REDUCING AGRICULTURE'S ENVIRONMENTAL IMPACTS

THROUGH DIVERSE PRODUCERS

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DECLARATION

I declare that this thesis is my own work. Where other authors have contributed, their contributions are declared at the end of each chapter. None of the work submitted for this thesis has been submitted, in whole or part, for any previous degree.

ABSTRACT

The world food system is characterised by millions of diverse producers yet approaches to increase productivity and environmental sustainability that are effective in light of this remain underexplored. Here I present data revealing that the environmental impacts and productivity of different producers are highly variable. I then present evidence that an effective approach to improve outcomes given this heterogeneity would require environmental and productivity monitoring by each producer and communication of this information up supply chains and through to consumers. With colleagues, I develop an environmental science toolkit to enable producers to monitor their environmental impacts and a filetype to represent agri-environmental data which would support producers to communicate their impacts. I then explore how an environmental impact labelling scheme could trigger the creation of this measurement and communication system while also incentivising substantial behavioural change. Overall, this thesis develops, and then starts delivering on, a sustainability and productivity solution for agriculture.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

“Nature has introduced great variety into the landscape, but man has displayed a passion for simplifying it. Thus he undoes the built-in checks and balances by which nature holds the species within bounds.”

— Rachel Carson, Silent Spring

“But heaven and earth was teeming around them, and how should this cease? They felt the rush of the sap in spring, they knew the wave which cannot halt, but every year throws forward the seed to begetting, and, falling back, leaves the young-born on the earth.”

— D.H. Lawrence, The Rainbow

“She glances more and more into nothing not realising the love behind her.”

— Yapacc ft. Antonia Serra via Guy J, Summer Moments

Chapter 1: Introduction

1.1. Theoretical background

Agricultural diversity can be defined as variability over time and space in the production practices used by farmers, the crops and animal products they produce, and the bio-physical structures of farms (e.g., soil types, rainfall, or remnant natural vegetation). There could be high or low diversity within a farm (Figure 1.1), across a landscape formed of many farms, and/or over time (e.g., if farms use continuous or diversified crop rotations).

Today, the diversity of the global agricultural production system is very high compared to other sectors of the economy. Worldwide, there are 570 million farms, cultivating around 7000 crop species and 40 animal species, operating in almost all geographies, climates, and soil types, using a wide range of production practices, and using land at varying intensities (FAO, 2014; Khoshbakht & Hammer, 2008; Rege & Mwai, 2006).

However, the idea of understanding and working with agricultural diversity does not seem to be widely held by researchers, businesses, and policymakers. Instead, the prevailing approach is to identify solutions to increase productivity and reduce environmental impacts which can be applied across the entire sector. There have been two contrasting consequences of this:

1) Farms often have to change their physical structure in order to adopt technologies and practices that are not tailored to the farm. The effect of this, along with other structural drivers such as the benefits of economies of scale, is increasing the homogenisation of agriculture at the global scale (IPES-Food, 2016). Because agriculture is the largest land use on earth (Foley et al., 2011) this is having tremendous consequences for nature.
2) In areas with high agricultural diversity to start with, and where farms are less able to change their structure (e.g., due to a lack of capital to install irrigation or drainage), cross-sectoral solutions have been less widely adopted and have been less effective.

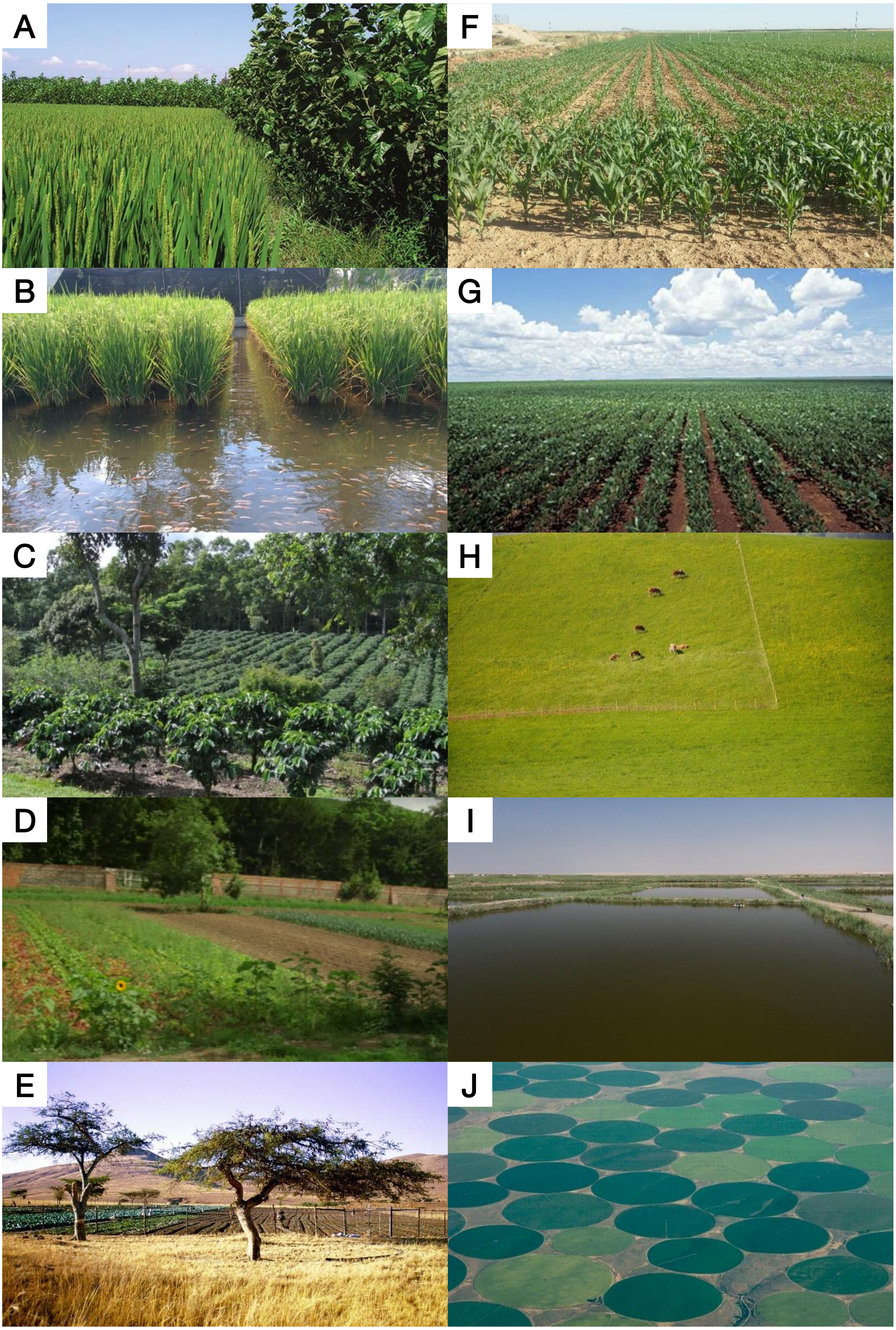
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Figure 1.1. Illustrative examples of agricultural diversity within the same farm. (**A-E**) Relatively high diversity. (**F-J**) Relatively low diversity. (**A**) A mulberry-rice intercropping system in Zhejiang, China (credit: Gongyin Ye). (**B**) A rice-aquaculture system in Subang, Indonesia (credit: Kembangraps via Wikimedia Commons). (**C**) A coffee plantation mixed with native trees in Costa Rica (credit: PxHere). (**D**) A vegetable farm in Oxfordshire, UK (credit: Permaculture Network, Tolhurst Organic). (**E**) Cereal and vegetable production in Kwa-Zulu Nata, South Africa (credit: Trevor Samson/World Bank via Flickr). (**F**) Maize row-cropping in Albacete, Spain (credit: Joseph Poore). (**G**) Soybean row-cropping in Mato Grosso, Brazil (credit: Jose Moraes via iStock). (**H**) Cattle grazing on large fields sown with grass in Bavaria, Germany (credit: PxHere). (**I**) Large-scale aquaculture in Fayoum, Egypt (credit: Samuel Stacey/Worldfish via Flickr). (**J**) Centre pivot irrigation in Washington state, USA (credit: Sam Beebe via Wikimedia Commons).

The technologies of the Green Revolution of the mid-20th century – mechanisation, high-yielding dwarf crop varieties, synthetic fertilizer, synthetic pesticide, and irrigation – illustrate these two contrasting effects particularly clearly. Overall, these technologies have delivered major productivity gains: between 1961 and 2019 the number of kilograms of food produced per person increased by nearly half, despite the global population increasing 2.5-fold (*FAOSTAT*, 2021). However, the farms that adopted these technologies often had to change their physical structures, leading to homogenisation (Table 1.1). For example, to use combine harvesters, hedgerows dividing fields have been cleared to provide machinery access, while synthetic fertilizers have replaced a function formerly fulfilled by farm animals, dramatically reducing the number of mixed crop-animal farms in many regions.

On the other hand, agricultural diversity has likely been one driver amongst many others which has affected the benefits and adoption of the Green Revolution technologies (Table 1.1). In

India for example, Green Revolution productivity gains were unequal: small farms and farms on sub-optimal sites fared far worse (Conway, 1999). African cereal yields are currently around 64% lower than the rest of the world, and some have put this down to the high diversity of African agricultural systems that makes many technologies difficult to deploy and of variable effectiveness (Frison, 2008; Macours, 2019; Voortman, 2013). In Africa there are many small farms, on soils with differing micronutrient needs, with slopes, aspects, and microclimates that can change over short distances, and a wide range of different crop diseases are present. Further, many farmers lack capital to change the structure of their farms, such as by installing irrigation.

Table 1.1. The effects of 1) productivity-enhancing technologies on agricultural diversity, and 2) agricultural diversity on the adoption and effectiveness of productivity enhancing technologies. This list focuses on the major Green Revolution technologies. The effects of other major practices and technologies, such as grassland improvement, drainage, and increased density of uniformity of cropping, are discussed elsewhere (Benton et al., 2003; IPES-Food, 2016). This table is not a comprehensive overview of the reasons for agricultural practice adoption and instead focuses on interactions with agricultural diversity; a comprehensive overview can be found in Magruder (2018).

Technology or Practice	Effects on Agricultural Diversity Where Adopted	Effects of Agricultural Diversity on Their Adoption and Effectiveness
Modern machinery (e.g., combine harvesters)	• Increased the need for large fields with easy access, leading to the clearance of field boundaries (White & Roy, 2015). For example, ~60% of hedgerows were removed between 1940 and 2000 in England and Wales, primarily to enable machinery access (Robinson & Sutherland, 2002).	• Modern machinery has been minimally adopted in sub-Saharan Africa, which is partly due to small farm and field sizes (Daum & Birner, 2020). Specifically, over 60% of farms are less than one hectare in sub-Saharan Africa, while 50% of fields are less than 0.64 hectares (Lesiv et al., 2019; Lowder et al., 2016), and there were just 221,000 tractors in Africa in 2000 compared to nearly

Technology or Practice	Effects on Agricultural Diversity Where Adopted	Effects of Agricultural Diversity on Their Adoption and Effectiveness
		8 million in Asia and 11 million in Europe (Sims et al., 2016).
High yielding varieties	• Green Revolution breeding focused on high yielding crop varieties and primarily three crops: rice, wheat, and maize (Conway, 1999). There is evidence that crop genetic diversity is decreasing at a global level (Aguilar et al., 2015; Khoury et al., 2022) and the types of food produced are becoming more homogenous (Khoury et al., 2014). This may have affected human nutrition and made the food system more vulnerable to shocks (IPES-Food, 2016). • Animal breeding has also developed a small number of high yielding varieties for industrial conditions, and these breeds have now replaced most local breeds globally (Groeneveld et al., 2010)	• Few high-yielding varieties were available for variable African climatic and soil conditions, and the local demands of consumers. This has limited their adoption. Only recently have high-yield sorghum, millet, and cassava varieties become available (Pingali, 2012). • The promotion of high yielding European dairy cross-breeds in Africa and Asia has had limited success as this approach failed to account for local conditions (Widi, 2015).
Synthetic fertilizers	• Reduced the need for mixed farms which provide fertilizer as manure and slurry. By ~2010, mixed crop-animal farms occupied less than 10% of farmland in Europe and the USA, despite being the dominant farm type around 1900 (Garrett et al., 2020). • Reduced the need for fallow periods and nitrogen fixing crops to build soil fertility.	• Nitrogen and phosphorus fertilizers have been less effective and much less widely adopted in sub Saharan Africa because soils are far more variable and have greater needs for micronutrients (Voortman, 2013).
Synthetic pesticides	• Reduced the need for varied crop rotations to break pest cycles. For example, the number of crops produced per farm decreased from 5.1 in 1900 to 1.2 in 2002 in the United States (Dimitri et al., 2005).	• The adoption of synthetic pesticides is mainly affected by constrained by cost and accessibility rather than agricultural diversity (Grzywacz et al., 2014). However, their effectiveness is likely lower in diverse agricultural systems; for

Technology or Practice	Effects on Agricultural Diversity Where Adopted	Effects of Agricultural Diversity on Their Adoption and Effectiveness
	• Possibly reduced the need for natural habitat to harbour pest predators.	example greater integration of agriculture with natural ecosystems reduces the need for synthetic pesticides (Grzywacz et al., 2014).
Irrigation	• Reduced seasonal variance in agricultural areas (Benton et al., 2003). • Allowed types of agriculture to occur in places that are disconnected from natural conditions (e.g., Saudi Arabia).	• A more diverse range of crops, including rainfed or drought tolerant ones, decreases the need for irrigation and benefits of adopting it.

While slowly, businesses, consumers, and policymakers are making changes to cut their greenhouse gas emissions. However, some of the climate change mitigation solutions proposed could bring a new wave of agricultural homogenisation. On the other hand, agricultural diversity could affect the adoption and effectiveness of these solutions (Table 1.2).

Table 1.2. The potential effects of 1) climate change mitigation solutions on agricultural diversity, and 2) agricultural diversity on the adoption and effectiveness of climate change mitigation solutions. This is an illustrative list based on the 2014 IPCC "Mitigation of Climate Change" report (Intergovernmental Panel on Climate Change, 2014).

Solution	Effects on Agricultural Diversity Where Adopted	Effects of Agricultural Diversity on Their Adoption and Effectiveness
Substitution of meat and dairy for vegetable proteins	• Many of the new plant-based meat and dairy substitutes are based on just a handful of crops (primarily field peas, soybeans, oats, and wheat).	• Soils and climate in some areas means producing vegetable proteins is difficult (e.g., the Mongolian steppe).
Greenhouses and vertical farms	• Increases in the area under greenhouses would create expanses of homogenous urban area to the near complete exclusion of nature.	• Only a subset of crops can be produced in greenhouses, and even fewer in vertical farms.

Solution	Effects on Agricultural Diversity Where Adopted	Effects of Agricultural Diversity on Their Adoption and Effectiveness
Bioenergy from crops	• Only a small number of crops are currently being used at scale for bioenergy: maize, sugarcane, rapeseed, and sorghum.	• Not all soils, climates, and local markets are suitable for profitably growing bioenergy crops (Cronin et al., 2020).
Intermittent flooding of rice	• Precludes traditional systems which integrate fish, ducks, and nitrogen fixing water plants such as *Azolla* ssp.	• May be linked to lower grain yield and quality, and have negative impacts on nitrogen dynamics and pest management in some contexts (Massey et al., 2014).
No-tillage and residue retention	• Increases the need for other forms of weed control which is often met with the same broad-spectrum herbicides (e.g., glyphosate), reducing the richness and abundance of wild plants.	• The effects of no tillage on soil carbon and crop yields differ depending on soil and climate among other factors (Haddaway et al., 2017; Ladha et al., 2016). • Many farms require residue (e.g., straw) for animal feed or bedding.

Studies have found that decreasing agricultural diversity, mainly measured in terms of reduced field sizes or less varied crop rotations, has had substantial negative effects on local biodiversity (Benton et al., 2003; Collins & Fahrig, 2017; Ekroos et al., 2019; Fahrig et al., 2015; Hass et al., 2018; Kirk et al., 2011; M. B. Lee & Goodale, 2018; Martin et al., 2020; Monck-Whipp et al., 2018; Novotný et al., 2015; Palmu et al., 2014; Priyadarshana et al., 2021; Raderschall et al., 2021; Reynolds et al., 2018; Šálek et al., 2021; Sirami et al., 2019; Zhou et al., 2018). Some studies have also been able to directly control for the effects of other practices that tend to correlate with decreasing agricultural diversity, such as increased synthetic pesticide use, again finding that decreasing agricultural diversity has major negative effects (Chiron et al., 2014; Martin et al., 2020). In particular, the removal of hedgerows, ponds, and non-cropped areas has been an important driver of the decline in wild insects and birds; the increased homogeneity of crop varieties and the increased density and uniformity of crop stands has negatively affected a wide range of wild species, particularly insects; and the reduced seasonality caused by irrigation has negatively affected many wild bird species (Benton et al., 2003; Fahrig et al., 2011).

The same technologies which have reduced agricultural diversity have also increased crop yields and animal productivity in many regions, and some have claimed that higher yields have prevented deforestation elsewhere (Burney et al., 2010; Stevenson et al., 2013) potentially reducing net global biodiversity loss had these practices not been adopted (Fischer et al., 2008; Green et al., 2005). However, the main goal of most productivity-enhancing technologies is to make farms more profitable, less labour intensive, and to keep food prices low. For example, in the USA, one hour of wages in the manufacturing sector bought ~4kg of flour in 1900 compared to ~22kg in 2000 (Ritchie & Roser, 2021). Lower food prices have increased food consumption (which has both reduced hunger and increased obesity (Godfray et al., 2010; Sturm & An, 2014)), increased food waste (Rutten, 2013), and increased the mass production of cheap meat from grain (Godfray et al., 2018). The net effect of this, combined with growing human populations, has been the large scale clearance of land for agriculture (Curtis et al., 2018; Ellis et al., 2020). To date, as productivity has increased, so has land clearance for agriculture (Ewers et al., 2009; Kremen, 2015; Rudel et al., 2009). Evidence that the major productivity enhancing technologies have reduced overall environmental impacts is therefore tenuous.

In summary, while agricultural diversity remains high today, it is declining, in part because over the last hundred years, the same productivity-enhancing practices and technologies have been deployed across the entire sector. It could decline further if sector-wide sustainability solutions are pursued. This declining agricultural diversity has negative consequences for biodiversity. On the other hand, where agricultural diversity is high, the adoption and effectiveness of many productivity-enhancing technologies has been limited. This may be a reason why the Green Revolution had limited success in Africa. Agricultural diversity could also make many sustainability solutions less effective too.

To present this story about agricultural diversity is not to simplify the reasons why the Green Revolution had limited benefits in Africa, nor to criticise promising environmental or productivity solutions, nor to simplify the reasons behind the current biodiversity crisis. Instead, it is to elevate the importance of considering agricultural diversity when designing solutions to increase food security and environmental sustainability.

1.2. Goals of this thesis

This thesis has three goals:

1) To explore how agricultural diversity affects the environmental impacts and productivity of farmers and agricultural supply chains.
2) To explore productivity and sustainability solutions that are effective given agricultural diversity.
3) To develop new methods to represent and work with agri-environmental data from diverse producers and complex food supply chains.

At the same time, I have aimed to ensure that each chapter of this thesis supports the delivery of changes in consumer behaviour, producer behaviour, and policymaking.

1.3. Methodological approaches used

1.3.1. Environmental issues assessed

Agriculture causes multiple environmental issues, and is in fact, a leading cause of most of the environmental problems humanity creates (Campbell et al., 2017; Foley et al., 2005, 2011). Specifically, agriculture is a major cause of: biodiversity loss; deforestation; climate change;; terrestrial acidification; freshwater, marine, and terrestrial eutrophication; particulate matter emissions; ecological and human toxicity; smog (especially through crop residue burning); accelerated soil erosion; salinisation; water scarcity; phosphorus scarcity, and to some extent stratospheric ozone depletion (through agricultural N_2O emissions).

An assessment of agriculture's environmental impacts should ideally consider multiple issues to reflect the multi-dimensional nature of environmental problems and reflect possible trade-offs between improving one issue and worsening another. A weakness of many producer- and product-specific studies is that they only consider one environmental issue. For example, there is a large "carbon footprinting" literature where studies only report the greenhouse gas emissions of products (Röös et al., 2013). There are also "water footprinting" and "land footprinting" literatures too (Gerbens-Leenes et al., 2002; Hoekstra et al., 2011). On the other hand there are studies which quantify indicators for ten to twenty different environmental issues (Nemecek et al., 2005; Nemecek, Bengoa, et al., 2015). However, considering many environmental issues tends to make communication of results more complicated and means that more data are required to quantify these issues. This higher data requirement then affects the number of products or producers that can be assessed.

In Chapter 2, I focus on five environmental issues: land use, climate change, terrestrial acidification, freshwater and marine eutrophication, and water scarcity. These issues are chosen because they reflect areas where "planetary boundaries" may have been exceeded or are likely to do so (Steffen et al., 2015; Tuomisto et al., 2012) and where agriculture is a major known driver of these issues (Campbell et al., 2017).

Land use is not an environmental issue in itself, but in general, greater agricultural land use leads to natural habitat loss, loss of natural ecosystem function, and biodiversity loss (Alkemade et al., 2009; de Baan et al., 2012; Newbold et al., 2015). Converting land to agriculture in different locations has different consequences for biodiversity depending on how rich the biodiversity is in a certain location under natural conditions and how threatened different species are in that location (de Baan et al., 2013), and many different approaches have been developed to quantify the biodiversity effects of land transformation and land occupation at the level of specific producers and products (Winter et al., 2017). A major challenge is that the results from these approaches have yet to be reconciled to other well-grounded biodiversity indicators, such as the number of species on the IUCN red list or the changes in global biodiversity estimated through meta-analysis and modelling approaches (Newbold et al., 2015). I therefore chose not to present biodiversity loss data in this thesis due to this lack of reconciliation which is a fundamental shortcoming. However, Chapter 3 creates an online resource which contains biodiversity impact data for specific producers and products calculated using biodiversity models and leaves it to users of the platform to decide how to work with it.

Another major limitation is my omission of pesticide toxicity data from this thesis. Global agricultural pesticide use is at its highest recorded levels, with 4.2 billion kilograms of active ingredient used in 2019 (*FAOSTAT*, 2021). While some of the most ecologically toxic pesticides have been banned (e.g., organochlorides through the 2001 Stockholm Convention) there is evidence that these bans have simply shifted the toxic effects of pesticides from birds and mammals to plants and invertebrates (Schulz et al., 2021). The data I was able to access describing farms and their practices did not have sufficient information on pesticide usage split out by pesticide brand or active ingredient, and a key focus of Chapter 3 is to enable the consistent representation and storage of pesticide usage data for specific farms.

In Chapter 4 I include a broader discussion about how to choose which environmental issues to assess, arguing that for businesses and policymakers, it is more practical to quantify a smaller set of issues and manage the issues not quantified with minimum performance standards.

1.3.2. Productivity issues assessed

Agricultural productivity is a measure of the quantity or value of crops and animal products produced per unit of a resource such as land or labour (Sadras et al., 2015). Productivity issues can occur across all crops or animals, certain crops or animals, and/or in certain years and regions.

A range of agricultural productivity issues require research and resources. In sub-Saharan Africa, low production per unit of land is thought to be a leading cause of hunger (FAO, 2021c; Sanchez, 2002) (although internationally, food distribution is the problem because we already produce enough to feed everyone (*FAOSTAT*, 2021)). Variable productivity in Africa, largely due to droughts affecting harvests, is also a major driver of acute hunger and famine (FAO, 2021c). Low productivity of certain nutrient rich foods can cause malnutrition (IFAD, 2014) and around 22% of children suffered from stunting linked to malnutrition worldwide in 2020 (FAO, 2021c). Low agricultural value per unit of labour is also a major cause of poverty (Sachs et al., 2004).

In Chapter 2 I focus on the productivity of agricultural land, captured through the land use indicator. Land use provides an alternative and more holistic metric for agricultural productivity than crop or animal yields per hectare because it accounts for uncultivated periods such as long fallow periods, unproductive periods such as orchard establishment, for multi-cropping, and for multi-year production cycles (like beef production). A definition of the land use indicator is provided in Materials and Methods, Section 6a. In Chapter 2 we also include basic nutritional information to support comparisons between different but nutritionally comparable products; e.g., we use the indicator “land use per 100g protein” for different protein-rich products, or “land use per 1000kcal” for starch-rich crops (Cassidy et al., 2013). In Chapter 3 we explore the land use indicator in more depth using a case study. In that Chapter we also present a data structure that also allows economic indicators, such as revenue and costs, to be stored in a consistent way. In Chapter 4 I discuss and environmental impact label which represents environmental impacts per unit of product. There are three ways to improve performance: reduce environmental impacts (the numerator) while holding production the same; increase production (the denominator) while holding environmental impacts the same; or reduce food losses and wastage in the supply chain. Put differently, the label presented in Chapter 4 measures "sustainable intensification" which is defined as a process to "achieve higher agricultural yields whilst simultaneously reducing the negative impact of farming on the environment" (T. Garnett et al., 2013; Godfray, 2015; Godfray & Garnett, 2014).

1.3.3. Approaches used to quantify the environmental issues

Environmental issues occur when the total emissions of a substance, the use of a resource, or the change in population or function of a wild species causes damage to living beings or natural ecosystems as a whole. Environmental issues can either be quantified at source (e.g., 250kg CO_2 emitted per hectare from a farm when agricultural limestone is applied and hydrolyses), quantified after they have aggregated to the regional or global level (e.g., 420 parts per million of atmospheric CO_2), or quantified in terms of their effect (e.g., 1 degree Celsius of global warming compared to pre-industrial times).

Because the focus of this thesis is on specific producers and their products, I use methods which quantify environmental issues at source. Where possible, the indicators are aggregated to the global level or national level to check whether the data reconcile to known global or national totals (supplementary materials for Chapter 2 and Chapter 3). A limitation of prior studies is that they did not perform these global reconciliations (Clune et al., 2017; Tilman & Clark, 2014) creating uncertainty about whether their results are representative.

To quantify environmental issue at source, they can either be directly measured or modelled. Examples of direct measurement are: lysimeters to measure nitrate leaching below agricultural fields; measuring water consumption with water meters; or using mark-recapture methods to estimate species abundance. There are a few examples of multi-indicator studies using measured data and they tend to be limited to certain regions or products (Ladha et al., 2016). Instead the general approach is to use meta-analysis to generalise measured data from many studies to the global or regional level (Newbold et al., 2015; Stehfest & Bouwman, 2006). A strength of studies or meta-analyses using primary data is their data quality and potential to quantify environmental issues without modelling error, but a limitation is that these studies generally focus on a small number of indicators.

