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International demand for food and services drives environmental footprints of pesticide use

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Pesticides are well-recognised pollutants that threaten biodiversity and ecosystem functioning. Here we quantify the environmental footprints of pesticide use for 82 countries and territories and eight broad regions using top-down multi-region input-output analysis. Pesticide footprints are expressed as hazard loads that quantify the body weight (bw) of non-target organisms required to absorb pesticide residues without experiencing adverse effects. We show that the world's consumption in 2015 resulted in 2 Gt-bw of pesticide footprints. Of these, 32% are traded internationally. The global average per-capita pesticide footprint is 0.27 t-bw capita^{-1} y^{-1}, with high-income countries having the largest per-capita footprint. China, Germany, and United Kingdom are the top three net importers of pesticide hazard loads embodied in commodities, while the USA, Brazil, and Spain are the three largest net exporters. Our study highlights the need for policies to target pesticide use reduction while ensuring adverse impacts are not transferred to other nations.

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Over the past five decades, modern agriculture, driven by the Green Revolution, has achieved unprecedented high yields through irrigation and the extensive use of synthetic fertilisers and pesticides[1]. Unfortunately, this strategy of intensive food production is not currently sustainable because it deteriorates terrestrial and aquatic ecosystems, depletes water resources, and contributes towards climate change[2–4]. To date, efforts to quantify the environmental footprints of global production and consumption have covered a wide range of indicators[5], including greenhouse gas emissions[6], water scarcity[2,7], biodiversity[8,9], nitrogen pollution[10], acidification[2], land use[2,11,12], and others, but they have largely missed to represent the environmental pressures exerted by pesticide use.

The use of pesticides can exert pressures on the environment by causing biodiversity loss[13,14] and creating disruptions to ecosystem functioning and services that regulate pollination, natural pest control, soil respiration, nutrient cycling, and others[15,16]. Hence, reducing the potential environmental risks of pesticide use is an important goal of agricultural and environmental policies worldwide[17]. For example, the Farm to Fork Strategy in the European Union, which targets the transformation into a fair, healthy, and environmentally-friendly food system by ensuring sustainability throughout the entire food supply chain[18], provides an opportunity to establish pesticide reduction strategies within a holistic framework that encompasses all actors in the food supply chain[17]. One important step to establish such a holistic framework is to quantify the footprint of pesticide use, starting from the primary producer to final consumer, and to understand how international trading drives pesticide use among nations to highlight the potential footprint leakage if a nation's pesticide policy were to shift domestic production towards imports.

Thus far, environmental impact assessments have considered two kinds of indicators: pressure-oriented indicators (based on elementary flows, such as emissions to environment) and impact-oriented indicators (such as mid-point and end-point impacts on human health and ecosystem), both stemming from the literature on life cycle assessments (LCAs)[19,20]. Pesticides have primarily been considered as part of chemical footprints, which have since been assessed using bottom–up LCAs and impact-oriented indicators such as USEtox[21–24]. These bottom–up LCAs, whilst providing specificity in terms of impacts of specific products and processes, do not account for hot-spots of pesticide use impacts driven by final consumption of goods and services, and the contribution of globalisation and international trade in driving pesticide use by industries. Furthermore, bottom-up LCAs require the selection of a system boundary as part of the assessment[25], thus are not suited to quantifying indirect supply chain impacts of pesticide use.

To quantify the environmental footprint of pesticide use at the global economy-wide level, we use the top–down approach that is based on multi-region input-output (MRIO) analysis. MRIO analysis has been carried out at multiple scales for analysing environmental and social impacts of consumption[26]. Specifically, this technique offers the ability to assess international supply chain linkages, a capability not provided by bottom–up assessments, for analysing how trade relationships (imports and exports) contribute to unintended environmental and social effects globally. Recently, with the advent of the Global Industrial Ecology Virtual Laboratory Platform (Global IELab), construction of customised trade databases has been made possible. This advance has led to assessments of specific products and regions[27] from an international trade perspective.

Here, we define the pesticide footprints as the hazard loads (HL) of pesticides used on crop production for satisfying the consumption of goods and services, with the hazard loads measuring the total body weight (bw) of non-target organisms required to absorb pesticides accumulated in the environment at an annual intake that will not result in observable adverse effects ("Methods"). A higher value signifies a greater environmental pressure. The pesticide hazard load used here bases upon a similar concept as the total applied toxicity indicator (TAT)[28]. Specifically, the hazard load is defined as $HL = \sum[M_i/(NOAEL_i \times 365)]$, where M_i [kg-pesticide] is the total mass of active ingredient i accumulated in the environment and $NOAEL_i$ [kg-pesticide kg-bw^{-1} day^{-1}] is the no-observed adverse effect level of active ingredient i in mammals and birds (see details in "Methods"). The hazard load defined here does not account for pesticide effects on human health and acute toxicities on non-target organisms due to immediate exposure right after an application event. Based on this definition, we analyse the pesticide footprints embedded in the global agriculture trade system by linking a global database of pesticide applications (PEST-CHEMGRIDSv1.0[29], estimated based on USGS[30] and FAOSTAT[31] data), a global-scale mechanistic environmental model[32], and a global supply-chain model[33] featuring international trade data for 82 countries and territories and eight broad regions. The 82 selected countries and territories are either top agriculture producers, top pesticide users or having high and upper-middle income economies[31], and the remaining countries and territories were grouped into eight regions according to geographic locations and whether they are members of Annex-I parties in the United Nations Framework Convention on Climate Change[34] (see Supplementary Table 1 for the aggregation).

We first quantified the pesticide residues (i.e., the amount of applied pesticides not degraded by environmental processes) in different cropping systems using a mechanistic, spatially-explicit, and time-resolved model fed with georeferenced databases of soil properties, agricultural practices, and hydrometeorological variables ("Methods"). Although there are more than a thousand of active ingredients registered as pesticides[35], we modelled in this study the residues of 80 active ingredients used on crop production (Supplementary Table 2) and excluded the use of pesticides in non-cropland setting such as pastures, rangeland, aquaculture, livestock production (e.g., cattle dip), and urban areas (e.g., dwellings, railways, gardens). We then calculated the hazard loads corresponding to the modelled pesticide residues and traced their flow along international trade routes, starting from producing nations to end consumers, using a MRIO supply-chain model to quantify the pesticide footprints of nations as both producers and consumers. MRIO models allow for the scanning of multiple supply chain networks across countries and regions. For quantifying the environmental pressures associated with pesticide use in supply chains, we considered the final consumption of commodities at a global level by 90 countries/regions, and traced more than a billion supply chain connections to trace the primary production of goods (e.g., crop production), transformation of goods into secondary products (e.g., processed food) and finally consumption by an end user (e.g., households in each of the 90 countries/regions). We assessed footprints according to the primary producer to final consumer perspective to identify pesticide hazard loads taking place in primary producing areas, driven by final consumption, and the final point of sale to final consumer perspective for linking pesticide hazard loads with commodities that are finally consumed by end users. It is important to analyse both perspectives to get a holistic view of the pesticide hazard loads that occur in primary producing countries and those that are embodied in supply chains of secondary and tertiary sectors. Since our analyses include only the use of pesticides in cropland, all animal-based products (including raw meat and eggs) are considered as secondary products, and hence the pesticide footprints embedded in animal-based foods are stemmed from feed (e.g., grains, cereal residuals, oilcakes).

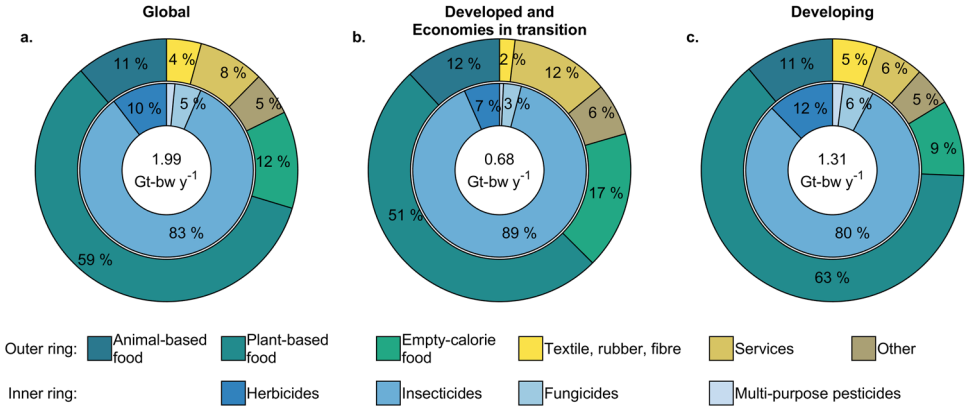

Fig. 1 Pesticide footprints embedded in the world's consumption across different sectors. a–c correspond to the consumption globally, in developed and economies in transition countries, and in developing countries, respectively. The total pesticide footprints include contributions from herbicides, insecticides, fungicides, and multi-purpose pesticides and are expressed as giga tonnes of human body weight per year (Gt-bw y^{-1}). Multi-purpose pesticides refer to pesticides that are used for more than one functions. The footprints embedded in different sectors were analysed using final point of sale to final consumer perspective. Details of region grouping, pesticide classification, and sector aggregation are provided in Supplementary Tables 1–2 and Supplementary Data 1.

The footprints embedded in services (e.g., hotels and restaurants) and other sectors (e.g., construction) are due to the consumption of food and textiles within those sectors. Analyses conducted in this study are relative to the year 2015.

