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Global greenhouse gas emissions from animal-based foods are twice those of plant-based foods

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Agriculture and land use are major sources of greenhouse gas (GHG) emissions but previous estimates were either highly aggregate or provided spatial details for subsectors obtained via different methodologies. Using a model–data integration approach that ensures full consistency between subsectors, we provide spatially explicit estimates of production- and consumption-based GHG emissions worldwide from plant- and animal-based human food in circa 2010. Global GHG emissions from the production of food were found to be 17,318 ± 1,675 $TgCO_2eq\,yr^{-1}$, of which 57% corresponds to the production of animal-based food (including livestock feed), 29% to plant-based foods and 14% to other utilizations. Farmland management and land-use change represented major shares of total emissions (38% and 29%, respectively), whereas rice and beef were the largest contributing plant- and animal-based commodities (12% and 25%, respectively), and South and Southeast Asia and South America were the largest emitters of production-based GHGs.

The global population has quadrupled over the last century. Demographic growth and associated economic growth have increased global food demand and caused dietary changes, such as eating more animal-based products. The United Nations projects that food production from plants and animals will need to increase 70% by 2050, compared to 2009, to meet increasing food demand[1]. This will drive the expansion of food subsectors, including crop cultivation and livestock production, as well as product transportation and processing, materials (fertilizer and pesticides) and irrigation[2]. Increased food production may accelerate land-use changes (LUCs) for agriculture, resulting in greater greenhouse gas (GHG) emissions, reduced carbon sequestration and further climate change. Developing climate mitigation strategies will require estimates of all major GHG emissions (for example, CO_2, CH_4 and N_2O) from the production and consumption of total and individual plant- and animal-based food from all food-related subsectors, such as land-use change and farmland activities, at local, regional and global scales—which is the overall objective of this study. Such comprehensive and quantitative estimates require a framework that dynamically represents the environmental, management and human drivers of major GHGs while satisfying carbon and nitrogen mass-conservation among plant and livestock production and consumption systems.

Previous efforts have been made to assess GHG emissions from agriculture, forestry and other land use (AFOLU)[3,4], a critical subset of food systems emissions[5–7]. The recent Intergovernmental Panel on Climate Change (IPCC) Special Report on Climate Change and Land (SRCCL)[6] and subsequent work[7] quantified emissions within and beyond the farm gate, the latter referring to emissions caused by food systems that are not covered by AFOLU sectors, such as fertilizer manufacturing, product processing and transportation (Fig. 1), to be in the range of 10,800–19,100 $TgCO_2eq\,yr^{-1}$ for the decade 2008–2017. These estimates combined results from diverse studies on farm-gate agriculture and associated land use[4] with global estimates of emissions along the supply chain up to retail and consumption, each study using a different methodology. The annual assessment of the global carbon budget provides CO_2-only emissions from LUC[8]. In contrast, the Food and Agriculture Organization (FAO) gives CO_2 emissions from forest LUC and peatland degradation[9], but those studies do not cover emissions from changes in agricultural management intensity[8]. Moreover, CH_4 and N_2O emissions from agricultural activities are provided globally by different datasets[10,11], usually based on estimation approaches defined by the IPCC Guidelines[12]. The IPCC AR5 WG3[3] and FAOSTAT[4] quantified regional GHG emissions from subsectors of agriculture and land use. There are also studies focusing on spatially explicit GHG emissions for selected crops[13], emissions of the life cycle of agricultural production[5], such as the FAO GLEAM model to estimate global livestock emissions for 2005[14], and accounting for carbon opportunity costs of agricultural land[15].

This study quantifies CO_2, CH_4 and N_2O emissions from the production and consumption of all plant- and animal-based foods on a grid scale using a consistent unified model–data integration framework. Our approach builds upon and extends the data and methods published in the literature by implementing them into the Integrated Science Assessment Model (ISAM)[16].

Our approach advances the field for three main reasons. First, we have a dynamic representation of environmental drivers, such as climate, CO_2 and of direct human drivers (LUC) using a consistent set of mass-conservative equations and parameters for biophysical and biogeochemical processes to estimate the plant carbon and nitrogen dynamics. In comparison, inventory-based methods, such as those used by the IPCC[12], usually consider environmental factors as static functions[12]. Second, we estimate CO_2 emissions and

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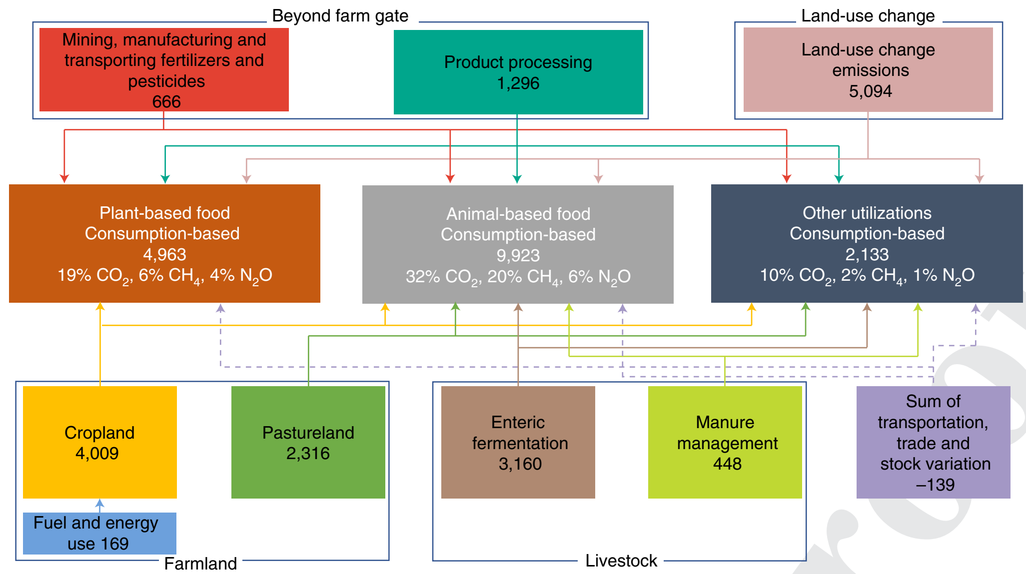

Fig. 1 | GHG emissions from different subsectors of plant- and animal-based food production/consumption. The contributions of individual GHGs provided are the percentage of the total emissions. Solid arrows indicate production-based emissions, and solid and dashed arrows combined are consumption-based emissions. The values in the boxes are mean values for 2007–2013, which may slightly differ from the median values of 10,000 Monte Carlo simulations in the text. Values are expressed in $TgCO_2eq$.

sinks from changes in agricultural land management intensity from a set of diverse and spatially variable practices such as ploughing the soil, planting crops, fertilization, irrigation, harvesting grains and recovering crop residues. In comparison, most global vegetation models have a very simple or no representation of those practices, and bookkeeping models used for land-use emissions ignore changes in management intensity[3]. Third, we separate emissions from feed production in cropland and grazing land so that they can be attributed to livestock production, based on the commodity balance between production and consumption, which allows us to attribute the total food-related GHG emissions specifically to plant- and animal-based human food.

