumption of beef led to 28% of China's growth of animal-based emissions. Beef's contribution is similar to pork which dominates China's meat market. Emissions from beef consumption constitute 64% of animal-based emissions in Brazil, and over 50% occurred in the Rest of Latin America and the Caribbean (LAC), the USA, Japan, and Southeast Asia. Emissions from India's dairy consumption increased considerably by 1.2 times, reaching 78% of national animal-based emissions as well as over 1/5 of global dairy emissions in 2019. Dairy consumption in Russia, Oceania, and European countries also contributed to over half of national animal-based emissions.

The consumption of grains and oil crops is responsible for 43% (3.4 Gt CO_2-eq in 2019) and 23% (1.9 Gt CO_2-eq) of global plant-based emissions, respectively (Suppl. Fig. 2, details of uncertainty ranges see Suppl. Table 2). Rice contributes to over half of the global grain-related emissions (1.7 Gt CO_2-eq), with Indonesia (20%), China (18%), and India (10%) being the top three contributors. Soybean (0.6 Gt CO2-eq) and palm oil (0.9 Gt CO2-eq) have the largest shares in global emissions from oil crops with 30% and 46%, respectively. Brazil's demand for soy-related food products generated the largest percentage of the world's soybean-related emissions (45%) in 2000, but it was replaced by China (32%) after 20 years. Indonesia, the world's leading consumer of palm oil, has the largest emissions from palm oil (35% of the global total in 2019), followed by Southeast Asia (13%), Western Europe (10%), and China (9%).

(Insert Fig. 1 here)

There are apparent inequalities in per capita emissions induced by food consumption worldwide, but the disparities have been gradually declining ((Insert Fig***. 2 here)***). Consistent with the scope of production-based estimates[1,2,33], global average per capita emissions from food supply chains have increased from 1.8 (95% CI 1.6-3.1) to 2.1 (1.5-2.7) t CO_2-eq during the study period (details of uncertainty ranges see Suppl. Table 5). Australia has the highest average animal-based emissions (4.9 t CO_2-eq/person in 2019) from consumption, followed by Brazil (3.0 t/person), Canada (2.5 t/person), and the USA (2.1 t/person) (Suppl. Fig. 3, details of uncertainty ranges see Suppl. Table 6). Although developed countries emit more animal-based emissions per capita (1.7 t CO_2-eq/person) than the global average, differences exist between these affluent countries. For example, people in Australia, Canada, and the USA have higher per capita animal-based emissions than Western Europeans (1.4 t CO_2-eq/person) mainly due to higher red meat consumption. Indonesia (3.9 t CO_2-eq/person in 2019), Oceania (2.6 t/person), and Brazil (2.0 t/person) have the highest level of plant-based emissions per capita despite a downward trend (Suppl. Fig. 4). Canada (1.8 t CO_2-eq/person) and European countries (1.3 t CO_2-eq/person) have larger average plant-based emissions than other developed countries, mainly due to large demand for oil crops (e.g., palm oil) and stimulants (e.g., coffee). Although below the global average of animal- (1.0 t CO_2-eq/person in 2019) and plant-based emissions (1.1 t/person), per capita GHG emissions of the top two most populous countries, China (1.4 t/person) and India (1.0 t/person), increased by 64% and 19%, respectively.

(Insert Fig. 2 here)

International trade has reshaped food emission patterns

Fig. 3 and Suppl. Fig. 5 show the countries with the largest amounts of emissions embodied in food imports and exports, and their ratio of domestic emissions to consumption-based emissions in 2019. Emissions from most major exporters are dominated by two categories – oil crops and beef. Indonesia (307 Mt CO_2-eq in 2019) and Brazil (196 Mt CO_2-eq) are the world's largest exporters of embodied emissions from oil crops, dominated by palm oil and soybean, respectively. Indonesia's export of oil crop emissions almost tripled during the study period, while Brazil's emissions increased by 18%. Australia (200 Mt CO_2-eq in 2019) and Brazil (144 Mt CO_2-eq) export the largest amounts of beef-related emissions, followed by India (44 Mt CO_2-eq) and the USA (30 Mt CO_2-eq). We found that major net exporters, excluding Malaysia which highly relies on meat imports (from India, Australia, etc.), create over 70% of their food emissions within their national boundaries. As the world's largest net exporter, Brazil's emission exports reached the highest level in the mid-term of the study period (720 Mt CO_2-eq in 2010) and declined (to 581 Mt CO_2-eq in 2019) in the later period.