Examples of modelling approaches include: the DNDC model for quantifying soil emissions including nitrate leaching (University of New Hampshire, 2012); or models for estimating biodiversity loss detailed in the LC-Impact guidelines (Verones et al., 2016). These models are generally built by statistically relating data on soil and climate measurements, agricultural inputs, and production practices to measured environmental outcome data. To date, prior studies have applied these models to national or regional statistical data to generate estimates of national or global environmental impacts (Crippa et al., 2021; Janssens-Maenhout et al., 2017; Springmann et al., 2018). However, however a limitation is that they only assessed national impacts rather than producer-level impacts. Other studies have applied these models to producer specific data, but a limitation of these studies is they only considered a small number of products or producers (Nemecek, Bengoa, et al., 2015) or a large number of producers but for specific products and countries only (Cui et al., 2018).

In this thesis, I mainly use primary data describing producers' inputs, practices, and products, sometimes gap filled with secondary data (for example using geospatial datasets to add climate measurements), and then apply models to calculate environmental impacts. Using models is currently the only feasible way to quantify environmental impacts across many producers in many regions. However, models for certain emissions and resource uses have not yet been developed and in Chapter 2 I build new models to close gaps in the literature: a nitrate and ammonia leaching model based on a meta-analyses of 91 studies; new models for methane emissions and nutrient losses from aquaculture systems (supplementary materials for Chapter 2); and enhancements to models that others had built to estimate deforestation and soil carbon stock changes. In Chapter 3, colleagues and I report a technical advance which creates a single data format to represent both measured and modelled data in the same data format. This will better enable meta-analyses of measured data in the future, enable easier model building, and also enable analyses that blend modelled and measured data. In Chapter 4 I discuss how modelling environmental impacts provides a globally scalable way for farmers to quantify and manage their sustainability.

Life Cycle Assessment (LCA) provides a framework to sum up multiple emissions and resource uses created throughout a supply chain into final indicators called "midpoint" or "endpoint" indicators (Cucurachi et al., 2019). The processes for conducting LCAs have been standardised by the ISO guidelines in particular ISO 14040:2006, ISO 14041:1999, ISO 14042:2000, and ISO 14043:2000.

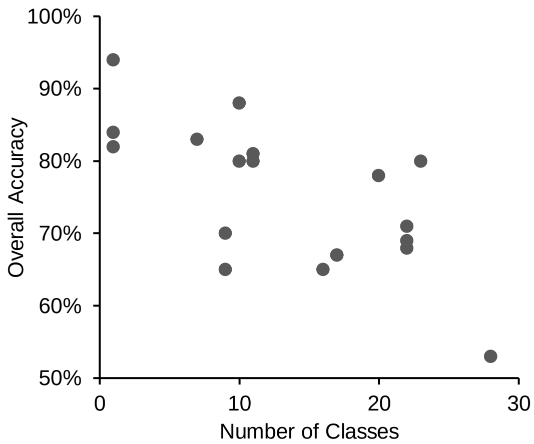
Midpoint refers to a stage where multiple different emissions or resource uses begin sharing a common environmental mechanism (Goedkoop et al., 2009; Verones et al., 2016). For example, each nitrogen and phosphorus emission released to freshwater may have different bio-chemical pathways, but at some point, they will likely cause eutrophication. To represent this, each emission into water can be multiplied by a factor representing its freshwater or marine eutrophication potential and can then be summed into final midpoint indicator representing total freshwater or marine eutrophication potential. This creates a single metric from multiple emissions, making it easier to interpret and use, and providing a summary measure of the environmental problem in question.

There are generally three endpoint indicators: damage to ecosystems (sometimes measured as species destined to extinction per year); damage to human health (often measured in terms of disability adjusted human life years); and resource depletion (often measured in terms of a resource such as antimony). Midpoint indicators are converted into these common units using weights based on their effect on each endpoint indicator. The converted midpoints are then summed into a final single score for each endpoint. For example, each litre of freshwater withdrawals in each river basin will cause a certain amount of biodiversity loss. Leading approaches for endpoint analysis include ReCiPe (Goedkoop et al., 2009) and LC-Impact (Verones et al., 2016). However, the main limitation of these methods is that they have not yet been reconciled to other datasets estimating global biodiversity loss (such as the IUCN Red List) or reconciled to datasets on human health impacts (such as the Global Burden of Disease dataset).

All chapters use or recommend using Life Cycle Assessment as this is the most widely accepted and theoretically robust method for full supply chain multi-indicator assessment. Chapter 2 uses midpoint indicators only as we did not include enough midpoint indicators to quantify endpoint indicators, and because there is a lack of research on the ability of endpoint methods to predict actual outcomes (e.g., observed species loss). Chapter 3 presents a calculation toolkit which calculates both midpoint and endpoint indicators. Chapter 4 discusses the value of using endpoint indicators to prioritise and weight different midpoint indicators.

Remote sensing is another approach which could potentially quantify agricultural diversity, and it has been used to quantify environmental indicators such as deforestation (Hansen et al., 2013). The remotely sensed images themselves are measured data, but virtually all images which are used to estimate agri-environmental indicators are corrected, cleaned, processed, and then classified using models. Specifically, classification converts images into maps with discrete or continuous classes representing things of interest (e.g.,

Figure 1.2. Overall accuracy plotted against number of classes for the major global land cover maps (Table S1).



cropland, pastureland, crop types, or hedgerows) or variables of interest (e.g., crop yield). However, there are some major challenges with using remote sensing to characterise agriculture and its diversity. Firstly, with each additional class or feature that is added to the classification, the accuracy of the classification deteriorates (Figure 1.2), and multiple classes would be desirable to characterise agricultural diversity. Correcting for loss of accuracy generally requires more training and validation data, and such data are cost and time intensive to amass. Secondly, there are major challenges in differentiating grasslands grazed by domesticated herbivores from grasslands grazed by wild herbivores. This is a serious problem because pastures and rangelands are the largest type of agricultural land, covering 33% of the world's land surface according to some estimates (Ellis et al., 2020). Thirdly, while prior research has characterised agricultural diversity by estimating spatial metrics from satellite images (such as the contrast between pixels), this makes a major and currently untested assumption that these simple metrics reflect agricultural diversity (X. Liu et al., 2020; Tuanmu & Jetz, 2015). Fourthly, another research project merged multiple geospatial maps that had already been classified and used clustering to identify different agricultural systems, but this only identified 86 distinct terrestrial systems which the authors recognised was too low (Bossio et al., 2021). Hence, despite the potential of remote sensing to address the goals of this thesis, I largely exclude it because of these limitations. I use remotely sensed data for other purposes including ascertaining climate data in Chapters 2 and 3. In Chapter 4 I discuss how remotely sensed data could be used to validate farmer reported crop yields or other data.

1.3.4. Assessing outcomes beyond environment and productivity

This thesis focuses on environmental impacts and agricultural productivity, considering the full food supply chain (from input production to food retail), and Chapter 4 uses a review of empirical studies on behaviour change by businesses and individuals. Despite this broad scope, and the focus on stakeholder decision making, multiple aspects of the food system are not explored quantitatively or in depth, for example national level economic or social aspects of adopting environmental impact labelling, or the implications of focusing on environmental impacts for animal welfare.

In Chapter 5 in particular, I use a food systems approach as a framework to qualitatively explore the effects of the proposed environmental and productivity solutions for different stakeholders. I also use a food systems approach to contextualise the overall findings of this thesis and deliver a more nuanced discussion. In Chapter 2 I consider multiple stakeholders and trade-offs when exploring the mitigation framework and in Chapter 4 I explore how an environmental impact labelling scheme could become widely adopted and also to explore potential adverse effects.

A food systems approach can be defined as one that gathers "all the elements (environment, people, inputs, processes, infrastructures, institutions, etc.) and activities that relate to the production, processing, distribution, preparation and consumption of food, and the outputs of these activities, including socio-economic and environmental outcomes" (High Level Panel of Experts on Food Security and Nutrition (HLPE), 2014). Figure 1.3 presents the food systems framework used, which includes drivers, activities, and outcomes. It is based on prior research (Ericksen, 2008; Ingram, 2011) with three changes:

1) Animal welfare/suffering is included as an outcome given there are tens of billions of sentient animals involved in agricultural production.
2) Food systems outcomes are framed in both positive and negative language (rather than just positive language like "wealth" and "employment" (Ericksen, 2008; Ingram, 2011)). An example of a negative outcome is the poverty trap created for millions of farmers whose farms are too small and unproductive to generate surplus income for their families to invest in education or health (Sachs et al., 2004).
3) The food system is situated in the context of the broader economic system by indicating the share of agriculture relative to other sectors for employment, GDP, and

environmental issues. This is important because the contribution of agriculture to GDP and employment shrinks as economies industrialise, reaching on average less than 1% of GDP and 3% of employment in high-income countries. This implies that trade-offs between economic and social goals, on at least the GDP and employment indicators, decline as economies industrialize. It is also important because it indicates that solutions to food systems problems can come from outside of the food system. For example, while increasing productivity in agriculture may help with smallholder poverty traps, the main poverty alleviating solution that has been realized in every industrialised country worldwide is new employment opportunities in industry and services.

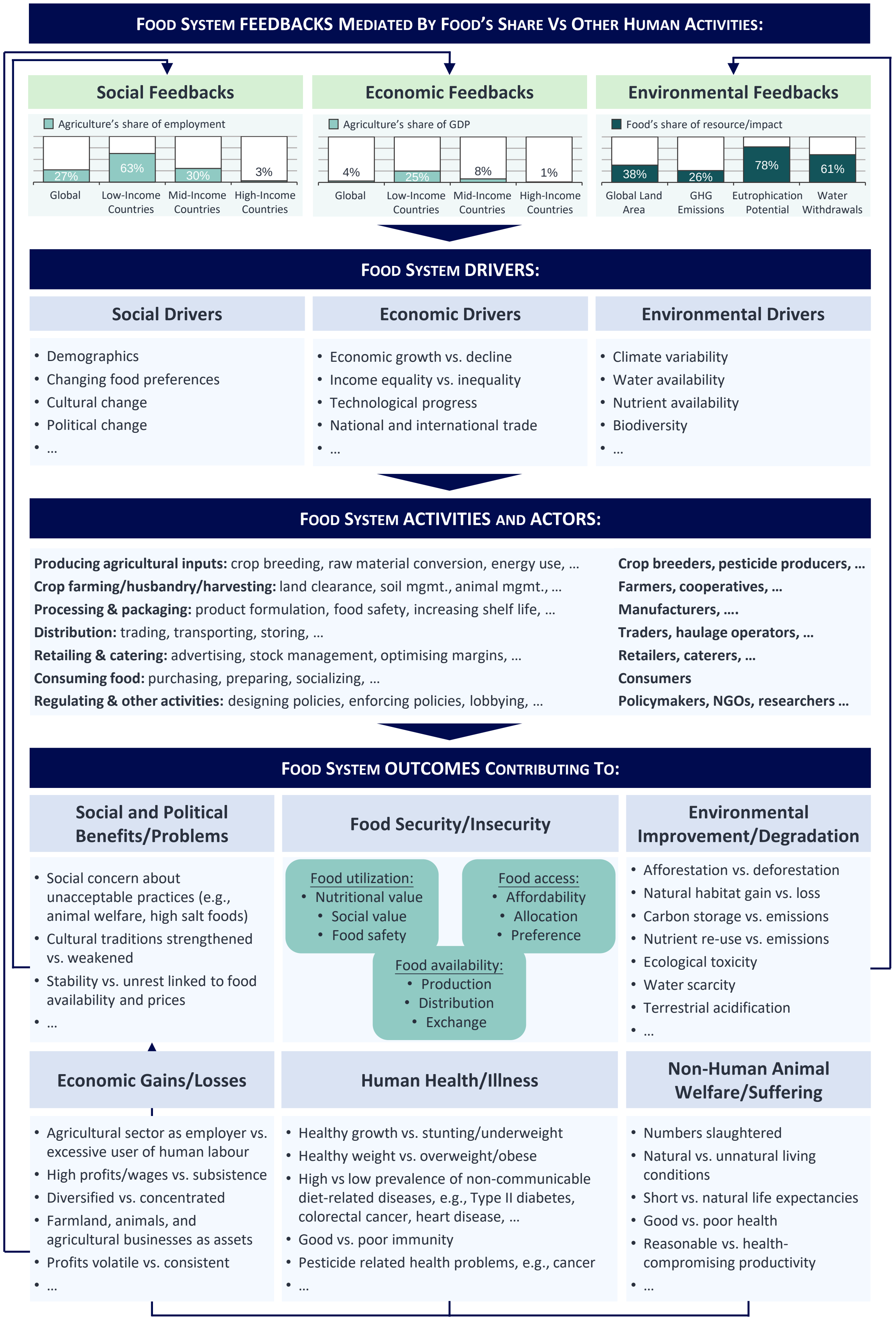


Figure 1.3. Food system outcomes to related to their activities, drivers, and feedbacks.

GDP and employment data from World Bank (2022), environmental data from Chapter 2.

1.4. Chapter summaries

Chapter 2: Reducing food's environmental impacts through producers and consumers. In this Chapter, Thomas Nemecek and I explore how environmental impacts and productivity vary across different food producers and products. To do this, we use a meta-analysis of 750 Life Cycle Assessment (LCA) studies, reporting data on 38,700 farms and 1600 processors, packaging types, and retailers, in 120 countries, and covering five environmental impact indicators: land use, greenhouse gas emissions, terrestrial acidification potential, freshwater and marine eutrophication potential, and scarcity weighted water use. The land use indicator serves both as an environmental and productivity indicator because land use is the inverse of yield corrected for fallow duration and multi cropping. These data from LCA studies are substantially corrected for differences in methodology, weighted for how much each observation represents of global food production, and then our data sample is scaled up to the global level and reconciled to other global datasets. We identify high variability in environmental impacts, with up to 50-fold differences between producers of the same product, and nearly 200-fold differences between different protein rich products per 100g of protein (beef versus pulses). This variability indicates substantial opportunities to reduce these impacts through production practice change and diet change. For example, we estimate that global adoption of a diet without animal products would reduce global greenhouse gas emissions across all sectors of the economy by 28% and liberate 3.1 billion hectares of land from production. Using techniques such as regression and variance decomposition, we explore the data to develop sustainability solutions that would be effective given the diversity of the agricultural system. Specifically, our findings support an approach where producers monitor their own environmental impacts using digital tools, flexibly meet environmental targets by choosing from multiple practices, and communicate their impacts up the supply-chain and through to consumers.

Author contributions: J.P. conducted the analysis and wrote the chapter. J.P. and T.N. contributed to study design, data interpretation, and reviewed the chapter.

Chapter 3: HESTIA: A harmonised way to represent and share agri-environmental data. In this chapter, a team of colleagues (Guillaume Royer, Valentina Caldart, Patrik Henriksson, Ben Belton, Sarah Halevy, Gary Powney, Juan Sabuco, and Rich Grenyer) and I develop the ideas from Chapter 2 in three ways. Firstly, we present a filetype that would allow data describing food producers and their environmental impacts to be stored in a consistent and unambiguous way. Our format is designed to represent field trial data, agricultural survey data, and Life Cycle Assessment data, but could also store data collected with digital farm monitoring tools. Using test datasets, we show that our format can represent data describing diverse producers and preserve high levels of detail from the original sources. This data format could support the type of supply chain communication we discuss in Chapter 2. It could also unlock data exchange between researchers. Secondly, we present a software toolkit which automatically validates farmer data, augments these data (e.g., using geospatial datasets on soil and climate), and then calculates life cycle environmental impact indicators from these data. This toolkit can be embedded in the digital tool's farmers are already using, empowering the monitoring we discuss in Chapter 2. Thirdly, given the high demand I received for the data presented in Chapter 2, we create an online data platform (https://hestia.earth) to store methodologically harmonised environmental impact information on food products and make that information publicly available. The principal source of the ~250 datasets currently on the platform is published field trials, published LCAs, and farmer surveys. We also develop software to automatically aggregate these data into average environmental impacts for different food products in different countries. Combined, this work creates a new resource for researchers and builds part of the digital foundations for more sustainable food supply chains.

Author contributions: J.P. conceptualised the research and methods with input from P.H., S.H., R.G., and G.R. J.P. designed the data structure. G.R. designed and built the overall software architecture. G.R., J.S., G.P., and J.P. developed the calculation engine. J.P. and V.C. led the data curation and upload process with input from P.H. and B.B. P.H, J.P., and B.B. provided data resources. S.H., R.G., and J.P. administered the project. J.P. wrote the original draft. All authors contributed to reviewing and editing the chapter.

Chapter 4: Environmental impact labelling for more sustainable and productive food supply chains. In this chapter, E.J. Milner-Gulland and I explore a promising mechanism to bring the mitigation framework developed in Chapter 2 to life. We present the idea that environmental impact labels would trigger food supply chains to start measuring and communicating their environmental impacts. Using a wide-ranging literature review, we present evidence that measuring and communicating environmental impacts delivers substantial behaviour change by farmers, food processors, and consumers. It would also create information to implement policies linked to environmental impacts (such as taxes or minimum performance standards). We specifically focus on a label that expresses environmental impacts per unit of food. This means there are three ways to improve performance: reduce environmental impacts, increase productivity (e.g., increase crop yields), or reduce food losses and waste. Improvements in the outcomes measured by the label could therefore also support improvements in food security. We explore further choices around label design including which products and indicators to include. Finally, we explore how to achieve widespread adoption of such a scheme, and argue that producers, NGOs, existing labelling schemes, and policymakers have complementary roles to play. Throughout we identify the most pressing questions for future research.

Author contributions: J.P. undertook the literature review and wrote the original chapter draft. J.P. and E.J.M.G. reviewed and edited the chapter.

Chapter 2: Reducing food's environmental impacts through producers and consumers

J. Poore & T. Nemecek

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Abstract: Food's environmental impacts are created by millions of diverse producers. To identify solutions that are effective under this heterogeneity, we consolidated data covering five environmental indicators; 38,700 farms; and 1600 processors, packaging types, and retailers. Impact can vary 50-fold among producers of the same product, creating substantial mitigation opportunities. However, mitigation is complicated by trade-offs, multiple ways for producers to achieve low impacts, and interactions throughout the supply chain. Producers have limits on how far they can reduce impacts. Most strikingly, impacts of the lowest-impact animal products typically exceed those of vegetable substitutes, providing new evidence for the importance of dietary change. Cumulatively, our findings support an approach where producers monitor their own impacts, flexibly meet environmental targets by choosing from multiple practices, and communicate their impacts to consumers.

2.1. Introduction

With current diets and production practices, feeding 7.6 billion people is degrading terrestrial and aquatic ecosystems, depleting water resources, and driving climate change (Foley et al., 2011; Godfray et al., 2010). It is particularly challenging to find solutions that are effective across the large and diverse range of producers that characterise the agricultural sector. More than 570 million farms produce in almost all the world's climates and soils (FAO, 2014); each using vastly different agronomic methods; average farm sizes vary from 0.5 hectares in Bangladesh to 3000 hectares in Australia (FAO, 2014), average mineral fertilizer use ranges from 1kg of nitrogen per hectare in Uganda to 300kg in China (*FAOSTAT*, 2021); and although four crops provide half of the world's food calories (*FAOSTAT*, 2021), more than 2 million distinct varieties are recorded in seed vaults (FAO, 2010b). Further, products range from minimally to heavily processed and packaged, with 17 of every 100kg of food produced transported internationally, increasing to 50kg for nuts and 56kg for oils (*FAOSTAT*, 2021).

Previous studies have assessed aspects of this heterogeneity by using geospatial data sets (Carlson et al., 2016; Gerber et al., 2013; West et al., 2014), but global assessments using the inputs, outputs, and practices of actual producers have been limited by data. The recent rapid expansion of the life cycle assessment (LCA) literature is providing this information by surveying producers around the world. LCA then uses models to translate producer data into environmental impacts with sufficient accuracy for most decision-making (Recommendation 2013/179/EU on the Use of Common Methods to Measure and Communicate the Life Cycle Environmental Performance of Products and Organisations, 2013; Hellweg et al., 2014; Paustian, 2013).

To date, efforts to consolidate these data or build new large-scale data sets have covered greenhouse gas (GHG) emissions only (Clune et al., 2017; Gerber et al., 2013; Tilman & Clark, 2014), agriculture only (M. Clark & Tilman, 2017; de Vries et al., 2010; Nijdam et al., 2012; Tilman & Clark, 2014), small numbers of products (M. Clark & Tilman, 2017; de Vries et al., 2010; Gerber et al., 2013; Nijdam et al., 2012), predominantly Western European producers (M. Clark & Tilman, 2017; Clune et al., 2017; de Vries et al., 2010; Nijdam et al., 2012; Tilman & Clark, 2014), and have not corrected for important methodological differences between LCAs (M. Clark & Tilman, 2017; Clune et al., 2017; de Vries et al., 2010; Nijdam et al., 2012; Tilman & Clark, 2014). Here, we present a globally reconciled and methodologically harmonised database on the variation in the environmental impacts of different foods across different producers and across five environmental impact indicators. Our results show the need for far-reaching changes in how food's environmental impacts are managed and communicated.

2.2. Building the multi-indicator global database

We derived data from a comprehensive meta-analysis, identifying 1530 studies for potential inclusion, which were supplemented with additional data received from 139 authors. Studies were assessed against 11 criteria designed to standardise methodology, resulting in 570 suitable studies with a median reference year of 2010 (supplementary materials for Chapter 2). The data set covers ~38,700 commercially viable farms in 119 countries (fig. S2) and 40 products representing ~90% of global protein and calorie consumption. It covers five important environmental impact indicators (Steffen et al., 2015): land use; freshwater withdrawals weighted by local water scarcity; and GHG, acidifying, and eutrophying emissions. For crops, yield represents output for a single harvest. Land use includes multiple cropping (up to four harvests per year), fallow (uncultivated periods between crops), and economic allocation to crop coproducts such as straw. This makes it a stronger indicator of both farm productivity and food security than yield.

The system we assess begins with inputs (the initial effect of producer choice) and ends at retail (the point of consumer choice) (fig. S1). For each study, we recorded the inventory of outputs and inputs (including fertilizer quantity and type, irrigation use, soil, and climatic conditions). Where data were not reported, for example, on climate, we used study coordinates and spatial data sets to fill gaps. We recorded environmental impacts at each stage of the supply chain. For GHG emissions, we further disaggregated the farm stage into 20 emission sources. We then used the activity data (i.e., soil and climate data and data on inputs, products, and practices) to recalculate all missing emissions. For nitrate leaching and aquaculture, we developed new models for this study (supplementary materials for Chapter 2).

Studies included provided ~1050 estimates of post-farm processes. To fill gaps in processing, packaging, or retail, we used additional meta-analyses of 153 studies providing 550 observations. Transport and losses were included from global data sets. Each observation was weighted by the share of national production it represents, and each country by its share of global production. We then used randomisation to capture variance at all stages of the supply chain (supplementary materials for Chapter 2).

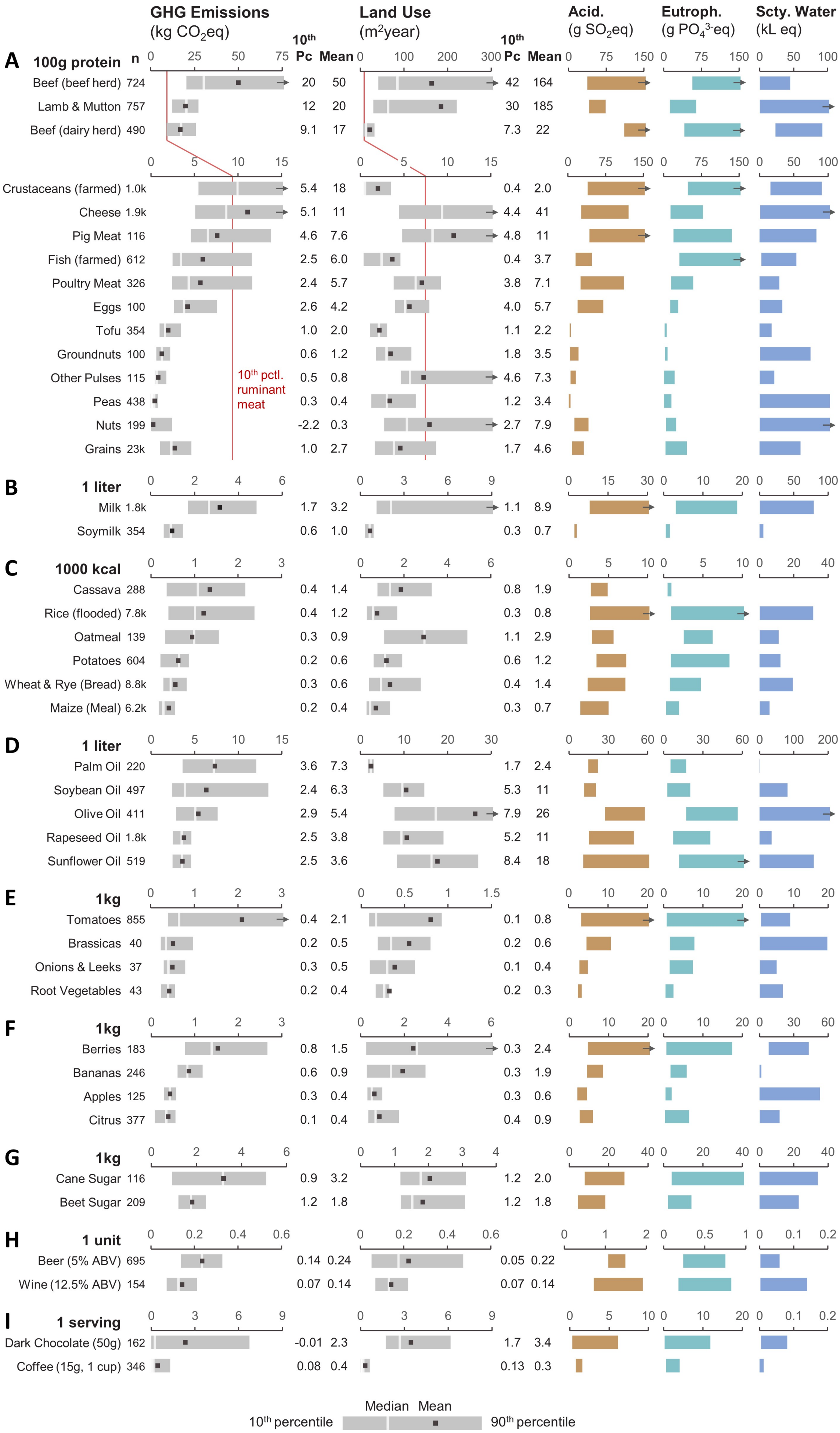
We validated the global representativeness of our sample by comparing average and 90th-percentile yields to Food and Agriculture Organization (FAO) data (*FAOSTAT*, 2021), which reconcile to within ±10% for most crops. Using FAO food balance sheets (*FAOSTAT*, 2021) we scaled up our sample data. Total arable land and freshwater withdrawals reconcile to FAO estimates. Emissions from deforestation and agricultural methane fall within ranges of independent models (supplementary materials for Chapter 2).