In this study, livestock emissions only include emissions from enteric fermentation and manure management, which we define according to the IPCC[12] and FAOSTAT[17]. Meanwhile, we define animal-based food emissions as the emissions from all subsectors caused by or associated with the production and consumption of animal-based food (Methods and Table 1). In addition, we include LUC emissions from the expansion of agricultural land (crop plus grazing land) and from beyond farm-gate emissions under the life-cycle assessment (LCA) framework of Poore and Nemecek[5] to include emissions from fertilizers, pesticides and pre-plate product processing and transportation. Although LUC and beyond farm-gate emissions have been addressed in other studies[3–7], we provide here more details for individual plant- and animal-based food items at a finer spatial scale.

In summary, GHG emissions are estimated for 171 crops and 16 animal products at a 0.5°×0.5° spatial resolution over the entire globe around the year 2010. This year is the mean of the 2007–2013 period, the most recent for which the required data are available—particularly commodity balances for crop and livestock and forage feed data (from FAOSTAT data as part of the GCAM Data System[18]). Our estimates are aggregated into more than 200 countries and nine regions (Supplementary Fig. 1), created by grouping countries into macrogeographical coherent zones[19]. We combine CO_2, CH_4 and N_2O emissions by their 100 yr global warming potentials[3] caused by or associated with different subsectors of plant- (crop and grazing land) and animal-based food production and consumption within countries, where consumption-based emissions are calculated by combining emissions from transportation, stock variation, import and export with the estimates of production-based emissions.

Results

Agricultural land and biomass. The estimated agricultural biomass production for 171 crops listed in Supplementary Table 1 and grazing land (see Supplementary Methods 1.1 for definitions) for human food and animal feed, LUC areas associated with this production, and other non-food utilization such as fibre, rubber and cotton, but not energy crops, are linked consistently to the ISAM simulation module for GHG emissions.

We estimated the global total above-ground biomass production from cropland and grazing land to be 8,970 TgC yr^{-1} (Supplementary Tables 2 and 3), including 9% for plant-based human food, 27% for animal feed and 20% for non-food products. The rest of the biomass production includes 2% of burned agricultural residue and 42% of residues left as litter and stover (excluding used residues such as feed; Supplementary Table 2). Our historical LUC area based on ISAM[20] and the LUH2 datasets[21] indicates a net agricultural land area increase of 0.11 Mha yr^{-1} during 2007–2013, including 2.12 Mha yr^{-1} of other land converted to agricultural land and 2.01 Mha yr^{-1} of agricultural land converted to other lands (Supplementary Table 2). More results are reported in Supplementary Discussion 1 and Supplementary Fig. 2.

The estimated livestock feed demand is 2,450 TgC yr^{-1}. This demand is supplied as follows: 23% from crop grain, 12% from forage crops, 21% from crop residue, 42% from grazing feed (feed produced by grazing land) and 2% from scavenging and other feed (Supplementary Discussion 1, Supplementary Table 5). The average conversion efficiency from feed to livestock products is 5.17% based on biomass, 6.22% based on calories and 8.49% based on the protein of livestock products (Supplementary Discussion 3 and Supplementary Fig. 3). Livestock products are split among 16 domesticated animal categories (Supplementary Table 4). Notably, we considered the utilization of crop residues for feeding livestock—an important link between crop and livestock production systems often ignored in other models.

Table 1 | Production- and consumption-based GHG emissions from different subsectors of plant- and animal-based food

Subsector		Plant-based food	Animal-based food	Other utilizations
Land-use change	Cropland CO_2	2,050 ± 120 (12%)	1,634 ± 97 (9%)	921 ± 54 (5%)
	Grazing land CO_2		468 ± 28 (3%)	21 ± 1 (0%)
Farmland	Cropland	2,055 ± 1,432 (12%)	1,466 ± 179 (9%)	654 ± 237 (4%)
	• CO_2	• 364 ± 17	• 848 ± 50	• 263 ± 15
	• CH_4	• 1,003 ± 1,424	• 99 ± 139	• 168 ± 233
	• N_2O	• 688 ± 132	• 520 ± 99	• 223 ± 43
	Grazing land		2,245 ± 141 (13%)	69 ± 4 (0%)
	• CO_2		• 1,723 ± 101	• 53 ± 3
	• N_2O		• 521 ± 99	• 16 ± 3
Livestock	Enteric fermentation CH_4		3,061 ± 802 (18%)	95 ± 25 (0%)
	Manure management		434 ± 117 (3%)	13 ± 3 (0%)
	• CH_4		• 308 ± 48	• 10 ± 2
	• N_2O		• 127 ± 108	• 3 ± 3
Beyond farm gate	Mining, manufacturing and transporting fertilizers and pesticides CO_2	269 (2%)	280 (2%)	117 (1%)
	Product processing CO_2	734 (4%)	199 (1%)	524 (3%)
	Transportation, trade and stock variation CO_2	−148 (−1%)	198 (1%)	−206 (1%)
Sum (production-based emission)	5,109 ± 1,436	9,796 ± 850	2,413 ± 246	
Sum (consumption-based emission)	4,961 ± 1,436	9,994 ± 850	2,207 ± 246	

Values are expressed in $TgCO_2eq$, and numbers in parentheses are the percentage of each emission to total emissions. The sum of the consumption-based emission includes all numbers in the column, whereas the sum of production-based emission includes all numbers, except for the row 'Transportation, trade and stock variation CO_2'.

GHG emissions from food production. From a food production perspective, global total food-related GHG emissions, including farmland, livestock and LUC, amounts to $17{,}318 \pm 1{,}675\ TgCO_2eq\,yr^{-1}$ (median ± s.d. of 10,000 Monte Carlo simulations; see Supplementary Methods 5 and Supplementary Table 12), consisting of 61% CO_2, 27% CH_4 and 12% N_2O emissions (CH_4 and N_2O amounts in $CO_2eq\,yr^{-1}$) (Fig. 1).

Farmland (E_{farm}), LUC (E_{luc}), livestock (E_{live}) and beyond-farm-gate emissions (E_{bfg}) account for 38%, 29%, 21% and 12% of total production-based emissions from food systems, respectively (Table 1). E_{farm} includes CO_2, CH_4 and N_2O emissions from farmland activities (Methods).

South and Southeast Asia (SSEA) have emitted the greatest food-production-related emissions (23%). However, this region has low per-capita emissions and is the only one where plant-based emissions are larger than animal-based emissions (Fig. 2). SSEA also has the largest per unit area emission. South America (SA) is the second-largest emitter (20%) and has the largest emissions from animal-based food. SA also has the largest emissions per capita among all the regions.