Overtaking US and Japan, China is by far the world's largest importer of embodied emissions (585 Mt CO_2-eq in 2019). China's imports of embodied emissions are dominated by oil crops (46%) and pork (16%), and both import volumes have quadrupled mainly due to an increase in China's domestic demand for palm oil (+4.6 times), soybean oil (+1.8 times), and soybean cake for pig feed (+4.5 times). Beef makes up the largest component of embodied emission imports from the USA (39% in 2019), Japan (42%), Russia (51%), and South Korea (43%), while oil crops (mainly palm oil, soy) account for a large share in imports of embodied emissions by India (88%) and the Netherlands (51%). Over this period, ~30% of consumption-based food emissions in developed countries were generated overseas. This ratio in developed countries with only a weak degree of self-sufficiency, such as Japan, South Korea, and European countries, reached over 60%. In contrast, developing countries generated 91% of food-related emissions within national boundaries in 2000, although this ratio declined to 85% in 2019.

(Insert Fig. 3 here)

We observe that the patterns of emissions embodied in international trade of food have changed gradually, in which developing countries, especially China, are playing an increasingly important role (Fig. 4). Between 2000 and 2019, the share of emissions embodied in international trade to total consumption-based food emissions increased from 14% to 19%. In 2019, 16% of animal-based and 21% of plant-based food emissions were embodied in trade. Over this period, imports of embodied emissions of developed countries kept constant (~1.1 Gt CO_2-eq), but its share in global trade declined from 56% to 39%. In 2000, the USA, Japan, and Western European countries, which are the world's richest countries, dominated international trade with their imports contributing to nearly half of the total food-related emissions embodied in global trade. By 2019 this share has dropped to 31%, while China has become the largest importer of embodied emissions (22%). For example, the largest embodied emission flows to China, i.e., imports from Brazil (319 Mt CO_2-eq) and Indonesia (69 Mt CO_2-eq), increased around fourfold, respectively, while flows from Brazil (-62%) and Indonesia (-33%) to Western Europe, which were the largest in the beginning, decreased. However, emission transfers within Europe have intensified, such as flows between Western European countries (+53%). Animal-based and plant-based emissions embodied in food exports to developing countries have increased by 84% and 1.5 times. Increased food demand in developing countries creates a substantial increase in emission outsourcing to major food exporting countries, including Indonesia (+71%), Brazil (+65%), Australia (+34%), Canada (+42%), and the USA (+43%).

(Insert Fig. 4 here)

Drivers of emissions of the global food system

We apply structural decomposition analysis (SDA) to investigate the contributions of different driving factors across the entire food supply chains to the variations of food-consumption emissions globally and in different regions and countries (Fig. ***5*** and Suppl. Table 7). Population growth was a significant contributor to emission rise in most countries/regions (except Japan and Russia), which increased global total emissions by 30% during the study period. The greatest emission increase driven by population was in South Asia (+71%), Sub-Saharan Africa (SSA) (+64%), Near East and North Africa (NENA) (+59%), and India (+42%). Above countries/regions have a high population growth rate (over 30%) (Suppl. Table 8), with SSA being the highest (71%). The rising per capita consumption level was another important driver of the global emission increase (+19%) over the period. Per capita consumption drove up food emissions in almost all developing countries, ranging from a modest +9% in LAC to +61% in China. Except for Indonesia and SSA (over 90% are plant-based) where farmland expansion leading to extensive land-use change, over 50% of per capita consumption-related emission increases in developing countries are generated by growing demand for animal-based food, such as China (+60%), India (+87%), NENA (+77%) and LAC (nearly 100%) (Suppl. Table 7). However, declining demand for animal-based food led to the decline of embodied emissions in Australia (-38%), Japan (-7%), the USA (-6%), and Canada (-9%). These countries' per capita consumption of red meat, such as beef (-53%, -22%, -13%, and -7%, respectively), have declined over this period (Suppl. Fig. 6).