2.3. Environmental impacts of the entire food supply-chain

Today's food supply chain creates ~13.7 billion metric tons of carbon dioxide equivalents (CO_2eq), 26% of anthropogenic GHG emissions. A further 2.8 billion metric tons of CO_2eq

(5%) are caused by nonfood agriculture and other drivers of deforestation (supplementary materials for Chapter 2). Food production creates ~32% of global terrestrial acidification and ~78% of eutrophication. These emissions can fundamentally alter the species composition of natural ecosystems, reducing biodiversity and ecological resilience (Bouwman et al., 2002). The farm stage dominates, representing 61% of food's GHG emissions (81% including deforestation), 79% of acidification, and 95% of eutrophication (table S18).

Today's agricultural system is also incredibly resource intensive, covering ~43% of the world's ice- and desert-free land. Of this land, ~87% is for food and 13% is for biofuels and textile crops or is allocated to nonfood uses such as wool and leather. We estimate that two-thirds of freshwater withdrawals are for irrigation. However, irrigation returns less water to rivers and groundwater than industrial and municipal uses and predominates in water-scarce areas and times of the year, driving 90-95% of global scarcity-weighted water use (supplementary materials for Chapter 2).



GHG Emissions (kg CO2eq)
Land Use (m2year)
Acid. (g SO2eq)
Eutroph. (g PO43-eq)
Scty. Water (kL eq)
10th Pc Mean
10th Pc Mean
A 100g protein n
Beef (beef herd) 724 20 50 42 164
Lamb & Mutton 757 12 20 30 185
Beef (dairy herd) 490 9.1 17 7.3 22
Crustaceans (farmed) 1.0k 5.4 18 0.4 2.0
Cheese 1.9k 5.1 11 4.4 41
Pig Meat 116 4.6 7.6 4.8 11
Fish (farmed) 612 2.5 6.0 0.4 3.7
Poultry Meat 326 2.4 5.7 3.8 7.1
Eggs 100 2.6 4.2 4.0 5.7
Tofu 354 1.0 2.0 1.1 2.2
Groundnuts 100 0.6 1.2 1.8 3.5
Other Pulses 115 0.5 0.8 4.6 7.3
Peas 438 0.3 0.4 1.2 3.4
Nuts 199 -2.2 0.3 2.7 7.9
Grains 23k 1.0 2.7 1.7 4.6
10th pctl. ruminant meat
B 1 liter
Milk 1.8k 1.7 3.2 1.1 8.9
Soymilk 354 0.6 1.0 0.3 0.7
C 1000 kcal
Cassava 288 0.4 1.4 0.8 1.9
Rice (flooded) 7.8k 0.4 1.2 0.3 0.8
Oatmeal 139 0.3 0.9 1.1 2.9
Potatoes 604 0.2 0.6 0.6 1.2
Wheat & Rye (Bread) 8.8k 0.3 0.6 0.4 1.4
Maize (Meal) 6.2k 0.2 0.4 0.3 0.7
D 1 liter
Palm Oil 220 3.6 7.3 1.7 2.4
Soybean Oil 497 2.4 6.3 5.3 11
Olive Oil 411 2.9 5.4 7.9 26
Rapeseed Oil 1.8k 2.5 3.8 5.2 11
Sunflower Oil 519 2.5 3.6 8.4 18
E 1kg
Tomatoes 855 0.4 2.1 0.1 0.8
Brassicas 40 0.2 0.5 0.2 0.6
Onions & Leeks 37 0.3 0.5 0.1 0.4
Root Vegetables 43 0.2 0.4 0.2 0.3
F 1kg
Berries 183 0.8 1.5 0.3 2.4
Bananas 246 0.6 0.9 0.3 1.9
Apples 125 0.3 0.4 0.3 0.6
Citrus 377 0.1 0.4 0.4 0.9
G 1kg
Cane Sugar 116 0.9 3.2 1.2 2.0
Beet Sugar 209 1.2 1.8 1.2 1.8
H 1 unit
Beer (5% ABV) 695 0.14 0.24 0.05 0.22
Wine (12.5% ABV) 154 0.07 0.14 0.07 0.14
I 1 serving
Dark Chocolate (50g) 162 -0.01 2.3 1.7 3.4
Coffee (15g, 1 cup) 346 0.08 0.4 0.13 0.3
Median Mean
10th percentile 90th percentile

Figure 2.1. Estimated global variation in GHG emissions, land use, terrestrial acidification, eutrophication, and scarcity-weighted freshwater withdrawals, within and between 40 major foods. n = farm or regional inventories. Land use is area times years occupied (m^2·year). (**A**) Protein-rich products. Grains are also shown here given they contribute 41% of global protein intake, despite lower protein content. (**B**) Milks. (**C**) Starch-rich products. (**D**) Oils. (**E**) Vegetables. (**F**) Fruits. (**G**) Sugars. (**H**) Alcoholic beverages (1 unit = 10ml alcohol). (**I**) Stimulants.

2.4. Highly variable and skewed environmental impacts

We now group products by their primary dietary role and express impacts per unit of primary nutritional benefit (Figure 2.1 and fig. S3). Immediately apparent in our results is the high variation in impact among both products and producers. Ninetieth-percentile GHG emissions of beef are 105kg of CO_2eq per 100g of protein, and land use (area multiplied by years occupied) is 370 m^2·year. These values are 12 and 50 times greater than 10th-percentile dairy beef impacts (which we report separately given that its production is tied to milk demand). Tenth-percentile GHG emissions and land use of dairy beef are then 36 and 6 times greater than those of peas. High variation within and between protein-rich products is also manifest in acidification, eutrophication, and water use.

Within the major crops wheat, maize, and rice, 90th-percentile impacts are more than three times greater than 10th-percentile impacts on all five indicators. Within major growing areas for these crops (the Australian wheat belt, the U.S. corn belt, and the Yangtze river basin), land use becomes less variable, but we observe the same high levels of variation in all other indicators. This variability, even among producers in similar geographic regions, implies substantial potential to reduce environmental impacts and enhance productivity in the food system.

For many products, impacts are skewed by producers with particularly high impacts. This creates opportunities for targeted mitigation, making an immense problem more manageable. For example, for beef originating from beef herds, the highest-impact 25% of producers represent 56% of the beef herd's GHG emissions and 61% of the land use (an estimated 1.3 billion metric tons of CO_2eq and 950 million hectares of land, primarily pasture). Across all products, 25% of producers contribute on average 53% of each product's environmental impact (fig. S3). For scarcity-weighted freshwater withdrawals, the skew is particularly pronounced: Producing just 5% of the world's food calories creates ~40% of the environmental burden. We will now explore how to access these mitigation opportunities through heterogenous producers.

2.5. Mitigation through producers

2.5.1. Enable producers to monitor multiple impacts

The first step in mitigation is estimating producer impacts. Prior research (M. Clark & Tilman, 2017; Gerber et al., 2013; West et al., 2014), has suggested that readily measurable proxies predict farm-stage impacts, avoiding the need for detailed assessment. From our larger data set, which includes more practices and geographies than prior studies, we assess the predictive power of common proxies, including crop yield, nitrogen use efficiency, milk yield per cow, liveweight gain, pasture area, and feed conversion ratios. Although most proxies significantly covary with impact, they make poor predictors when used alone, explaining little of the variation among farms (R^2 = 0-27% in 47 of 48 proxy-impact combinations assessed) (fig. S4).

Prior research has also suggested using one impact indicator to predict others (Röös et al., 2013). We find weakly positive and sometimes negative relationships between indicators. For similar products globally, correlations between indicators are low (R^2 = 0-30% in 26 of 32 impact-impact combinations assessed) (fig. S4). Pork, poultry meat, and milk show higher correlations between acidification and eutrophication ($R2 \leq 54\%$), explained by the dominant role of manure in these impacts, but this does not generalise to other products or indicators. The same conclusion holds for farms in similar geographies or systems (fig. S5).

Monitoring multiple impacts and avoiding proxies supports far better decisions and helps prevent harmful, unintended consequences. However, two recent studies suggest that data on practices and geography, required to quantify impacts, must come directly from producers (Beza et al., 2017; Paustian, 2013); that quantifying impacts with the use of satellite or census data misses much of the variation among farms.

2.5.2. Set and incentivise mitigation targets

When land use or emissions are low, we find trade-offs between indicators for many crops (fig. S5). This reflects diminishing marginal yield with increasing inputs as crops tend toward their maximum yields (Cui et al., 2014). For example, for already low-emission Northern European barley farms, halving land use can increase GHG emissions per kilogram of grain by 2.5 times and acidification by 3.7 times. To explore trade-offs further, we pair observations from the same study, location, and year that assess a practice change (fig. S6). Of the nine changes assessed, only two (changing from monoculture to diversified cropping and improving degraded pasture) deliver statistically significant reductions in both land use and GHG emissions.

Geography influences these trade-offs. For example, in the Australian wheat belt, where farmers practice low-rainfall, low-input farming, we find that both output per hectare and GHG emissions are in the bottom 15% globally. The environmental and social importance of different impacts also varies locally, given land scarcity, endemic biodiversity, and water quality, among other factors. Setting regional and sector-specific targets will help producers navigate trade-offs and make choices that align with local and global priorities.

2.5.3. Meet targets by choosing from multiple practice changes

To meet these targets, policy might encourage widespread adoption of certain practices. However, the environmental outcomes of many practices, such as conservation agriculture (Ladha et al., 2016), organic farming (fig. S6), and even integrated systems of best practice (Cui et al., 2018), are highly variable. Using our data set, we can generalise these findings. To do this, we disaggregate each environmental indicator into its sources or drivers. We consider practice change as a package of measures that targets one or more of these sources. If producers have different impact sources, the effects of practice change will be variable.

We find that sources of impact vary considerably among farms producing the same product (Figure 2.2 and figs. S7-S9). Priority areas for reducing impact for one farm may be immaterial for another. For example, measures to reduce direct nitrous oxide emissions from synthetic and organic fertilizer, such as biochar application, are included in many mitigation estimates (Smith et al., 2014). However, for a third of global crop calorie production, these emissions represent less than 5% of farm-stage GHGs. It may be the case that low-impact farms have similar impact drivers. We again find variable sources of impact, even for low-impact farms (Figure 2.2, C and D). Reducing impacts means focusing on different areas for different producers and, by implication, adopting different practices.

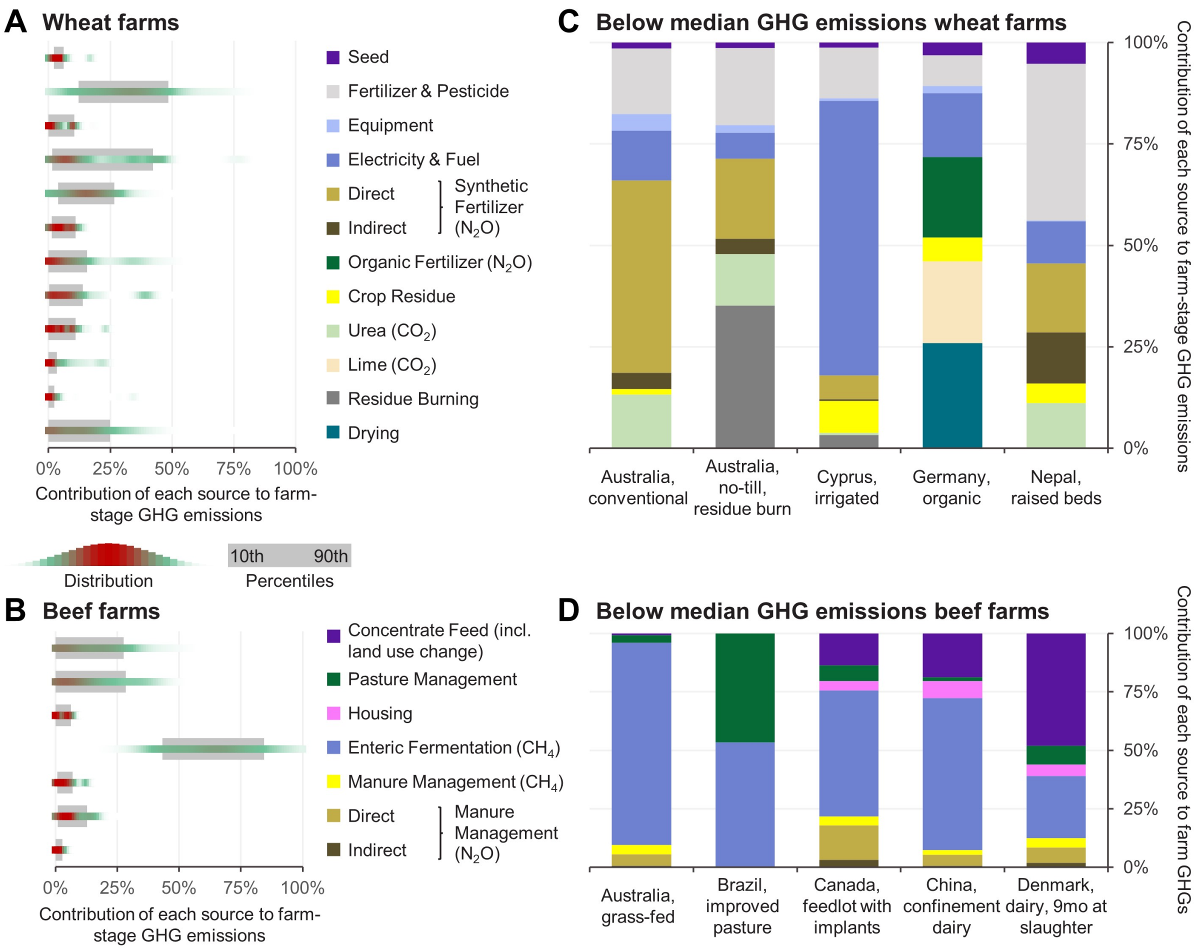


Figure 2.2. Contributions of emission sources to total farm-stage GHG emissions. (**A**, and **B**). Gray bars show 10th- and 90th-percentile contributions. Shaded bars represent the distribution. For example, the 90th-percentile contribution of organic fertilizer N_2O to farm-stage emissions is 16%, but for most wheat producers the contribution is near 0%. Density is estimated using a Gaussian kernel with bandwidth selection performed with biased cross-validation. (**C**, and **D**) Contributions of emission sources for example producers with below median GHG emissions.

To explore this further, we use sensitivity analysis (Song et al., 2016) to decompose the variance in each product's impact into its sources. Numerous sources contribute to variance (fig. S10). Most notably, for all crop calorie production globally, differences in fallow duration and multiple cropping drive 40% of the variance in land use. This is important as most strategies to increase productivity are focused on increasing single crop yields (Q. Yu et al., 2017). But for many producers, increasing cropping intensity through the use of early-maturing varieties, intercropping, catch crops, and enhanced irrigation can provide more economically viable and trade-off–free ways to boost productivity and reduce impacts (Q. Yu et al., 2017).

Geography plays a major role in this variation and affects the economic and environmental desirability of different practices (German et al., 2017). However, at the heart of agriculture is changing site conditions to enhance productivity (such as liming, terracing, or installing drainage), meaning that statements on the importance of geography have limitations. Nevertheless, some impact sources stand out. We find that freshwater aquaculture ponds create 0-450g of methane per kg of liveweight (for context, enteric fermentation in dairy cows creates ~30-400g per kg of liveweight). Of this variation, a third is explained by temperature (supplementary materials for Chapter 2), which accelerates methanogenesis and net primary production. Improving aeration and limiting addition of surplus feed to ponds can abate these emissions, particularly important in warm countries. Further, for every kilogram of nitrogen applied to crops, between 60-400g is lost in reactive forms. Of this wide range, ~40% is explained by site conditions, including soil pH, temperature, and drainage (supplementary materials for Chapter 2). Prior research has also found that the potential of soil to store carbon varies significantly with soil properties, slope, and prior practice (Lal, 2018).

Providing producers with multiple ways to reduce their environmental impacts recognises the variability in sources and drivers of impact but requires a step change in thinking: that practices such as conservation agriculture or organic farming are not environmental solutions in themselves but options that producers choose from to achieve environmental targets.

However, some practice changes can be pursued across all producers. Methane from flooded rice, enteric methane from ruminants, and concentrate feed for pigs and poultry are sizeable globally, representing 30% of food's GHG emissions; are material for all producers, contributing at least 17% of farm-stage emissions (Figure 2.2B and fig. S7); and can be mitigated with relatively trade-off–free approaches such as shorter and shallower rice flooding (Smith et al., 2007), improving degraded pasture (fig. S6), and improving lifetime animal productivity (Gerber et al., 2013). Further, emissions from deforestation and cultivated organic soils drive on average 42% of the variance in each product's agricultural GHG emissions (fig. S10) and dominate the highest-impact producers' emissions (fig. S11), further justifying ongoing efforts to curb forest loss and limit cultivation on peatlands.

2.5.4. Communicate impacts up the supply-chain

Processors, distributors, and retailers can substantially reduce their own impacts. For any product, 90th-percentile post-farm emissions are 2-140 times larger than 10th-percentile emissions, indicating large mitigation potential (fig. S12). For example, returnable stainless-steel kegs create just 20g of CO_2eq per litre of beer, but recycled glass bottles create 300-750g of CO_2eq, and bottles sent to landfills create 450-2500g of CO_2eq.

Processing, more durable packaging, and greater usage of coproducts can also reduce food waste. For example, wastage of processed fruit and vegetables is ~14% lower than that of fresh fruit and vegetables, and wastage of processed fish and seafood is ~8% lower (Gustavsson et al., 2013). Providing processors and retailers with information about the impacts of their providers could encourage them to reduce waste where it matters most. For products such as beef, distribution and retail losses contribute 12-15% of emissions (fig. S13), whereas the sum of emissions from packaging, transport, and retail contributes just 1-9%. Here, reducing losses is a clear priority.

As a third strategy, procurement could source from low-impact farms. Although this strategy is important, and possible only with information about the impacts of providers, it has clear limitations. To be effective, it relies on high-impact production not simply being purchased elsewhere in the market. The case of the Roundtable on Sustainable Palm Oil (RSPO) shows that this is hard to achieve: despite one-fifth of 2017 palm oil production being certified, there remains virtually no demand in China, India, and Indonesia (Waldman & Kerr, 2014). Alternatively, this strategy would be effective if higher prices for sustainable production incentivised low-impact producers to increase output or high-impact producers to change practices. The case of organic food shows how passing premiums to consumers limits total market size and widespread practice change.

However, processors and retailers routinely demand that products meet taste, quality, and food safety standards. These markets are concentrated, with just 10 retailers representing 52% of U.S. grocery sales and 15% of global sales (*Euromonitor*, 2018). This sometimes means that standards achieve market transformation (Nepstad et al., 2013), where virtually all producers adhere to gain market access. A fourth strategy for producers is setting environmental standards. These are particularly important: Although many environmental issues can be monitored and mitigated in a flexible way, issues such as harmful pesticide usage and deforestation require strict controls, and issues such as on-farm biodiversity are hard to quantify (German et al., 2017). Procurement, farming organisations, and international policy-makers must come together to implement a safety net for global agriculture—comprehensive standards to manage the worst and hardest-to-quantify environmental issues, extending the successes of existing schemes and enabling a flexible mitigation approach to operate effectively. This idea is developed further in Chapter 4, section 4.2.3.

2.6. Producer mitigation limits and the role of consumers

Though producers are a vital part of the solution, their ability to reduce environmental impacts is limited. These limits can mean that a product has higher impacts than another nutritionally equivalent product, however it is produced.

In particular, the impacts of animal products can markedly exceed those of vegetable substitutes (Figure 2.1). To such a degree that meat, aquaculture, eggs, and dairy use ~83% of the world's farmland and contribute 56-58% of food's different emissions, despite providing only 37% of our protein and 18% of our calories. Can animal products be produced with sufficiently low impacts to redress this vast imbalance? Or will reducing animal product consumption deliver greater environmental benefits?

We find that the impacts of the lowest-impact animal products exceed average impacts of substitute vegetable proteins across GHG emissions, eutrophication, acidification (excluding nuts), and frequently land use (Figure 2.1 and data S2). These stark differences are not apparent in any product groups except protein-rich products and milk.

Although tree crops can temporarily sequester carbon and reduce nutrient leaching, the impact of nuts is dominated by low-yielding cashews and water-, fertilizer-, and pesticide-intensive almonds. Production of nuts doubled between 2000 and 2015 (*FAOSTAT*, 2021), and more work is required to improve their resource use efficiency. Although aquaculture can have low land requirements, in part by converting by-products into edible protein, the lowest-impact aquaculture systems still exceed emissions of vegetable proteins. This challenges recommendations to expand aquaculture (Godfray et al., 2010) without major innovation in production practices first. Further, though ruminants convert ~2.7 billion metric tons of grass dry matter, of which 65% grows on land unsuitable for crops (Mottet et al., 2017), into human-edible protein each year, the environmental impacts of this conversion are immense under any production method practiced today.

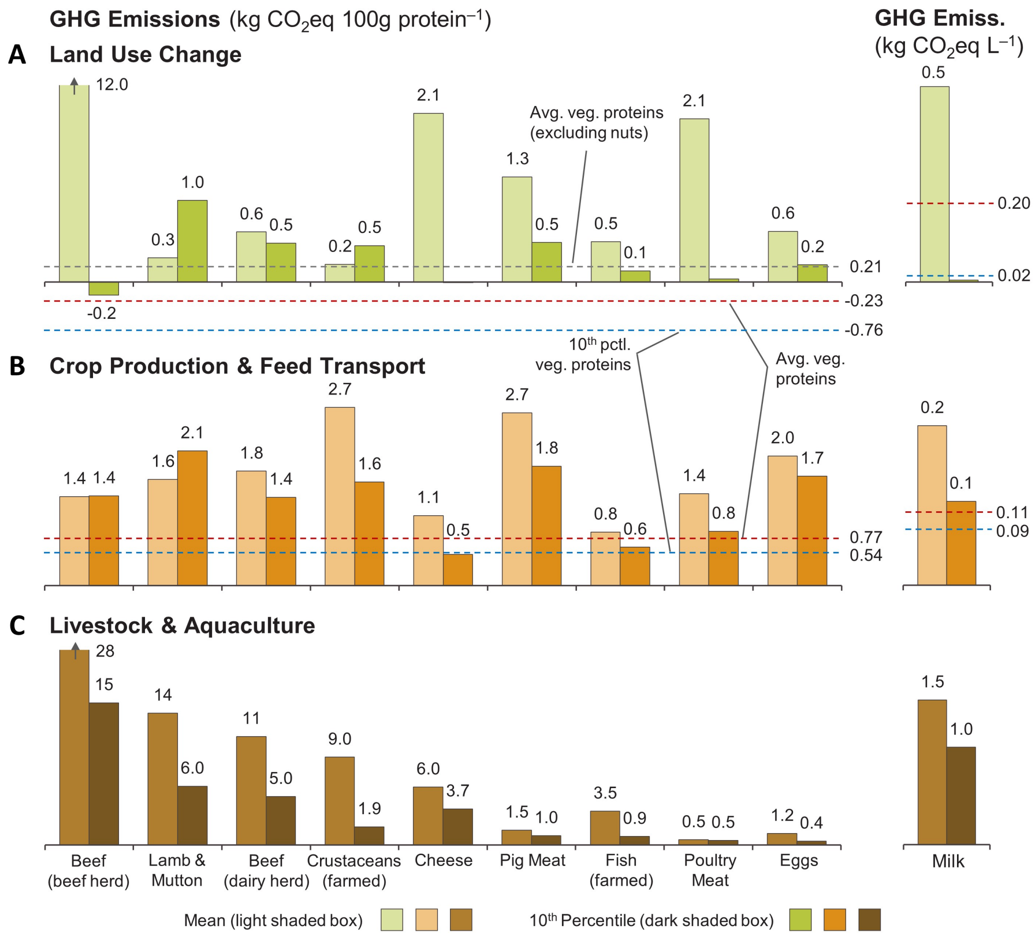


Figure 2.3. Mean and 10th percentile GHG emissions of protein-rich products across three major production stages. Red lines represent average vegetable protein emissions, and blue lines represent 10th-percentile emissions. The grey line represents average emissions excluding nuts, which can temporarily sequester carbon if grown on cropland or pasture. To calculate 10th-percentile emissions by stage, we averaged across farms that have total emissions between the 5th and 15th percentiles, controlling for burden shifting between stages.

Using GHG emissions (Figure 2.3), we identified five primarily biophysical reasons for these results. These reasons suggest that the differences between animal and vegetable proteins will hold into the future unless major technological changes disproportionately target animal products. First, emissions from feed production typically exceed emissions of vegetable protein farming. This is because feed-to-edible protein conversion ratios are greater than 2 for most animals (Mottet et al., 2017; Tilman & Clark, 2014); because high usage of low-impact by-products is typically offset by low digestibility and growth; and because additional transport is required to take feed to livestock. Second, we find that deforestation for agriculture is dominated (67%) by feed, particularly soy, maize, and pasture, resulting in losses of above- and below-ground carbon. Improved pasture management can temporarily sequester carbon (Smith et al., 2014), but it reduces life-cycle ruminant emissions by a maximum of 22%, with greater sequestration requiring more land. Third, animals create additional emissions from enteric fermentation, manure, and aquaculture ponds. For these emissions alone, 10th-percentile values are 0.4-15kg of CO_2eq per 100g of protein. Fourth, emissions from processing, particularly emissions from slaughterhouse effluent, add a further 0.3-1.1kg of CO_2eq, which is greater than processing emissions for most other products. Last, wastage is high for fresh animal products, which are prone to spoilage.

2.7. Mitigation through consumers

Today, and probably into the future, dietary change can deliver environmental benefits on a scale not achievable by producers. Moving from current diets to a diet that excludes animal products (table S15) (Springmann, Mason-D’Croz, et al., 2016) has transformative potential, reducing food’s land use by 3.1 (2.8-3.3) billion hectares (a 76% reduction), including a 19% reduction in arable land; food’s GHG emissions by 6.6 (5.5-7.4) billion metric tons of CO_2eq (a 49% reduction); acidification by 50% (45-54%); eutrophication by 49% (37-56%); and scarcity-weighted freshwater withdrawals by 19% (−5 to 32%) for a 2010 reference year. The ranges are based on producing new vegetable proteins with impacts between the 10th- and 90th-percentile impacts of existing production. In addition to the reduction in food’s annual GHG emissions, the land no longer required for food production could remove ~8.1 billion metric tons of CO_2eq from the atmosphere each year over 100 years as natural vegetation re-establishes and soil carbon re-accumulates, based on simulations conducted in the IMAGE integrated assessment model. For the United States, where per capita meat consumption is three times the global average, dietary change has the potential for a far greater effect on food's different emissions, reducing them by 61-73%. See supplementary text (supplementary materials for Chapter 2) for diet compositions and sensitivity analyses and fig. S14 for alternative scenarios.

Consumers can play another important role by avoiding high-impact producers. We consider a second scenario where consumption of each animal product is halved by replacing production with above-median GHG emissions with vegetable equivalents. This achieves 71% of the previous scenario's GHG reduction (a reduction of ~10.4 billion metric tons of CO_2eq per year, including atmospheric CO_2 removal by regrowing vegetation) and 67, 64, and 55% of the land use, acidification, and eutrophication reductions. Further, lowering consumption of more discretionary products (oils, sugar, alcohol, and stimulants) by 20% by avoiding production with the highest land use reduces the land use of these products by 39% on average. For emissions, the reductions are 31 to 46%, and for scarcity-weighted freshwater withdrawals, 87%.