Results and discussion

Pesticide footprints embedded in the world's consumption. Our study accounts for 3.24 megatonnes (Mt) of pesticides, representing about 79% of the global pesticide use estimated by FAOSTAT for 2015, which is 4.09 Mt[31] (Supplementary Fig. 1a). At the national level, our analyses include approximately 63, 70, and 70% of the pesticide use in China, the USA, and Brazil, respectively, which are the top three largest pesticide consumers (Supplementary Fig. 1a). The active ingredients included in our analyses fall within three functional classes, namely, herbicides (1.6 Mt globally), insecticides (0.20 Mt), and fungicides (0.40 Mt). In cases where an active ingredient belongs to more than one functional class, we classified it as a multi-purpose pesticide (0.9 Mt). Comparing against FAOSTAT data[31], our study accounts for approximately 70%, 98%, and 76% of herbicide use in Brazil, France, and Columbia, respectively (Supplementary Fig. 1b), whereas it includes less than 30% of the insecticide and fungicide use (Supplementary Fig. 1c, d). This is because 30% of the total pesticide mass included in our study was attributed to multi-purpose pesticides, which can be used as insecticides, fungicides, or both.

Using a spatially-explicit environmental model, we estimated the amount of applied pesticides that remained in the environment. We benchmarked the modelled pesticide residues in the topsoil against field measurements reported in Silva et al. for 11 European Union countries[36], which is one of the most extensive sampling campaigns for pesticide residues in agricultural soils. Our model estimated that croplands in Denmark, France, and Portugal had a 95th-percentile total pesticide residue of 0.9, 1.1, and 2.5 mg kg-$soil^{-1}$, respectively (Supplementary Fig. 2a). These values are relatively close to the maximum pesticide residues recorded by Silva et al.[36] in croplands of those countries, which are 1.2, 1.1, and 2.9 mg kg-$soil^{-1}$, respectively. Our estimates generally show higher median residues than in Silva et al. [36]. We also compared the number of detectable active ingredients in the topsoil estimated by our model against data reported in Silva et al.[36]. An active ingredient is considered detectable if its residue is greater than the typical laboratory limit of quantification (≈0.01 mg kg-$soil^{-1}$). The number of detectable active ingredients estimated by our model generally falls within the ranges reported in Silva et al.[36], with slight overestimation for Portugal and Italy (Supplementary Fig. 2b). Across the croplands in the 11 European Union countries, our model estimated a median residue of 0.31, 0.01, 0.03, 0.02, and 0.03 mg kg-$soil^{-1}$ for glyphosate, tebuconazole, azoxystrobin, propiconazole, and chlorpyrifos, respectively (Supplementary Fig. 3). These estimates match relatively well with data in Silva et al.[36], which reported a median residue of 0.14, 0.02, 0.03, 0.02, and 0.03 mg kg-$soil^{-1}$, respectively (Supplementary Fig. 3). We underline that there are some differences in the statistics of our model estimates as compared to those of field measurements in Silva et al.[36]. These differences may stem from differences in sample size as Silva et al.[36] has only 30 samples per country, whereas our model includes all the croplands in a country and therefore has a substantially bigger sample size than Silva et al.[36].

Of the 3.24 Mt of pesticides accounted in our analysis, our model estimated that approximately 9.3% (i.e., 0.302 Mt) accumulated in the environment and this corresponds to a hazard load of 1.99 gigatonnes of body weight (Gt-bw). Of these, 34% (0.68 Gt-bw) are attributed to consumption in developed and economies in transition countries (referred to as developed countries hereafter), where 18% of the world's population resides. The remaining 66% (1.31 Gt-bw) are caused by consumption in developing countries, where most of the world's population resides (Fig. 1). Insecticides are the largest contributors to the global pesticide footprints, contributing more than 80%, followed by herbicides that contribute about 10% of the total footprints.

Plant-based foods bear the largest portion of the global pesticide footprints (59%, Fig. 1), with the orchards fruits and grapes sector being the main contributor, accounting for 17% of the global footprints (0.34 Gt-bw, Supplementary Fig. 4), while animal-based foods contribute to about 11% (Fig. 1). Our analysis also shows that a substantial fraction (17%) of the pesticide footprints in developed countries is attributed to the consumption of empty calorie food products such as soft drinks, alcoholic drinks, chocolates, ice-creams, and sugars (Fig. 1b). In contrast, these food items contribute only 9% of the footprints in developing countries (Fig. 1c).

Clothing and textile related sectors (e.g., cotton, rubber, other fibres) bear approximately 4% of the global pesticide footprints

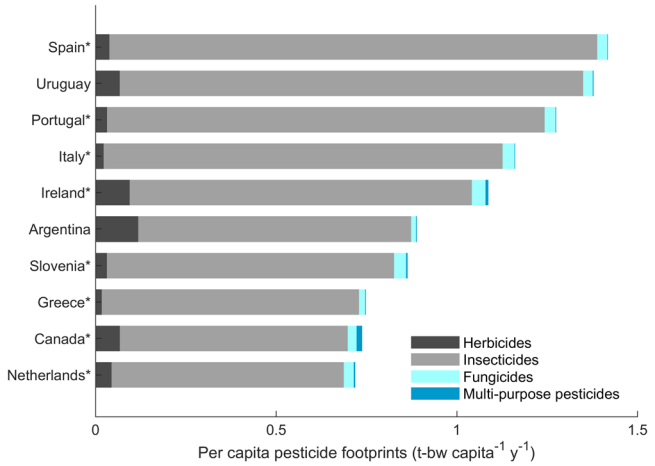

Fig. 2 Top 10 countries with the highest per-capita pesticide footprints embedded in their consumption. *Developed and economies in transition countries. Broad regions are not included in this plot but are represented in Supplementary Fig. 6.

(Fig. 1a). The consumption of food and textile products in servicing and other industrial sectors contributes to about 8 and 5% of the global pesticide footprints, respectively. Footprints in other industrial sectors also include those stemmed from crop residues used for feed (see Supplementary Data 1). Within the servicing sectors, hotels and restaurants and food services are the main contributors (Supplementary Fig. 4). We also found that the fraction of footprints embedded in servicing sectors is much higher in developed than in developing countries (Fig. 1b, c).

Using the primary producer to final consumer perspective, we found that approximately 49% of pesticide footprints caused by the consumption in developed countries (0.33 Gt-bw) are embodied in international trade (i.e., the pesticide hazard loads were occurring abroad), while the consumption of imported goods contributes only 23% of the pesticide footprints in developing countries (0.30 Gt-bw). Globally, around 32% of the pesticide footprints are traded internationally (i.e., 32% of global pesticide hazard loads occurred outside of the country of final consumption). This percentage is comparable to the international trade embodiments of other environmental impacts (10–70%[26]), such as global biodiversity loss (30%[8]), greenhouse gas emissions (19–24%[37]), nitrogen emissions (25–27%[10]), and nitrogen-related water pollution (13%[38]). Among all primary sectors, the pesticide footprints embodied in international trade are the highest in spices (about 63% are internationally traded), followed by soya beans and nuts sectors that internationally traded about 61 and 57% of the embedded footprints, respectively (Supplementary Fig. 5).

Per-capita pesticide footprints. Globally, the average per-capita pesticide footprints resulted from consumption is 0.27 t-bw capita^{-1} y^{-1}, with a variation that ranges between 0.01 and 1.6 t-bw capita^{-1} y^{-1} depending on countries and regions. All the top-10 countries and territories having the highest per-capita pesticide footprints are within the high-income economies (Fig. 2), 8 of which are developed countries. Spain has the highest per-capita footprint, which is about 11 and 105% higher than its bordering countries—Portugal and France, respectively (Supplementary Fig. 6). In fact, international assessments have reported that a high fraction of food produced in Spain contained high levels of pesticide residues[39]. The high per-capita footprint in Spain stems from the high use of pesticides, possibly due to shortcomings and incongruences in Spanish pesticide policy[40]. However, only about 23% of the footprints in Spain are embodied in international trade (Supplementary Fig. 7), whereas, in Portugal and France, about 45 and 75% of the pesticide footprints come from abroad. Many European countries have a high per-capita pesticide footprint with more than 90% of the footprints coming from abroad, such as Netherlands, Belgium, Denmark, Norway, Sweden, Germany, and Switzerland (Supplementary Figs. 6 and 7).

Net importers and exporters of pesticide footprints. We calculated the net trade balances of the selected 82 countries and territories and eight broad regions using the primary producer to final consumer perspective to identify the net importers and net exporters of pesticide footprints. A net importer exerts more environmental pressures (i.e., more pesticide hazard loads) abroad due to their consumption than locally for exports, and vice versa for net exporters. Such information is unique to assessments done using MRIO models and is unable to be derived from traditional LCA datasets. The core of this assessment lies at the heart of MRIO models that capture data on international imports and exports. We quantified net importers and net exporters by following through the supply chain networks for each of the 90 countries/regions; and identifying countries that are primarily driving pesticide hazard loads outside their territories due to their consumption (net importers), and countries that are being impacted domestically for producing exports to satisfy foreign consumption (net exporters). The status of countries as net exporters or net importers is determined by a range of factors, such as resource endowments, the dependency of the economy on agricultural exports, trade agreements, tariffs and policies, and the stringency of environmental regulations.

Among all the net importers, 32 countries out of 52 are developed countries (Supplementary Fig. 8). China, being the world's biggest agricultural importer[41], is the largest net importer of commodities embodied with hazard loads caused by the use of insecticides and herbicides, followed by Germany, the UK, and Japan (Fig. 3a). About 44% of the pesticide hazard load-embodied commodities imported into China originated from the USA, about 12% from sub-Saharan countries, and about 8.7% from Brazil. Unexpectedly, India also appears as one of the top-five net importers with about 18% of the imported pesticide hazard load-embodied commodities coming from the USA, mainly due to the imports of cotton and nuts, and 16% from Argentina for soya beans and other oil-bearing crops. When considering the population size, high-income countries such as Ireland, Denmark, Norway, Qatar, and Sweden appear to have the highest per-capita net import (Fig. 3b).

We also found that EU27 member states import from elsewhere approximately 0.06 Gt-bw of hazard loads caused by the use of active substances that were banned in their own countries (i.e., about 34% of their imported pesticide footprints). Specifically, banned substances contribute to more than 90% of the total imported footprints in Sweden, Denmark, Germany, Finland, Lithuania, and Latvia—noting that these countries have one of the most stringent regulations on pesticide use[42,43].