Despite the upward trend of global food emissions by other drivers, emission intensity, measured by the amount of emissions per unit of weight of food product, was the dominant factor offsetting parts of emission growth, decreasing global emissions by 37%, avoiding additional 5.2 Gt CO_2-eq emission globally. Emission intensity includes three components, i.e., the intensity of LULUC, agricultural production, and beyond-farm activities. The effect of substantially declining emission intensity from LULUC activities was responsible for over 5.4 Gt CO_2-eq global emission decline (-39%) with other factors held constant and had a prominent effect on emissions in countries with extensive land use activities, such as Brazil (-90%), SSA (mainly South and Central African regions) (-57%) and Indonesia (-46%) (Suppl. Table 7). However, the driving effects of emission intensity related to agricultural production and beyond-farm processes slightly increased the world's emissions by 149 Mt CO_2-eq (+1%) and 63 Mt CO_2-eq (+0.5%), respectively. Our decomposition results show that a sharp drop in Brazil's emissions (by ~1 Gt CO_2-eq) during the period from 2010-2015 is attributed to the contribution of decreasing LULUC emission intensity. The root cause of the decrease in LULUC emission intensity is shrinking LULUC activities (largely deforestation) and associated emissions. After a series of measures[34], such as the Forest code[35] and Amazon Soy Moratorium[36], for legally limiting deforestation activities in Amazon, Brazil’s deforestation rate reached a historically low level in 2010-2015, with a reduction of 50-80% compared with 2004[37] but this trend has significantly changed under the following political leadership[38].

Over this period, changes in the trade structure increased global emissions by 8% (1.1 Gt CO_2-eq) through increasing exported products from regions and countries with emission-intensive production, while a decline in food consumption from domestic supply in importing regions and countries reduced global emissions by 5% (0.7 Gt CO_2-eq). In 2000-2015, food importers became increasingly dependent on exports of emission-intensive products from agricultural suppliers including Brazil and Indonesia. As a result, international food trade accelerated global emissions. However, international trade tends to reduce emissions of global food consumption after 2015 with the improvement of production productivity in exporting countries.

(Insert Fig. 5 here)

Discussion and conclusions

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

Our results show considerable differences in food consumption and associated emissions across countries. Residents in the first group of countries have an animal-dominated (especially beef) diet and larger associated emissions compared with other groups, while the third group is generating increasing consumption of beef and dairy due to the demand for improving living standards and diet diversity. As for the same protein content, red meat, especially beef, generates more emissions than poultry, fish, and plant-based protein products[39]. Thus, the growth of the global population and rising per capita demand for emission-intensive food are likely to boost emissions further. Diet shifts, including reducing excessive intake of red meat or improving shares of plant-based protein, will not only reduce emissions but avoid health risks such as obesity and cardiovascular disease[40]. However, widespread and lasting diet shifts (e.g., the EAT-Lancet diet[41]) are very difficult to achieve within a narrow timeframe. Therefore, incentives that encourage consumers to reduce red meat or buy products with higher environmental dividends through eco-labeling, adding taxes or subsidies reflecting some of the environmental costs in product prices, and education on actual food emissions could help to reduce food emissions[7,39].

International food trade policies incorporating environmental externalities which are less covered in production-side policies are urgently needed to avoid possible emission leakage and realize emission reduction across supply chains. Emissions outsourced through international food trade increased by ~1 Gt CO_2-eq over the study period, accelerating global emission increase and unequal distribution. Countries in the second and third groups have considerably lower PBE[2] than CBE by outsourcing their domestic food emissions through imports from agricultural suppliers such as Brazil, Indonesia, and Oceania. Emissions embodied in these food imports vary considerably depending on the originating countries, while the world's main food suppliers are not regions with the highest efficiency. For example, the total emission intensity of production per kilogram of beef in Western European countries (range from 15-17 kg CO_2-eq) is far less than in Brazil (44-46 kg CO_2-eq) (Suppl. Fig. 7), but the latter is the largest beef exporter for European countries[42]. Countries with high efficiency for domestic production import emission-intensive products from regions with a large scale of LULUC activities or low agricultural efficiency will tend to increase emissions of the global food system. Although the magnitude of food emissions embodied in global trade is considerable, proposals for measures to avoid carbon leakage such as the EU's proposed Carbon Border Adjustment Mechanism[43] have rarely been extended to include agricultural or food-related emissions. Key emission-intensive products which dominate international food trade (e.g., beef from Australia, beef and soybean from Brazil, palm oil from Indonesia) could be targets of such taxation policies. Our data and model with information at the product level can help quantify the size of the necessary adjustment.