Communicating average product impacts to consumers enables dietary change and should be pursued. Though dietary change is realistic for any individual, widespread behavioural change will be hard to achieve in the narrow timeframe remaining to limit global warming and prevent further, irreversible biodiversity loss. Communicating producer impacts allows access to the second scenario, which multiplies the effects of smaller consumer changes.

2.8. An integrated mitigation framework

In Figure 2.4 we illustrate a potential framework implied by our findings, prior research, and emerging policy (Recommendation 2013/179/EU on the Use of Common Methods to Measure and Communicate the Life Cycle Environmental Performance of Products and Organisations, 2013). First, producers would monitor their impacts using digital tools (Denef et al., 2012). Data would be validated against known ranges for each value (e.g., maximum yields given inputs) and validated or certified independently. In the United States these tools have already been integrated with existing farm software in Africa and South Asia they are being trailed with 2G mobile phones (GSMA, 2017); and in China they have been operated by extension services with extremely successful results (Cui et al., 2018).

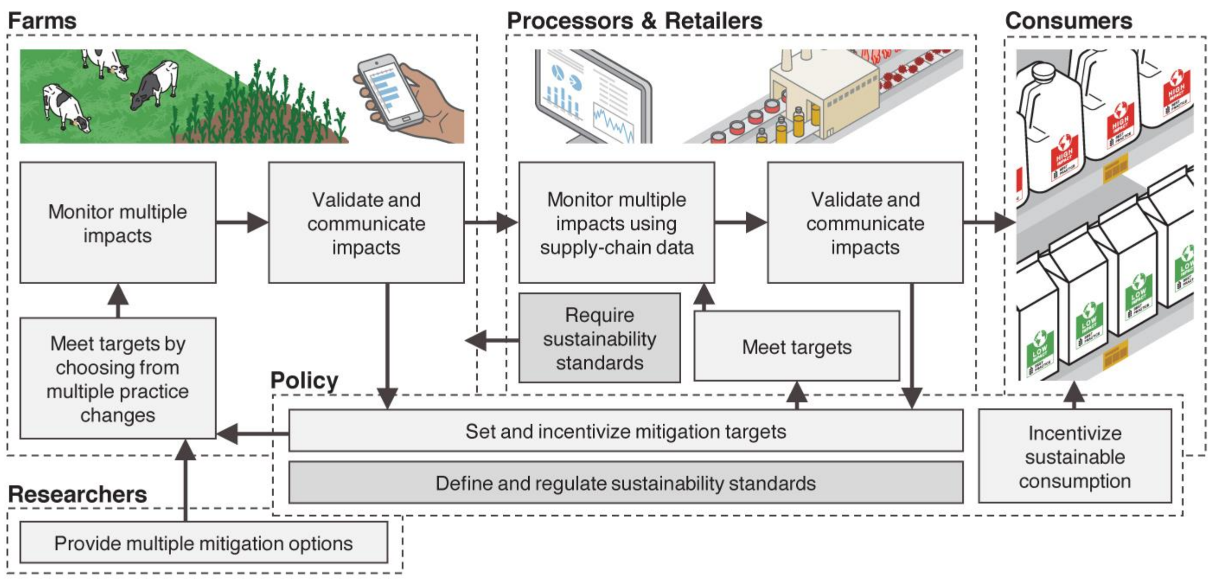


Figure 2.4. Graphical representation of the mitigation framework.

Second, policy-makers would set targets on environmental indicators and incentivise them by providing producers with credit or tax breaks or by reallocating agricultural subsidies that now exceed half a trillion dollars a year worldwide (OECD, 2017). Other targets for the food system are discussed in Chapter 5, section 5.2. Third, the assessment tools would provide multiple mitigation and productivity enhancement options to producers. Ideally these tools would become platforms that consolidate the vast amounts of research conducted by scientists around the world, while also sharing producer best practices. In particular, practice sharing offers a very effective way to engage producers (Cui et al., 2018). Maximum flexibility also ensures least-cost mitigation (Segerson, 2013) and supports producer-led innovation (Cui et al., 2018).

Finally, impacts would be communicated up the supply chain and through to consumers. For commodity crops that are hard to trace (Waldman & Kerr, 2014), this may not be feasible and mitigation efforts may have to focus on producers. For animal products, stringent traceability is already required in many countries (*40*), suggesting that communicating impacts is most feasible where it matters the most. Communication could occur through a combination of environmental labels, taxes or subsidies designed to reflect environmental costs in product prices (Springmann, Mason-D'Croz, et al., 2016), and broader education on the true cost of food.

We have consolidated information on the practices and impacts of a wide range of producers. From this research, we have provided a unified exposition of the environmental science for making major changes to the food system. We hope this stimulates progress in this crucially important area.

DATA AND MATERIALS AVAILABILITY

A Microsoft Excel file allowing full replication of this analysis, containing all original and recalculated data, has been deposited on the Oxford University Research Archive (doi.org/10.5287/bodleian:0z9MYbMyZ).

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Chapter 3: HESTIA: A harmonised way to represent, share, and analyse agri-environmental data

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Abstract: Enabling farmers and food processors to measure their environmental impacts and productivity and communicate this information up supply chains and to researchers would support improvements in agricultural productivity and sustainability. Here we present a consistent and unambiguous format to represent agri-environmental data describing specific farms and food supply chains. Using test datasets, we show that our format can represent data describing diverse producers and preserve high levels of detail from the original sources. We also describe a software toolkit that automatically validates, augments, and calculates environmental impact indicators from these data. Finally, we present an open-access data platform (https://hestia.earth) which currently stores data from over 250 public sources in this format. We use a survey of 935 maize-pigeon pea farms to demonstrate the process. This work creates a new resource for researchers and builds part of the digital foundations for more sustainable food supply chains.

3.1. Introduction

Large amounts of data describing the productivity and environmental sustainability of farms, food products, production practices, and new technologies are created each year. These data are of critical importance for understanding and improving food security and environmental sustainability. However, these data are currently stored in different databases and documents, mostly with different fields, different definitions of those fields, different units, different minimum data requirements, and different degrees of validation. Using and sharing this information is therefore difficult, time consuming, and prone to error. For example, meta-analyses in agriculture document substantial challenges in accessing and re-using data (supplementary materials for Chapter 2) (Pittelkow et al., 2014; Seufert et al., 2012). A filetype that was sufficiently flexible to represent the diversity of agriculture and its environmental issues, while also being rigid enough to ensure the same data are represented consistently, could help improve data sharing in agri-environmental research and in agricultural supply chains.

Here we focus on data from three major sources due to their similarities, the benefits of data exchange within and between these areas, and the limited work on standardisation in these areas to date. They are: farm surveys; experimental field trials; and Life Cycle Assessments (LCA) related to food and agriculture. At their core, they store similar data on inputs, outputs, and production practices. Farm survey data often includes more economic data around input and product prices. Experimental field trial data are typically more detailed and include more soil and climate measurements and measured emissions data. LCA data use a range of inputs (such as survey data, national statistics, and field trial data) and then from model outputs, adds estimated emissions (e.g., CO_2), resource uses (e.g., water), and environmental impact indicators (e.g., global warming potential, measured in CO_2 equivalents), and also includes the environmental impacts from other supply-chain stages.

Standardising and making these data more accessible could enable scientific advances within these areas, greater interdisciplinary research between them, and support on-the-ground improvements in sustainability and productivity. For example:

- A pool of harmonised farm-specific survey data could thoroughly describe global farming practices, enabling more precise and relevant research.
- A pool of harmonised LCA data could provide rich detail on the environmental impacts of supply chains, uncovering problems and opportunities, and helping target research.
- A pool of harmonised experimental field trial data could help direct new research, uncover new trends, and make it easier to build models using these data (e.g., the IPCC (Intergovernmental Panel on Climate Change, 2006) builds many of their emissions models from experimental field trial data).
- Comparing field trial data to farm surveys gives can give metrics like the "yield gap" (which is sometimes defined as the difference between yields under experimental conditions and typical farmer conditions (Sadras et al., 2015)), and harmonised data would make it easier to generate these metrics and analyse their drivers.
- Building models from experimental data using the same definitions of each data field would make the model easier to use in subsequent LCAs (or other modelling applications).
- If digital tools which automatically conduct environmental assessments (such as the Cool Farm Tool (Hillier et al., 2011) or Field to Market (Field to Market, 2022)) used a consistent data format, they could more easily benchmark farmer data against survey or experimental data.
- A standardised format could help farmers and food processors report their GHG emissions (reporting GHGs is becoming increasingly common in many countries), and

standardisation could help make it clear why different methodologies for calculating environmental impacts can give dramatically different results (fig. S16).

We did not focus on some data areas because the data representation, storage, and usage requirements are very different from the areas we did focus on. Specifically, we did not focus on representing data flowing from farm equipment because frameworks like AgGateway ADAPT (AgGateway, 2022), agrirouter (DKE-Data, 2022), JoinData (*JoinData*, 2022), api-agro, and DataLinker (Rezare Systems, 2022) have already made substantial progress here. We did not include data structures for farm task management and advisor recommendation, as these are covered by ADAPT among other frameworks. We also did not focus on satellite or other geospatial datasets of agricultural inputs, practices, and outputs, as typical applications require ways to store raster and vector data which are optimised to minimise computer memory requirements, and there has already been substantial progress in harmonising these datasets (e.g., that driven by the Open Geospatial Data Consortium).

3.1.1. Existing work on data harmonisation in our three focus areas

To date, harmonisation of farm survey data has focused on national and regional level parameters of interest (such as national crop yields) (FAO, 2005). However relatively little harmonisation has been undertaken on data describing farm-specific management practices (such as crop rotations). For example, while the FAO publish much survey data on their Microdata website describing specific farms (FAO, 2021b), the data fields used by these surveys are not typically comparable and the levels of data validation are very different. Further, some survey datasets impute missing values (e.g., replacing outliers with the median during data cleaning), and imputed data can negatively affect the performance of statistical models using these data (Sterne et al., 2009), yet there is often a lack of information about which data points were imputed.

Harmonisation of field trial data has focused on specific research topics and has yet to be generalised. Much field trial data are currently stored in journal articles and their supplementary materials, reports, and unstructured data libraries such as GARDIAN (CGIAR, 2022c) and the Ag Data Commons (USDA, 2022a). There is ongoing work to rename data fields in the datasets stored in unstructured libraries using controlled vocabularies (e.g., the Agronomy Ontology (CGIAR, 2022a), the Crop Ontology (CGIAR, 2022b)), and then automatically convert them into a consistent format (AgMIP, 2022). However, existing converters are focused on crops only, not all fields in the datasets have corresponding terms in the ontologies meaning conversion is partial, and there is currently no data validation. Some methodologically harmonised platforms for field trial data exist, but they also remain focused on certain areas, for example The Global Yield Gap Atlas (University of Nebraska & Wageningen, 2022) consolidates experimental crop yield data and selected yield covariates only, AgEvidence (Atwood & Wood, 2020) consolidates yields and soil measurements data focused on conservation agriculture in the US, and the Global N2O Dashboard consolidates experimentally measured N_2O emissions data (CGIAR, 2022d). Quantitative meta-analyses also consolidate and harmonise field trial data, but they are typically static outputs and are focused on answering a specific question. Other harmonised datasets come from specific field stations in specific geographies, such as the e-RA Archive from the Rothamsted field stations in the UK (Rothamsted, 2022) or the LTAR archive from long-term research stations across the USA (USDA, 2022c).

Harmonisation of LCA data is receiving growing attention, but LCA data specific to agriculture and food remains relatively unstructured. There are three major filetypes for storing LCA data: ILCD (European Commission, 2022; Wolf et al., 2012), ecoSpold2 (Ecoinvent, 2022), and OpenLCA (openLCA, 2022). While these filetypes are well suited for life cycle inventory data (an inventory is the emissions created and resources used to produce a certain quantity of a product), they are not well suited for storing activity data (which are all the data required to create the inventory using models, such as data on soil, climate, inputs, products, and practices). Activity data are therefore often stored in separate unlinked files or databases which makes remodelling and validation difficult or impossible. Further, activity data often comes from a mixture of sources, including farm surveys, field trials, previous LCAs, or global datasets, yet it is often difficult to understand the source of each data point. There has also been standardisation of LCA methods (in particular ISO 14044: 2020, ISO 14042:2000, PAS 2050:2011, and the EU's Product Environmental Footprint category rules), however they do little to standardise how data are represented (Heijungs et al., 2021). There are also repositories of LCA data, including the Federal LCA Commons (USDA, 2022b), Global LCA Data Access Network (United Nations Environment Programme (UNEP), 2021), and the Life Cycle Data Network (European Commission, 2021), but files in these repositories do not share a common vocabulary. Large LCA datasets have been generated by single providers (e.g., ecoinvent (Wernet et al., 2016), GLEAM (FAO, 2010a), and AgriBalyse (Colomb et al., 2014)), but each dataset uses different data structures, vocabularies, and methods; while they are internally consistent, they are difficult to compare between.

3.1.2. Chapter overview

Here we attempt to solve some of the issues around agri-environmental data interoperability and data exchange. Firstly, we describe a way to represent data from farm surveys, experimental field trials, and LCAs in a flexible yet unambiguous way. To support users, we document five examples of converting data into this format, and with these examples, we show that our data structure can capture virtually all of the data from the original sources. Next, we describe the https://hestia.earth platform which allows data in this file format to be uploaded, validated, downloaded, and shared. We then describe software for augmenting data in this format using geospatial datasets and other sources, and for performing LCAs on these data.

Finally, we describe an application of the entire process by uploading a survey of 935 maize-pigeon pea farms in Myanmar to the https://hestia.earth platform and describe the results of the automatically conducted comparative LCA of these farms that is performed by the platform.

3.2. A standardised format to represent agri-environmental data from three data areas

A key design choice was to split the data structure into a schema and Glossary of Terms. The schema defines data fields which are common to virtually all datasets and defines the overall structure of the data. The Glossary of Terms (controlled vocabulary) contains tens of thousands of possible names for items in the agri-food system and these terms are only used as needed (e.g., to define the name of an Input such as urea fertilizer). The schema is compact and more stable, whereas new terms can be added easily to the Glossary making it more dynamic and flexible.

We created an initial version of the schema based on the OpenLCA schema and an initial version of the Glossary primarily based on FAOSTAT terms, and then used five test/training datasets to refine and develop the schema and glossary. We document the conversion process for these five datasets from their native format into the HESTIA format and document how validation issues were resolved (see supplementary text). We also provide stable links to the uploaded files and to their location on the HESTIA platform. The five test datasets are a mixture of new datasets and existing datasets; and include a survey of 935 maize-pigeon pea farms in Myanmar (Food Security Policy Project, 2020); a meta-analysis of 559 nitrate leaching experiments from 91 studies (supplementary materials of Chapter 2); a nitrogen leaching experiment with monthly time series of measurements (Engström et al., 2011); an environmental LCA of trout, tilapia, and tambaqui systems in Peru (Avadí et al., 2015); and an environmental LCA and inventory analysis of vegetable oil crushing and refining plants across Europe (Schneider & Finkbeiner, 2013). Through this process, we were able to represent all of the data reported in the studies on their Inputs, Outputs, Practices, Emissions, and environmental impacts. This demonstrates that, based on these test datasets, the data format presented here is capable of representing data from different producers and from different sources. A critical next step is to test the data format using unseen validation datasets, but we leave this to future work.

3.2.1. Schema

Within the schema, data are organised into different nodes (Figure 3.1). Nodes are then linked using an identifier (`@id`). Many datasets duplicate the same data (e.g., data on the same plot is often duplicated for each treatment occurring on that plot). Splitting data into unique nodes allows the same data to be re-used without duplication making it easier to validate data, manage linkages between datasets, and update values. For example, data describing a field for growing crops could be reused by each cropping cycle that occurs on that field.

Each node can contain meta-data and holders for further data called blank nodes. The structure of each node is defined by the Schema **(**available at: https://hestia.earth/schema). The seven types of nodes are:

1. Cycles, which describe a production cycle (e.g., growing a crop or processing food). They contain blank nodes for data on Inputs, Emissions, Products, and Practices; a data Completeness assessment, which describes how complete the Inputs and Products data are; and Transformations, which describe the conversion of one Product to another in the same Cycle.
2. Sites, which describe where production took place (e.g., a field for growing crops). They contain blank nodes for data on Measurements, Infrastructure, and Practices.
3. Organisations, which describe organisations who manage Sites (e.g., a farm).
4. Impact Assessments, which describe the environmental impacts of producing one unit of a Product during a Cycle. They contain blank nodes for environmental impact Indicators.
5. Sources of data, which contain Bibliographies,

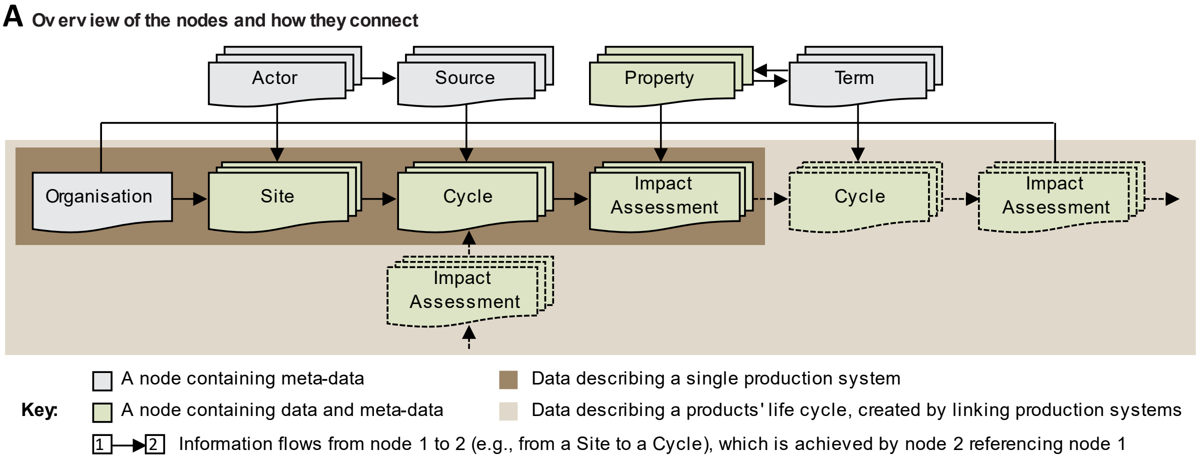
6. Actors, who upload or create data.

7. Terms, which are items from a Glossary of Terms.

One additional blank node, called a Property, describes a property of the data (such as the dry matter of a crop). Properties can be added to Inputs, Emissions, Products, Practices, and Measurements. Properties are also added to some Terms where they describe a default property of that Term (e.g., the typical dry matter of a crop), and in doing so, describe the Term itself.

We used the JSON-LD (JSON Linked Data) format to structure the data, but the JSON-LD format maps directly onto a row-column format if the user requires this. It therefore works with non-relational databases (such as stores of JSON-LD files in folders), relational databases, or row-column files such as CSV or Microsoft Excel files. In JSON-LD, each node gets its own file (e.g., `site-1.jsonld`), whereas in the row-column format each node defines the prefix of the column header (e.g., `site.description`, where `site` is the node and `description` is the field).

A key benefit of JSON is it allows substantial detail to be added to a single data point if needed, but if the data fields are not needed, no extra memory is used. For example, an Input such as pig slurry fertilizer can have a detailed application schedule of dates and amounts, its own data source which is distinct from the main Cycle, a list of Properties such as the nitrogen and phosphorus content of the slurry, and an associated Impact Assessment which would provide the environmental impacts of producing that slurry and transporting it to the field where it is applied. This level of detail is essential for fully representing our data sources yet enabling this in row-column formats is inefficient.



B An illustration of a Cycle and its blank nodes, using example data in JSON -LD format

`{"@context": "https://hestia.earth/schema/Cycle.jsonld",`	A link to a file containing links to definitions of each field.
`"@id": "vc664x8",`	A unique identifier for the Cycle.
`"@type": "Cycle",`	The type of the node (here a Cycle).
`"endDate": "1989-12-31",`	The end date.
`"startDate": "1989-06-01",`	The start date.
`"startDateDefinition": "harvest of previous crop",`	A definition of the start date (drawn from a list).
`"functionalUnit": "1 ha",`	The functional unit (what the data is expressed per).
`"site": {`	A link to the Site node that this Cycle occurred on.
`"@id": "bbscc9",`	A unique identifier for the Site.
`"@type": "Site"},`	
`"defaultSource": {`	A link to the default Source for each data item. A different source
`"@id": "s66765d",`	can be added to each Input, Emission, Product, and Practice if
`"@type": "Source",`	they are different).
`"name": "Gigou (1990)"}`	
`"dataCompleteness": {`	The data completeness assessment, stating whether all of the data
`"@type": "Completeness",`	for each type of Input and Product is present in this data file.
`"electricityFuel": false,`	
`...`	
`"pesticidesAntibiotics": true},`	
`"inputs": [`	A list of Inputs used during the Cycle.
`{"@type": "Input",`	
`"term": {`	The type of Input is defined by a Term from the Glossary of Terms.
`"@id": "CAS-34494-04-7",`	A unique identifier for the Term (here the CAS number).
`"@type": "Term",`	
`"name": "Glyphosate",`	
`"units": "g active ingredient"},`	The units are defined by the Term, and are always the same.
`"value": [400]`	The amount used which is an array e.g., for application schedules
`"impactAssessment": {"@id": "8gghha"}}`	A link to the Impact Assessment, containing data on the
`],`	environmental impacts of producing the Input.
`"emissions": [...],`	A list of Emissions created during the Cycle.
`"products": [...],`	A list of Products created during the Cycle.
`"practices": [...],`	A list of Practices used during the Cycle.
`"dataPrivate": "false"}`	Whether the data are private or not.

Figure 3.1. A graphical overview of the data structure. (**A**) An overview of the nodes and how they connect. The two-way reference between Property and Term means that the names of Properties are defined by Terms, while other Terms can have Properties which describe them (e.g., a Property can be created using the Term `Active Ingredient` and an additional Term e.g., `Glyphosate-isopropylammonium` and a value e.g., 41%; in the Glossary of Terms, this Property is added to the Pesticide brand name Term `Glyphosate 41% Super Concentrate`, which states that a herbicide contained 41% glyphosate in its isopropylamine

salt form). (**B**) An illustration of a Cycle and its blank nodes, using example data in JSON-LD format.

3.2.2. Glossary of Terms

Describing data with consistent terms makes data exchange possible and we created a searchable Glossary of Terms at https://hestia.earth/glossary. The Glossary was built from existing glossaries, and our primary goal was compliance with FAOSTAT terminology. The Glossary is open source, open to contributions (although contributions are approved by our team), free to access, released with a CC0 licence, and follows principles for scientific data sharing (Wilkinson et al., 2016).

Terms in the Glossary are given unique and meaningful identifiers to make them easy to use. In general, the identifier of a Term is simply its `name` with special characters removed and then converted into camel case. For example, the identifier for "Diesel" is `diesel`. For chemicals, the identifier is the CAS number. For regions, which are drawn from the GADM glossary (Hijmans et al., 2018), we use the GADM identifier. Terms are described with meta data, default Properties, and hyperlinks to terms in other glossaries (e.g., Feedipedia (Feedipedia et al., 2015), AGROVOC (FAO, 2021a)). The Term's data are provided in JSON-LD and on a webpage with a URL made up of "https://hestia.earth/term/" and the `@id` e.g., https://hestia.earth/term/diesel. Referring to Terms is then done in the same way that any other nodes are linked. For example `{"cycle.inputs.0.term.@id": "diesel"}` states that the diesel was an Input into the Cycle and links the Cycle to that Term. The Glossary also ensures that each `name` is unique which means that Terms can also be referred to using their `name` instead. In CSV files, the term `@id` can be included in the column header to simplify files (e.g., `cycle.diesel.value`).

The Glossary specifies the units which data must be in (e.g., diesel must be in kg). Prescribing units removes some freedom, but it makes data validation and data re-use easier and less error prone.

3.2.3. Defining whether data are complete

If a data item is not present (e.g., Glyphosate is not present in a Cycle), it could either mean it was not present in reality, or that it was present but no data were recorded. It is very important to differentiate these two situations as this affects subsequent data analysis and interpretation. To deal with this, we require a data Completeness assessment for the Inputs and Products of all Cycles. We structure the Completeness assessment using term types from the Glossary (e.g., a term type is `pesticideActiveIngredient` which includes all the pesticide active ingredient terms). For groups of Terms in the Glossary, the Completeness assessment defines whether the absence of an Input or Product means it has a value of zero or means it was not recorded. For example, if completeness is marked as `true` for `pesticideAntibiotic` but no pesticides are recorded in the Cycle, this means the value of every pesticide term defined in the Glossary is equal to zero, or that pesticides were not used.

For other nodes, differentiating no data from zero values is either not required or is not critical enough to justify a Completeness assessment. For Measurements, there is no ambiguity between missing data and zero-values, and any missing Measurement is simply missing. For Practices, a data Completeness assessment is not currently used because the range of possible practices is too large. Further, different Practices tend to manifest as different Inputs and Products for which we do have a Completeness assessment. For Emissions, Terms are defined in the HESTIA Glossary in such a way that they include both the emitted substance, where the substance was emitted to, and the source of the emission (e.g., `NH3, to air, fertilizer`). By defining emissions in this way, it minimises ambiguity in the data, and creates an implied mapping between the Inputs and Products data (for which we have a

Completeness assessment) and the Emissions. With models and a theory of how Inputs, Products, and other data create Emissions, it is possible to assess the completeness of the Emissions data, and we provide a default set of models which does this in the calculation engine which is discussed below.

3.2.4. Creating supply chains using Impact Assessments

Impact Assessments are a specific node used in LCAs. Here they are defined as representing the emissions (e.g., `NH3, to air, fertilizer`), resource uses (e.g., `Freshwater withdrawals`), and characterised impact indicators (e.g., `Scarcity weighted water use`) per unit of Product produced during a Cycle. The functional unit of the Impact Assessment is defined by the functional units of the Product (e.g., kg), and the amount is always set to one (e.g., 1 kg). This restriction simplifies subsequent calculations on the data and helps reduce ambiguity. Post processing by the user of the data can then be used to change the functional unit (e.g., from 1 kg to 100g protein) or Cycle data can be used if a 1-hectare functional unit is of interest.

To represent a supply-chain, an Impact Assessment can be linked to the Input of a Cycle (e.g., an Impact Assessment representing the manufacture of urea fertilizer could be linked to the urea Input used by a farmer). Nodes therefore follow this order: Impact Assessment(s) > Cycle > Impact Assessment(s). In manual data uploads, linking nodes like this can be time consuming, so for Emissions related to Inputs production (i.e., the Emissions created by prior Cycles) it is possible to work the other way round by adding the Emissions related to Inputs production directly to the Cycle and stating which Input(s) they are associated with (e.g., `emissions.0.inputs.0.name`). In the future, we may allow supply chains to be created without going via Impact Assessments, although the benefit of going via Impact Assessments is all the data are standardised per unit of product.