Surprisingly, many of the net exporters are countries within high- and upper-middle income economies (Supplementary Fig. 8). The USA is the largest net exporter of commodities embodied with hazard loads caused by insecticides and herbicides, with the major final destinations being China (34%), Japan (7.1%), and Mexico (6.9%, Supplementary Table 3). However, the USA is also a net importer of hazard loads caused by fungicides and multi-purpose pesticides (Fig. 3a). Brazil is the second largest net exporter with the major final destinations being

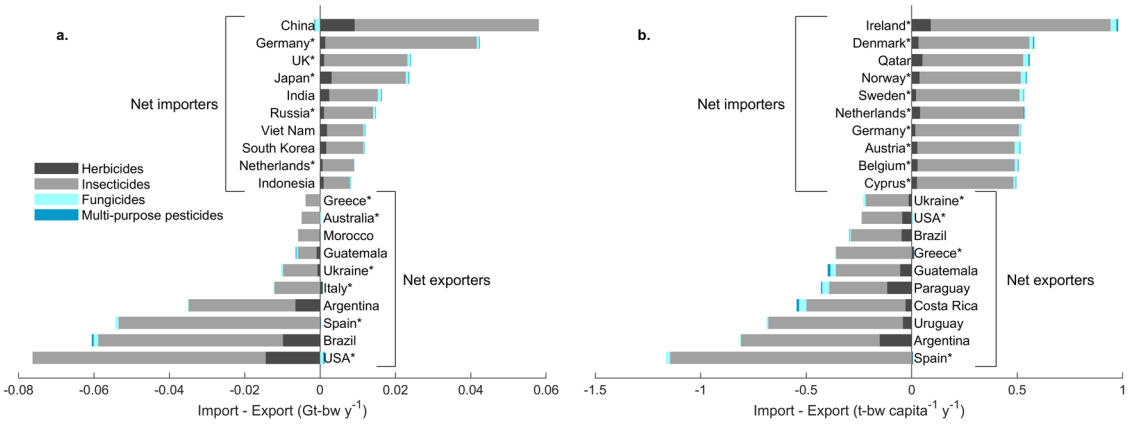

Fig. 3 Pesticide footprints embodied in the international trade for the top-ten net importing and exporting countries. a Total net imports and exports. **b** per-capita net imports and exports. Net importers are exerting more environmental pressures abroad as a result of their consumption of imported products and services than locally due to their exports, and vice versa for net exporters. Analysis was conducted based on primary producer to final consumer perspective. *Developed and economies in transition countries. Broad regions are not included in this plot but are represented in Supplementary Fig. 8.

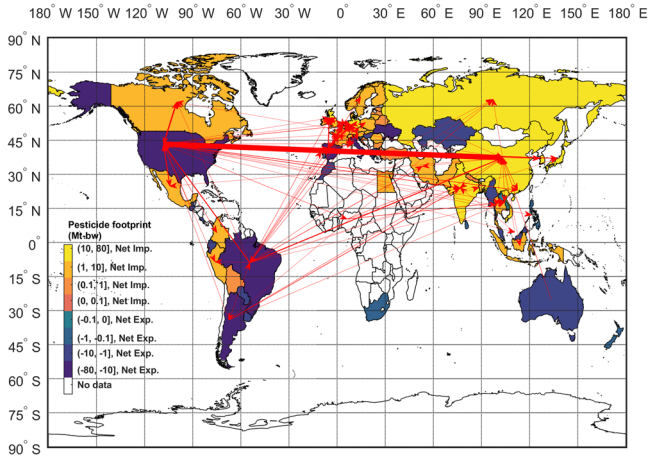

Fig. 4 Top 100 international flows of embodied pesticide footprints between countries of final sale and countries of consumption. Red lines represent the flows with the flow volume proportional to the line thickness (the thicker the line, the larger the flow volume). The colour map represents the footprint embodied in imports minus the footprint embodied in exports on a scale from −80 to 80 megatonnes of body weight (Mt-bw). Net imp. refers to net importer and Net exp. refers to net exporter.

the USA (13.5%, for nuts and orchard fruits and grapes), China (12%, for nuts and soya beans), and Germany (6.9%, for orchard fruits and grapes and nuts, Supplementary Table 3). Approximately 61% of pesticide footprints embodied in Brazil's exports (0.04 Gt-bw) is caused by consumption in developed countries, especially the USA, Germany, and the UK. In contrast, only 29% of the hazard loads occurring in Argentina as a result of its exports is due to consumption in developed countries. The major final destinations of hazard loads embodied in Argentina's exports are Brazil (12.4% of the total exported footprints, mainly for wheat), China (11%, mainly for soya beans), and India (8%, mainly for soya beans, Supplementary Table 3).

International flows of embodied pesticide footprints between countries of final sale and countries of final consumption. Tracing the flows of embodied pesticide footprints along the supply chains based on final point of sales to final consumer perspective, we found that the largest international flow occurs from the USA to China (0.029 Gt-bw, Fig. 4), of which 73.4% are associated to soya beans and 5.7% to other grains (Supplementary Table 4). On the other hand, <0.002 Gt-bw flows from China to the USA, with textiles and wearing apparel being the sector that bears the largest portion of traded footprints (24.4%).

Within the EU27, we found substantial flows from Spain to Germany (0.0084 Gt-bw, world's second largest) and France (0.008 Gt-bw, world's third largest), with major trading commodities being non-leguminous vegetables and fruits, orchard fruits and grapes, and nuts (Supplementary Table 4). Italy also exports 0.004 and 0.002 Gt-bw to Germany and France, respectively, involving similar commodities as Spain. Overall, 0.091 Gt-bw of hazard loads are traded between the EU27 member states, with the major final destinations being Germany, France, Italy, Poland, and Belgium.

Pesticide hazard loads across food products. We compare the pesticide footprints embedded in various food items by normalising the footprints against mass, calories, and protein (Fig. 5). In this analysis, we observe substantial variations in the embodied pesticide footprints across both producing countries and food products, with some plant-based foods having higher pesticide footprints than animal-based foods. Among all food products, orchard fruits and grapes have the highest footprints per unit mass and per unit calories. Among all grains, wheat has the lowest pesticide footprint per unit calories (Fig. 5b). Rice has per-calories footprints about 1.3 times higher than wheat, while the pesticide footprint of maize is about 3.5 times higher than wheat. Among all protein-rich crops, soya beans have the lowest pesticide footprint per unit protein, while nuts have the highest (Fig. 5c). Raw meat (includes all types of meat) has slightly higher pesticide footprint per unit protein (1.35 kg-bw kg-protein^{-1}) than soya beans (1.24 kg-bw kg-protein^{-1}), while eggs have the lowest per-unit protein footprint (Fig. 5c). Animal-based oils and fats have comparable per-calories footprints as other plant-based oils, but they are about 2.3 times higher than soya bean and maize oils (Fig. 5b). The assessment presented here considers all upstream supply chains for production of food products (for example: crops, grains, vegetables, fruits, meat, dairy, eggs and other products), including feed production. MRIO analysis captures the production and consumption of feed, and associated pesticide hazard loads, through multiple supply chain networks needed for satisfying final consumption of food products.

Our findings partly contrast with the footprint analyses of greenhouse gas emissions and land use, where animal meats were shown to have higher environmental footprints[2] but aligns with

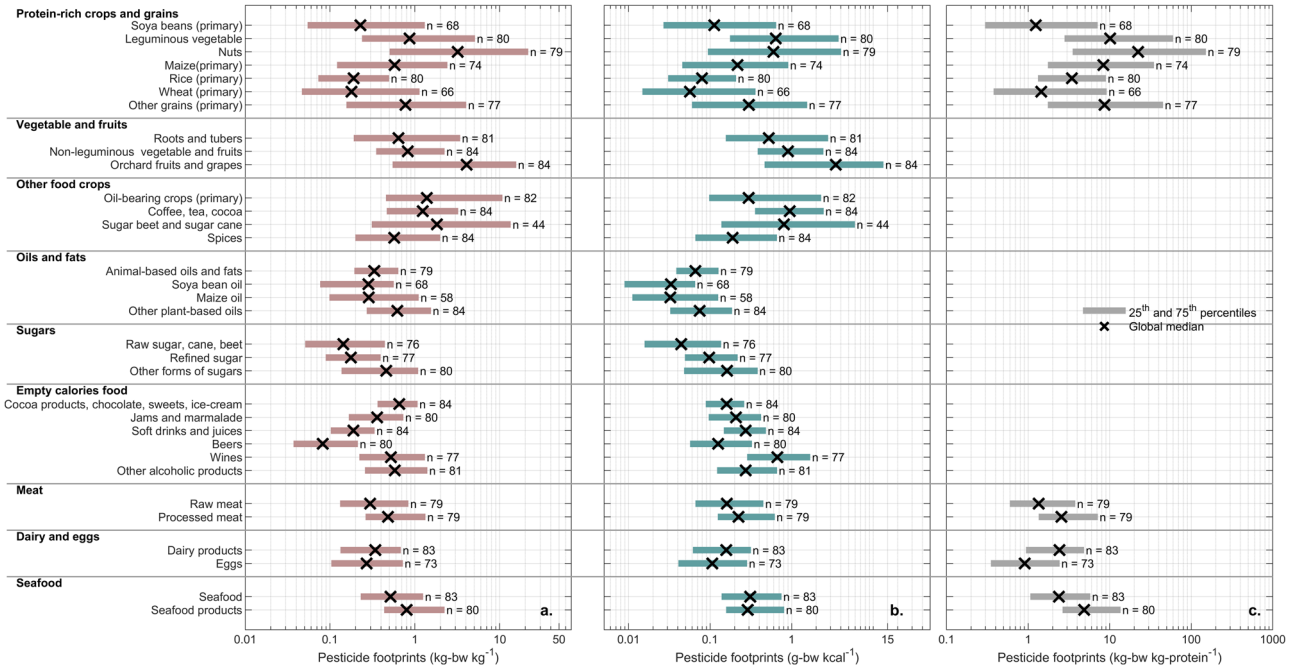

Fig. 5 Pesticide footprints embedded in food products. Footprints expressed as per kilogram food product (**a**), per kilocalories (**b**), and per kilogram protein (**c**). The bars show the 25th and 75th percentile values across different producing countries. The cross markers show the global median values. *n* represents the number of producing countries included. Footprints per kilogram protein are not represented for "Vegetable and fruits", "Other food crops", "Oils and fats", "Sugars", and "Empty calories food".

bottom–up LCA analysis of pesticide toxicity hazard conducted for crop and livestock production in Australia[23], where the authors also find that livestock production bears lower ecotoxicity hazards than crop production, noting that they also did not account for the direct application of pesticides on animal skins to combat flies and flees. Because the direct application of pesticides on animal skins constitutes only a small fraction of the total pesticides used[44], its inclusion will not change our finding that animal-based foods bear lower pesticide footprints than some of the plant-based foods such as orchard fruits and grapes and nuts. We acknowledge that further analysis should be conducted to verify this finding when the information on the direct use of pesticides on livestock and in aquaculture becomes publicly available. In addition to the use of pesticides, antibiotics and other agrochemicals such as plant growth regulators are also used in livestock and crop production, and hence, further analyses accounting for those inputs are required to achieve a comprehensive assessment of the environmental footprints of agriculture production.