A series of trade policies are accelerating emissions through increasing food imports from countries/regions with emission-intensive production. For instance, the EU's Green Deal encourages less intensive agriculture in Europe and increasing imports of agricultural products from countries such as Brazil, the USA, Indonesia, and Malaysia[44]. Another example that leads to emissions increase through trade is the US-China trade war, which led China to import more soybean from Mercosur countries to reduce its dependence on the USA[45]. Above imports from major suppliers induced by demand led to a surge in deforestation and associated emissions. However, trade between diverse international partners provides opportunities to ameliorate emissions by allowing consumers to choose products from places with less emission-intensive production. Long-term commitments are needed to comprehensively assess emissions embodied in the entire supply chain for trade-offs between domestic production and imports from multiple origins, thereby minimizing global impacts.

Furthermore, our study traces the origins and emission intensities of specific products which ultimately flow to final consumers. Results show that reducing PBE through agricultural intensification with technology improvement or lower levels of resource inputs (reflected in lower emission intensity), especially for agricultural producers from group four with abundant natural resources (e.g., forests, peatland)[46] which generated vast amounts of emissions from widespread LULUC activities such as deforestation, is vital for mitigating climate effects across food supply chains. Changes in consumer behavior or trade policies (e.g., proposed legislation to eliminate deforestation by European countries[47]) in the second and third group of countries can trigger deeper impacts via food supply chains and eventually improve production-side efficiency for the fourth group[48]. Altered levels and composition of food consumption (with less emission-intensive products) could reduce land use change, relocate production to places with fewer emissions, or incentivize food suppliers to decrease emission intensity as well as avoid destructive environmental impacts (e.g., through the Amazon Soy Moratorium[36,49]). However, we find that the fourth group of countries themselves have substantial consumption-based emissions due to the domestic demand for emission-intensive products (e.g., oil crops). Raising awareness and legislation nationally to reduce emissions from food production are needed across these countries, otherwise the domestic leakage may offset part of the emission reduction brought by supply chain measures[49].

Methods

Food consumption accounting

We apply the physical trade flow (PTF) approach proposed by Kastner et al.[25,50] to calculate the consumption of 153 food products (both primary and processed products) (Suppl. Table 9, 10) based on the physical trade between 181 countries or areas in five given years (2000/2005/2010/2015/2019) (Supplementary Methods 1.1). We use the criteria proposed by the United Nations[51] to define developed and developing countries (Suppl. Table 3). Countries or areas are classified into 18 countries/regions for comparison according to geographical locations (Suppl. Fig. 8, Suppl. Table 4). The PTF approach by Kastner et al. allows tracing product flows through international supply chains as well as final consumers to which products ultimately flow based on domestic production and bilateral trade between countries. We use data from the detailed trade matrix of products on FAOSTAT[30] to construct the matrix showing the physical flows between counties. All data are in units of mass (metric tonnes). Detailed data sources used for this study are shown in Supplementary Methods 1.2 and Suppl. Table 11. We mainly use the reported import data by assuming that imports are more reliable due to the strict custom records[52]. The PTF approach assumes that the domestic production and imported products are proportionally distributed between domestic supply and exports. Because of the limited shelf life of food and the relatively small share of agricultural commodities used for food stocks, this study does not include variations in stocks.

The PTF approach by Kastner et al. is suitable for linking consumption and associated environmental impacts to crop cultivation or livestock raising (on-farm stages)[25] at a product level[23]. To investigate the GHG emissions of processed products generated during on-farm processes, we transform the bilateral trade matrix of processed products using the ratio of sources for primary products, which is developed based on the proportion of domestic production and imports of primary products (Supplementary Methods 2.2). We use conversion factors for agricultural commodities from FAO[53] to convert the processed products into primary products, and some missing factors are supplemented by using the factors from the GTAP Data Base with Nutritional Accounts[54] (Supplementary Methods 2.2 and Suppl. Table 9). Therefore, we can obtain the new production and bilateral trade matrix of the processed products in the form of primary equivalents, which trace the sources of raw materials for processed product production and the destination where these processed products are finally consumed (Supplementary Methods 2.3). Here we simplify the calculation by ignoring the difference between inputs during the production of processed products and assuming all primary products used as raw materials are consumed in one place. Furthermore, agricultural products for non-food use are excluded by using data of non-food use commodities from the food balance sheet on FAOSTAT[55] (Supplementary Methods 2.5).