3.2.5. Data validation

We provide a free and open-source software package which provides code to validate data (described at: https://hestia.earth/docs/#validate-csv-json-files). Validators are split into hard (which identify problems which must be resolved) and soft (which identify potential problems, although these can be ignored). Examples of hard validators include: checking if coordinates are in the correct region and country; and checking that certain data items are between upper and lower bounds. Soft validators include: checking if Sites with a `siteType` of `cropland` intersect with cropland in the MODIS (Sulla-Menashe & Friedl, 2018) land cover map; checking whether crop residue is within ±25% of that estimated using the IPCC (Intergovernmental Panel on Climate Change, 2006) default model which is based on crop type and yield.

3.3. A toolkit to gap-fill data and calculate environmental impacts

We provide a library of models which augment and recalculate data (documented at: https://hestia.earth/docs). The models include geospatial gap-filling models, which add data to Sites using satellite-based or other geospatial datasets; lookup-based gap-filling models, which add data to Cycles; calculation models, which estimate emissions and resource uses; and Life Cycle Assessment (LCA) models which estimate full supply chain environmental impacts. These models are controlled by an orchestrator which determines which models to run and in what order. We provide a default set of models and a default order to run them in, but a user can add further models and change the order. The goal of the gap-filling models is to try and move each data area marked as `incomplete` in the Completeness assessment to `complete`, as well as to add Site Measurements which can improve the accuracy of Emissions models. The goal of the default calculation and LCA models is to calculate all of the sources of emissions, types of resource use, and characterised indicators which are defined in fig. S1, using the models defined in that chapter and updated using the 2019 IPCC (IPCC, 2019) and

EMEP-EEA (European Environment Agency (EEA), 2019) guidelines. The full set of models currently available are documented at https://hestia.earth/docs.

For the environmental impacts of Input production (e.g., the production of fertilizer) we have linked terms in the Glossary to processes in the ecoinvent database (Wernet et al., 2016) under an agreement with ecoinvent to use some key processes in our calculation engine.

There are often cases where multiple models calculate the same Emission or resource use, and the order to run these models is also defined by the orchestrator. The current default ordering of such models uses the IPCC system of three Tiers, which broadly categorises models by how much they account for geographic and other factors. It attempts to run the highest tier model first and if that fails because there is insufficient data (e.g., missing data on a certain Measurement needed to run the model) it moves to the less detailed and lower tiers of model. In an ideal situation, models would be organised based on their degree of fit to a reference dataset, so the models with the highest predictive power are run first, however more work is required to build such a reference dataset.

Sometimes data will already exist that one of the models could calculate (e.g., N_2O emissions from synthetic fertilizer may already be present in the Cycle), and the orchestrator also determines what to do in these situations. The default rules are that: measured Emissions are never replaced; if the model that the data was originally calculated under used a higher tier than available in the HESTIA calculation engine, the data are not replaced; otherwise, the data are recalculated using the same model as used by the Cycle and replaced if they are over ±5% different to the output from the HESTIA models. Note that all possible models have Terms in the Glossary.

This three-step process of: 1) gap-filling; 2) recalculating data that were missed to align to a consistent system boundary; and 3) replacing data that didn't match the outputs of our models; harmonises different data to substantially increase its comparability (fig. S16).

3.4. A platform for sharing agri-environmental data

3.4.1. Upload and download

We built a data platform (available at: https://hestia.earth) which enables users to upload, archive, and download data in the HESTIA format. The current platform primarily targets researchers who wish to share their data and use such data but is open to anyone who needs harmonised and validated agri-environmental data to support their work. Our main target uploaders are large institutional data holders, such as the CGIAR centres and national research organisations, and our platform has so far been developed with members of these organisations as partners.

After creating an account, users can currently upload data by using a Wizard which provides a set of interactive forms directly linked to the Schema and Glossary (Figure 3.2A) or by directly uploading a csv or Excel file which follows the Schema and Glossary. It is also possible to use a hybrid of both, where the Wizard is used to format the first rows of data, the Wizard output is exported to a csv, and the csv is completed offline. Another hybrid approach is to upload a csv into the Wizard, and finalise any edits there, before submitting.

The https://hestia.earth platform provides methods to make data upload easier. Firstly, if bibliographic data are available on Mendeley, the user only needs to upload the title or the DOI of the document rather than typing out the entire bibliography. Secondly, we automatically link to a publicly available pdf version of the article or report behind the data using Unpaywall. Thirdly, we provide convenience functions in the Wizard itself, including a unit converter, maps to draw field boundaries on, and instant Glossary validation.

Uploaded data then get validated and if validation succeeds, are stored on the platform. At validation the user receives automatically generated hard or soft error messages (Figure 3.2B). A final validation step is currently performed by the https://hestia.earth team. When validation succeeds, data are stored and nodes are assigned a new unique and permanent `@id`, which is also the IRI of the node (e.g., https://www.hestia.earth/cycle/w4ktlmhphazd) (Figure 3.2C). That page provides an overview of the uploaded data, including maps of the study location, data tables, and graphical summaries. It provides the original user upload, and a recalculated view, where the default gap-filling and calculation engine models have been run. If the data were marked as private, they will only be available to view by the person who uploaded them (this is useful, for example, if a researcher wants to embargo data before publication). Otherwise, they will be publicly accessible.

Data can be discovered using text search, map search, or filtering, and then downloaded through the website or API. Data can be downloaded as individual JSON-LD files (one for each node) or csv files containing data on all the nodes of interest. These csv files can be very data rich, containing detailed information on many thousands of data points, and we also provide ways to select and group fields of interest.

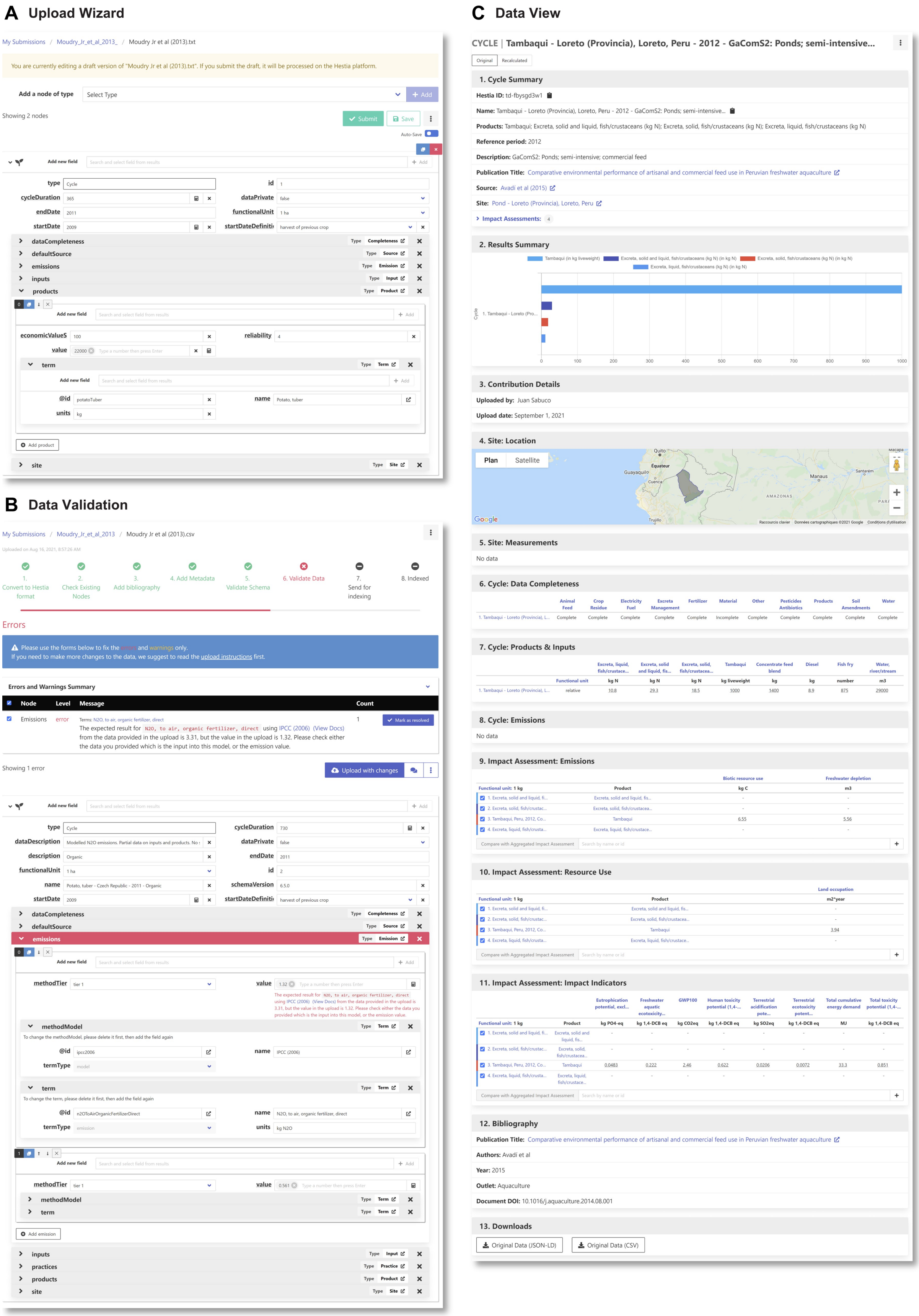

A Upload Wizard
B Data Validation
Errors
Errors and Warnings Summary
C Data View
CYCLE | Tambaqui - Loreto (Provincia), Loreto, Peru - 2012 - GaComS2: Ponds; semi-intensive...
1. Cycle Summary
2. Results Summary
3. Contribution Details
4. Site: Location
5. Site: Measurements
6. Cycle: Data Completeness
7. Cycle: Products & Inputs
8. Cycle: Emissions
9. Impact Assessment: Emissions
10. Impact Assessment: Resource Use
11. Impact Assessment: Impact Indicators
12. Bibliography
13. Downloads

Figure 3.2. Screenshots of the https://hestia.earth platform. (**A**) The upload wizard provides a set of interactive forms which are directly connected to the schema and Glossary of Terms. This supports getting data into the HESTIA format. CSV files can be uploaded and downloaded from the Wizard, and then edited offline which is useful for large uploads. (**B**) The data validation view which is shown following the upload of a file. Detailed error messages are given at each stage. (**C**) The data view on the https://hestia.earth website displays the content of the underlying JSON-LD file(s) in an interactive view, with maps, graphs, hyperlinks to the Glossary, and hyperlinks to the original article or dataset. The "Recalculated" button at the top provides the results following gap-filling and recalculation.

3.4.2. Aggregation

We also automatically aggregate data on the platform into to estimate population-level parameters of interest. We define the populations of interest as the ~600 crop and animal products in the Glossary (e.g., `Wheat, grain`) for each country. Due to insufficient data to create annual estimates, we currently specify the time period of interest as each decade for which there is data.

There are multiple expected sources of bias in the sample data (i.e., the data on the HESTIA platform), and we have designed the automatic inference process to reflect or account for these where possible. Firstly, the samples can be small or zero for many products. Further, because data remain incomplete in many areas for many Cycles (even after gap-filling and re-calculation), the sample size is different for each blank node. To recognise this, we report the sample size and sample standard deviation behind the population level estimates which would allow a user to calculate indicators of sample reliability like the standard error. Unless the data are clearly bounded, the amount of data required to support an accurate estimate of the minimum and maximum is typically very large, and we do not report these descriptive statistics.

Secondly, the sample is not random because it is primarily from research studies. Research data are often biased towards systems like organic farming of interest to researchers (Chapter 2), as well as being biased towards research stations. To handle sampling biases, we stratify the sample based on whether the Cycle is organic or conventional and (for crops only) whether it is irrigated or rainfed, which are known to be practices of agri-environmental importance (Licker et al., 2010; Seufert & Ramankutty, 2017) and for which we have independent data to estimate the strata size. Results for these strata are available for download as they are of general interest. An example would be "Wheat, grain – France – Organic, Rainfed – 2010-2019". While this stratification removes many sources of bias, meaning the observations within each strata tend towards a random sample, there remain likely sources of bias (e.g., towards other systems of research interest like no-tillage) and further work is required to identify approaches to reliably correct for these.

To understand the degree of remaining bias, we calculate indicators from the sample which we can compare to census data (i.e., near population-level data). Specifically, we compare the following to country-level data from FAOSTAT: crop yield; milk yield per cow; and liveweight per head. The same comparisons were reported for the dataset behind Chapter 2 (see Tables S10 to S11) and for the HESTIA platform, they are available on a dashboard which is updated weekly (https://www.hestia.earth/aggregation/dashboard).

3.5. Application: a large-scale LCA of maize and pigeon pea farms in Myanmar

3.5.1. Background

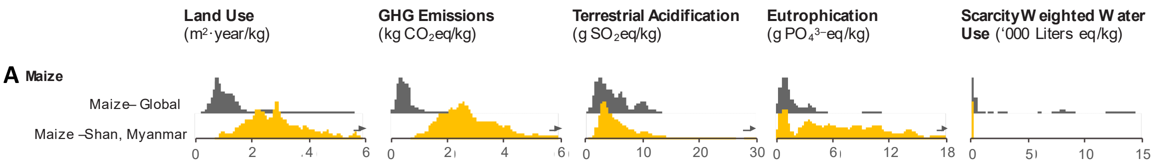
Maize is a major export crop for Myanmar. International demand is driven by animal feed production, in particular Chinese demand for chicken feed (*FAOSTAT*, 2021; Woods, 2015a, 2015b). Southern Shan is a major production region, representing around 21% of Myanmar's maize production (Aung, 2018). Hybrid maize varieties dominate (86% of households); maize is primarily grown in the monsoon season under rainfed conditions (>99% of households); maize is primarily fertilized with inorganic fertilizers (87% of households); and synthetic pesticide use is limited (25% of households) (Fang & Belton, 2020; Win & Zu, 2019). Pigeon peas are also an important export crop, mainly supplying India, however in 2018 the Indian government banned imports fundamentally changing market conditions, leading many farmers to leave the crop in the field as it was unprofitable to harvest.

3.5.2. Dataset

935 farms in the Southern Shan region of Myanmar, which cultivated maize and/or pigeon peas, often using intercropping (fig. S15), were surveyed in June-October 2018 (Food Security Policy Project, 2020). Farms were stratified by area to obtain a representative sample. Further information on the survey design, dataset, and the process of converting the original dataset into the HESTIA format are provided in the supplementary materials for Chapter 3. In the sample, 52% of plots were mono-cropped maize, 13% were mono-cropped pigeon pea, and 35% were intercropped maize-pigeon pea. An analysis of the economic and productivity aspects of these data has previously been undertaken (Fang & Belton, 2020; Win & Zu, 2019) and here we use the HESTIA platform to assess environmental and further productivity aspects.

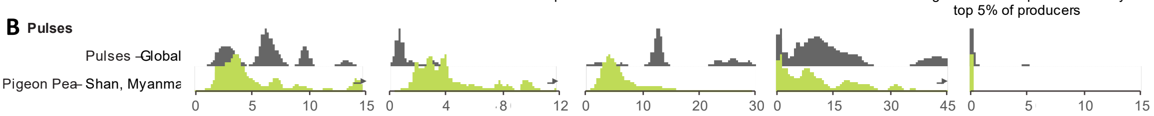
All geographic information were automatically gap filled using global datasets (supplementary materials of Chapter 2). Quantities of crop residue were also automatically gap filled using the IPCC (2019) models (which we adjusted for intercropping to avoid double counting the intercept term in these models) (IPCC, 2019), and fates of crop residue estimated based on a global dataset of crop residue fates by country and crop (supplementary materials of Chapter 2). Other emissions, resource uses, and characterised impact indicators were automatically calculated using the models described in the supplementary materials of Chapter 2.

3.5.3. Results



	Land Use Global	Land Use Shan	GHG Global	GHG Shan	Terr. Acid. Global	Terr. Acid. Shan	Eutroph. Global	Eutroph. Shan	Water Global	Water Shan
Sample size farms	6180	818	6180	818	680	818	569	818	6180	818
Mean	1.6	3.4	0.79 (0.48)	3.2 (0.50)	4.9	7.8	2.1	9.1	6000	0
Median	1.0	2.9	0.49 (0.43)	2.7 (0.37)	4.2	5.0	1.2	7.3	200	0
10th percentile	0.6	1.7	0.24 (0.24)	1.7 (0.19)	1.8	2.6	0.6	0.8	0	0
90th percentile	3.1	5.5	1.1 (0.72)	5.1 (0.88)	9.8	15.0	4.1	19	13,000	0
FisherPearson skew	4.7*	3.6*	16* (2.7*)	3.8* (1.2*)	0.86*	5.9*	2.4*	2.5*	8.8*	-
Impact of top 25% producers	57%	44%	62% (41%)	43% (52%)	47%	58%	60%	56%	46%	-

Values in parentheses exclude GHG emissions from land use change
Share of impact caused by the top 5% of producers



	Land Use Global	Land Use Shan	GHG Global	GHG Shan	Terr. Acid. Global	Terr. Acid. Shan	Eutroph. Global	Eutroph. Shan	Water Global	Water Shan
Sample size farms	115	397	115	397	100	397	95	397	115	397
Mean	6.7	11	1.1 (1.1)	11 (0.87)	16	10	14	27	19	0
Median	6.2	4.7	0.69 (0.69)	4.5 (0.44)	13	5.4	11	11	0	0
10th percentile	2.6	2.2	0.58 (0.57)	2.2 (0.20)	6.3	2.9	0.9	1.0	0	0
90th percentile	13.1	29	2.9 (2.8)	28 (1.9)	26	18	40	75	39	0
FisherPearson skew	1.4*	10.7*	1.4* (1.4*)	10* (1.4*)	0.22	19*	1.2*	14*	4.3*	-
Impact of top 25% producers	45%	69%	54% (54%)	70% (58%)	43%	64%	57%	75%	84%	-

Values in parentheses exclude GHG emissions from land use change
Share of impact caused by the top 5% of producers

Figure 3.3. Variability in the productivity and environmental impacts of maize and pigeon pea producers in the Shan region of Myanmar compared to the global distribution of producers. (**A**) Maize producers. (**B**) Pigeon pea producers compared to all pulse producers. Myanmar data are from a survey of 935 farms in the Shan region (supplementary materials for Chapter 3) and global data are from Chapter 2. For Myanmar, data are weighted based on the area-based sample weights multiplied by crop yield to generate production weights, and for the global data, observations are weighted by the estimated share of global production represented by the observation (supplementary materials for Chapter 2) and then resampled 10,000 times. Histograms represent the density of observations at different value intervals for each indicator. They are normalized and smoothed using a Gaussian kernel with bandwidth selection performed using visual inspection of the data. Heights of the distributions were rescaled for display to set the largest bin count equal to one. Black arrows indicate that >5% of the data lie outside the plot. Fisher-Pearson skews are presented and * indicates 90% confidence that the sample is not from a normal distribution based on the Shapiro-Wilk W test. For GHG

emissions, values in parentheses represent GHG emissions excluding emissions above and below ground carbon stock change related to deforestation and other land use change. All characterisation models are the same as Chapter 2.

The average land use per kilogram of marketable maize grain is 3.4 m^2·year in southern Shan, compared to 1.6 m^2·year globally (Figure 3.3). Land use is a function of crop yield, the amount of multi cropping, how long the fallow period is, the allocation to any coproducts produced (we handle this using economic allocation, and treat pigeon peas as a coproduct), and the amount of seed produced (supplementary materials for Chapter 2). Here, almost all the difference is explained by crop yields, which were 3.2 t/ha in southern Shan, compared to 5.3 t/ha globally. While there was no multi cropping in the Southern Shan sample, compared to around 20% of maize being multi-cropped globally (database behind Chapter 2), the fallow period in Southern Shan was 0.15 years for every one year cultivated, compared to 0.29 years for every one year cultivated globally. In total, the effects of less multi-cropping but also less fallow largely cancel out. When intercropped, pigeon peas generated relatively little revenue compared to maize, because they were typically planted one row of pigeon peans to four or five rows of maize, and because prices were depressed in 2018, 95% of the impacts on average went to maize. Because globally, intercropping is uncommon and maize stover is only occasionally sold, the global economic allocation was fairly similar at 92%. In summary, here, crop yields explained most of the difference in land use between maize from Southern Shan and maize produced globally.

Comparing intercropped to mono-cropped maize, yields of intercropped maize were 2.9 t/ha compared to 3.5 t/ha for mono-cropped maize (a 14% difference). However, land use was more similar, 3.5 vs 3.2 m^2·year respectively (a 9% difference). Here, the land use indicator is useful in situations where multiple crops create valuable products from the same area of land.

Interestingly, while the yield for pigeon peas is nearly ten times lower than maize (389 kg/ha on average), the land use per kilogram is only three times higher (11 m^2·year). This is because, on average across the intercropping and monocropping systems, 47% of the land area of each plot was allocated to maize. Also interestingly, the yield difference between inter-cropping and monocropping was relatively small (339 kg/ha vs 526 kg/ha respectively) given pigeon peas were sown one row of peas per four or five rows of maize. While the economic benefits of pigeon peas were low, they can be relatively productive when intercropped, generating protein rich food.

While just fifteen out of the 833 Cycles producing maize were not harvested (e.g., because the crop failed), 125 out of the 534 Cycles producing pigeon peas were not harvested due to the import ban. However, reflecting Cycles with failed harvests in the two productivity metrics used here – crop yield and land use – is currently not possible. The first methodological challenge is that, under most definitions, yield is calculated as quantity harvested divided by area harvested, rather than quantity harvested divided by area sown (FAOSTAT, 2013), and under some definitions, failed or discarded harvests are then counted as crop losses. This means crop yields only reflect successful harvests, creating a potential bias in this metric. An alternative metric that uses area sown as the denominator may be a useful compliment to the current yield metric, adding to other calls for alternative productivity metrics that account for multi-cropping and nutrition (Cassidy et al., 2013; Sadras et al., 2015). The second methodological challenge is that while land use accounts for many things that crop yield does not (such as fallow periods), it cannot be used if a harvest fails because the denominator would be zero. This highlights a key methodological challenge for the land use indicator which needs resolving, particularly because this indicator is used in many subsequent calculations in LCA methods (e.g., biodiversity loss related to land use (de Baan et al., 2013)).

Greenhouse gas emissions per kilogram of maize and pigeon pea produced in Southern Shan were four and ten times higher than the global average comparison respectively. This was entirely due to greenhouse gas emissions from land use change. Removing emissions from land use change and emissions are effectively the same or lower than the global average. In HESTIA and Chapter 2, emissions from land use change are calculated using a model which looks at the expansion of each crop at the national level and compares that to the contraction of forest and other natural land (supplementary materials of Chapter 2). While we use a national model, and more work is required to develop regionally specific land use change models, the devastating effects of deforestation for cropland are very clear in satellite photos of Southern Shan (Figure 3.4). The survey data also confirms these results, with a huge 1.9% of farms reporting that the land cover in the previous year was forest. Unlike Brazil where much deforestation occurred on relatively undisturbed forest, the deforestation in Myanmar occurred as shifting cultivation ran out of forest area to rotate into due to increased demand for maize, and more farms became tied to certain plots of land (Win & Zu, 2019).

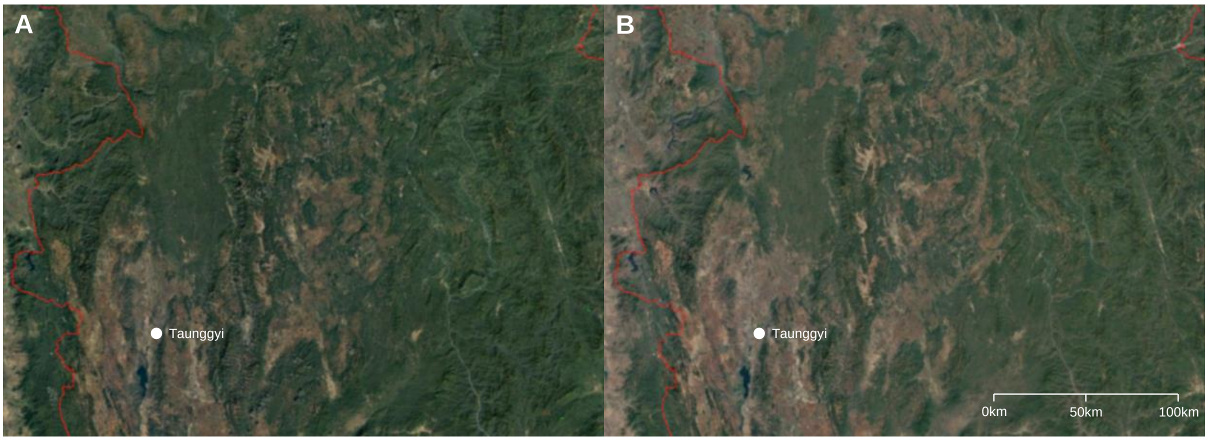


Figure 3.4. Landsat images showing forest loss in the Southern Shan region of Myanmar. (**A**) December 1984. (**B**) December 2020. Images are natural colour composites and green is forested area while brown is primarily cropland. Red lines are the boundary of the Southern Shan region and images are focused on the centre of Southern Shan.

Acidification potential per kilogram of maize was higher in Southern Shan than global, but for pigeon peas it was lower in Southern Shan. Much of the variation acidification potential is explained by the ratio of inputs to crop yield. Freshwater and marine eutrophication potential was higher in Southern Shan for both products, and the variability was also substantially higher too. Eutrophication potential is strongly affected by geographical factors, such as slope (Scherer & Pfister, 2015), and in Southern Shan, slope ranged from 5 to 13%, compared to just 0.9% for maize globally, driving much of the difference in eutrophication potential. This highlights the importance of including geographic factors in assessments of eutrophying nitrogen and phosphorus emissions from farms.

Overall, this application demonstrated the potential to automatically run the environmental modelling aspects of a Life Cycle Assessment on typical data describing farms. This could open up the potential for automated LCA modelling at the global scale.

3.6. Discussion

We have presented a data structure that can consistently represent agri-environmental data from three major data areas that can describe a very wide range of different farms, food processors, and agricultural supply chains. By splitting the data structure into a Schema and Glossary of Terms, we can quickly add new Terms to the Glossary to deal with items or practices in the agri-food system if they are not currently supported. Widespread adoption of this data format could help improve knowledge exchange between researchers, farmers, food companies, and other actors seeking to use these data.

We welcome anyone to raise new issues to improve our data format (at: https://gitlab.com/hestia-earth/hestia-schema or https://gitlab.com/hestia-earth/hestia-glossary/). Our current key development goals include:

- Integrating out data format into farm monitoring tools software through partnerships.

- Creating automatic converters from existing filetypes to the HESTIA filetype (e.g., converters from the DNDC filetype (University of New Hampshire, 2012), the OpenLCA filetype (openLCA, 2022), and the ecoSpold2 filetype (Ecoinvent, 2022));
- Adding better meta-data fields to describe experimental or sampling designs.
- Expanding the Glossary of Terms to cover antibiotics and more farm management practices.
- Creating toolkits to allow easy use of our data format in statistical software like R.