Limitations and uncertainties. We acknowledge that there are limitations and uncertainties underlying in our analyses. The PEST-CHEMGRIDSv1.0 database[29] does not include all active ingredients used in croplands. The selection of the top 20 most used active ingredients in each cropping system by mass may miss to include those that have a high toxicity but used at a low dosage over a small surface area. The first step of the estimation of application rates in PEST-CHEMGRIDS assumes that the relationships between pesticide application rates and covariates (e.g., hydrometeorological conditions, soil properties, agricultural practices and socio-economy) in the USA are similar to those in other countries for the same type of cropping system. We note that this assumption may miss to capture conditions that do not happen in the USA but occur in other parts of the world. To account for national factors, the application rate estimates based on statistical inference were then constrained against country-specific pesticide use data from FAOSTAT. There are uncertainties within the FAOSTAT data especially in Africa and Oceania regions where the response rates to pesticide use questionnaire were lower than 20%[31]. In addition, national regulations on pesticide use and cultivation of pesticide-resistant genetic-modified crops were explicitly accounted for in PEST-CHEMGRIDS, but it did not consider sub-national regulations and farmers' preferences, which are currently unknown or cannot be retrieved at the geographic scale of this work.

The estimation of pesticide application rates in PEST-CHEMGRIDS and the modelling of pesticide environmental concentrations rely on the crop maps in Monfreda et al.[45] to provide the geographic distribution of individual crops. Although Monfreda et al.[45] is currently the only dataset that provides the global spatial distribution of 175 crops, those maps refer to circa 2000. As global cropland has increased by about 4% from year 2000 to 2015[31], the use of crop maps in Monfreda et al.[45] may lead to a general slight underestimation of global pesticide footprints. Specifically, uncertainty in crop surface area will affect the estimation of pesticide hazard loads, which will then affect the values of the direct intensities (i.e., impact per dollar output, **q**, "Methods"). An increase in crop area will lead to an underestimation of the direct intensities, whereas a decrease will result in an overestimation.

The pesticide footprints quantified in this work did not include pesticide use in non-cropland settings, such as pastures, rangeland, livestock production, aquaculture, and urban areas. Information about the direct use of pesticides (e.g., the quantity and type of active ingredients) in livestock production, aquaculture, and urban areas is very limited and generally not available for most countries. Although pastures take up around two-third of global agricultural land[31], only a small fraction of grazing area is managed and cultivated in many parts of the world. For example, >90% of permanent pastures in China, India, Argentina, Mexico, and Australia are natural and unmanaged[31,46,47]. In managed pastures, pesticides are normally used during sowing. Because pastures are

mostly perennial crops, they are not sown every year. For instance, a survey study shows that the majority of farmers (>80%) re-planted <25% of their pasture land in a year[48]. Hence, pastures have, on average, low annual pesticide inputs.

Although our estimates of pesticide residues in soil were within the observed ranges reported in Silva et al.[36], the comparison was done only for agricultural soils in European Union countries. Furthermore, our estimations of pesticide residues and hazard loads rely on the assumption that crops for both local consumption and exports were grown using the same pesticide application rates. However, producers targeting export may adjust their pesticide application to adhere to the maximum residue limits for pesticides in food established by the importing countries, such as the European Union[49]. Without accounting for potential differences in pesticide application rates for local consumption and exporting crops, our analysis may overestimate or underestimate the pesticide footprints traded internationally, depending on the limits applied in different countries.

The pesticide hazard loads estimated here did not reflect the effects of pesticides on human health (e.g., carcinogenic effects are not accounted for) and their acute toxicities to non-target organisms as a result of immediate exposure after an application event. There may be an underestimation of pesticide footprints because the hazard loads were estimated based on the NOAEL values for mammals and birds only (expressed as mass of pesticide per unit body weight) and some active ingredients can be more toxic to other non-target organisms not considered here. We did not account for the effects to other non-target organisms (e.g., fish and earthworms) because their ecotoxicities are commonly expressed as median lethal concentrations (LC50), which cannot be easily converted to per-unit body weight for hazard load calculation.

MRIO analysis relies on the assumption that a change in demand or output of an industry will result in a proportional change in production. This technique translates financial expenditure to impacts, i.e. the greater the spending on a food commodity, the greater the impact. Our analyses reflect the pesticide use and trading patterns of the year 2015. Changes in pesticide use and trading patterns over time can alter the pesticide footprints. Based on previous studies on a range of other environmental indicators, the key drivers of negative environmental impacts are affluence (consumption per capita) and population growth[50,51], which resulted in an increase of environmental footprints from 1990 to 2015 despite improvements in energy efficiency[52]. Moreover, the future projections provided in PEST-CHEMGRIDS database show an increasing trend in pesticide application rates. Hence, we may expect pesticide footprints to increase over time. Future work could focus on quantifying drivers of pesticide footprints by using structural decomposition analysis[53].

To account for limitations in pesticide hazard load estimation and variations in trade flows, we conducted an uncertainty analysis based on Monte-Carlo approach ("Methods"), where we perturbed the pesticide applications, the NOAEL values, and the intermediate and final demands. Our uncertainty analysis shows that, across all countries and regions, the standard deviations of the total pesticide footprints ranged between 2.4 and 16% of the reference values, with an average of 4.5% (Supplementary Data 2).

Conclusions

Our study depicts the role of international trades in governing pesticide contamination. Understanding the flow of pesticide footprints through supply chains is important to help establish international policies that contribute towards sustainable agriculture. In particular, our analyses identify the leakage of pesticide footprint. We show that the consumption in developed countries has a substantial contribution to the pesticide contamination occurring in other countries. Specifically, more than 90% of pesticide footprints imported by some European countries were caused by active substances that were banned for use in those importing countries. Hence, a reciprocal pesticide regulation may need to be implemented for imports to discourage the consumption of imported commodities produced using the substances banned in the importing country. Countries importing pesticide footprint should also contribute a fair share in the effort to develop technology for sustainable pest management and the implementation of remediation projects to reduce pesticide contamination in exporting countries. To reduce environmental impacts from global food production, our study suggests that, in addition to sustainable pest management strategies that reduce pesticide use[54], the strategy of shifting human diet towards plant-based foods should be accompanied by the promotion of awareness to minimise food waste and food loss, reduction of overconsumption, and a decrease in the consumption of empty-calorie foods (e.g., sweets, soft drinks, and alcoholic drinks).

While our study uses the best available georeferenced dataset for pesticide use in global cropland, access to more detailed and extensive datasets of pesticide use in all possible settings, including livestock production, aquaculture, and urban usage, is of utmost importance to achieve a holistic view of global pesticide contamination and its associated footprints along supply chains. Many countries require pesticide applicators in agriculture settings to record the location, timing, pesticide types, and rates of applications, but these data are only publicly available as aggregated values at the national level, with California being the only region that releases highly temporally and spatially granular databases of crop- and active ingredient-specific application rates[55]. To the best of the authors' knowledge, no country or region has released recent pesticide use data on livestock production and aquaculture. Moreover, the georeferenced pesticide application data used in our work relies on country-level data provided by FAOSTAT collected via questionnaire, which also contain uncertainties especially in Africa and Oceania regions where the questionnaire response rates were below 20%[31]. The inaccessibility to high-quality pesticide use data can hinder the advancement of pesticide policies[55], and thus we urge an international effort to reform the legal framework of data distribution to allow authorities to report and make detailed pesticide use data open access.

Methods

Summary. In this study, we quantified the pesticide footprint as the hazard load measuring the body weight of non-target organisms required to absorb pesticide residues accumulated in the environment without experiencing adverse effects. This indicator considers the fact that the use of pesticides may or may not create pressure to ecosystems, depending on their degradability and toxicity. The degradation efficiency of pesticides can vary spatially because pesticide degradation and transport are controlled by hydroclimatic conditions and soil properties[56,57]. Hence, we used a process-based and spatially explicit environmental model to estimate residues of 80 active ingredients across various cropping systems at the global scale with a resolution of 0.5° × 0.5° (i.e., about 55 km × 55 km at the equator with bounding box 180°E–180°W; 90°S–90°N). From the model outputs, we calculated the total mass of each active ingredient that accumulated in the environment and the corresponding pesticide hazard loads in each cropping system for 168 crop producing countries, which we then linked to the multi-region input–output (MRIO) classification that consists of 6357 sectors (aggregated into 83 sectors; Supplementary Data 1) and 221 countries and territories (with 82 countries and territories selected and others grouped into eight broad regions; Supplementary Table 1). These steps yield the so-called satellite account that was then linked to an MRIO table to undertake a consumption-based footprint assessment and obtain the footprint of each active ingredient embodied in the production of goods and services. Satellite account is the term used to describe a physical data set (in this study: data on pesticide hazard loads) that can be linked to an MRIO table for footprint assessments. A consumption-based assessment enables the quantification of pesticide footprint at various stages from primary production to intermediate

production to final consumption. The analysis conducted in this study corresponds to the pesticide application and international trading patterns of the year 2015.