Plant-based food production. Production-based GHG emissions from plant-based food amount to $5{,}109 \pm 1{,}436\ TgCO_2eq\,yr^{-1}$, which is 29% (19% CO_2, 6% CH_4 and 4% N_2O) of total GHG emissions. Within all subsectors of plant-based emissions (Fig. 1 and Table 1), E_{farm} is the greatest, contributing ~12% of the total (Supplementary Fig. 5a). E_{farm} of plant-based food is composed of CH_4 (6%), N_2O (4%) and CO_2 (2%) emissions. E_{farm} CH_4 emissions are generated from rice cultivation, which is the most GHG-intensive grain among all plant-based foods (Fig. 3a and Supplementary Fig. 4). E_{farm} N_2O and CO_2 are major contributors to wheat and maize emissions. Wheat has the largest harvest area among all 171 crops and is the second most GHG-intensive plant-based commodity (5%; Fig. 3a), largely because of its E_{farm} (2%).

E_{luc} of plant-based food (Supplementary Fig. 5c) caused by cropland expansion contributes 12% of total food emissions. It consists of 5% soil disturbance emissions and 7% biomass loss emissions. E_{luc} of rice and wheat are the highest among all plant-based food, contributing 3% and 1% of total food emissions. Although wheat is mainly cultivated in temperate regions where E_{luc} is less intensive, the large harvest area still makes its E_{luc} the second largest.

SSEA and China and Mongolia (CM) are the top GHG-contributing regions for plant-based food production and contribute 11% and 6%, respectively, of total food-related GHG emissions (Fig. 2). In these two regions, China, India and Indonesia are the countries with the most GHG emissions from plant-based food production (Fig. 4), contributing 7%, 4%, and 2%, respectively, of global food-related GHG emissions. These regions and countries account for the largest share of the world's population, and their demands for more food and land drive LUC and cause CO_2 emissions. In addition, SSEA and CM produce more than 90% of the rice in the world[22]. Therefore, they are responsible for the majority of CH_4 emissions from rice cultivation (Supplementary Fig. 4).

Animal-based food production. Production-based GHG emissions from animal-based food are $9{,}796 \pm 850\ TgCO_2eq\,yr^{-1}$, which are 57% (30% CO_2, 20% CH_4 and 7% N_2O) of the total GHG emissions. E_{farm} of animal-based food (Supplementary Fig. 5b), which includes E_{farm} from cropland (8%) and grazing land (13%) that produces feed, accounts for 21% of total emissions. E_{farm} of cropland is transferred to animal-based food emissions through accounting for the crop production used as feed. Top feed-producing crops include maize, wheat and soybean. E_{farm} of grazing land (13%) is generated from grazing feed production. E_{live} (20%) is another dominant contributor to animal-based food emissions (Supplementary Fig. 5g),

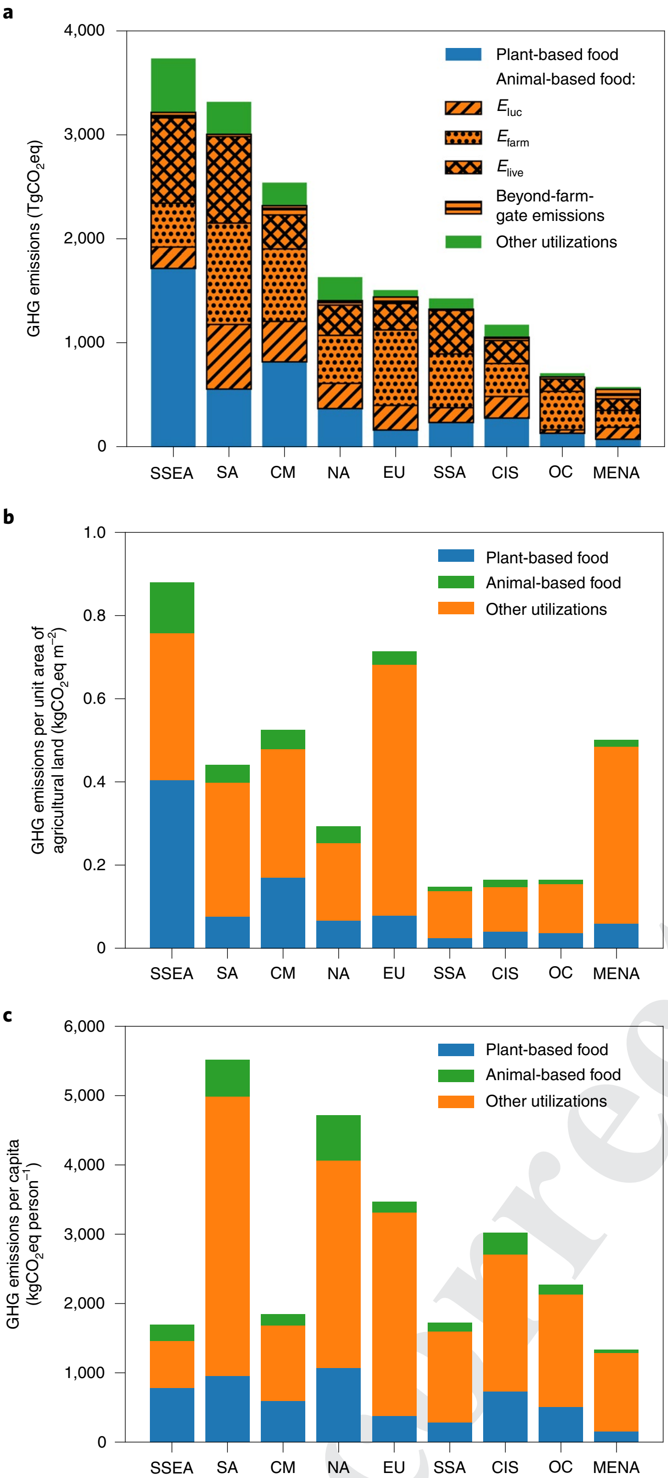

Fig. 2 | GHG emissions from the productions of plant-based food, animal-based food and others. a, Emissions in different regions. **b**, Emissions per unit area of agricultural land. **c**, Emissions per capita. (Supplementary Fig. 1 shows the spatial domains for the nine regions: NA, North America; SA, South America; EU, European Union; MENA, Middle East and North Africa; SSA, sub-Saharan Africa; CIS, Commonwealth of Independent States; CM, China and Mongolia; SSEA, South and Southeast Asia; OC, Oceania and other East Asia).

including 18% CH_4 emissions from enteric fermentation of ruminant animals and 2% from manure management. E_{farm} and E_{live} are the largest major components of emissions from beef and cow milk production. These two commodities contribute the most (25% and 10%, respectively) to the total animal-based food GHG emissions (Fig. 3b).