Quantification of consumption-based food emissions

By combining the emission intensity (the amount of emissions per unit weight of food product) and the consumption matrix (see Suppl. Fig. 9 for the accounting framework), the consumption-based emissions of each product are calculated as follows[25]:

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

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

To obtain the emission intensity along supply chain processes, we distribute the annual GHG emissions (including CO_2, CH_4, and N_2O) from LULUC, agricultural, and beyond-farm activities to plant- and animal-based products using the similar approach performed by Hong et al.[10]. CH_4 and N_2O are converted into CO_2 equivalents using the 100-year global warming potential values of 28 and 265 from IPCC AR5[56]. National emission data are obtained from the FAOSTAT Climate Change dataset[31] (Suppl. Table 11), which provides data of country- and process-specific emissions from the food system based on activity data and IPCC Tier 1 Methodology. Results of consumption-based emissions of CO_2, CH_4, and N_2O are shown in Suppl. Fig. 10 and Suppl. Data 2. Detailed GHG categories and emission processes are shown in Suppl. Table 12.

Allocation of LULUC emissions to food products

A top-down approach is applied to allocate production-based LULUC emissions due to the expansion of cropland or pasture[2,32] to primary products. LULUC emissions include: (1) CO_2, CH_4, and N_2O from burning (of forests, savanna, humid tropical forests, and organic soils), (2) CO_2 from net forest conversion, and (3) CO_2 and N_2O from the drainage of organic soils. We assume that LULUC emissions are directly related to land use areas for the production of primary products[10,57,58] and distribute the annual LULUC emissions to products according to harvested cropland areas or pasture areas for feeding livestock in a given year. LULUC emission intensities are calculated using the production and LULUC emissions of primary products (Supplementary Methods 3.1). All data of emission amounts[31], land use areas[59], and production quantity[60] are obtained from FAOSTAT[2,3,32]. Legacy emissions cumulated in land due to LULUC activities over time or absorbed emissions by land due to agriculture abandonment are not incorporated. Based on the LULUC emission intensities of each product, we assign LULUC emissions to final consumers using the PTF approach as *Equation 1*. Results of consumption-based LULUC emissions in 181 countries are shown in Suppl. Fig. 11

and Suppl. Data 3.

Allocation of agricultural emissions to food products

Emissions from agricultural production for crops are: (1) N_2O from crop residues, (2) CH_4 and N_2O from burning crop residues, (3) N_2O from synthetic fertilizer, (4) N_2O from the use of synthetic fertilizer, (5) N_2O from manure applied to soils, (6) CH_4 from rice cultivation and (7) CO_2, CH_4 and N_2O from energy use for crop cultivation[2,3,32]. We allocate production-based agricultural emissions[31] to crops and calculate agricultural emission intensities based on the production of crops from FAOSTAT[60] (Supplementary Methods 3.2). Emissions from crop residues[61] are allocated by Nitrogen contents and production of specific crops, while emissions from burning residues[62] are distributed by the amounts of burned biomass of crops. N_2O from synthetic fertilizers is allocated to primary crops according to their fertilizer input rate[63,64] and harvested areas from FAOSTAT[60]. Emissions from manure applied to soils and rice cultivation[31] are distributed by harvested areas of crops and rice production quantity[60], respectively. In addition, we use the impact coefficient of food products (emission per unit weight of the product)[39,65] (Suppl. Table 13) to assign emissions of energy use to products.

Emissions from the agricultural production of livestock (meat, dairy, and eggs) are generated in five main processes: enteric fermentation, manure management, feed production, manure left on pasture, and energy consumption. Country- and animal-specific emissions from enteric fermentation (CH_4) of ruminant animals[66] and manure management (CH_4 and N_2O)[67] based on Tier 1 level are obtained from FAOSTAT[2,3,32], and then allocated to livestock products using FAOSTAT statistics of production[10]. FAOSTAT provides data on emissions generated in manure left on pasture (N_2O)[68] as well. Emissions of manure left on pasture are allocated into livestock products according to the pasture areas needed for feeding different animals, and then the emission intensity is calculated based on production amounts of livestock products.