Definition of pesticide footprint. The potential consequence of pesticide contamination embedded in a product is commonly quantified through the chemical footprint[21], which is calculated using the bottom-up life cycle assessment (LCA) approach[22]. Here, we investigate the pressure (instead of the consequence) exerted by pesticide use at the global economy-wide level using the top-down approach that is based on environmentally-extended input-output analysis.

We define the pesticide footprints as the hazard loads (HL) of pesticides used in the supply-chain for satisfying the consumption of goods and services. HL measures the body weight (bw) of non-target organisms required to absorb pesticide residues (i.e., the amount of pesticides not degraded by environmental processes and accumulated in the environment) without experiencing adverse effects, noting that an effect does not imply mortality. This definition accounts for two important elements that make pesticide use a pressure on the natural environment, i.e., accumulation and toxicity. In other words, pesticides will not exert pressure on ecosystems if they can be fully degraded by environmental processes and if they are non-toxic to non-target organisms. Specifically, the pesticide footprint, quantified as hazard load, is defined as $\mathrm{HL} = \sum[M_i/(\mathrm{NOAEL}_i \times 365)]$, where M_i [kg-pesticide] is the total mass of active ingredient i accumulated in the environment and NOAEL_i [kg-pesticide kg-bw^{-1} day^{-1}] is the no-observed adverse effect level of active ingredient i in non-target organisms. A higher value of HL signifies a higher environmental pressure. We consider the total accumulated mass without partitioning the mass to different environmental compartments with the justification that pesticides can move through different compartments over time and that we aim to quantify the overall pressure, in line with other environmental footprint indicators, such as the nitrogen footprint[10]. We acknowledge that the values of NOAEL can vary across various species, and hence, by taking a conservative measure, we compared the NOAEL values reported by various data sources for mammals and birds (Supplementary Data 3) and we used the minimum values for the calculation of pesticide footprint.

Our definition of pesticide footprint is pressure-oriented, in contrast to the commonly used impact-oriented chemical footprint. Pressure-oriented indicators focus on human activities resulting from the needs and drivers that may exert pressures on the environment by the use of resources, emissions, release of substances into the environment and/or land-use change. Impact-oriented indicators focus on the consequences on ecosystem and human health, which may require the knowledge of the exposure level of non-target organisms to the pesticides. While impact-oriented indicators can provide insight into the impacts of a specific product or process at a local scale, it is currently technically challenging to apply on a global scale. Pressures, on the other hand, can vary at spatial and geographical scales without the need to make assumptions around exposure level. Our definition of pesticide footprint allows pesticide use to be assessed across 90 countries/ regions, and provides opportunities for comparison within a family of environmental footprints (e.g., carbon, nitrogen, water, material, energy, biodiversity) in future studies to investigate trade-offs in order to achieve a holistic understanding of the sustainability and equity of resource use across nations from both production and consumption perspectives[5].

Pesticide application data. The type and quantity of active ingredients used in different cropping systems at specific geographic locations were obtained from the PEST-CHEMGRIDS v1.0 database[29]. This database provides the global georeferenced annual application rates of 95 active ingredients used in the year 2015 in ten crop groups that include six dominant (i.e., alfalfa, corn, cotton, rice, soybean, and wheat) and four aggregated crops (i.e., vegetable and fruits, orchards and grapes, pasture and hay, and other crops), accounting for a total of 175 crops. The crop aggregation follows the classification of the USGS Pesticide National Synthesis Project[30] (see Table 2 in Maggi et al.[29] for detailed classification). Briefly, the "vegetable and fruits" includes legumes, roots and tubers, bush fruits, and herbaceous crops; the "orchards and grapes" includes nuts, fruit trees, and vines; "pasture and hay" includes forage crops and grasslands used for grazing, while the "other crops" includes other cereals, oil crops, and fibre crops. The data have an original resolution of 5 arcmin (about 10 km × 10 km at the equator), encompassing 38.54 million km^2 of agricultural land (including pastures) in 168 countries. In this work, we excluded the use of pesticides on pasture and hay because only a small fraction of grazing area is managed and cultivated in many parts of the world[31] and pastures are mostly perennials that do not require frequent re-planting[48], hence having low annual pesticide inputs. We also excluded three other active ingredients (i.e., calcium polysulfide, *Bacillus amyloliquefaciens*, and petroleum oil) due to insufficient data on the physicochemical properties required for residue estimation. Hence, we modelled 80 active ingredients in total across 11.85 million km^2 of croplands.

The application rates were estimated by re-analysis of the USGS Pesticide National Synthesis Project database[30], which reports 512 active ingredients used in the above major and aggregated crop groups in the United States from 1992 to 2016. In each of the crop groups, the top 20 active ingredients with the highest total mass used were selected. This selection results in 200 active ingredients, but some of them are recurring across different crop groups. Hence, in total, PEST-CHEMGRIDS v1.0 database includes 95 unique active ingredients and represents about 84% of the total pesticide mass used in the United States in 2015. The selected active ingredients are among the most widely used pesticides around the world identified by Li[58] through compilation of pesticide consumption data in various countries across Asia, Europe, North and South America, Africa, and Oceania. Estimates of application rates at the global scale provided in PEST-CHEMGRIDS were calculated using spatially-conditioned statistical methods that accounted for soil physical properties (soil textures, carbon content, porosity, and thickness, and water table depth), hydroclimatic variables (precipitation, atmospheric temperature, solar radiation, net primary productivity, actual evapotranspiration, and thermal climatic classification), agricultural quantities (nitrogen and phosphorous fertilisation, crop yield, crop water security), and socio-economic indices (population density, gross domestic product, and human development index, see Table 1 in Maggi et al.[29] for the full list of public inventories used for spatial estimates). In addition to those quantities used in spatial analysis, the estimates explicitly consider the country-specific approval for adopting genetically modified pesticide-resistant crops as reported by the International Service for the Acquisition of Agri-Biotech Applications[59], and the country-specific pesticide bans (or not approved for use) as reported by the European Commission[42] and PAN database[43]. Additionally, other national factors (e.g., policy, agricultural practices, infrastructure capacities, access to pesticides) were implicitly accounted for by constraining the estimates against country-level pesticide use data reported by FAOSTAT[31]. Estimates in 28 countries (Supplementary Table 1) were not constrained against FAOSTAT because data in those countries were not available. To control the quality of the estimates, the source data and spatial inference methods used for the estimation were benchmarked and validated. Furthermore, the estimates were also benchmarked against independent and publicly available national active ingredient use data from Australia, the United Kingdom, South Korea, and South Africa, and cross-checked against the application rates recommended by manufacturers or regulatory bodies. Information about the type and quantity of active ingredients applied in agricultural fields is currently very scarce and sparse[55], and therefore we acknowledge that benchmarking the estimates for all countries is currently not possible. Despite the limitations (see details in Limitations and uncertainties section), PEST-CHEMGRIDS is currently the only publicly available, data-driven, and evidence-based inventory of crop-specific and georeferenced application rates of active ingredients.

Estimation of pesticide residue at the global-scale. The transport and degradation rate of pesticides depend on the physicochemical properties of active ingredients as well as environmental conditions. For two countries with different hydroclimatic and soil conditions, the amount of pesticides accumulated in the environment in those countries can be substantially different even if they applied the same quantity and same type of active ingredients. Moreover, environmental conditions can also vary within the same country, and hence the total pesticide mass accumulated in the environment (i.e., the pesticide residues) resulting from crop production in a nation has to be estimated at sub-national or sub-county levels.

Here, pesticide residues were estimated using a process-based and spatially-explicit environmental model[32], with crop-specific and georeferenced active ingredient application rates sourced from PEST-CHEMGRIDS database as described above. The model considers the water, gas, and heat flow along a one-dimensional variably-saturated soil column, the diffusion and advection of dissolved chemicals, and the volatilisation, adsorption, and degradation of the selected active ingredients. The modelling was conducted using the general-purpose multi-phase and multi-component bioreactive transport simulator (BRTSim v4.0e[60]), which solves for the continuity and conservation laws of mass and energy flows using hybrid explicit-implicit numerical techniques within finite volumes, and non-isothermal equilibrium and kinetic reactions describing pesticide degradation, adsorption, and volatilisation. Specifically, the water flow is modelled using the Richards equation along with the relative permeability-water potential-saturation relationships of the Brooks–Corey model. The advection and diffusion of aqueous chemicals are modelled by the Darcy's and the Fick's equations, respectively. Diffusion of gaseous compounds is also explicitly described using the Fick's law. Using the mass action law, volatilisation is modelled as a function of the Henry's law constants of active ingredients, while the adsorption is modelled as a function of the soil organic carbon partition coefficients of the various active ingredients and the soil organic carbon content, soil bulk density, and soil moisture. The degradation of pesticides is described by first-order kinetics with an explicit accounting for biological activity, soil moisture content, soil temperature, soil pH, and soil organic carbon content. The solving equations are described in detail in Maggi[61] and Tang and Maggi[32].