E_{luc} of animal-based food (12%) includes 5% from soil disturbance and 7% from biomass loss (Supplementary Fig. 5d). E_{luc} and E_{farm} are the major sources of GHG emissions of meat products from monogastric animals, such as pork and chicken meat, mainly because we account for the GHG emissions from the production and trade of crop feed for these animals.

The most prominent emitting regions for animal food production are SA (14% of total food-related emissions), SSEA (9%) and CM (8%) (Fig. 2a). China (8%) in CM, Brazil (6%) in SA, the United States (5%) in North America (NA) and India (4%) in SSEA are the countries with leading GHG emissions from the production of animal-based foods (Fig. 4). Beef and cow milk are the commodities that contribute most to the largest emitting regions and countries. E_{farm} and E_{live} are the most dominant components of GHG emissions of animal-based food production in these regions and countries (Supplementary Fig. 5b,g). These regions and countries have the largest herd size of cattle supporting meat and dairy production, demanding more crop and grazing feed and causing more farmland CO_2 emissions. E_{luc} associated with animal feed production in Brazil is the highest among all countries, mainly because of deforestation caused by grazing land expansion[23].

GHG emissions from food consumption. Consumption-based emissions are calculated by combining transportation, stock variation and international trade, based on the FAOSTAT commodity trade dataset[24,25], with our estimates of production-based emissions for each commodity and subsector (Methods).

For the 2010 base year, roughly 16% and 17% of global total GHG emissions were transferred among regions due to the import and export of food, here plant- and animal-based food (including import and export of feed) combined. Imports transferred 4% of plant-based food and 12% of animal-based food from producers to consumers. If attributing emissions to importing consumers, we can say that imports transferred 5% of plant product emissions and 12% of animal product emissions. It should be noted that GHG emissions are not exactly balanced between import and export[25], in part due to the emissions attributed to stock variation ($-38\,TgCO_2eq\,yr^{-1}$), and transportation emissions ($202\,TgCO_2eq\,yr^{-1}$), as well as slight inconsistencies in the FAOSTAT import and export amounts of plant- and animal-based food.

SSEA has caused the greatest GHG emissions from plant-based food exports (Fig. 5). Tropical regions such as SSEA and SA are experiencing an expansion of agricultural land for the production of plant-based commodities such as coffee, tea, bananas, citrus fruits, palm oil, rubber, sugarcane and grazing feed for animal-based food production, which is to a great extent driven by international trade[26]. The expansion of agricultural land is predominantly achieved by conversion from natural vegetation such as forest, which causes significant LUC and E_{luc} (ref. [26]). These regions thus cause more GHG emissions from exports, particularly related to E_{luc}.

The EU has caused the most GHG emissions from both animal-based food imports and exports, mainly because of the large amount of the internal trades between EU countries[25]. SA, NA and OC also cause large amounts of GHG emissions, predominantly due to their leading positions in exporting animal-based food such as beef[25].

Discussion

Overall, our estimates of GHG emissions from food systems account for 35% of global total anthropogenic GHG emissions. At the same time, we do not account for food-related emissions through specific human/climate disturbances, such as savannah burning, peat drainage and peat fires[3,13,17,27]. By adding all emissions from total savan-

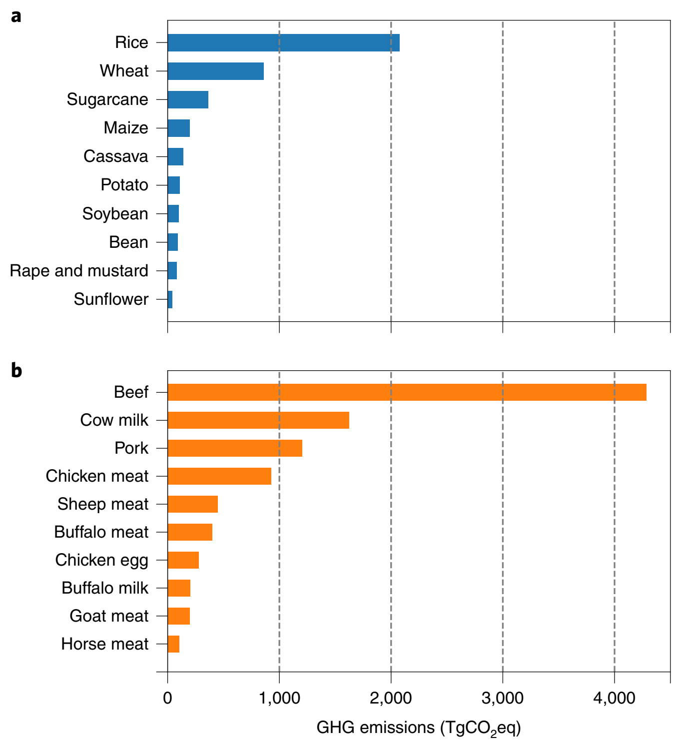

Fig. 3 | GHG emissions from the productions of top-contributing commodities. a, Top ten plant-based food commodities. **b**, Top ten animal-based food commodities.

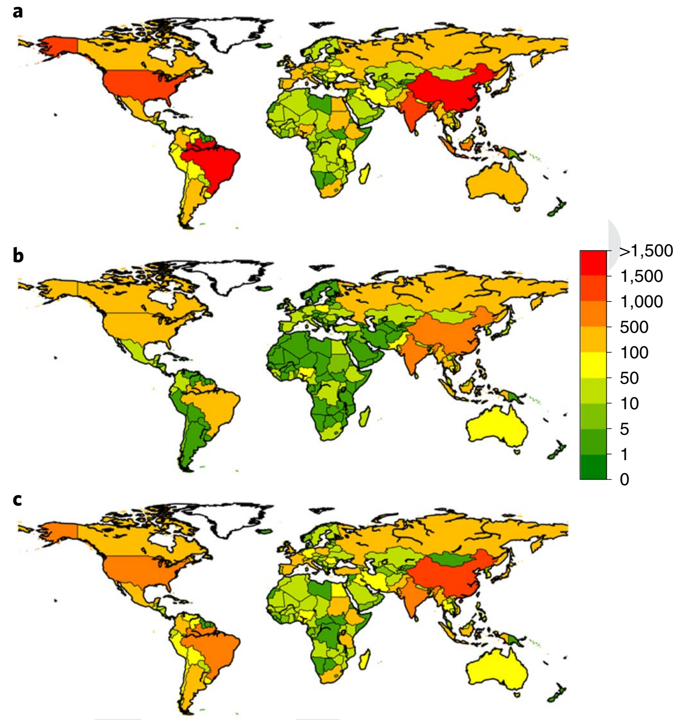

Fig. 4 | GHG emissions from food production at the country scale. a, Total emissions from food production. **b**, Emissions from plant-based food. **c**, Emissions from animal-based food. Values are expressed in $TgCO_2eq$.

nah burning and drained peat[17,27] (not only related to food systems), our total food-related emissions will be ~37% of total GHG emissions, compared to the IPCC SRCCL estimated percentage range of 21–37%[6], and 26% according to Poore and Nemecek[5]. Without E_{bfg}, our estimated GHG emissions are 31% of global total anthropogenic GHG emissions[3], compared to 24% from AFOLU in IPCC AR5[3]. While our overall estimated emissions match well with the higher-range value of the IPCC SRCCL[6], it should be noted that we estimate emissions from subsectors for the human food systems using a consistent data-modelling framework, which ensures the carbon and nitrogen balance among biomass flows by considering detailed biophysical and biogeochemical processes.