We also presented a software toolkit that automatically validates, augments, and calculates environmental impact indicators from data in this format. A key goal of this toolkit was to start making models for calculating environmental impacts more easily available; for example, it could be integrated into the accountancy or task management software that many farmers already use; or used by existing and new sustainability monitoring tools. It could also be used to power new research, for example allowing new Life Cycle Assessments to be easily and quickly conducted. Our current key development goals include:

- Packaging up our models into an easy-to-use application programming interface (API) which would remove the need for users to install and update the models and dependencies and enable real-time access to the latest Glossary of Terms.
- Add more models, for example better models to estimate historical deforestation on a particular Site or to estimate soil carbon stock changes.
- Improve the run order of the models so they are based on their predictive power over a reference dataset rather than a simple tier system.

We also presented a data platform, allowing users to freely upload and retrieve both original, recalculated, and aggregated data describing farms, agri-food processors, agri-food supply chains, and final products. The data platform has the potential to increase structured data sharing, particularly between researchers, enabling new scientific research and discovery around sustainability and productivity issues in agriculture. Our current key goals here include:

- Increasing the volume of data on our platform, particularly focusing on products and countries where we are underrepresented (e.g., we currently have a limited amount of data on cattle production systems on the platform).
- Increase the user friendliness of the platform.

DATA AND MATERIALS AVAILABILITY

All data are freely available at https://hestia.earth/. The software toolkit and additional software libraries are freely available at https://gitlab.com/hestia-earth.

ACKNOWLEDGEMENTS

The work behind Chapter 3 was funded with generous grants from WWF-UK and The Login5 Foundation. Additional grants from Worldfish, Ardevora, and Plant ETP amplified this work. We are also grateful for the data provided by ecoinvent on the environmental impacts of key agricultural inputs, to GitLab for free usage provided to academic projects, and to Google Earth Engine for free usage.

Chapter 4: Environmental impact labelling for more sustainable and productive food supply chains

J. Poore & E.J. Milner-Gulland

Abstract: Delivering a sustainable and secure food system is a global priority. However, information about the environmental impacts of food producers and products is limited today, hampering progress towards this goal. Environmental impact labelling is a concrete action to trigger the generation of environmental information in supply chains and encourage improvements in sustainability and agricultural productivity. A well-designed environmental impact labelling scheme would require farmers to monitor their environmental impacts and productivity with digital tools, and these tools could then deliver customized advice to farms. Better environmental information would enable and encourage behavior change by actors throughout the supply chain, including consumers. The information impact labelling creates could enable effective outcome-based policies. To realize its full transformational benefits, widespread adoption and international collaboration will be required.

4.1. Introduction

Environmental impact labelling (defined in Table 4.1), the schemes behind them (which include the technology and governance for measuring and communicating environmental information in supply chains), and the policies linked to the information on the labels, have substantially reduced environmental impacts and improved resource use efficiency in multiple sectors of the economy (IEA, 2021; IPCC, 2007a; The International Water Association (IWA), 2019). Energy use labelling schemes and associated minimum energy efficiency policies have been called “the cornerstone of most national energy efficiency and climate change mitigation programs” by the International Energy Agency, improving the energy efficiency of the products they target at rates two- to three-times faster than in countries or under counterfactuals without labelling (IEA, 2021). Water use labelling schemes have been successful in multiple countries (The International Water Association (IWA), 2019). For example, in Australia they reduced indoor water consumption by 13% between 2006 and 2020 compared to a counterfactual (Figure 4.1K).

Table 4.1. Types of environmental information on products. Definitions are generalized from ISO 14025, 14024, and 14021 respectively to cover more cases.

	Focus of this Review		
	Environmental Impact Labels	**Standards-Based Labels**	**Environmental Claims**
Definition	A presentation of quantified environmental information related to producing or consuming a product to enable comparisons between products fulfilling the same function.	An indication that a product has met environment-related performance criteria.	Statements, symbols, or graphics describing an environmental aspect of a product.
Examples	• 1kg CO_2eq / kg • Impact Grade A	• Rainforest Alliance • Organic	• Eco-friendly • Low water use
Key Options	• If production-related, considers the life cycle of the product and is generally calculated using Life Cycle Assessment (LCA) • Single or multi-indicator	• Considers part or the whole life cycle of the product • Criteria can be informed by LCA • Certain technologies can be precluded	• Claims can be self-declared or determined independently • Claims can be specific or vague • Claims can be verifiable or non-verifiable
Comparisons Between Products	Intended if the methods and product function are the same.	Intended, but only meaningful if the majority of products are assessed.	Generally not possible.
Improvement by Producers Reflected	Reflects improvements in environmental outcomes (although can be hindered if comparative ranking schemes are not updated).	Once the standard is met, improvement is generally not reflected.	Improvements are generally not reflected.
Global market share	~0% of food retail revenue in ~2018 (Figure 4.2).	~4% of farm-gate revenue in ~2018 (Figure 4.2).	~30-35% of food and packaged goods retail revenue in ~2015 (Lucas et al., 2021; Nielsen, 2015).

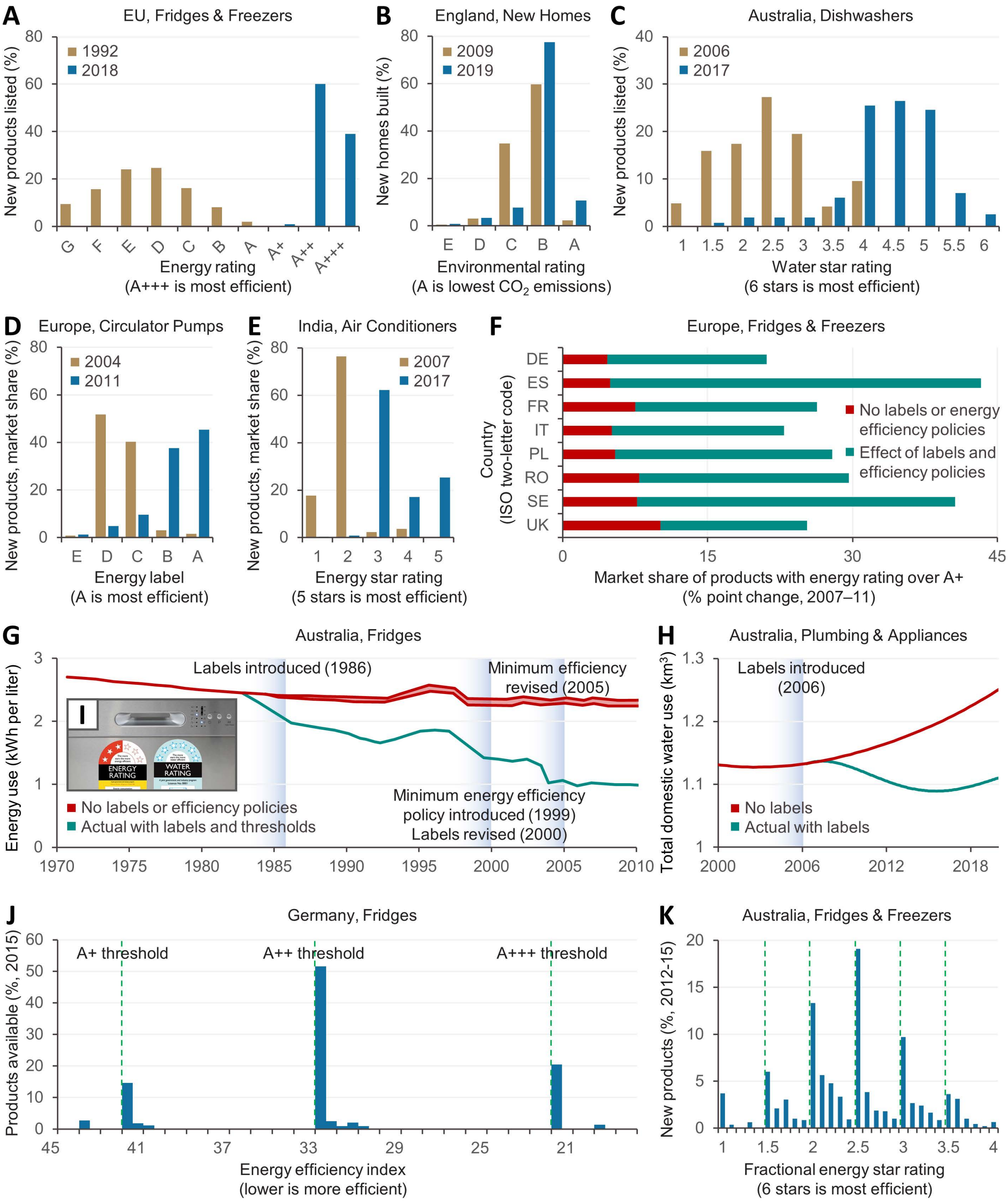


Figure 4.1. Evidence from datasets and empirical studies on the effects of energy, water, and greenhouse gas emissions labelling in non-food sectors of the economy. (**A-E**) Change in the share of new products over time by label band (Alliance for an Energy Efficient Economy (AEEE), 2015; APPLiA, 2021; Bureau of Energy Efficiency (BEE), 2021; Simon Fane et al., 2018; Ministry of Housing Communities and Local Government, 2021; Ruby, 2015). The first year is when the scheme began; the second is the last year for which data were available under

the grading rules of the first year. For example (**A**) in 1992 when fridge and freezer energy labelling began in the EU, 75% of fridges and freezers were rated G to D, while in 2018, 99% were rated A++ or A+++. (**F**) Results of a modelling study decomposing the change in the share of new products into the underlying rate of technological improvement (red) and the additional effect of energy labels and minimum energy efficiency policies (green) (Schleich et al., 2021). (**G-H**) Results from modelling studies estimating a counterfactual without energy labels and minimum energy efficiency policies (red) compared to actual data (green) (S. Fane et al., 2020; Lane & Harrington, 2010). Blue lines represent dates when labelling or minimum energy efficiency policies were introduced or revised and fading indicates that these policies were announced before introduction. (**I**) An example of multi-indicator labelling on dishwashers in Australia. (**J-K**) Distributions by energy use index or fractional star rating (Andor et al., 2020; Michel et al., 2015), showing that producers just exceed the threshold to achieve the next best rating.

The food sector causes immense environmental damage and agricultural resource use efficiency is well below potential in many regions (Foley et al., 2011; Godfray et al., 2010). In response, many environmental labelling schemes have emerged (Gulbrandsen, 2006). However, evaluations of whether the major schemes have reduced environmental impacts or increased productivity typically find insignificant effects (DeFries et al., 2017; Meemken, 2020; Oya et al., 2018; van der Ven et al., 2018), and existing labels play a minor role in consumers' food choices in the shops today (Grunert et al., 2014).

One reason for their limited effectiveness is that in food there are over 65 different labels worldwide which certify around 4% of global food revenue as environmentally sustainable using different criteria (Figure 4.2). This means there is a near-universal lack of comparable sustainability information about food. It also means that producers can choose to certify with less restrictive or less well enforced schemes, or simply not certify at all (van der Ven et al., 2018). By contrast, where labelling has been successful, a single standardized scheme covers every product in the market.

Another reason is that, in food, all the major schemes are standards-based (Figure 4.2). They communicate that a standard was met (e.g., "Rainforest Alliance Certified") rather than reporting the environmental impacts of the product (Table 4.1). Once the standard has been met, there are few incentives for continuous improvement by producers. Some standards-based schemes, including Rainforest Alliance, have recently sought to address this problem and now require a mix of mandatory and farmer-determined ongoing improvements to keep the standard, but there is no evidence yet on their effectiveness of compliance rates. Further, because standards-based labels do not label products as unsustainable, they do little to discourage unsustainable food purchasing in supply chains and unsustainable consumption. In sectors where labelling has been successful, all products report an environmental impact or resource use indicator and each product is compared against alternatives. This encourages producers to continuously improve and businesses or consumers buying products to change purchasing behaviour (Bleda & Valente, 2009).

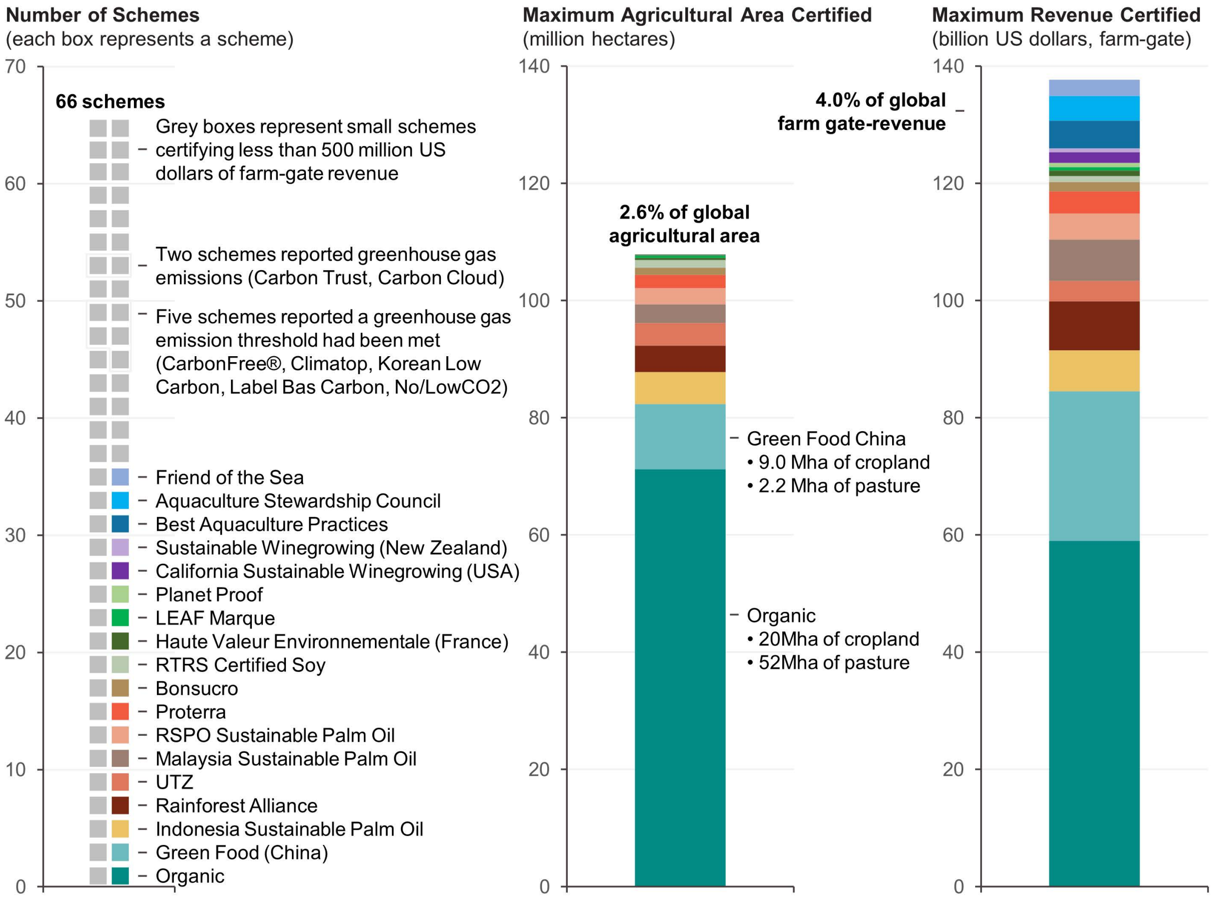


Figure 4.2. The number of existing environmental labelling schemes in food, their maximum certified area and farm-gate revenue in ~2018. Long list of existing labels from (EcoLabel Index, 2021; International Trade Centre (ITC), 2021; SAI Platform, 2021). Capture fish, textiles, and biofuels are excluded; single company schemes (e.g., Nespresso AAA) are excluded; business-to-business schemes (e.g., 4C) are excluded; schemes where environment is not the primary focus (e.g., Fairtrade) are excluded; schemes without a consumer facing logo (e.g., GlobalG.A.P.) are excluded. ~50 organic and biodynamic schemes with different certifiers/criteria are grouped into a single "organic" scheme. Certified area per country per product from (Certified California Sustainable Winegrowing, 2020; efeca, 2020; Environmental Investigation Agency (EIA), 2020; Green Food China, 2018; LEAF, 2020; C.-S. Lee & Yang, 2021; Meier et al., 2020; Ministère de l'Agriculture de l'Alimentation, 2020; New Zealand Winegrowers, 2016; *Planet Proof*, 2021; Willer et al., 2020). Multi-cropped areas are counted once. If multiple schemes certify the same area, the area is counted each time as

there is insufficient data to adjust for this (Meier et al., 2020), hence "maximum" certified area. Farm-gate revenue is calculated from certified area and country average farm-gate revenue per product per hectare (*FAOSTAT*, 2021) following (Voora et al., 2020). If certifications include animal products, farm-gate revenue is calculated from total agricultural revenue per hectare per country. Certified aquaculture volume from (Global Aquaculture Alliance, 2018; Potts et al., 2016; Roebuck & Wristen, 2018) and total aquaculture volume and revenue from (FAO, 2020). Total global agricultural area and farm-gate revenue from (*FAOSTAT*, 2021) adjusted to exclude non-food products using food's agricultural area share (Chapter 2). For the area and volume estimates, 37 schemes lacked reliable data and likely certified less than 500 million US dollars of farm-gate revenue (if these schemes in fact certified 500 million dollars each, the certified farm-gate revenue share increases to 4.5%).

It might be argued that water- and energy-efficiency labels have been successful simply because they reveal which products deliver long-term cost savings to consumers, whereas in food the benefits of purchasing more sustainable products are non-financial or external to the consumer, suggesting environmental impact labels may be less successful. However, multiple international surveys have found that environmental concerns are as important as long-term cost savings in predicting purchases of water- and energy-efficient products (Dieu-Hang et al., 2017; Gaspar & Antunes, 2011; Handa et al., 2021; Millock & Nauges, 2010). In food, studies have found consumers are willing to pay higher prices for more sustainable products (Bastounis et al., 2021), and that consumers change purchasing in response to environmental information (Potter et al., 2021).

In many non-food sectors environmental impacts are largely created during consumption, and labels therefore report expected environmental impacts and express them per unit of consumption (e.g., 95 grams of CO_2 emitted per kilometre driven). By contrast, in food, environmental impacts are almost entirely created during agricultural production and in supply chains (Crippa et al., 2021). To reflect this, an effective food environmental impact label would report the environmental impacts of production and express these impacts per unit of food produced. This means improvements can be achieved in three ways: 1) reducing environmental impacts, 2) increasing productivity (e.g., increasing crop yields), or 3) reducing food losses and waste in the supply chain (T. Garnett et al., 2013). An impact labelling scheme in food could therefore enhance productivity, food security, and waste-reduction as well as environmental sustainability. This is a critical concept that underpins the rest of this Review. Here we do not consider a label that expresses environmental impacts per hectare of land, because if environmental improvements were achieved by reducing yield, and market demand remains the same, production would occur elsewhere (called "leakage").

The potential of environmental impact labelling in food is already attracting policy and industry interest (LOI N° 2020-105 Du 10 Février 2020 Relative à La Lutte Contre Le Gaspillage et à l'économie Circulaire, 2021; Food Labelling (Environmental Sustainability) Bill, 2021). However, to date, research has focused on how these labels affect consumer behaviour (Taufique et al., 2022), missing the broader effects these schemes can have. Here we consolidate research from disparate sources on the potential effects of an environmental impact labelling scheme on the productivity and environmental sustainability of the entire food supply chain, as well as exploring the effects of policies linked to these labels. We leave analysis of the economic and social aspects to future work. We then explore choices around designing the scheme, including methodology and governance. Finally, we explore how environmental impact labelling could become widely adopted in food.

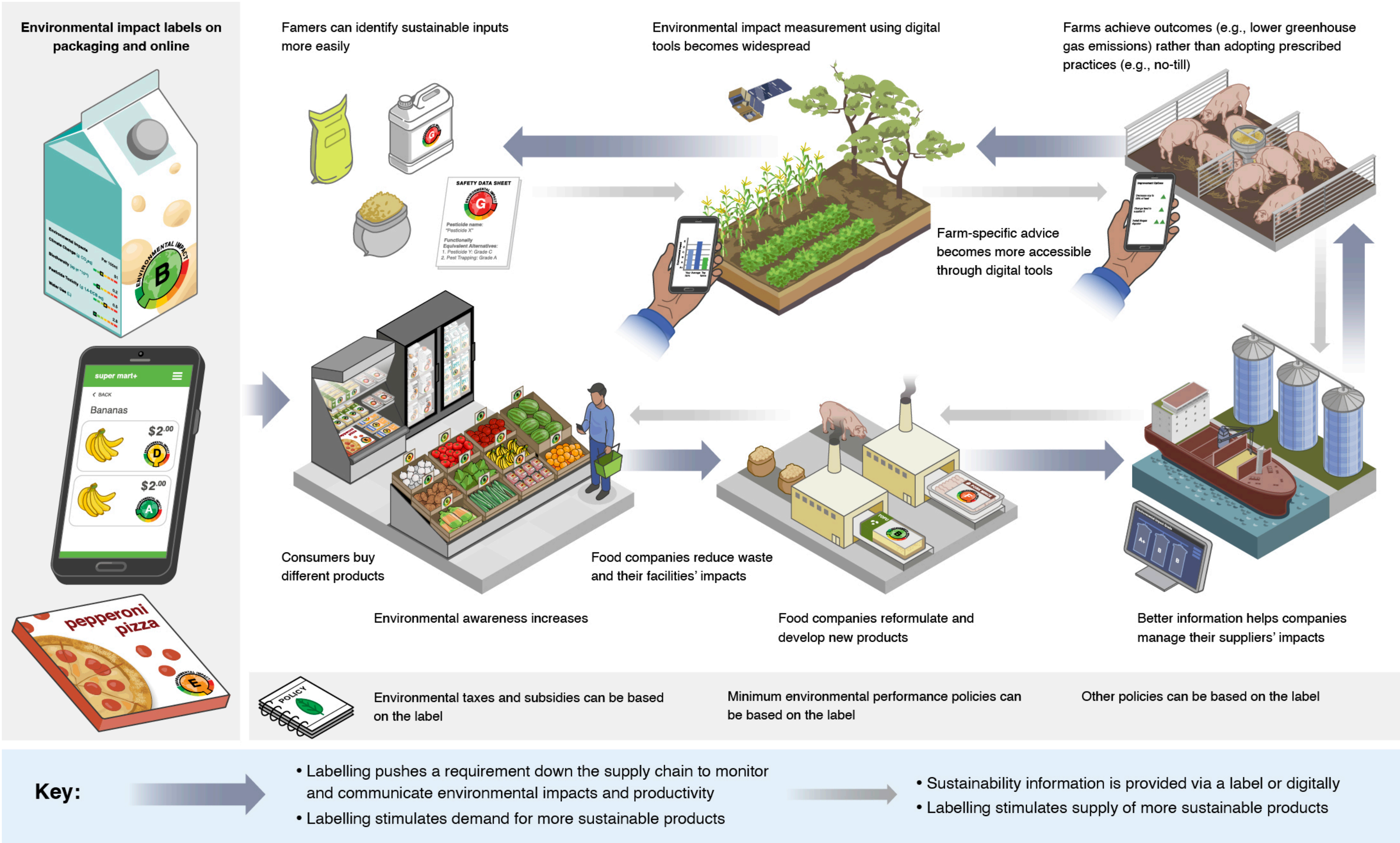


Figure 4.3. A graphical representation of the potential effects of environmental impact labelling on the food supply chain.

4.2. Effects on agriculture

4.2.1. Environmental impact measurement using digital tools becomes widespread

Today very few farms measure important environmental indicators like greenhouse gas emissions, biodiversity, or pesticide toxicity. Without measurement, these issues cannot be properly managed. A food environmental impact labelling scheme – that was both well adopted and based on farm-specific data rather than secondary data – would create a requirement for farms to measure their environmental impacts and productivity. This would help scale up environmental monitoring worldwide.

Environmental impacts can be estimated easily and cheaply using digital tools which apply models to data describing a farm's inputs, outputs, practices, soil, and climate. Examples include the Cool Farm Tool and Field to Market. These tools require a computer or smartphone with internet access, but these barriers to adoption are rapidly diminishing: in 2020, 94% of the global population could access mobile internet signal and smartphones are becoming ubiquitous worldwide; for example, smartphone use increased from 30% to 63% of adults in South Asia between just 2016 and 2020 (GSMA, 2021).

Simply measuring environmental impacts can help reduce them. Farmers can understand areas which are causing most impact, some of which might be straightforward to address. Evaluations of the Cool Farm Tool found that farmers using the tool reduced their greenhouse gas emissions per kilogram of product by 12 to 15% over one to three years (Table 4.2). Qualitative evaluations and case studies have found other monitoring tools also help reduce environmental impacts (Perez & Cole, 2020). However, evaluations using control groups and assessment periods that are sufficiently long to understand persistence are entirely lacking today, presenting a major research need. Research is also required on whether the record-keeping requirements benefit or burden farmers overall, and, if there is a burden, critical analysis is needed of whether it is justified by the improvements experienced.

Validation of the accuracy of farmer-submitted data is critical. Satellite data can detect crop types, growing seasons, irrigation, and other important factors (Karthikeyan et al., 2020), and are already used by the EU to validate subsidy returns (European Commisson, 2018). Other validation approaches include linking the digital tools to data on the purchases of pesticides and fertilizers and then requiring that the farmer accounts for their subsequent usage. However, many environmentally important practices (such as how pesticides were applied) cannot yet be automatically validated, so in-person validation will remain important in some areas until advances in automated validation reduce this cost.

4.2.2. Farm-specific advice becomes more accessible through digital tools

Because digital monitoring tools are collecting farmer data, this creates an opportunity to use these data to deliver farm-specific productivity and sustainability advice to each farm. This is important because there are different ways to manage each farm to improve outcomes (Chapter 2) (X. P. Chen et al., 2011; Vanlauwe et al., 2010) yet current advice can be generic, for example blanket fertilizer recommendations for a crop in an entire country (Arouna et al., 2021). Digital tools are also a very scalable and low-cost way to deliver advice. For example, Precision Agriculture for Development's digital tools increased their reach by one million farms in 2020 at a cost of 1.30 US dollars per farm per year (Precision Agriculture for Development, 2020). For context, the principal source of independent expert agronomic advice in many countries is extension workers, but in Latin America, in-person extension costs 44 to 2,400 dollars per farm reached per year (Davis et al., 2020), and in Africa there is just one extension worker per 550 farms (Davis et al., 2020; Lowder et al., 2016). For farmers already using digital productivity or profitability tools, an environmental impact labelling scheme would create incentives for these tools to include environmental indicators.

Evaluations in China, Nigeria, and India, lasting between one and nine years and using a control group, found that digital tools delivering farm-specific sustainability and productivity advice increased crop yield by 6.8 to 18% and reduced nitrogen use or nitrogen losses per kilogram of grain by 0.4 to 25% (Table 4.2). Depending on factors like literacy rates, advice was either delivered directly to farmers through the software or delivered via extension services or community leaders who used the software. Voice recognition could also help where literacy is low. Digital tools can provide further services to farmers, including access to training, credit, insurance, subsidies, and markets. A preliminary review in Africa found these digital services increased crop yields substantially (CTA, 2019). There is now a major research need for robust evaluations on the effects of digital sustainability and productivity advice in different countries and farming systems, and development of the fundamental software and data to provide globally scalable site-specific advice.