The model was then deployed on a three-dimensional grid resolved at 0.5° × 0.5° resolution horizontally and extended vertically over two atmospheric and three soil layers in the root zone (0 to 100 cm depth) and one additional soil layer down to either the equilibrium water table or the bedrock. Pesticides were applied at the first soil layer following the crop calendar maps[62]. Incoming water fluxes (precipitation and irrigation) and solar radiation (shortwave and longwave) were also applied at the first soil layer, while the evapotranspiration was allocated over the soil profile according to crop root distributions estimated based on the maximum crop rooting depth[63]. For the degradation rates to reach a near steady-

state, the model was run for 48 years using the annual active ingredient application rates of the year 2015 and the time series of precipitation, crop evapotranspiration, irrigation, and solar radiation that spanned from 1970 to 2017. In total, we modelled 11.85 million km^2 of croplands selected based on the crop area maps distributed along with PEST-CHEMGRIDS, which were originally produced by Monfreda et al.[45]. In total, 32,768 geographic grid cells were modelled.

We sourced the georeferenced soil texture, bulk density, pH, and organic carbon content from the SoilGrids2.0[64], soil porosity from SoilGrids1.0[65], soil permeability, pore volume distribution index, air-entry suction, heat capacity, and heat conductivity from Dai et al.[66], equilibrium water table from Fan et al.[67], soil thickness from Pelletier et al.[68], and soil residual liquid saturation from Zhang et al.[69]. Time series of precipitation, atmospheric temperature, longwave and shortwave solar radiation, and potential evapotranspiration were sourced from the Climatic Research Unit datasets[70]. Irrigated area was determined based on the crop water security indicator map[71]. The physicochemical properties of the active ingredients were sourced from the Pesticide Properties DataBase (PPDB)[35]. All datasets used to feed the model are described in detail in Table S1 of the Supplementary Information in Tang and Maggi[32]. In this work, all georeferenced data products (including pesticide applications) were harmonised to 0.5° × 0.5° resolution with either a mass-conservative interpolation for quantities related to mass or energy (e.g., rainfall) or a linear interpolation otherwise (e.g., temperature).

This modelling framework has been previously used to study the dynamics of various compounds at plot to global scales, including the dynamics of atrazine[72], glyphosate[73], and soil carbon and nitrogen[74]. We benchmarked the modelled soil moisture, temperature, and pH against the CPC Soil Moisture dataset[75], the NOAA/NCEI land surface temperature dataset[76], and the SoilGrids2.0 dataset[64], respectively. We also benchmarked the estimated pesticide residues in soil against field measurements reported in Silva et al.[36] (Supplementary Figs. 2 and 3). In addition to benchmarking, we also assessed the sensitivity of model input variables[32] and we propagate the uncertainties from residue estimation to the overall uncertainties in pesticide footprint calculation (see sections below).

From the near steady-state simulation, we then calculated the undegraded fraction of active ingredient i in cropping system j at time $t = t^*$ for each grid cell k as $F^k_{i,j}(t^*) = M^k_{i,j}(t^*)/\sum_{t=0}^{t=t^*} M^k_{A\,i,j}(t)$, where $\sum_{t=0}^{t=t^*} M^k_{A\,i,j}(t)$ is the cumulative applied mass from $t = 0$ to t^* and $M^k_{i,j}(t)$ is the instantaneous total pesticide mass present in the atmosphere and soil in gaseous, dissolved, and adsorbed forms. We then calculated the average undegraded fraction $\bar{F}^k_{i,j}$ over the last five years of the simulation, which was later used to build the satellite account for the MRIO table.

MRIO analysis. Input–output (IO) analysis was developed by the Nobel Prize Laureate, Wassily Leontief[77] in the 1930s. This technique relies on input-output tables that capture interdependencies between economic sectors. IO tables can be either national (e.g., for individual countries—USA, Australia, etc.) or global (e.g., a multi-regional IO table). Today, statistical agencies around the world publish IO tables[78,79], which have been used for numerous social and environmental footprint assessments of international trade[26]. The pesticide footprints of nations are yet to be quantified.

MRIO tables capture interactions between sectors in more than one country, and specifically include data on international trade. We constructed a customised MRIO table for this study on the Global Industrial Ecology Virtual Laboratory Platform (Global IELab)[33]. The platform enables the construction of global international trade databases and provides the most detailed resolution of 6357 sectors for 221 countries and territories. Due to computational constraints in developing a MRIO table with the highest resolution of sectors and regions, the IELab offers the capability to construct MRIO tables with specified regional and sectoral resolution. In this study, we aggregated the 6357 sectors into 83 sectors (see Supplementary Data 1). We selected 82 countries and territories which are either the top agriculture producers and top users of pesticides according to FAOSTAT[31] or having high and upper-middle income economies, and we grouped the other countries and territories into eight broad regions following their geographic location and whether they are members of the Annex-1 parties in the United Nations Framework Convention on Climate Change (UNFCCC)[34] (see Supplementary Table 1).

The mathematics underlying IO analysis includes three key matrices: (i) the intermediate demand (**T**), (ii) the final demand (**Y**), and (iii) the value added (**v**). The intermediate demand matrix includes elements ($T_{a,b}$) that represent the supply of commodity a for use by industry b. The **T** matrix constructed in this study covers primary (e.g., livestock, crops), secondary (e.g., dairy products) and tertiary (e.g., services) sectors. The final demand matrix (**Y**) captures the consumption of goods and services ($Y_{b,c}$) by so-called final consumers, c such as households, government and inventories. The elements in the value-added matrix ($v_{p,a}$) include the contribution of primary inputs p, such as wages and salaries, subsidies, into the production of commodities by industry a.

The consumption-based calculation for the quantification of pesticide footprint proceed as follows: first, the total output (**x**) of an input-output system is calculated as: $\mathbf{x} = \mathbf{T}\boldsymbol{\imath}^T + \mathbf{y}\boldsymbol{\imath}^y$, where $\boldsymbol{\imath} = \{1, 1, \ldots, 1\}$ is a summation operator. Following, the calculation of the direct requirements matrix $\mathbf{A} = \mathbf{T}\hat{\mathbf{x}}^{-1}$ provides insights on the inputs required by each of the 83 sectors of the economy for the production of output. The hat symbol denotes diagonalisation of the total output vector **x**. The matrix **A** is further used to derive the fundamental Leontief input-output equation: $\mathbf{x} = (\mathbf{I}-\mathbf{A})^{-1}\mathbf{y}$, where **I** is the identity matrix and $(\mathbf{I}-\mathbf{A})^{-1}$ is the Leontief inverse **L** that provides the supply chain perspective. For calculating the pesticide footprint, the satellite account **Q** is post-multiplied by the inverse of diagonal **x** to obtain impacts per dollar of output (also known as direct intensities): $\mathbf{q} = \mathbf{Q}\hat{\mathbf{x}}^{-1}$. Total intensities are then derived as: $\mathbf{m} = \mathbf{qL}$. Total intensities capture both direct and indirect impacts, which yield footprints when post-multiplied with final demand: $\boldsymbol{f} = \mathbf{my}$.

Constructing the satellite account for the MRIO table. We first disaggregated the ten crop groups (i.e., denoted by index j) into 175 individual crops (i.e., denoted by index n) following the crop aggregation reported in Table 2 in Maggi et al.[29]. Specifically, we calculated the mass of active ingredient i accumulated in the environment as a result of its use for the production of individual crop n in each grid cell k as $M^k_{i,n} = R^k_{i,j(n)} \times A^k_n \times \bar{F^k_{i,j(n)}}$, where $R^k_{i,j(n)}$ and $\bar{F^k_{i,j(n)}}$ are the median annual application rate and the average undegraded fraction of active ingredient i in the $j(n)$ crop group for which the individual crop n belongs to. A^k_n is the harvested area of crop n obtained from Monfreda et al.[45]. For example, the individual crop "apples" belongs to the "orchards and grape" crop group, and thus the accumulated mass of active ingredient i due to apple production was determined by multiplying the application rate of active ingredient i in "orchards and grape" [kg-pesticide applied m^{-2}] with the harvested area of apples [m^2] and the undegraded fraction in "orchards and grape" [kg-pesticide accumulated/kg-pesticide applied]. The corresponding hazard load is then calculated as $\mathrm{HL}^k_{i,n} = M^k_{i,n}/(\mathrm{NOAEL}_i \times 365)$.

We next calculated the total hazard load of each active ingredient in the production of each individual crop for each country m ($\mathrm{HL}^m_{i,n}$) by summing $\mathrm{HL}^k_{i,n}$ across all the grid cells belonging to that country. To construct the satellite account for the MRIO table, we aligned the country-specific hazard load of each active ingredient for the 175 individual crops with the sector classifications of the MRIO database. The alignments between crop groups, the 175 individual crops and the sector classification in MRIO table are reported in Supplementary Data 1.

Data analyses. To highlight the contribution of different types of pesticides, we grouped the pesticide footprints into four classes, namely herbicides, insecticides, fungicides, and multi-purpose pesticides (multi-purpose pesticides refer to pesticides that belong to more than one functional classes, i.e., they can be used as either herbicides, insecticides or fungicides, Supplementary Table 2). To determine whether a region is a net importer or net exporter of pesticide hazard load-embodied commodities, we calculated the difference between the total pesticide hazard load embodied in the imports (final consumers) and the exports (first producers) of goods and services in that region. In consumption-based analyses, we considered the consumption of both locally-produced and imported products and services. When analysing the total footprint embodied in a commodity or service, we considered the cumulative footprint of the entire supply chain, starting from first producers to final sales. We calculated the pesticide footprint of different food products in terms of per unit mass, per unit calories, and per unit protein. We used the basic price of export (i.e., trade value/trade quantity) obtained from the UN Comtrade Database[80] to calculate the pesticide hazard loads embodied in one kilogram of food produced in each producing country. Countries where the basic price were not available were excluded from the analysis. The calories and proteins contained in per kilogram of food products were obtained from the USDA National Nutrient Database[81]. For all per-capita analyses, the population counts of each region in 2015 were obtained from FAOSTAT[31].