As the basis for calculating feed emissions, we estimated the total feed demand and its compositions. Our feed amount calculation method (Supplementary Methods 1.4) is unique and detailed compared to other published studies, including IPCC AR5 WG3[3] (Supplementary Discussion 4 and Supplementary Table 7), because it ensures that the amounts of different types of feed are consistent with crop and grazing land productions, which are cross-validated with published datasets[22,28]. Our method also ensures the balance between different types of feed supply and total demand not only on the global scale but also in each individual country. Overall, our estimated feed demand (2,450 $TgC\,yr^{-1}$) is 20% lower than IPCC AR5 estimates[3], but is within the range of previous studies (which range from ~2,000 to 3,000 $TgC\,yr^{-1}$, see Supplementary Table 7).

Our farmland CO_2 emission (E_{f_CO2}) is the net carbon flux of cropland and grazing land, which includes both carbon fixation by plant photosynthesis and carbon loss such as soil emissions and livestock respiration (Supplementary Methods 2.3). Our estimated soil emissions (sum of soil disturbance and tillage emissions E_{t_CO2}, see Supplementary Table 15) and livestock respiration emissions are 2,377 and 4,920 $TgCO_2eq\,yr^{-1}$, respectively.

Our study considers several emissions which others have not. Our estimated net E_{f_CO2} of $3{,}084 \pm 181$ $TgCO_2eq\,yr^{-1}$ (Supplementary Table 15) was derived from a detailed mathematical algorithm for agricultural land management intensity and practices, but is typically assumed to be zero[3]. Our estimated E_{bfg} (2,123 $TgCO_2eq\,yr^{-1}$) accounts for different subsectors (mining, manufacturing and transporting agricultural materials, and food processing and transportation) at the global scale (Supplementary Discussion 5 and Supplementary Table 8), which is about half of the aggregate value reported by the IPCC SRCCL[6] value. Our estimated food processing and transportation emissions are close to the values presented by Poore and Nemecek[5]. Our total E_{farm} ($6{,}493 \pm 1{,}896$ $TgCO_2eq\,yr^{-1}$) is 2–4 times higher than that reported by FAOSTAT[4], Poore and Nemecek[5] and EDGAR[29] (Supplementary Table 8), mainly because we included the farmland CO_2 emissions.

Compared to the state of the art and the representation of plant-based practices in this study, knowledge about livestock management and emissions is considerably less advanced because much more detailed GHG emission estimates are available for all subsectors of plant-based practices. Our estimated E_{live} emissions ($3{,}608 \pm 836$ $TgCO_2eq\,yr^{-1}$) are similar to those reported by FAOSTAT, but our combined E_{farm} and E_{live} emissions are ~60% higher than in the IPCC SRCCL[6] (also because of our farmland CO_2 emissions). Our estimated E_{luc} ($5{,}096 \pm 301$ $TgCO_2eq\,yr^{-1}$) is similar to the IPCC AR5[3] and SRCCL[6] values and higher than the values reported by FAOSTAT[4] and Poore and Nemecek[5]. Our simulated farmland CH_4 emissions are similar to those in EDGAR[29] and higher than those reported by Carlson et al.[13], Poore and Nemecek[5] and FAOSTAT[4], but the estimated uncertainty range is large. Our estimates for N_2O from cropland and grazing land are consistent with FAOSTAT[4], and slightly higher than those in EDGAR v.4.3.2[29]. Our food-related emissions for most of the countries are either higher or about the same compared with FAOSTAT. Our total emissions are ~90% more than FAOSTAT total emissions in circa 2010 (Supplementary Table 8), mainly because we account for E_{bfg} and farmland CO_2 emissions. Further

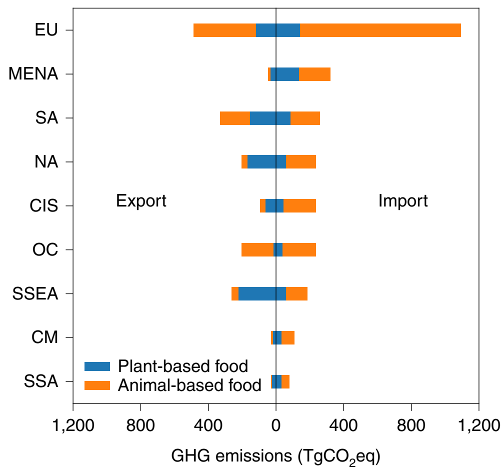

Fig. 5 | GHG emissions due to import and export of plant- and animal-based food in different regions. Animal-based food values include emissions from import and export of livestock feed.

discussion on the comparison with other studies is provided in Supplementary Discussion 5.

Our framework can address many important issues related to developing mitigation strategies for food-related GHG emissions. For example, we can study the soil emission reduction due to land management practices such as no-till or reduced tillage. In addition, we can account for carbon sequestration due to reforestation of agricultural land freed from livestock production under the scenario of transitioning from animal-based diets to plant-based diets.

Finally, we estimated GHG emissions from the food sector but did not consider the opportunity costs of lost carbon sequestration capacity of agricultural land that would otherwise revert to forest if allowed to return to its natural state. Future studies should consider these costs, as well as management strategies for enhancing carbon sequestration on marginal lands, to estimate net carbon flux based upon alternative dietary and land-use scenarios. These estimates, combined with results from our study, would provide a comprehensive science-based framework that could then help policymakers assess climate change mitigation strategies that harness the natural regenerative capacity of our planet.

Methods

To quantify the total food-related GHG emissions, we first estimated the total crop and grazing biomass, including livestock feed, and then partitioned the total biomass between plant- and animal-based food (livestock feed) and other utilizations.

Based on the estimated biomass, we calculated and partitioned the production-based GHG emissions from plant and livestock to plant- and animal-based food and other utilizations. After that, we calculated GHG emissions from the consumption-based perspective, taking into account transportation, international trade (import and export) and stock variation. We estimated the consumption-based emissions to explicitly account for the GHG emissions caused by trade. This was especially important for regions and countries which import and/or export large amounts of plant- and animal-based food in the context of better tracing food systems' global and regional GHG footprints.