4.2.3. Farms achieve outcomes rather than adopting prescribed practices

Prescribed practices dominate much environmental management today. For example, standards-based labels certify that certain practices were followed, while policymakers widely promote systems of practice such as conservation agriculture (Prestele et al., 2018). In general, prescribed practices have very variable effects on different farms, with a tendency towards sustainability and productivity improvements, but frequently showing no effects and sometimes worsening outcomes (Chapter 2) (DeFries et al., 2017; Tuck et al., 2014; van der Ven et al., 2018). A major challenge is that the practices available are chosen by policymakers or other standard-setters who are unlikely to have detailed knowledge about specific farms. Further, by design, prescribed practices restrict choice in many important areas (e.g., preventing the use of synthetic fertilizer in organic farming). By contrast, environmental impact labels incentivize improvements in environmental outcomes. These outcomes can be achieved in whatever way the farmer chooses. This encourages innovation, supports farmer choice, and enables least-cost mitigation (Jaffe et al., 2002; Segerson, 2013).

Despite the increased focus on outcomes prompted by environmental impact labelling, rules and prescribed practices will remain critical for managing many issues. These include: impacts not included in the labelling scheme; problems that could be effectively managed with clearcut rules such as not burning crop residue near urban areas or ensuring appropriate animal welfare; practices that should be avoided entirely such as agricultural organochloride use; and solutions that work best at the landscape level across many producers, such as creating interconnected wildlife refuges.

Table 4.2. Potential effects of environmental impact labelling from lab and real-world interventions with farmers, supply chains, and consumers. An obelisk (†) indicates the effect is calculated relative to a control group. An asterisk (*) indicates a real-world evaluation. GHG = greenhouse gas.

	Evaluation Description	Evaluation Duration	Change in Indicator Over Period
Effects on agriculture			
Environmental impact measurement using digital tools becomes widespread	US organic egg producers measuring their GHG emissions* (Vetter et al., 2018)	3 years	• GHG emissions per kg of eggs: −15%
	Dairy farmers in 13 countries measuring their GHG emissions* (Cool Farm Alliance, 2020)	1 year	• GHG emissions per kg milk: −12%
Farm-specific advice becomes more accessible through digital tools	Nigerian rice farmers receiving site-specific advice from a digital tool* (Arouna et al., 2021)	2 years	• Yield: +6.8%† • Nitrogen use per kg grain: −5.2%†
	Nigerian maize farms receiving site-specific advice from a digital tool* (Oyinbo et al., 2022)	2 years	• Yield: +18%† • Nitrogen use per kg grain: −0.4%†
	Chinese cereal farmers receiving site-specific advice from digital tools via extension* (Cui et al., 2018)	9 years	• Yield: +11%† • GHG emissions per kg grain: −17%† • Reactive nitrogen loss per kg grain: −25%†
	Indian vegetable farmers receiving site-specific advice from a digital tool via their cooperative leader* (Rajkhowa & Qaim, 2021)	1 year	• Yield: +11%† • Nitrogen expenditure per kg grain: −4.6%† • Pesticide expenditure per kg grain: −6.5%†
Farms achieve outcomes rather than adopting prescribed practices			*No evaluations found*
Effects on supply chains			

	Evaluation Description	Evaluation Duration	Change in Indicator Over Period
Farmers can identify sustainable inputs more easily	German cereal farmers choosing pesticides with toxicity labels (Buchholz & Musshoff, 2021)	5 cycles	• Pesticide toxicity index: −6.0%† • Profits: Insignificant effect†
Better information helps companies manage their suppliers' impacts	Danish pig farms enabled by their buyer to monitor, reduce, and report their GHG emissions* (Danish Crown, 2020)	3 years	• GHG emissions per pig: −6.7%
Food companies reformulate and develop new products	Multinational company changing purchasing from high- to low-emissions products* (General Mills, 2020)	9 years	• Company-level GHG emissions: −11%
	38 caterers monitoring the GHGs of the 920 million meals they serve* (Waite et al., 2021)	3 years	• GHG emissions per meal: −16%
Food companies reduce waste and their facilities' impacts	UK companies disclosing food waste* (WRAP, 2020)	2 years	• Processing or retail food waste: −17%
	UK companies disclosing their GHG emissions* (Downar et al., 2020)	9 years	• GHG emissions: −16%† • Cost of goods sold: +9.0%†
Consumers buy different products	Online supermarket displaying multi-indicator labels (Muller et al., 2019)	1 shop	• GHG emissions per kg: −12%† • Acidifying emissions per kg: −11%† • Eutrophying emissions per kg: −18%† • Nutrition and prices: Insignificant effect†
	Online supermarket displaying GHG labels and a summary of the basket's emissions (Kanay et al., 2021)	3 shops	• GHG emissions per kg: −15%†
	Canteen displaying GHG labels (Osman et al., 2021)	1 week	• GHG emissions per meal: −9.8%†

	Evaluation Description	Evaluation Duration	Change in Indicator Over Period
	Canteen displaying GHG labels (Brunner et al., 2018)	7 weeks	• GHG emissions per meal: −3.6%†
	Canteen displaying GHG labels* (Spaargaren et al., 2013)	5 weeks	• GHG emissions per meal: −3.0%†
Consumers can buy “less and better”			*No evaluations found*
Environmental awareness increases, enabling stronger measures			*No evaluations found*
Effects of policies linked to the label			
Environmental taxes and subsidies can be based on the label	Danish 2013 pesticide toxicity tax* (Miljø-og Fødevareministeriet, 2018)	6 years	• Total toxicity of pesticide sales: −58%
	Canteen with tax (£63 per t CO_2) (Osman et al., 2021)	1 week	• GHG emissions per shop: −4.9 to −11%†
	Canteen with tax (£63 per t CO_2) returned as subsidy on low GHG foods (Osman et al., 2021)	1 week	• GHG emissions per shop: −9.4 to −15%†
	Shop with tax (£70 per t CO_2) returned as subsidy on all foods (Panzone et al., 2021)	2 weeks	• GHG emissions per shop: −21%†
Minimum environmental performance policies can be based on the label			*No evaluations found*
Other policies can be based on the label			*No evaluations found*

4.3. Effects on supply chains

4.3.1. Farmers can identify sustainable inputs more easily

Farmers purchase around 400 million metric tons of fertilizer, seed, and pesticide a year (*FAOSTAT*, 2021), but there is little comprehensible information communicated to them about the environmental impacts of these inputs. For example, Safety Data Sheets are the principal mechanism for communicating pesticide toxicity information, but they primarily provide lethal dose 50 numbers (e.g., "Oral LD50 (rat): >5,000 mg/kg") coupled with usage guidance and warnings (Rother, 2018). Simple overall toxicity scores are not provided, nor are comparisons against functionally similar pesticides and non-chemical methods. Few countries use behavioural mechanisms like colour schemes to make the information salient. Safety Data Sheets are read by just 30% of farmers in some regions (Dayanidhi et al., 2016) and for conscientious farmers, substantial research is required to make an informed choice.

Labelling agricultural inputs in a similar format to food environmental impact labelling (Figure 4.3) would help make environmental information more available, more easily understood, and more salient to farmers. For example, in a virtual farming study, traffic light toxicity labels on pesticides led farmers to reduce the overall toxicity of their pesticide use by 6.0% over five cropping cycles (Table 4.2). Famers would also need to input the toxicity and usage data into their digital monitoring tools to quantify total effects and communicate this information up the supply chain. With this information, the tools can provide advice and decision support to famers. For example, a study developed a digital tool to automatically identify alternative pesticides or doses which could reduce ecological toxicity by over ten-fold without compromising performance or increasing cost (Steingrímsdóttir et al., 2018). Similar approaches could be used for other inputs like fertilizer. For the producers of agricultural inputs, labelling also creates a standardized way to demonstrate the environmental performance of their products.

4.3.2. Better information helps companies manage their suppliers' impacts

To label final food products with their environmental impacts, intermediaries, processors, and retailers would need to collect data from the farms supplying them (Figure 4.3). Despite hundreds of food companies setting ambitious targets to reduce the environmental impacts of their supply chains (their "Scope 3" emissions), few collect data on their suppliers' environmental impacts today. We assessed the Carbon Disclosure Project submissions (CDP, 2021) and sustainability reports for the year 2019 for the top 50 global food processors by revenue and found that while 36 have set greenhouse gas emissions targets for their suppliers, just nine were collecting emissions data from the farms supplying them, with the rest primarily using global or regional average emissions datasets.

The companies which are already collecting supplier environmental impact data show this is feasible. For example, FrieslandCampina collected biodiversity impact data on nearly 100% of their member dairy farmers in 2019 (FrieslandCampina, 2019). Danish Crown collected greenhouse gas emissions data on half their pork purchases in 2020 (Danish Crown, 2020) and then used these data for their corporate sustainability reporting. Smaller food companies may currently not have enough influence over their suppliers to require environmental impact data; a labelling scheme which made on-farm data collection and communication widespread could address this.

With environmental information from their suppliers, food companies are already using multiple strategies to enable and encourage their suppliers to improve. Danish Crown provided their pork suppliers with an analysis of their sources of impact and options to improve, which was followed by a 6.8% cut in their suppliers' emissions per pig over three years (Table 4.2). Other companies disclose their strategies but not their effectiveness. For example, Kellogg's identifies their highest-impact suppliers and targets them with advice. Fonterra identifies their lowest-impact suppliers and enables them to share knowledge with other farms.

FrieslandCampina pays higher prices to suppliers with high biodiversity scores (FrieslandCampina, 2019).

4.3.3. Food companies reformulate and develop new products

Nutritional labelling has already been effective at incentivizing food processors and caterers to reformulate and launch new products (Shangguan et al., 2019; Vermote et al., 2020). Examples of reformulations which can deliver environmental benefits include blending plant-based protein into meat burgers or using plant-based milk instead of dairy milk in bakery products (Chaudhary & Tremorin, 2020). Reasons for reformulating following labelling include avoiding loss of sales from disclosing negative product attributes, minimizing the risk of future regulation, competing on the attributes highlighted by the label (Golan et al., 2007), or because individuals within companies have environmental values and respond to the new information.

While there are currently no studies to our knowledge on the effects of environmental impact labelling on reformulation and new product development, there are multiple isolated cases of food companies using and responding to environmental information. For example, General Mills delivered an 11% reduction in their greenhouse gas emissions per year over nine years primarily due to reduced purchasing of dairy and other high-emissions ingredients (Table 4.2). The World Resources Institute created a tool which calculated the greenhouse gas emissions of the ingredients used by caterers, which was followed by a 16% reduction in the greenhouse gas emissions per meal over approximately 3 years as caterers shifted from beef and dairy to vegetables and grains (Table 4.2). An environmental impact labelling scheme could help scale these effects to the level of the whole food sector and provide additional stimuli catalyzing reformulation.

To enable these changes, the information provided must allow comparisons between different but potentially substitutable commodities (e.g., beef against pulses) and not just comparisons between different producers of the same commodity. Standards-based schemes, however, only state whether a producer of a certain commodity has met some standard. RSPO goes further and actively prohibits comparison with other commodities (RSPO, 2020), stating "Members must not make claims which imply that the removal of palm oil from a product is a preferable social or environmental sustainability outcome to the use of RSPO certified sustainable palm oil" (RSPO, 2017). Environmental impact labelling schemes can generate standardized information to enable both within- and between-product comparison of functionally equivalent products, but functional equivalence is difficult to define, and we discuss key methodological choices later.

4.3.4. Food companies reduce waste and their facilities' impacts

Companies representing ~50% of UK food production now disclose their food waste, which was followed by a 17% reduction in food waste over approximately two years (Table 4.2). Also in the UK, public companies have been mandated to disclose the greenhouse gas emissions of their own facilities since 2013, which led to a 16% reduction in emissions compared to a control group over nine years (Table 4.2). It is reasonable to think similar benefits could be achieved if companies disclosed product-level environmental impacts through a label. However, when companies use different methods to disclose their impacts or can choose not to disclose, the effectiveness of disclosure is reduced and schemes can even be counter-productive (Velte et al., 2020), highlighting the importance of methodological harmonization and widespread adoption.

4.3.5. Consumers buy different products

Today, buying sustainable food is difficult and time-consuming (Young et al., 2010) and it is easy to unknowingly purchase products which cause substantial environmental harm. In a systematic review of 76 interventions, sixty found that making environmental information available to consumers increased the sustainability of food selection, purchase, and consumption (Potter et al., 2021). However, these studies considered choices between just two products on average, meaning the results of this systematic review are hard to generalize to real-world settings where consumers are choosing between many products (e.g., 1000 to 20,000 food products in a single supermarket in industrialized countries (EY et al., 2014)). Three studies tested environmental impact labels in real-world supermarkets, and all found impact labels led consumers to reduce environmental impacts, but their interventions were limited to between five and 37 products (Perino et al., 2014; Vanclay et al., 2010; Vlaeminck et al., 2014), also making these results hard to generalize.

Two more recent studies used virtual online supermarkets with enough products to represent a plausible food shop: environmental impact labels led consumers to reduce the impacts of their shop by 12 to 18% (Table 4.2). In canteens, real-world and virtual experiments have found 3.0 to 9.8% reductions in impacts (Table 4.2). The higher effect in retail over catering may be because canteens have fewer choices than supermarkets, meaning consumers are less likely to find a product that is both appealing and low environmental impact, or it may just be an artefact of the experiments. Nevertheless, these studies remain experimental and real-world testing is now needed. Longer-term evaluations will also be critical; specifically, evidence in non-food sectors has found it takes many years for consumers to fully understand and build trust in environmental impact labels (Mills & Schleich, 2010; Thøgersen, 2002).

The information created by an impact labelling scheme can also be used to help consumers make sustainable choices even more easily. For example, one study found that allowing online shoppers to filter by low emissions foods was very effective at reducing emissions (Panzone et al., 2021) while another study found that positioning low emission foods first in real canteens reduced emissions (E. E. Garnett et al., 2020).

4.3.6. Consumers can buy "less and better"

The large-scale retail and catering studies in the previous section used product average environmental impacts, and therefore incentivized changes between products (e.g., beef to chicken). Environmental impact labels can also provide information about the sustainability of different producers of the same product. With this information, consumers could both reduce consumption of a high-impact product and purchase from lower-impact suppliers of that product (what some have called "less and better" (Resare Sahlin et al., 2020)). For example, if global beef consumption was reduced by 50% by reducing consumption from the highest impact producers, and the protein deficit made up with vegetable proteins, agricultural land requirements would reduce by 1.2 billion hectares and greenhouse gas emissions by 4.0 billion metric tons of CO_2eq (Chapter 2). This is a huge 25% reduction in agricultural land and a 7% reduction in greenhouse gas emissions across all sectors of the economy. These benefits are so large because a relatively small number of high-impact producers cause a disproportionate share of the environmental harm (Chapter 2). The effects of consuming fewer discretionary products (such as chocolate), consuming less food overall, and wasting less food, could also be magnified into larger environmental benefits if consumption reductions target the highest-impact products (Chapter 2). While modelling has revealed the potential benefit, behavioural research is now needed to study the realizable benefit.

4.3.7. Environmental awareness increases, enabling stronger measures

Environmental impact labels provide sustained and consistent messaging, which builds consumer awareness. Increased environmental awareness can then increase public acceptability of stronger measures by businesses and policymakers to address environmental problems (Marteau, 2017). In a parallel example, consumer awareness of caged hen welfare increased demand for free-range eggs while free-range egg labelling (which began in the 1980s) increased consumer awareness about hen welfare, and enabled consumers to make informed choices (Scrinis et al., 2017). This growing consumer awareness made it easier for retailers and policymakers to make welfare-improving changes: starting in the 1990s many food retailers, particularly in Europe and Australia, enacted 100% free-range egg policies in their stores despite continued demand for caged eggs; and in 1999, the EU enacted regulations to ban the worst types of cage. Research has attributed this action to labelling and consumer awareness (Scrinis et al., 2017).

4.3.8. In some circumstances, labelling can have adverse effects

Environmental impact labelling might worsen the status of indicators reported on the label through unexpected effects. In non-food sectors, the cost savings created by energy labelling led some consumers to purchase more or larger products, called the "rebound effect" (Inoue & Matsumoto, 2019). In food, environmental impact labelling could lead to higher agricultural productivity, potentially reducing food prices (e.g., if producers focus on improving productivity, the denominator in the label and a powerful way to reduce impacts per unit of food, rather than on reducing environmental impact, the numerator (Lam et al., 2021)). On the other hand, investments to increase sustainability may increase food prices. No evaluation of the potential effects of impact labelling on food prices, supply, and demand has been conducted, and this is an urgent research need. There is also some evidence that after people reduce their environmental impacts in some area (e.g., food) they increase them elsewhere (e.g., travel) (Meijers et al., 2019) although it is not clear how well these studies replicate or if they apply here.

Environmental impact labelling could potentially worsen issues which are not included in the labelling scheme, particularly if these issues are already insufficiently managed by existing policies or standards. For example, in experiments, environmental impact labelling led to high-impact beef being replaced by lower-impact chicken (Brunner et al., 2018). Producing a metric ton of meat carcass requires around 610 chickens to be slaughtered compared to around 5 cows

(*FAOSTAT*, 2021) raising ethical problems. Another challenge is that some farmers may see price decreases or lose market access if their products are identified as high environmental impact, which might create social welfare problems if they cannot improve (e.g., their land is only suitable for producing high-environmental impact products like beef or if they cannot afford to adopt more sustainable practices). Food system approaches combined with modelling are required to identify stakeholders and the potential effects of impact labelling on them, creating the information to understand trade-offs between economic, social, animal welfare, food security, and environmental goals. Complimentary policies can minimize trade-offs with issues not included in the scheme, for example subsidies for research and development of lab grown meat or subsidies to diversify farm income.

4.4. Effects of policies linked to the label

4.4.1. Environmental taxes and subsidies can be based on the label

Pricing an environmental externality with a tax, subsidy, emissions trading scheme, or other financial instrument, is an important part of the policy toolkit (Hepburn et al., 2020) and has been a powerful addition to impact labelling schemes in non-food sectors. However, a lack of environmental impact information is a key reason why agriculture is currently excluded from environmental impact pricing policies (Isermeyer et al., 2019). Instead, many countries pay farmers to adopt practices thought to go beyond business-as-usual. For example, farmers in the EU were paid around 17 billion euros in 2020 for adopting various climate and biodiversity-friendly practices (Stolze et al., 2016). Problematically, there is little data on whether these payments reduced overall biodiversity losses or greenhouse gas emissions (Alliance Europe, 2019). Impact labelling schemes create information on the environmental impacts of farms, so policies can be directly linked to this information. The same information allows policies to be evaluated and adjusted.

Taxes can also be applied to final food products. Research in virtual canteens and supermarkets has found that greenhouse gas emission taxes which increased prices by 1.0 to 6.8% lead to emissions reductions of 4.9 to 21% (Table 4.2). The larger emissions reductions and lower price increases were achieved by redistributing the tax as a subsidy to other foods. Environmental information is necessary for these policies and a labelling scheme would provide this. In non-food sectors, taxes on final products have also led to substantial behaviour change by manufacturers (Mock, 2015), but there is currently no equivalent evidence in food. However, a tax linked to the toxicity of each pesticide sold to farmers was introduced in Denmark in 2006. This led to a 58% reduction in the total toxicity of purchased pesticides over six years, demonstrating major mitigation by producers (Table 4.2).

4.4.2. Minimum environmental performance policies can be based on the label

Minimum environmental performance policies remove the highest impact products from the market. They generally rely on the data generated by environmental impact labelling schemes (such as the greenhouse gas emissions of a product). If well enforced, they are a highly effective and predictable mechanism to achieve sustainability goals (Sonnenschein et al., 2019). They work by removing choices available to consumers and incentivizing producers to improve in order to remain in the market. They are currently used in 97 countries (CLASP, 2021). For example, in Malaysia since 2014, appliances with a 1-star rating cannot be sold or imported (Salleh et al., 2019). In food, such policies could be particularly effective because around 25% of producers cause 53% of each product's environmental impact (Chapter 2). However, there is need for research into the economic and social consequences of such policies in the food sector.

4.4.3. Other policies can be based on the label

Public procurement spend represents 10-30% of global GDP and a growing share of this spend is linked to the grades of environmental impact labels in non-food sectors (UNEP, 2017). For example, many European public bodies can only purchase vehicles with emissions corresponding to an approximately B grade or higher (Quintero et al., 2019). Governments can also offer loans for sustainable investments. For example, in Germany, loans are offered to improve household energy ratings (Henger et al., 2013). Governments can also act as a powerful intermediate buyer. For example, in India, the government bought millions of energy efficient lights and re-sold them to consumers, which provided manufacturers with capital to increase production and compete and decreased risks associated with capital investment, cutting prices of the most efficient lights by 70% in four years (Chunekar et al., 2019). Different advertising and promotional policies for different products could also be linked to the label grade.

4.5. Designing the labelling scheme

4.5.1. Governance

Trust in the information behind a labelling scheme is critical for its success. This can be achieved through good governance, including: ensuring financial independence of the governing body from label users; ensuring the scheme is transparent and science-based; engaging stakeholders early; and regularly re-appraising the scheme in light of new information (Burgass et al., 2017). The organizations who often taken on this role are national or international governments (such as the EU or UN) or trusted well-funded independent groups with substantial convening and organizational capability. However, initial private sector attempts at developing such a scheme (e.g., France's "Eco-Score") can create viable options and enable early piloting.

Good governance will also be essential to increase the accuracy of the environmental models used by the digital farm monitoring tools and in supply chains. Many existing farm monitoring tools use models which were built for national greenhouse gas inventories (Macsween &

Feliciano, 2018) yet these models have low accuracies when applied to individual fields (S. J. Del Grosso et al., 2016; Ogle et al., 2010; Tesfaye et al., 2021). However, existing models with higher predictive power generally require more data (S. J. Del Grosso et al., 2016), and the need to collect these data could reduce usage or burden farmers. To incentivize new model development, ensure poor performing models are not used, and deliver this without substantially increasing the data-collection burden on farmers, a governing body could set and update minimum predictive thresholds for environmental models against reference databases of field-measured emissions and biodiversity data.

Further, where low predictive accuracy persists, different models could give very different results for the same field, enabling users to "shop around" for tools which represent them more favourably. One solution is for the governing body to standardize which models can be used across tools. Ideally this standardization would be international, ensuring that different countries can't gain competitive advantage by using models which present their performance more favourably.

4.5.2. Products included

While labelling virtually all products using farm-specific and supply chain specific data is critical to enable the system-wide transformation we have discussed, careful exceptions could make the scheme more cost-effective without compromising its overall success. For example, to reduce costs, food processors might use average environmental impacts instead of farm-specific data for ingredients which represent a small share of a product's overall environmental impact.

Products might also be temporarily excluded if there are scientific challenges associated with monitoring or comparing their environmental impacts, and instead managed with standards. For example, overharvesting is a dominant environmental problem for wild-caught foods such as fish, but there are currently few reliable methods to compare indicators of overharvesting to indicators relevant to agriculture and aquaculture, suggesting wild-caught foods should be excluded from early versions of the scheme until this research challenge is overcome.

4.5.3. Functional unit

The functional unit (what the environmental impacts are expressed "per") can link environment indicators to agricultural productivity and human nutrition. A mass-based functional unit (e.g., 100 grams) creates a strong link to both environmental impact and agricultural productivity and is also easily understood (Lemken et al., 2021). However, including some aspects of nutrition in the functional unit (e.g., 100 grams of protein, for products that are generally consumed for protein) would allow more meaningful comparisons between functionally similar products with different nutritional densities such as beef and beans (Grigoriadis et al., 2021). In particular, this would help consumers and others buying food to realize the tremendous environmental benefits of diets low in animal products.

Multiple research challenges remain outstanding here. While accounting for nutrition in a detailed way can penalize improvements in productivity or sustainability which reduce nutritional density (Cassidy et al., 2013; Fan et al., 2008), trying to control for multiple nutrients in an environmental label could make it too complicated and mix important information which is better conveyed separately (e.g., with nutritional labelling). Further, not all nutrients need to be obtained from a single food, and product-specific nutritional measures can easily fail to capture this (Muller & Ruffieux, 2020). Additionally, not all food is bought for nutrition, and it remains unclear how environmental information should be communicated when there is a choice to simply consume less of something without replacing it with something else (e.g., chocolate).

4.5.4. Choosing and weighting indicators

Food production causes many environmental issues and single-indicator labels (e.g., "carbon labels") miss environmental problems of high global concern. However, requiring that the supply chain measures and reports many indicators (e.g., the twenty indicators of the EU's PEF scheme) would make an impact labelling scheme difficult to manage and comprehend. One solution would be select a subset of the highest priority indicators to include in the impact labelling scheme and manage the rest with standards. For example, the PEF ozone depletion indicator could be managed by stronger regulation of ozone-depleting substances.

Consumer research suggests weighting different indicators into a single score makes a label easier to comprehend (Hagmann & Siegrist, 2020; Weber, 2021). Some products can perform well one indicator but badly on another (e.g., low pesticide toxicity but high water use) and single scores can help producers and consumers navigate these trade-offs because the weights behind them state which indicators are most important. More broadly, different environmental issues are of different importance, yet the weights assigned to them are often implicit (for example based on media or political attention) and an explicit and transparent weighting between indicators could help create societal alignment around environmental goals.

Different approaches are available to prioritize and weight indicators. Early approaches were based on taking averages of public or expert opinions or by assessing progress towards policy targets (Sala et al., 2018), but these approaches placed strong faith in people's opinions and current policy, lacking a robust scientific basis. More recently, models such as LC-Impact (Verones et al., 2016) have built empirical models of how much issues such as deforestation and pesticide toxicity contribute to "final" environmental and human outcomes. The main final outcomes considered are biodiversity loss, human health, and natural resource depletion. However, there is a knowledge gap around how accurately LC-Impact and other similar models predict observed data (such as historical biodiversity loss). There has also been insufficient analysis of the value judgements behind weighting and prioritization approaches; interdisciplinary research on this topic incorporating ethics is therefore a priority.

4.5.5. Benchmarking and grading

Benchmarking and grading converts data which can be difficult to interpret (e.g., "5E-15 species destined for extinction per year per 100g protein") into a comparative message (such as "Grade A"). Grades trigger stronger behavioural responses than numerical information by providing a simple mental shortcut that enables easier and faster decisions (Andor et al., 2020; IPSOS & London Economics, 2014; Lupiáñez-Villanueva et al., 2018; Newell & Siikamäki, 2014). Consumers seem to perceive "Grade A" as an anchor point, and anything less than A as a loss (Ölander & Thøgersen, 2014). The greatest behavioural response seems to occur in grades A to G, while grades such as A+ and A++ stimulate less change by consumers and producers (Commission Delegated Regulation (EU) 2019/2016 of 11 March 2019 Supplementing Regulation (EU) 2017/1369 of the European Parliament and of the Council with Regard to Energy Labelling of Refrigerating Appliances and Repealing Commission Delegated Regulation, 2019; Ölander & Thøgersen, 2014). However, some consumers value more detailed information which can help increase the credibility of the label (Andor et al., 2019; Millie et al., 2019; Potter et al., 2021), and a solution could be to put grades on the front-of-packaging or prominently online, and provide more detail on the back-of-packaging and elsewhere online.