Robustness checks and uncertainty of estimates. We conducted robustness checks to test if variations in climatic patterns and soil properties would affect the estimation of pesticide hazard loads. In this first robustness test, we randomly selected 1000 grid cells and repeated the model runs (only the environmental model) using rainfall, evapotranspiration, solar radiation, and air temperature time series of the last 17 years (i.e., from 2001 to 2017). In the second test, we repeated the model runs of the 1000 random grid cells with a ± 50% variation in the soil carbon content. Changes in climatic patterns resulted in an average of -0.33% change (25th percentile: −1.2%, 75th percentile: 0.3%) as compared to the reference simulation, whereas a ±50% variation in soil carbon content resulted in an average of 5.9% change (25th percentile: −4.6%, 75th percentile: 10.7%, Supplementary Fig. 10).

To quantify the overall uncertainties associated with pesticide footprints, we conducted Monte-Carlo simulations. This method of uncertainty quantification has previously been carried out for footprint studies[10,82]. Firstly, we quantified the uncertainties in pesticide hazard load estimations by performing a global sensitivity analysis on the pesticide application rates, undegraded fractions, and the NOAEL values. We randomly sampled across the variable space that spans within +/−50% of the reference values using a Gaussian distribution that has a mean around the reference value and a standard deviation of 15% of the reference value. We conducted 8000 realisations to obtain the standard deviations of pesticide hazard loads embedded in each sector and region, which were then used for uncertainly quantification of pesticide footprints.

MRIO databases are compiled from primary data, hence are associated with measurement errors. These errors propagate from raw data collection to MRIO compilation to pesticide footprint assessments[83–85] and can be quantified using

Monte-Carlo techniques[86,87]. Here, we follow the approach outlined in Lenzen et al.[82] by propagating uncertainty using data on standard deviations for the intermediate demand (σ_T) and final demand (σ_y) sourced from the Global MRIO Lab[33], and pesticide hazard loads (σ_Q) calculated as described above to perturb the **Q**, **T** and **y** data, then calculating the perturbed pesticide footprints. These perturbed footprints were calculated from 1,000 Monte-Carlo runs. Standard deviations of the pesticide footprints were then calculated from the standard deviations of the perturbations. The mathematical formulations of these Monte-Carlo runs are detailly described in Heijungs and Lenzen[85] and Lenzen et al.[88]. We presented the standard deviations of the total pesticide footprints for all countries and regions of the MRIO table in Supplementary Data 2 and we showed the probability distribution of the Monte-Carlo runs in Supplementary Fig. 9.

Data availability

The georeferenced data on pesticide residues were distributed via *figshare* at https://doi.org/10.6084/m9.figshare.12966323[32,89]. The country-based pesticide footprint data are reported in Supplementary Data 2 accompanied with this manuscript. All Supplementary Data files, source data used in Figs. 1–5, and the crop-specific georeferenced pesticide hazard load maps were distributed via *figshare* at https://doi.org/10.6084/m9.figshare.19612173[90].

Code availability

The BRTSim software used to estimate the pesticide residues can be freely downloaded from https://sites.google.com/site/thebrtsimproject. An example of input files required to run the model can be downloaded via *figshare* at https://doi.org/10.6084/m9.figshare.12966323[32,89]. The footprint analysis was conducted using the IELab, which can be accessed via https://ielab.info/.

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References

1. Matson, P. A., Parton, W. J., Power, A. G. & Swift, M. J. Agricultural intensification and ecosystem properties. *Science* **277**, 504–509 (1997).
2. Poore, J. & Nemecek, T. Reducing food's environmental impacts through producers and consumers. *Science* **360**, 987–992 (2018).
3. Tilman, D., Balzer, C., Hill, J. & Befort, B. L. Global food demand and the sustainable intensification of agriculture. *Proc. Natl Acad. Sci. USA* **108**, 20260–20264 (2011).
4. Tang, F. H., Lenzen, M., McBratney, A. & Maggi, F. Risk of pesticide pollution at the global scale. *Nat. Geosci.* **14**, 206–210 (2021).
5. Hoekstra, A. Y. & Wiedmann, T. O. Humanity's unsustainable environmental footprint. *Science* **344**, 1114–1117 (2014).
6. Tilman, D. & Clark, M. Global diets link environmental sustainability and human health. *Nature* **515**, 518–522 (2014).
7. Lenzen, M. et al. International trade of scarce water. *Ecol. Econ.* **94**, 78–85 (2013).
8. Lenzen, M. et al. International trade drives biodiversity threats in developing nations. *Nature* **486**, 109–112 (2012).
9. Wilting, H. C., Schipper, A. M., Bakkenes, M., Meijer, J. R. & Huijbregts, M. A. Quantifying biodiversity losses due to human consumption: a global-scale footprint analysis. *Environ. Sci. Technol.* **51**, 3298–3306 (2017).
10. Oita, A. et al. Substantial nitrogen pollution embedded in international trade. *Nat. Geosci.* **9**, 111–115 (2016).
11. Springmann, M. et al. Options for keeping the food system within environmental limits. *Nature* **562**, 519–525 (2018).
12. Weinzettel, J., Hertwich, E. G., Peters, G. P., Steen-Olsen, K. & Galli, A. Affluence drives the global displacement of land use. *Glob. Environ. Chang.* **23**, 433–438 (2013).
13. Beketov, M. A., Kefford, B. J., Schäfer, R. B. & Liess, M. Pesticides reduce regional biodiversity of stream invertebrates. *Proc. Natl Acad. Sci. USA* **110**, 11039–11043 (2013).
14. Li, Y., Miao, R. & Khanna, M. Neonicotinoids and decline in bird biodiversity in the United States. *Nat. Sustain.* **3**, 1027–1035 (2020).
15. Chagnon, M. et al. Risks of large-scale use of systemic insecticides to ecosystem functioning and services. *Environ. Sci. Pollut. Res.* **22**, 119–134 (2015).
16. Köhler, H. R. & Triebskorn, R. Wildlife ecotoxicology of pesticides: can we track effects to the population level and beyond? *Science* **341**, 759–765 (2013).
17. Möhring, N. et al. Pathways for advancing pesticide policies. *Nat. Food* **1**, 535–540 (2020).
18. European Comission. *Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions: A Farm to Fork Strategy for a Fair, Healthy and Environmentally-Friendly Food System COM/2020/381 Final* (European Comission, 2020).
19. Weidema, B. P. in *Perspectives on Social LCA* 11–23 (Springer, 2020).
20. Bare, J. C., Hofstetter, P., Pennington, D. W. & De Haes, H. A. U. Midpoints versus endpoints: the sacrifices and benefits. *Int. J. Life Cycle Assess.* **5**, 319–326 (2000).
21. Vanham, D. et al. Environmental footprint family to address local to planetary sustainability and deliver on the SDGs. *Sci. Total Environ.* **693**, 133642 (2019).
22. Sala, S. & Goralczyk, M. Chemical footprint: A methodological framework for bridging life cycle assessment and planetary boundaries for chemical pollution. *Integr. Environ. Assess. Manag.* **9**, 623–632 (2013).
23. Navarro, J., Hadjikakou, M., Ridoutt, B., Parry, H. & Bryan, B. A. Pesticide toxicity hazard of agriculture: regional and commodity hotspots in Australia. *Environ. Sci. Technol.* **55**, 1290–1300 (2021).
24. Rosenbaum, R. K. et al. USEtox—the UNEP-SETAC toxicity model: recommended characterisation factors for human toxicity and freshwater ecotoxicity in life cycle impact assessment. *Int. J. Life Cycle Assess.* **13**, 532–546 (2008).
25. Lenzen, M. Errors in conventional and input-output—based life—cycle inventories. *J. Ind. Ecol.* **4**, 127–148 (2000).
26. Wiedmann, T. & Lenzen, M. Environmental and social footprints of international trade. *Nat. Geosci.* **11**, 314–321 (2018).
27. Malik, A. et al. International spillover effects in the EU's textile supply chains: A global SDG assessment. *J. Environ. Manag.* **295**, 113037 (2021).
28. Schulz, R., Bub, S., Petschick, L. L., Stehle, S. & Wolfram, J. Applied pesticide toxicity shifts toward plants and invertebrates, even in GM crops. *Science* **372**, 81–84 (2021).
29. Maggi, F., Tang, F. H., la Cecilia, D. & McBratney, A. PEST-CHEMGRIDS, global gridded maps of the top 20 crop-specific pesticide application rates from 2015 to 2025. *Sci. Data* **6**, 1–20 (2019).
30. Baker, N. T. *Estimated Annual Agricultural Pesticide Use by Major Crop or Crop Group for States of the Conterminous United States, 1992–2016* (U.S. Department of the Interior and U.S. Geological Survey, 2017).
31. FAOSTAT. Database collection of the Food and Agriculture Organization of the United Nations. http://www.fao.org/faostat/en/#data (2018).
32. Tang, F. H. & Maggi, F. Pesticide mixtures in soil: a global outlook. *Environ. Res. Lett.* **16**, 044051 (2021).
33. Lenzen, M. et al. The Global MRIO Lab–charting the world economy. *Econ. Syst. Res.* **29**, 158–186 (2017).
34. United Nations Framework Convention on Climate Change (UNFCCC). United Nations climate change. https://unfccc.int/process/parties-non-party-stakeholders/parties-convention-and-observer-states (2021).
35. Lewis, K., Tzilivakis, J., Warner, D. & Green, A. An international database for pesticide risk assessments and management. *Hum. Ecol. Risk Assess. Int. J.* **22**, 1050–1064 (2016).
36. Silva, V. et al. Pesticide residues in European agricultural soils–a hidden reality unfolded. *Sci. Total Environ.* **653**, 1532–1545 (2019).
37. Wood, R. et al. Growth in environmental footprints and environmental impacts embodied in trade: resource efficiency indicators from EXIOBASE3. *J. Ind. Ecol.* **22**, 553–564 (2018).
38. Wan, L., Cai, W., Jiang, Y. & Wang, C. Impacts on quality-induced water scarcity: drivers of nitrogen-related water pollution transfer under globalization from 1995 to 2009. *Environ. Res. Lett.* **11**, 074017 (2016).
39. Poulsen, M. E., Andersen, J. H., Petersen, A. & Jensen, B. H. Results from the Danish monitoring programme for pesticide residues from the period 2004–2011. *Food Control* **74**, 25–33 (2017).
40. González, P. A., Parga-Dans, E. & Luzardo, O. P. Big sales, no carrots: assessment of pesticide policy in Spain. *Crop Protect.* **141**, 105428 (2021).
41. Jiang, H. China: evolving demand in the world's largest agricultural import market. https://www.fas.usda.gov/data/china-evolving-demand-world-s-largest-agricultural-import-market (2020).
42. European Commission. PLANT EU Pesticides database. https://ec.europa.eu/food/plant/pesticides/eu-pesticides-db_en (2016).
43. Watts, M. PAN International consolidated list of banned pesticides. http://paninternational.org/pan-international-consolidated-list-of-banned-pesticides/ (2019).
44. Osteen, C. D. & Szmedra, P. I. *Agricultural Pesticide Use Trends and Policy Issues (No. 1473-2020–1574)* (United States Department of Agriculture (USDA), 1989).
45. Monfreda, C., Ramankutty, N. & Foley, J. A. Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000. *Glob. Biogeochem. Cycles* **22**, GB1022 (2008).
46. Australian Bureau of Statistics. *Land Management and Farming in Australia-2016-17* (Australian Bureau of Statistics, 2018).
47. Koli, P. & Bhardwaj, N. R. Status and use of pesticides in forage crops in India. *J Pestic. Sci.* **43**, 225–232 (2018).
48. Rijswijk, K. & Brazendale, R. Pasture renewal practices, experiences and attitudes: a comparison over time. *J. NZ Grasslands* **78**, 51–56 (2016).