From the production-based perspective, the GHG emissions from plant- and animal-based food included the following subsectors (Fig. 1): emissions from land-use change for agricultural land expansion (E_{luc}); farmland emissions (E_{farm}) from farming activities such as ploughing soil, planting and fertilizing crops, harvesting crop grains and recovering crop residues for feedstock, and from fuel and electricity consumption by machines used in farming; livestock emissions (E_{live}) including CH_4 emissions from enteric fermentation by ruminant animals and CH_4 and N_2O emissions from manure management; beyond-farm-gate emissions (E_{bfg}), including mining, manufacturing and transportation of nitrogen, phosphorus and potassium (NPK) fertilizers, and pesticides, which were applied to agricultural land to produce crop and grazing biomass; as well as product processing emissions due to fuel and electricity consumption for production of crop (such as emissions from drying, peeling and milling processes) and livestock commodities (such as emissions from slaughtering and butchering).

From the consumption-based perspective, we calculated emissions from production, import, export and stock variation of plant and livestock, and what was consumed as plant- and animal-based human food and other utilizations. We estimated the net GHG emission transfers among different countries via international trade, that is, export and import, and emissions from the stock variation of plant and livestock products based on agricultural biomass. We also considered GHG emissions due to domestic and international transportation in consumption-based emissions.

Agricultural biomass. We estimated dry-matter biomass carbon of 171 crops by multiplying the crop production in circa 2010 with crop-specific dry-matter content and carbon content per unit of dry matter (Supplementary Table 1)[30–32] (Supplementary Methods 1.1). We first produced the spatially explicit production data of all crops in circa 2010 (Supplementary Methods 1.2 and 1.3). In addition, we calculated the amount of crop biomass for different utilizations based on the commodity balance reported by FAOSTAT[24] as described in detail in the section Emissions partitioning to different utilizations. We also estimated the crop residue biomass for all 171 crops (Supplementary Methods 1.2 and 1.3).

We first calculated the feed demand for 16 major livestock animals in each country by multiplying the animal-specific feed demands per head[33] by the number of live animal heads[22] (Supplementary Table 4). Then we quantified the biomass supply amounts from five sources to meet the feed demand in each country—namely, crop grain feed, forage crop feed, crop residue feed, grazing feed and scavenging and other feed as described in Supplementary Methods 1.4. To ensure that the supply (including import and export) and demand of feed were equal in each country, we developed a schematic algorithm to reconcile the feed demand and supply amount at the country level (Supplementary Methods 1.4 and Supplementary Fig. 6).

GHG emissions from food production. The total GHG emissions from food production are the sum of emissions from LUC, E_{luc}, farmland, E_{farm}, livestock, E_{live}, and beyond the farm gate, E_{bfg}.

LUC. LUC activities cleared existing ecosystems, their biomass and disturbed the soil, generating GHG emissions. This cleared biomass was either directly lost, for instance, through fire, or used to make different products. We assigned the carbon and nitrogen stored in these products into four pools: agriculture and agriculture products in a 1 yr product pool, paper and paper products in a 10 yr product pool, lumber products in a 100 yr product pool and long-lived products in a 1,000 yr product pool. In one particular year, we assumed the emission caused by product pools was the sum of the 1 yr pool, 1/10th of the 10 yr pool, 1/100th of the 100 yr pool and 1/1,000th of the 1,000 yr pool. The waste biomass was either burned or left on the ground as litter. For the emissions caused by soil disturbance, we assumed a certain amount, depending upon the region and soil type, of the topsoil soil organic carbon was lost in the first year when LUC occurred[34]. We used the historical LUC areas from Hurtt et al.[21], and processed these to drive the ISAM model using the methodology developed by Meiyappan and Jain[20]. In order to represent the LUC emissions for 1 yr circa 2010, we calculated the average E_{luc} emissions from 2007 to 2013, which was consistent with the time frame of other emission calculations in this study.

Farmland. Farmland emissions included all emissions due to farming activities, such as ploughing soil, planting and fertilizing crops, harvesting crop grains and recovering crop residues. Fuel and energy use emissions were also part of E_{farm}.

Fuel and energy use. Fuel and energy use emissions included GHGs emitted from fuels and electricity consumption by farm machinery, including irrigation. We used the energy use emissions (excluding fuel oil and energy for fisheries and transportation emissions) from FAOSTAT[17], and distributed these emissions to individual crops based on their harvested area. FAOSTAT fuel and energy use emissions included agriculture and forestry, and fishery emissions. Because we excluded fishery emissions, these data covered the emissions from both plant cultivation and livestock (for example, energy used in milking machinery and stables) on farmland. Therefore, we assumed that our farmland 'fuel and energy use emissions' covered both plant- and animal-based products. Our distribution method assumed the same GHG emissions on each unit of harvested area in the individual country. Given the small contributions of fuel and energy use emissions (~1% of our total food-related emissions), this relatively simple estimation method to calculate the fuel and energy use emissions in each country did not add much uncertainty to the total GHG emissions. The FAOSTAT dataset was computed following the Tier 1 method of the IPCC 2006 Guidelines for National Greenhouse Gas Inventories[12], which calculates the emissions by multiplying fuel burning and electricity generation amounts by their emission factors[12].

CH_4 and N_2O. We assumed all farmland CH_4 emissions were generated from rice paddies (since the rest was treated elsewhere—under livestock). We used the ISAM CH_4 module[35] to simulate the wetland and non-wetland soil CH_4 emissions and explicitly separated the CH_4 emission from rice paddies (see Supplementary Methods 3.3 for a brief description of the model). We used the N_2O module[36] of the ISAM to simulate the N_2O emissions from cropland and grazing land (Supplementary Methods 3.2). The gridded fertilizer and manure input data for ISAM are described in the Data sources section.

CO_2. We estimated farmland CO_2 emissions using the ISAM model jointly with FAO crop production data. The farmland CO_2 emissions, E_{f_CO2}, were the difference between all carbon emissions and sequestrations in agricultural land. Here the positive values meant emissions, while the negative values indicated carbon sequestration. E_{f_CO2} was calculated using equation (1).

$$E_{f}\_CO2 = R_a + R_h + E_{t}\_CO2 + E_{h}\_CO2 + E_{w}\_CO2 - -GPP \quad (1)$$

where GPP is the gross primary productivity or gross CO_2 fixation by plants related to cropland and grazing land; R_a and R_h are autotrophic and heterotrophic respiration; E_{t_CO2} is carbon loss due to soil tillage; E_{h_CO2} is carbon loss due to harvest of biomass, including grain biomass and recovery biomass (for feed and other use); and E_{w_CO2} is carbon loss due to burning of waste biomass.