Emissions from feed crops are allocated to the livestock products that consume the feed during production. Emissions from feed crops, including barley maize, wheat, rapeseed cake, and soybean cake, for livestock production, are allocated to livestock according to the feed conversion ratios (FCRs) specific to each product at the national level[69-72]. FCRs are calculated based on the national feed use quantities[55] and weight factors of each livestock product[69,71,72] (Supplementary Methods 2.4). Then we calculate feed emissions per unit weight of animal-based products using the same approaches as crops. Moreover, we use data on production and emissions generated from the energy use of freshwater and marine products[73] to calculate the emission intensity from fishery production.

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

<u>Allocation of beyond-farm emissions to food products</u>

Bottom-up aggregation and top-down allocation approaches are combined to distribute beyond-farm emissions to products. Emissions from beyond-farm processes include: CO_2, CH_4, and N_2O from (1) processing, (2) packaging, (3) retail, (4) transport; (5) CO_2 and N_2O from fertilizer manufacturing; (6) CH_4 and N_2O from industrial wastewater treatment related to food. The statistical data of total national emissions in the above six processes are obtained from FAOSTAT[2,3,32]. National emissions from food processing, packaging, retail, and industrial wastewater treatment[31] are downscaled to the product level by using the impact coefficient of 153 products[39,65] (Supplementary Methods 3.3). Since the food-transport emissions are closely related to the transport distance and freight volume, we use the monetary values between transport and food-related sectors from the GTAP database[74] to distinguish emissions from domestic and international transport. Therefore, emission intensities of specific products at different distances (within or between countries) can be calculated using the impact coefficient for food transport. In addition, emissions of fertilizer manufacturing are allocated according to the same approach of distributing synthetic fertilizer-related emissions in agricultural production. Beyond-farm emissions are attributed to final consumers using the PTF approach shown in *Equation 1*. Results of consumption-based beyond-farm emissions in 181 countries are shown in Suppl. Fig. 11 and Suppl. Data 3.

Identification of driving factors

To understand the driving forces behind emissions of food consumption, we employ the Structural Decomposition Analysis (SDA), the widely adopted method in energy and emission studies[75], to decompose the global and regional emissions of 153 products as:

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

Equation 2

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

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

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

$$\Delta E = \sum_{i=1}^{153}\sum_j \Delta f_{ij}L_iR_iC_i\,p + \sum_{i=1}^{153}\sum_j f_{ij}\Delta L_iR_iC_i\,p + \sum_{i=1}^{153}\sum_j f_{ij}L_i\Delta R_iC_i\,p + \sum_{i=1}^{153}\sum_j f_{ij}L_iR_i\Delta C_i\,p + \sum_{i=1}^{153}\sum_j f_{ij}L_iR_iC_i\Delta p$$ *Equation 4*

where Δ represents changes in a factor from base year (*0*) to target year (*t*). Each of five terms in *Equation 4* denotes the contributions to emission changes which are triggered by one factor if other variables keep constant. The five factors in the SDA model can result in 5!= 120 first-orde decompositions, and here we use the solution named the average of two polar decompositions[75,76] to approximate the average of all possible decompositions. The *Euqation 4* are finally converted as:

$$\Delta E = \sum_{i=1}^{153}\sum_j 0.5\left(\Delta f_{ij}L_i^tR_i^tC_i^tp^t + \Delta f_{ij}L_i^0R_i^0C_i^0p^0\right) + \sum_{i=1}^{153}\sum_j 0.5\left(f_{ij}^0\Delta L_iR_i^tC_i^tp^t + f_{ij}^t\Delta L_iR_i^0C_i^0p^0\right) + \sum_{i=1}^{153}\sum_j 0.5\left(f_{ij}^0L_i^0\Delta R_iC_i^tp^t + f_{ij}^tL_i^t\Delta R_iC_i^0p^0\right) + \sum_{i=1}^{153}\sum_j 0.5\left(f_{ij}^0L_i^0R_i^0\Delta C_ip^t + f_{ij}^tL_i^tR_i^t\Delta C_ip^0\right) + \sum_{i=1}^{153}\sum_j 0.5\left(f_{ij}^0L_i^0R_i^0C_i^0\Delta p + f_{ij}^tL_i^tR_i^tC_i^t\Delta p\right) \qquad \text{Equation 5}$$