49. Kuchheuser, P. & Birringer, M. Pesticide residues in food in the European Union: analysis of notifications in the European Rapid Alert System for Food and Feed from 2002 to 2020. *Food Control* **133**, 108575 (2022).
50. Malik, A. & Lan, J. The role of outsourcing in driving global carbon emissions. *Econ. Syst. Res.* **28**, 168–182 (2016).
51. Soligno, I., Malik, A. & Lenzen, M. Socioeconomic drivers of global blue water use. *Water Resour. Res.* **55**, 5650–5664 (2019).
52. Lan, J., Malik, A., Lenzen, M., McBain, D. & Kanemoto, K. A structural decomposition analysis of global energy footprints. *Appl. Energy* **163**, 436–451 (2016).
53. Dietzenbacher, E. & Los, B. Structural decomposition techniques: sense and sensitivity. *Econ. Syst. Res.* **10**, 307–324 (1998).
54. Barzman, M. et al. Eight principles of integrated pest management. *Agron. Sustain. Dev.* **35**, 1199–1215 (2015).
55. Mesnage, R. et al. Improving pesticide-use data for the EU. *Nat. Ecol. Evol.* **5**, 1560–1560 (2021).
56. Charnay, M. P., Tuis, S., Coquet, Y. & Barriuso, E. Spatial variability in 14C-herbicide degradation in surface and subsurface soils. *Pest Manag. Sci.* **61**, 845–855 (2005).
57. Dechesne, A., Badawi, N., Aamand, J. & Smets, B. F. Fine scale spatial variability of microbial pesticide degradation in soil: scales, controlling factors, and implications. *Front. Microbiol.* **5**, 667 (2014).
58. Li, Z. The use of a disability-adjusted life-year (DALY) metric to measure human health damage resulting from pesticide maximum legal exposures. *Sci. Total Environ.* **639**, 438–456 (2018).
59. ISAAA. International service for the acquisition of agri-biotech applications GM approval database. http://www.isaaa (2018).
60. Maggi, F. BRTSim, a general-purpose computational solver for hydrological, biogeochemical, and ecosystem dynamics. Preprint at *arXiv* https://arxiv.org/abs/1903.07015 (2019).
61. Maggi, F. *BRTSim v5.0 Release A, A General-purpose Multiphase and Multispecies Computational Solver for Biogeochemical Reaction-advection-dispersion Processes in Porous and Non-porous Media User Manual and Technical Guide* (The University of Sydney, 2021).
62. Sacks, W. J., Deryng, D., Foley, J. A. & Ramankutty, N. Crop planting dates: an analysis of global patterns. *Glob. Ecol. Biogeogr.* **19**, 607–620 (2010).
63. Allen, R. G., Pereira, L. S., Raes, D. & Smith, M. *Crop Evapotranspiration-Guidelines for Computing Crop Water Requirements-FAO Irrigation and Drainage Paper 56* (FAO, 1998).
64. de Sousa, L. M. et al. SoilGrids 2.0: producing soil information for the globe with quantified spatial uncertainty. *Soil* **7**, 217–240 (2021).
65. Hengl, T. et al. SoilGrids250m: global gridded soil information based on machine learning. *PLoS ONE* **12**, e0169748 (2017).
66. Dai, Y. et al. A global high-resolution data set of soil hydraulic and thermal properties for land surface modeling. *J. Adv. Model. Earth Syst.* **11**, 2996–3023 (2019).
67. Fan, Y., Li, H. & Miguez-Macho, G. Global patterns of groundwater table depth. *Science* **339**, 940–943 (2013).
68. Pelletier, J. D. et al. *Global 1-km Gridded Thickness of Soil, Regolith, and Sedimentary Deposit Layers* (DAAC, ORNL Oak Ridge National Laboratory, 2016).
69. Zhang, Y., Schaap, M. G. & Zha, Y. A high-resolution global map of soil hydraulic properties produced by a hierarchical parameterization of a physically based water retention model. *Water Resourc. Res.* **54**, 9774–9790 (2018).
70. Harris, I., Osborn, T. J., Jones, P. & Lister, D. Version 4 of the CRU TS monthly high-resolution gridded multivariate climate dataset. *Sci. Data* **7**, 1–18 (2020).
71. Thenkabail, P. S. et al. *NASA Making Earth System Data Records for Use in Research Environments (MEaSUREs) Global Food Security Support Analysis Data (GFSAD) Crop Dominance 2010 Global 1 km V001* (NASA EOSDIS Land Processes DAAC, 2016).
72. La Cecilia, D. & Maggi, F. In-situ atrazine biodegradation dynamics in wheat (Triticum) crops under variable hydrologic regime. *J. Contam. Hydrol.* **203**, 104–121 (2017).
73. Maggi, F., la Cecilia, D., Tang, F. H. & McBratney, A. The global environmental hazard of glyphosate use. *Sci. Total Environ.* **717**, 137167 (2020).
74. Pasut, C., Tang, F. H., Hamilton, D., Riley, W. J. & Maggi, F. Spatiotemporal assessment of GHG emissions and nutrient sequestration linked to agronutrient runoff in global wetlands. *Glob. Biogeochem. Cycles* **35**, e2020GB006816 (2021).
75. Fan, Y. & Van Den Dool, H. Climate Prediction Center global monthly soil moisture data set at 0.5 resolution for 1948 to present. *J. Geophys. Res. Atmos.* **109**, D10102 (2004).
76. Menne, M. J., Durre, I., Vose, R. S., Gleason, B. E. & Houston, T. G. An overview of the global historical climatology network-daily database. *J. Atmos. Oceanic Technol.* **29**, 897–910 (2012).
77. Leontief, W. Quantitative input and output relations in the economic system of the United States. *Rev. Econ. Stat.* **18**, 105–125 (1936).
78. Eurostat. *Eurostat Manual of Supply, Use and Input-Output Tables* (European Commission, 2008).
79. United Nations. *Handbook of Input-Output Table Compilation and Analysis* (United Nations, 1999).
80. United Nations. UN Comtrade Database. http://comtrade.un.org/ (2017).
81. USDA. *USDA National Nutrient Database for Standard Reference* (United States Department of Agriculture, 2019).
82. Lenzen, M. et al. The carbon footprint of global tourism. *Nat. Clim. Chang.* **8**, 522–528 (2018).
83. Lloyd, S. M. & Ries, R. Characterizing, propagating, and analyzing uncertainty in life-cycle assessment: a survey of quantitative approaches. *J. Ind. Ecol.* **11**, 161–179 (2007).
84. Imbeault-Tétreault, H., Jolliet, O., Deschênes, L. & Rosenbaum, R. K. Analytical propagation of uncertainty in life cycle assessment using matrix formulation. *J. Ind. Ecol.* **17**, 485–492 (2013).
85. Heijungs, R. & Lenzen, M. Error propagation methods for LCA—a comparison. *Int. J. Life Cycle Assess.* **19**, 1445–1461 (2014).
86. Hondo, H., Sakai, S. & Tanno, S. Sensitivity analysis of total CO2 emission intensities estimated using an input–output table. *Appl. Energy* **72**, 689–704 (2002).
87. Lenzen, M. Aggregation versus disaggregation in input–output analysis of the environment. *Econ. Syst. Res.* **23**, 73–89 (2011).
88. Lenzen, M., Wood, R. & Wiedmann, T. Uncertainty analysis for multi-region input–output models–a case study of the UK's carbon footprint. *Econ. Syst. Res.* **22**, 43–63 (2010).
89. Tang F. H. & Maggi, F. Pesticide mixtures in soil: a global outlook. Dataset. figshare https://doi.org/10.6084/m9.figshare.12966323.v2 (2021).
90. Tang, F. H., Malik, A. Li, M., Lenzen, M. & Maggi, F. International demand for food and services drives environmental footprints of pesticide use. Dataset. figshare https://doi.org/10.6084/m9.figshare.19612173 (2022).

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Author contributions

F.H.M.T., A.M., M. Lenzen, and F.M. designed the study; F.H.M.T. and F.M. conducted the pesticide residue estimation modelling; A.M., M. Lenzen, and M. Li conducted the MRIO modelling; F.H.M.T. and A.M. conducted the analyses and wrote the paper; all authors contributed to data interpretation and manuscript editing.

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Competing interests

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Additional information

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