ISAM simulated E_{f_CO2} in a dynamic way for 16 major crops. The E_{f_CO2} for the rest of the 155 crops, a combination of C3 and C4 crops, was calculated using M3, FAOSTAT and ISAM model results for C3 and C4 generic crops described in detail in Supplementary Methods 1.3. After harvesting and recovery, we assumed a certain fraction (which varies from region to region) of the residual biomass was burned on the ground[37,38] (E_{w_CO2}). Remaining residual biomass after harvesting, recovering and burning went into the soil in the form of litterfall. Detailed processes were described by Jain et al.[19] and by Meiyappan et al.[34].

Livestock. In this study, livestock emissions only include emissions from enteric fermentation and manure management, which we define according to the IPCC[12] and FAOSTAT[17]. We used the country- and animal-specific CH_4 and N_2O emission factors from livestock enteric fermentation and manure management emissions from the FAOSTAT dataset[4,9,17] to calculate livestock emissions, E_{live} (see Supplementary Methods 2.2 for details).

Beyond the farm gate. Mining, manufacturing and transportation of fertilizers and pesticides. Agricultural materials were applied to agricultural land to produce plant biomass. We considered NPK fertilizers, and pesticide application emissions from mining of raw ores and fossil fuels to manufacturing and transportation to the farmland. We multiplied the application amounts and emission factors of NPK fertilizers and of pesticides to estimate the emissions from mining, manufacturing and transportation of fertilizers and pesticides (Supplementary Methods 2.1).

Processing. Food processing emissions were a component of E_{bfg}, which was part of both production- and consumption-based emissions. We included emissions from fuels and electricity consumption caused by the processing of crops needed before using, such as heat drying, peeling and grain milling (see Supplementary Table 9 for processed crops). For example, wheat grain was usually processed to wheat flour and wheat bran using mills, which consumed fuels or electricity and generated additional GHG emissions. We adopted the processing emission factors (Supplementary Table 9) from the Feedprint NL database (v.2019.00, Wageningen University & Research, 2019) to estimate the crop processing emissions. For the crops that were processed into multiple products (Supplementary Table 9), we allocated the GHG emissions of these crops to different products (Supplementary Methods 2.4).

Similarly, fuel and electricity were consumed during the processing of livestock products, such as slaughtering and butchering, which generated additional GHG emissions. We adapted the energy consumption amount of meat, dairy and egg productions and region-specific emission factors from GLEAM v.2.0[39].

GHG emissions from food consumption. Consumption-based GHG emissions were the sum of production-based emissions, emissions due to food transportation, emissions transferred among the importing and exporting countries and emissions from stock variation. To calculate the consumption-based GHG emissions, we first quantified the total consumption of plant biomass in each country using the commodity balance[24], which was the sum of production, import, export and stock variation. Next, we calculated the total consumption-based emissions. Finally, we partitioned total emissions into plant- and animal-based food, and other utilizations, based on the biomass consumption.

Plant biomass consumption. The consumption of crop biomass was calculated using the following relationship[24]:

$$\text{consumption}_{c,n} = \text{production}_{c,n} + \text{stock variation}_{c,n} + \text{import}_{c,n} - \text{export}_{c,n} \quad (2)$$

where consumption$_{c,n}$ is the biomass consumption of crop c in country n (kg); production$_{c,n}$ is the biomass production of crop c in country n (kg)*;* import$_{c,n}$ and export$_{c,n}$ are imported and exported biomass of crop c in country n (kg); and stock variation$_{c,n}$ refers to changes in stocks at all levels between the production and the retail levels (kg). All these values are calculated from the FAOSTAT dataset[25] and averaged from 2007 to 2013.

We estimated the imported and exported amounts of forage crop biomass by the approach described in Supplementary Methods 1.4. We assumed there were no import, export and stock variation for grazing feed. Therefore, the production-based and consumption-based GHG emissions were the same for grazing feed.

We used FAOSTAT numbers for the commodity balance and calculated production using our modelling framework. This approach inherently introduced some differences between our production calculations and FAO estimates. In FAOSTAT, stock variation was usually used to adjust the imbalance between production and consumption amounts[40]. We used the same approach and attributed the imbalance between production and consumption to stock variation. The adjustment of stock variation had a relatively small effect on total emissions (less than 0.2%).

Consumption-based emissions. We adapted the following equation from Cassidy et al.[41] to estimate the GHG emissions for consumption$_{c,n}$ by accounting for GHG emissions from stock variation and international trade (bilateral trade; see detailed discussion in Supplementary Discussion 5).

$$\text{GHG}_{c,n} = \left(\text{production}_{c,n} + \text{stock variation}_{c,n} - -\text{export}_{c,n}\right) \times \text{EI}_{c,n} + \sum \text{import}_{c,i} \times \text{EI}_{c,i} + E_{\text{trans}_{c,n}} \quad (3)$$

where GHG$_{c,n}$ are the GHG emissions from consumption of crop c in country n (kgCO_2eq); EI$_{c,n}$ is the weighted average GHG emission intensity of per kg crop c in country n (kgCO_2 eq kg^{-1}), which is defined as total production-based emissions (sum of E_{luc}, E_{farm}, E_{live} and E_{bfg}) for crop c in country n divided by production$_{c,n}$; $EI_{c,i}$ is the weighted average GHG emission intensity of per kg crop c in importing country i (kgCO_2eq kg^{-1}), which is calculated using the same method as for EI$_{c,n}$ but for importing country i; import$_{c,i}$ is the imported biomass of crop c from country i to country n; and $E_{\text{trans}_{c,n}}$ are the emissions from transportation of food c in country n. We assumed stock variation$_{c,n}$ has the same $EI_{c,n}$ as production$_{c,n}$.

Our approach ensured that all GHG emissions produced in one country (the sum of E_{luc}, E_{farm}, E_{live} and E_{bfg}) would be imported or exported to the trading partner countries along with the trade of food commodities. Our consumption-based GHG emissions could not rule out the effect of through-trade. We assumed that all products imported from a country were produced in that importing country. The through-trade might have a large effect on consumption-based GHG emissions in some countries, such as the Netherlands. To minimize the effect of through-trade, we reported our consumption-based GHG emissions at the regional scale.

Plant- and animal-based products were transported domestically and internationally by different transport modes, which generated GHG emissions. We calculated the transportation emissions, $E_{\text{trans}_{c,n}}$, based on the emission factors of different transport modes and transporting tonne-km of plant- and animal-based commodities (Supplementary Tables 10 and 11)[42,43]; 1 t-km represented the transport of 1 t (1,000 kg) of the commodity over a distance of 1 km.

Emissions partitioning to different utilizations. We calculated the plant-based GHG emissions from different utilizations based on the commodity balance of the FAOSTAT dataset[24]. This procedure did not generate additional GHG emissions; it only estimated the GHG emissions for different utilizations. The biomass balance was as follows:

$$\text{consumption}_{c,n} = \text{food}_{c,n} + \text{feed}_{c,n} + \text{others}_{c,n} \quad (4)$$

where food$_{c,n}$ and feed$_{c,n}$ refer to the biomass used as plant-based food and livestock feed for crop c in country n; and others$_{c,n}$ is the combined biomass for all non-food and non-feed utilizations.