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

Uncertainty assessment

Our results of global consumption-based emissions during different supply chain processes are generally consistent with global production-based food emission inventories from FAOSTAT[2,3,32,77]. Similar to the uncertainty analysis performed by Tubiello et al.[2,33,78] and Hong et al.[10], we conduct a Monte Carlo approach (running 10,000 simulations) to assess the uncertainty range of consumption-based emissions by simulating the varying activity data, emission factors and parameters for each process according to the default uncertainty ranges derived from the standard IPCC guidelines[79] and individual uncertainty ranges from previous studies (see Suppl. Table 14). Uncertainty ranges of 95% confidence intervals of consumption-based food GHG emissions are adopted. Detailed uncertainty ranges of food emissions are provided in Suppl. Table 1, 2, 5, 6 and Suppl. Data 8, 9. We only consider the uncertainties generated in the production processes and do not include the uncertainties caused by trade because we cannot obtain the uncertainty ranges of original statistical data for reported imports of agricultural products[11,19,28,80]. We recognize that the uncertainties of trade data in this study have an unknown magnitude.

Limitations

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

First, the PFT approach by Kastner et al.[25] allows us to quantify re-exports to other countries based on conversion matrices but ignores the connections with other sectors within the economy compared to the MRIO-based approach. We do not choose physical MRIO because the FABIO[27] is outdated, and Exiobobase[81,82] does not have as many countries and product detail as our database. The PTF approach we use is thus very suitable to capture relatively simple food supply chains but may ignore more complex processing and repacking steps in global supply chains and thus introduce some system boundary cut-off error[23]. A more feasible design in the next step requires integration with models such as MRIO to investigate the entire supply chain considering the heterogeneity of production inputs and connections between food-related and other sectors.

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

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

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

Data availability

The LULUC, agricultural and beyond-farm emissions data are curated by the FAO and freely available from FAOSTAT[77]. Population data used in this study are obtained from World Population Prospects of the United Nations[83]. Data of monetary values for transport and food-related sectors are obtained from GTAP database[74]. Supplementary methods, discussion, figures, tables and datasets used in the analysis can be found in the Supplementary Information files. More detailed results are available from the corresponding author on reasonable request.

Code availability

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

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Author contributions

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

Competing interests

The authors declare no competing interests.

Figure legends/captions

***Fig. 6: GHG emissions throughout global supply chains from consumption of food products by country in 2000 and 2019**. The background map shows the level of consumption-based emissions at the country scale. The pie chart shows the fraction of consumption-based emissions of animal-based and plant-based food products, and the size represents the total emissions for 18 countries/regions. AUS: Australia; BRA: Brazil; CAN: Canada; CHN: China; ROEA: Rest of East Asia; EE: East Europe; IND: India; IDN: Indonesia; JPN: Japanese; ROLAC: Rest of Latin America and the Caribbean; NENA: Near East and North Africa; ROO: Rest of Oceania; RUS: Russia; ROSA: Rest of South Asia; ROSEA: Rest of Southeast Asia; SSA: Sub-Saharan Africa; USA: United States of America; WE: Western Europe. Details for the division and scope of 18 countries/regions are shown in Suppl. Table 3, 4. Base map layer: "World Countries". Downloaded from http://tapiquen-sig.jimdo.com. Carlos Efraín Porto Tapiquén. Orogénesis Soluciones Geográficas. Porlamar, Venezuela 2015. Based on shapes from Environmental Systems Research Institute. Free distribution.*

Fig. 7: Per capita GHG emissions of food consumption by country in 2000 and 2019**. The background map shows the level of per capita consumption-based emissions at the country scale. The pie chart shows the fraction of average consumption-based emissions of animal-based and plant-based food products per person, and the size represents per capita emissions of 18 countries/regions. Abbreviations of 18 countries/regions and the source of base map are shown in **(Insert Fig. **1**

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

Fig. 9: Patterns of emission flows embodied in international trade of all types of (a), animal-based (b), and plant-based (c) food products among and within 18 countries/regions in 2000 and 2019 (unit: Mt CO_2-eq)**. Width of the lines represent the volumes of emissions embodied in trade from exporter to importer, and the color is the same as the exporter. Flows in the above Figure cover more than 90% of total emissions embodied in international bilateral trade annually as small flows are not shown here. Number in brackets represents the ratio of emissions embodied in trade to total consumption-based emissions. Abbreviations of 18 countries/regions are shown in **(Insert Fig. **1**

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

emissions in every period.

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