The food$_{c,n}$, feed$_{c,n}$ and others$_{c,n}$ values were collected from the FAOSTAT commodity balance sheet[24]. We combined biomass for processing, losses, seed production and other usages as others$_{c,n}$. Note that the processing usages in FAOSTAT were also used for food or feed. Here we excluded the food and feed usages in the processing but included them in the biomass for food and feed correspondingly. For instance, soybeans were processed to soybean oil and cake; these three commodities all had their commodity balances. The 'processing' term in the commodity balance of soybean included the 'production' term in the commodity balances of soybean oil and cake. In order to avoid double-counting, we subtracted the 'production' of soybean oil and cake from the 'processing' of soybean. The commodities that were transformed into products with other uses (not food or feed) or into products that were actually used as feed or food but the uses of which were not explicit or not reported in the FAOSTAT commodity balance (for example, bran, alcohol, molasses and sweeteners from maize or sugarcane) had their 'processing' use classified as 'other utilizations'. Note that our study only accounted for the processed products that appeared in the commodity balance of FAOSTAT[24].

Based on equation (4), we calculated the GHG emissions from plant-based food (food_GHG$_{c,n}$) for crop c in country n by:

$$\text{food\_GHG}_{c,n} = \frac{\text{food}_{c,n}}{\text{consumption}_{c,n}} \times \text{GHG}_{c,n} \quad (5)$$

where $GHG_{c,n}$ is calculated in equation (3). We then used the same method to calculate the GHG emissions from $feed_{c,n}$ and $others_{c,n}$. It should be noted that the FAOSTAT commodity balance sheet[24] combines some crops into a broader commodity item (see column 'Corresponding commodity item' in Supplementary Table 1). We followed the same scheme to combine the GHG emissions from crops into different commodity groups (Supplementary Table 1) and then estimated GHG emissions from $food_{c,n}$, $feed_{c,n}$ and $others_{c,n}$.

We attributed all crop GHG emissions, including fuel and energy use emissions, to food, feed and other usages through the commodity balance. The GHG emissions allocated to crop feed and emissions from forage feed and temporary grazing feed productions, including fuel and energy use emissions, were all attributed to animal-based food emissions.

We used the same approach as the consumption-based emissions of plant biomass (equations (3)–(5)) to account for the consumption-based GHG emissions from livestock products in each country, including production, import, export and stock variation, and the consumption-based GHG emissions from animal-based food and other utilizations. Note that parts of livestock meat, dairy, and egg products were used as feed according to the livestock commodity balance[25]. We considered the animal-based feed GHG emissions as part of the animal-based food emissions.

Data sources. *Spatial data for NPK fertilizers.* For cropland, we produced the spatial maps of NPK fertilizer application amount for different crops at 0.5°×0.5° for circa 2010 based on EarthStat nutrient application spatial data for NPK fertilizer application amount for circa 2000[44,45], M3-crop[28] and FAOSTAT dataset[22] for crop-specific production data (Supplementary Methods 4). The EarthStat total nitrogen input amount, the combined nitrogen amount of synthetic fertilizer, manure and atmospheric deposition, was used to project the total nitrogen use in circa 2010. The synthetic nitrogen fertilizer component was only used as model input, which was estimated at the spatial scale for different crops using a fraction of synthetic nitrogen fertilizer amount to total nitrogen application amount in cropland at the regional scale[46]. We used other datasets for manure nitrogen application for cropland[47] and nitrogen deposition data[48] at the grid level. The amount of pesticides was not available at a spatial scale. Therefore we used country-scale data, which we collected from FAOSTAT[46].

For grazing land, we used the gridded nitrogen inputs for circa 2010 from Xu et al.[47], including synthetic nitrogen fertilizer and manure nitrogen left on and applied to grazing land.

Spatial data for manure nitrogen and carbon. We considered nitrogen and carbon from manure in this study. Manure was either left on the grazing land or collected in feedlot and then applied to cropland and grazing land. CH_4 and N_2O emissions were emitted during the storage and composting processes of the collected manure, which we considered as part of the livestock emissions (see Livestock section).

For cropland, the crop-specific spatial data of manure nitrogen application amount was estimated in our produced nitrogen fertilizer application amount based on published datasets[28,44,45,48,49] (Supplementary Methods 4). For grazing land, we used the gridded nitrogen inputs for circa 2010 from Xu et al.[47], which provided manure nitrogen left and applied to grazing land separately. These crop and grazing land manure nitrogen data were at the gridded scale that was required by the ISAM simulations. The aforementioned nitrogen datasets[28,44,45,47,48] were all based on and consistent with FAOSTAT manure nitrogen data at the country scale[49]. Therefore, our usage of FAOSTAT manure management emissions was also consistent with these manure nitrogen input data. Manure contained both organic and mineral nitrogen. Plants could not directly use organic nitrogen. In the ISAM model, the organic manure nitrogen was gradually decomposed by soil microbes to mineral nitrogen. Part of it then entered into the soil mineral nitrogen pool together with the inorganic (mineral) manure nitrogen[19].

To obtain the spatial data for manure carbon, we first estimated the total manure carbon amount by multiplying the animal-specific manure production per head[33] by the number of live animal heads[22] in different countries (Supplementary Table 4). Then we calculated the global total manure nitrogen (estimated in the previous paragraph) and determined the global average C:N ratio of manure. Note that the different manure carbon and nitrogen sources might introduce inconsistency in the global manure C:N ratio estimation. We multiplied this C:N ratio by the spatial maps of manure nitrogen to get the gridded manure carbon map on a global scale. ISAM considered manure carbon in organic form as litterfall and simulated its impact on farmland CO_2 emissions through dynamic processes.

Uncertainty analysis. We estimated the uncertainty range of the GHG emissions for plant- and animal-based food through a Monte Carlo approach, which simulated the uncertainties caused by major contributors of the GHG emissions, such as E_{luc}, E_{farm} and E_{live} by referring to their individual uncertainty ranges from previous studies (Supplementary Methods 5 and Supplementary Table 12). In addition, we acknowledge that the uncertainties of all spatial data we cited from previous studies and produced in this study are largely of unknown magnitude.

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

The results for CO_2, CH_4 and N_2O from the plant- and animal-based food are available at the ISAM website http://climate.atmos.uiuc.edu/Food_Emissions. The results for individual plant- and animal-based commodities are available upon request.

Code availability

All codes are available upon request.

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Author contributions
X.X. and A.K.J. designed the framework of this study, collected data and analysed the results. X.X., P.S., S.S. and T.-S.L. performed the model simulations. P.C., F.N.T., P.S. and N.C. contributed to the interpretation and implication of the results. X.X. wrote the paper with inputs from all coauthors.

Competing interests
The authors declare no competing interests.

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