The most widely used benchmarking method in non-food sectors is to compare the product's impacts to others in a defined category (e.g., in food, this could be beef from a certain farm against all other protein-rich foods), making an allowance for future improvements, and using cut-off values to assign grades. An alternative might be to benchmark a product against a known ecological threshold or policy target, such as limiting warming to 1.5 degrees. These methodological decisions are extremely important, and to our knowledge, there are currently no experimental or model-based evaluations of how different grading methods would affect ultimate environmental outcomes.

4.5.6. Label design

While there is scope for different label designs, certain aspects stand out particularly strongly from research and experience to date. A near-global social norm is that red means "stop" and denotes "danger" while green means "go" and connotates "life" (H.-C. Yu, 2014), and labels that use red-green colours outperform those that do not (Meyerding et al., 2019; Panzone et al., 2020). Ensuring the label is distinctive and prominent to consumers is important (Carrero et al., 2021), and this probably requires a design that is different from existing nutritional and standards-based labels, as well as placing the label on the front of packaging. Seeking to drive both an emotional and rational response is important, and visual cues (for example integrating an image of planet earth into the label) may help trigger these cognitive processes (Dolan et al., 2012).

4.6. Achieving widespread adoption

The success of an environmental impact labelling scheme depends on virtually all producers monitoring and communicating their impacts, whether they are high- or low-impact (Hagmann & Siegrist, 2020). In some sectors, businesses alone have achieved sector-wide adoption, but has only happened when there are a small number of companies in the market and they all benefit economically from labelling (Ruby, 2015). This seems unlikely in food as the sector is relatively fragmented and many producers could lose out from labelling.

In some sectors, environmental NGOs have also been instrumental in increasing the adoption of labelling schemes (Gulbrandsen, 2006). Trust in business-led schemes can be low (Rubik & Frankl, 2005) and NGOs can help increase trust, which makes consumers more likely to purchase labelled products (Thøgersen, 2002). However, there are no examples to our knowledge of NGOs achieving sector-wide adoption.

Existing standards-based schemes could collaborate around a new impact labelling scheme. However, existing standards-based schemes differ substantially in the environmental issues they place value on and how they measure them (Dendler, 2014; International Trade Centre (ITC), 2017). That there is no single science-based definition of sustainability should not be surprising because science cannot tell us what to value, it can only give us facts and evaluate solutions. For example, it cannot tell us we should care about climate change, only that it is happening, its effects, and options for addressing it. To make progress, existing standards-based schemes could try to establish as much consensus as possible on a sector-wide environmental impact label, but still maintain their own labels reflecting their values. However, it is unclear whether there are sufficient incentives for them to do this, given their financial dependence on selling their own labels.

Given the above limitations on businesses, NGOs, and existing labelling schemes, government-mandated labelling is probably essential to achieve widespread adoption in food. Governments can also help standardize labelling methodology, provide initial funding to develop the scheme, help producers with the costs of transition and the risks of adopting new practices, and increase compliance (Banerjee & Solomon, 2003; Gulbrandsen, 2006). However, governments rarely act unilaterally without license from businesses and voters (Gröfke et al., 2021; Scrinis et al., 2017).

Stakeholder interviews therefore suggest widespread adoption of environmental impact labelling in food could happen in stages: early adoption driven by NGOs and companies who might benefit; later adoption by risk-averse actors such as large food companies; with policymakers encouraging or mandating labelling once the scheme is proven (Gröfke et al., 2021). This pathway mirrors other sectors: for example, UK window energy labels were developed by publicly-funded researchers; rapidly adopted by companies who could improve their efficiency and would benefit; encouraged by government in 2006; and in 2010 policymakers set a minimum grade of C for all new windows, effectively mandating labelling.

4.7. Conclusion

In agriculture, environmental impact labelling would help deliver many of the components necessary for the next agricultural revolution (Annan et al., 2016): the incentives to adopt digital farm monitoring tools, the data and digital infrastructure to deliver knowledge sharing and advice at scale, and a shift of focus from adopting practices to achieving productivity and sustainability outcomes. The information created can propagate through supply chains to incentivize more sustainable input production, enable product reformulation, change food purchasing, and increase environmental awareness. The information created would also enable effective policies to be designed, monitored, and implemented.

While the effects of each change are relatively small on their own (Table 4.2), in aggregate they can produce a large overall effect. For example, the effects of digital monitoring tools on farming are likely to be independent of, and additive to, reformulation and consumer behaviour. However, some of the changes will interact, diminishing or increasing others (D'Haultfœuille et al., 2016; Perino et al., 2014). While we need to better understand these interactions, it is clear that an environmental impact labelling scheme could bring together and trigger many powerful sustainability and productivity solutions. From a policy perspective, requiring an environmental impact label on food products is a relatively clear and unambiguous action to take. This aggregation of multiple effects, delivered through a relatively clear action, is what makes environmental impact labelling in food such a promising solution.

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Chapter 5: Discussion

Human beings have inflicted a devastating toll on natural ecosystems and the species that inhabit them. This century could bring further environmental tragedies, including the near complete loss of tropical coral reefs due to climate change (IPCC, 2018) and the deforestation of the majority of the Congo rainforest (Tyukavina et al., 2018). At the same time, some 770 million people suffered from hunger in 2020 (FAO, 2021c).

This thesis sought to understand and create solutions to environmental and productivity issues in the agricultural and food sectors. To understand these issues, I considered the diversity of agricultural producers and food supply chains in greater depth than has been done by prior research. I started by synthesising, harmonising, and analysing data from a large range of producers and products which provided rich data and new insights. From this foundation, I created and began implementing solutions to sustainability and productivity issues. Here I provide a brief summary of the main research results, the implications of these results, and then identify important areas for future work.

5.1. Summary of research results and implications

Chapter 1 extended the thinking of other researchers, particularly Emile Frison and Tim Benton (Benton et al., 2003; Frison, 2008; IPES-Food, 2016), to develop ideas about productivity and sustainability solutions under high agricultural diversity. I presented evidence that because the same solutions have been applied across the entire agricultural sector, this has led to: a) declining agricultural diversity, subsequently causing biodiversity loss; and b) these solutions being less effective in areas with high agricultural diversity and where farmers cannot standardise their farms (e.g., sub-Saharan Africa). This implied that to achieve environmental and productivity gains, we need to better understand the effects of agricultural diversity on productivity and environmental outcomes and design solutions that are effective under agricultural diversity.

Chapter 2 used a meta-analysis of Life Cycle Assessment studies to build a global dataset on the variability of environmental impacts across different food products and producers. The dataset extends and improves prior research (Clune et al., 2017; Colomb et al., 2014; Cui et al., 2018; de Vries et al., 2010; Gerber et al., 2013; Nemecek, Bengoa, et al., 2015; Nijdam et al., 2012; Tilman & Clark, 2014) by being methodologically-harmonised, reconciled to independently estimated values, multi-indicator, including a wider range of products and producers, and by focusing quantifying statistical measures of variability (such as percentiles and distributions, rather than means). A major finding was that there was very high variability in the environmental impacts and productivity between both different producers of the same product, and between different products. For example, there is a 29,600% difference in the land use and a 41,800% difference in the GHG emissions between 90th percentile impact beef producers and 10th percentile field pea producers per 100g of protein. Even considering arable land alone, there is still a 9000% difference between 90th percentile impact beef producers and 10th percentile impact field pea producers per 100g of protein. This implies there is substantial potential to change how food is produced, change which types of food we purchase, and change the producers we purchase from. Chapter 2 quantified some of these benefits; for example, a no animal products diet could reduce agricultural land use by 3.1 billion hectares (76%) while converting the food system from a net carbon source of around 13.7 billion tonnes of CO_2eq to a net carbon sink of around -1.0 billion tonnes of CO_2eq. This emissions reduction represents a 28% reduction across all sectors of the economy, making this the largest effect size found from diet change in the peer-reviewed literature to date.

Using the dataset presented in Chapter 2, and drawing on prior research, we developed a framework to increase environmental sustainability and productivity in the food system. It involves farmers measuring their impacts using digital tools, choosing from different sustainability and productivity options to improve performance, and communicating their results up the supply chain and through to consumers as an environmental impact label. A key difference between the Green Revolution of the mid-20th century and today is that digital technology allows us to understand individual farms, deliver options to improve that are tailored to their needs, and do this on a global scale. This means the advice can change to fit the farm, reducing the need for the farm to change to fit the advice.

Chapter 3 built a way to represent information describing diverse agricultural producers in data. It focused on data that famers and researchers would typically collect during record keeping or surveys that is necessary to track environmental and productivity indicators. In Chapter 3 we reviewed a range of existing data formats, but no data format has yet been built to represent such agri-environmental data consistently. A key finding was that our data format could consistently and comprehensively represent LCA data, farm survey data, and agricultural field trial data from multiple sources and different types of producer (we documented six examples of this in the chapter and referenced the online data platform which currently contains data from over 250 sources). The implication is that there are no longer excuses for different, incomparable, and opaque ways of representing data that have such high humanitarian and environmental importance. Standardisation around a data format would deliver major benefits, and this chapter shows that standardisation is feasible. Chapter 3 also presented a data platform for researchers to directly upload and share their research. This facilitates knowledge transfer, which would also deliver major benefits.

Chapter 3 then presented a software toolkit which validates, gap-fills, and calculates environmental impacts. This has multiple functions ranging from checking research data for errors or harmonising LCAs to use the same methods. A key function would also be to empower farmers to calculate their environmental impacts. Existing approaches to allow farmers to calculate their impacts are tied to certain software, meaning farmers need to install and use a new software package to access environmental monitoring. Instead, our toolkit can be embedded in the tools farmers are already using (such as record keeping tools). Other tools have further limitations (such as only calculating greenhouse gas emissions) or not validating farmer data. Combined with a desire by farmers to reduce their impacts, or combined with financial or non-financial incentives, this toolkit could directly support reductions in impacts.

Chapter 4 then explored the potential of environmental impact labelling as a solution to incentivise farmers to monitor their impacts and productivity and communicate this information up supply chains and though to consumers. Unlike prior analyses, which have focused on how environmental impact labels change consumer behaviour (Potter et al., 2021), this chapter identified evidence that an impact labelling scheme would change farmer behaviour, behaviour in supply chains, consumer behaviour, and support better policymaking. Table 4.2 presented effect sizes throughout the supply chain from lab-based and real-world evaluations. It would be erroneous to sum them up into a total effect size because: 1) many effects are overlapping; 2) because the persistence of these effects is not well established; and 3) because policy and adoption will have a major bearing on overall success. However, combined, they suggest that a well-designed environmental impact labelling could be an incredibly powerful sustainability and productivity solution for the food sector. This implies that environmental impact labelling should be prioritised as a solution.

5.2. Critical reflections on the mitigation solutions and future research directions

Here I use the food systems framework from Chapter 1 section 1.3.4 to structure further critical discussion on the mitigation solutions presented in this thesis (Figure 2.4, Figure 4.3) and identify future research directions.

5.2.1. Outcomes: Economic, Social, and Political

Overall, my research created solutions which, if adopted, would reduce agricultural land use, lead to farmland abandonment, and lead to many farms going out of business. Using case studies of farmland abandonment, I previously explored why this is a positive outcome for nature due to evidence that farmland abandonment leads to vegetation re-establishment and the return of wild animals (Poore, 2017). In Chapter 4 I discussed how other policies could be used to manage the economic and social effects of this transition for farmers livelihoods. A key example of this is the Grain for Green programme in China where over 60 billion US dollars have been invested since 1999 to revegetate 32 million hectares of unproductive farmland, and also to financially support farmers to find alternative and generally more remunerative jobs (Delang & Yuan, 2015). However, it is possible to foresee cases in countries (e.g., with government failures) where farmers would not receive assistance. While it might be argued that an environmental monitoring and impact labelling scheme would also not be implemented at-scale in countries with government failures, farmers could still be affected if their products are high environmental impact which limits their access to export markets.

As a first step towards understanding this, there is a critical need for geospatial modelling of the environmental, social, and economic costs and gains of environmental impact monitoring and labelling programmes at the level of individual farms. This modelling would also ideally explore how geography places mitigation limits on farmers; i.e., some farmers might not be able to reduce their impacts to sufficiently low levels given their soil or climate. I explored the role of geography in a preliminary way in fig. S11, and it was clear that geography is a major driver of environmental impacts. Key questions include: are farms with mitigation limits also on poor quality land? Because the land quality is poor, are these farms also some of the poorest? If so, will the social losses of such a transition to a low environmental impact food system be borne by the poorest if other policies cannot abate this?

In non-food sectors, environmental monitoring schemes have created jobs themselves. For example, energy standards and labelling schemes have created around one million jobs in Europe and 300,000 in the USA (IEA, 2021). Any evaluation of the social impacts of such schemes should consider their job creation potential in monitoring, compliance, research, and in low-environmental impact food businesses.

5.2.2. Outcomes: Food Security/Insecurity

Chapter 4 presented evidence that environmental impact labelling could increase agricultural productivity and reduce environmental impacts. However, there was no exploration of whether the improvements in environmental impacts would cost more, nor whether these costs are offset by productivity improvements. The effects on the price of food as a result of an environmental impact monitoring and labelling needs analysis.

Whether other aspects of food security would be affected also require analysis. For example, one study found that while the crop varieties of the Green Revolution substantially increased production, they led to 20-30% reductions in the micronutrient content of wheat (Fan et al., 2008). If managing foods for environmental impacts changes the locations in which food is produced (e.g., some countries, but nature of their geography, have high environmental impacts, and production declines in these locations) this could potentially cause food distribution issues if transport and logistics are not also adequately addressed.

5.2.3. Outcomes: Human Health/Illness

The mass based functional units used in Chapter 2, and suggested for the environmental impact labelling scheme in Chapter 4, have been criticised for failing to reflect the micronutrient contents of different foods and the nutritional benefits of meat in particular (McAuliffe et al., 2020). On the other hand an analysis took the data from Chapter 2 and compared environmental impacts expressed per kilogram of mass to human health outcomes, and found products with low environmental impacts also improved health outcomes, largely driven by the high environmental impacts and poor health impacts of meat and dairy (M. A. Clark et al., 2019). More research is needed to reconcile these differences.

5.2.4. Outcomes: Environmental

A key targeted outcome from the research and solutions in all chapters is improvements in environmental impacts. However, some environmental issues were not included. In particular, a major omission from Chapter 2 was the biodiversity impact of different products and practices, and future research could help create these data and improve methodology. A recent study has already used the dataset developed in Chapter 2 and applied the LC-Impact method for calculating the effects of land use on biodiversity, finding that animal product free diets reduce biodiversity impacts (WWF, 2020). However, there has yet to be any comprehensive research on the variability of biodiversity impacts across different producers beyond meta-analyses of specific products in specific regions (e.g., De Beenhouwer et al., 2013). Nor has there been any analysis around how well these biodiversity measures reconcile to other datasets like the IUCN Red List.

Further research could also provide an assessment of ecological toxicity of the pesticide use of specific producers and their products. This requires more data collection and data sharing around the pesticides used by different farmers, and the data platform and format described in Chapter 3 could support that. It also requires improvements in pesticide fate and toxicity modelling, and current research, such as the OLCA-Pest project, is beginning to address this (Nemecek et al., 2022).

There are major evidence gaps on the environmental impacts of producers and products, and these gaps may mean the mitigation solutions need adjustment to effectively achieve better environmental outcomes in different contexts. Geographically these evidence gaps are mainly in Africa and Central Asia (fig. S2). In terms of products, a recent study used the dataset behind

Chapter 2 to create a map of these evidence gaps which could guide future research (Halpern et al., 2019).

Chapters 2 and 4, and the current data behind the HESTIA platform (Chapter 3), use attributional LCA modelling to quantify the current average impacts of products. Consequential LCA is generally recommended for scenario analysis because it uses the marginal impacts of producing an additional unit of a product. Future scenario analysis, especially when considering complex changes like substitution of palm oil for sunflower oil, would therefore ideally use consequential LCA.

5.2.5. Outcomes: Non-Human Animals

Chapter 4 discussed how shifts to lower environmental impact meats (e.g., from beef to chicken) can lead to more animals being slaughtered, and this ethical problem needs close analysis. Another challenge is that for poultry, more intensive systems may lead to lower environmental impacts (Leinonen et al., 2014), although it is not clear if this translates to other types of animals like cows and sheep, and critical analysis of these trade-offs as well as better data on ruminant systems are needed.

Researchers have proposed methods to create quantitative indicators of animal welfare which can be integrated into a Life Cycle Assessment framework (Scherer et al., 2018), but there are substantial value judgements behind such frameworks including how lifespans, sentiency, and numbers of animals trade off, which need critical examination. In Chapters 2 and 4 I argued that focusing on a small number of indicators to manage through outcome-based methods (e.g., impact labelling) is an optimal approach. Issues that can be effectively managed by standards should be managed by standards. However, given that standards-based approaches are used today to manage animal welfare, and that farmed animals are often appallingly treated in food systems, would using outcome-based indicators to manage animal welfare be better?

5.2.6. Actors

A recent study took the framework developed in Chapter 2 and tested how to achieve it using stakeholder interviews with businesses and NGOs, finding that no single group of stakeholders could achieve it alone, and that sector-wide collaboration was necessary (Gröfke et al., 2021). This need for collaboration presents challenges and opportunities. In the case of the European Union's Product Environmental Footprint (PEF) pilots, which sought a collaborative approach, much of the scheme's content was watered down by business lobbying. For example, animal products could not be compared to vegetable proteins by design. However, there is currently no analysis or evaluation of why the PEF scheme became so diluted, and the above observation is based on my personal experience. In the case of the solutions presented here, there are both positive and negative incentives for businesses, and it can be hoped that the environmentally conscious individuals within businesses are able to exert positive influence. There is some evidence from organic labelling that consumers have been influential in determining how the scheme is implemented (Seufert et al., 2017). In the case of environmental impact labelling, consumers may create demand for indicators on the label such as human toxicity rather than ecological toxicity, and it is not clear what the implications of such demand would be on the overall scheme's success.

For farmers, an environmental impact labelling schemes could also involve upfront costs, require new or different kinds of inputs, and be knowledge intensive. These could create equity challenges for farmers in less industrialized countries who are less able to access finance and where education levels are lower. A social analysis of these issues would support our understanding of mitigation solutions in food.

5.2.7. Other technical research areas

Being able to automatically provide tailored advice to farmers was a major theme in Chapters 2 and 4. Much information about how to reduce environmental impacts is currently presented in academic journal articles. A major research breakthrough could be achieved if the findings from research studies could be automatically translated from journals and given to the right farmers at the right time. Another approach is to provide farmers with information about what other farmers are doing and research on machine learning techniques could identify ways to automate and tailor this data sharing. In particular, the data platform and filetype in Chapter 3 could support both these objectives.

More work is required to build emissions and resource use models that both: a) account for geographic conditions; and b) work with data it would be reasonable for farmers to collect. Simple models like the IPCC Tier 1 models do not generally include geographic information, whereas it is known that most agricultural emissions vary substantially based on geography (fig. S11). On the other hand, models like DNDC account for site specific information but required detailed information to run (Gilhespy et al., 2014) which would be labour intensive to collect. Models that combine both (a) and (b) will support farmers to improve performance. I developed one of these models for nitrate leaching (supplementary materials for Chapter 2), but a recent evaluation of my model against others found that it failed to capture the variation in leaching between two sites in Sweden (Henryson et al., 2020), implying more work is required.

Chapter 4 discussed the need for more experimental research on how monitoring and communicating environmental impacts affects the behaviour of farmers, businesses in the supply chain, and consumers. The data from Chapter 2 is already supporting such experiments: for example it has been linked to back-of-pack ingredient data for roughly 50,000 grocery items on a virtual online supermarket to compare scenarios where consumer have access to environmental labels versus where they do not (Potter et al., 2020); has been used to explore consumer responses to environmental information and taxes linked to environmental impacts (Faccioli et al., 2022); and the World Resources Institute has used it in their Cool Food Pledge tool which has been deployed across 38 companies producing 977 million meals per year to help them change sourcing – so far, these companies have reduced their emissions by 16% between their base year which was approximately 2017 and 2020 (Waite et al., 2021). However, as research is undertaken on the effects of generating and communicating environmental information in supply chains over the coming years, it will be critical to find ways to isolate and exclude studies that are simply poorly designed. For example, studies which provide farmers with digital tools developed on small budgets that might be difficult to use, need to be isolated from studies using well-designed and well-tested tools with a view to accurately establishing likely real-world effects.

5.3. Conclusion

While we have the resources and technology to solve environmental problems, it seems unlikely we will solve them without major changes to society, levels of education, and personal moral outlooks. Today, humans have more choices than ever before and while some of these seem banal, they can have major environmental consequences with virtually no personal consequences. For example, a kilogram of beef costs as little as £5 in the UK but beef requires on average 180 m^2 of land to produce (Chapter 2) and drives substantial deforestation (Curtis et al., 2018). A litre of glyphosate active ingredient can cost as little as £20 but have major negative effects on wildlife. In many cases, there are no social systems in place to help us make ethical choices, few good reasons provided to people for why they should reflect on their behaviour, and a general lack of education to enable people to deal with complex information. The lack of moral systems, moral education, and general education is a major flaw in our modern society. Relying on scientific, technological, or financial solutions to our problems will almost certainly be insufficient, and far deeper changes to our society cannot come soon enough.

SUPPLEMENTARY MATERIALS FOR:

Chapter 1: Introduction

Contains:

Table S1

Table S1. Global maps which include an agricultural class with a spatial resolution of at least 10km. Based on reviews by Waldner *et al*. (Waldner et al., 2015), Pérez-Hoyos *et al*. (Pérez-Hoyos et al., 2017), and Grekousis *et al*. (Grekousis et al., 2015). A review of regional maps, including CORINE for Europe, and the CDL for the USA, and Africover, are available in Grekousis *et al*. (Grekousis et al., 2015).

Name	Spatial Resolution	Years	Sensor	Classification legend	Classes	Change Detection	Overall Accuracy
Recent / regularly updated							
GLASS-GLC (H. Liu et al., 2020)	5km	'82-15	MODIS, AVHRR*	FROM-GLD adjusted †	7	Yes	83%
C6 MCD12Q1 (Sulla-Menashe & Friedl, 2018)	500m	'01-18	MODIS	IGBP UMD Plant Functional Traits 'LCCS2' ('land use') †	17 16 12 11	Not advised	67% - - 81%
ESA-CCI LC (European Space Agency (ESA) Climate Change Initiative (CCI), 2017)	300m	'92-18	MERIS FR, SPOT VGT	CCI-LC †	22	Limited years	71%
CGLS-LC100 (Buchhorn et al., 2020)	100m	'15	PROBA-V	LCCS based†	23/Continuous	No	80%
FROM-GLC (Gong et al., 2013; L. Yu et al., 2014)	30m	'10, '15, '17	Landsat TM, ETM+	FROM-GLC †	28/9	No	53%/70%
GlobeLand30 (J. J. J. Chen et al., 2014)	30m	'00 '10	Landsat TM, ETM+, HJ-1A/B	Globeland30	10	Unclear	80%
Not regularly updated							
GIAM (Thenkabail et al., 2009) / GMRCA (Biradar et al., 2009)	10km	'00	SPOT VGT, AVHRR	GMRCA	9/28	No	79%/92%$^{\varphi}$
GLC 2000 (Bartholomé & Belward, 2005)	1km	'00	SPOT4 VEGETATION	GLC 2000†	22	No	69%
UMD (M. C. Hansen et al., 2000)	1km	'92/93	AVHRR	UMD	16	No	65%

IGBP DISCover (Loveland et al., 2000)	1km	‘92/93	AVHRR	IGBP	17	No	67%
GLCNMO v3 (Kobayashi et al., 2017)	500m	‘03 ‘08 ‘13	MODIS	ST-LCG †	20	Not advised	78%
GlobCover (Bontemps et al., 2011)	300m	‘05 ‘09	MERIS FR	GlobCover†	22	Not advised	68%
Pittman *et al*. (Pittman et al., 2010)	250m	~‘05	MODIS	Cropland share (%)	1	No	-
Meta-maps, harmonising and averaging the maps above							
GLC-Share (Latham et al., 2014)	1km	‘14	-	SEEA legend †	11	No	80%
Geowiki IIASA (See et al., 2015)	300m	‘05	-	Herold *et al*. (Herold et al., 2008) †	10	No	88%
Waldner *et al*. (Waldner et al., 2016)	250m	~’14	-	Cropland share (%)	1	No	84-94%
Downscaled regional/national census/survey data using the maps above							
HYDE (Goldewijk et al., 2017) / LUH2 (Hurtt et al., 2011) Anthromes (Ellis et al., 2020)	10km	10,000BC -‘15	-	Crop & pasture classes Anthromes classes	6 20	Yes	-
Ramankutty *et al.* (Ramankutty et al., 2008)	10km	‘00	-	Cropland/pasture share (%)	2	No	-
IFPRI-IIASA (Fritz et al., 2015)	1km	‘05	-	Cropland share (%)	1	No	82%

* Pre-processed AVHRR data by Song et al.52; † Consistent with FAO-LCCS legend; φ Only validated on the irrigated and rainfed cropland classes respectively.

SUPPLEMENTARY MATERIALS FOR:

Chapter 2: Reducing food's environmental impacts through producers and consumers

Contains:

Materials & Methods

Supplementary Text

Figs. S1 to S14

Tables S2 to S17

Captions and hyperlinks for Data S1 to S2

Other Supplementary Materials for this chapter include the following:

Data S1 to S2 as xls files [Additional reference lists; Data in spreadsheet format].

Materials and Methods

1) *Study Scope*

a. *Temporal Scope*

Studies published online between 2000 and June 2016 were included, providing a window to reduce climatic variation while avoiding significant error by including outdated practices. The beginning of this period aligns with the release of standards for methodological harmonisation (Pryshlakivsky & Searcy, 2013) of Life Cycle Assessment (LCA) [ISO 14040:1997, ISO 14041:1999, ISO 14042:2000, and ISO 14043:2000]. Observations are approximately centred on the year 2010, and external data used relates to 2009-11.

b. *Production Practices*

Only commercially viable and currently existing production systems were included, avoiding assessment of the gap between identification and implementation of new practices (Smith et al., 2007). Foraged foods and subsistence farming were excluded.

c. *System Boundary*

The supply chain begins with the extraction of resources needed to produce inputs for agricultural production, the initial impact of choice by farmers, and ends at the retail store, the point of choice for consumers (fig. S1). Post-retail stages (cooking and consumer losses) were not considered owing to high variability and low data availability. Materials and Methods Section 6 justifies other exclusions.

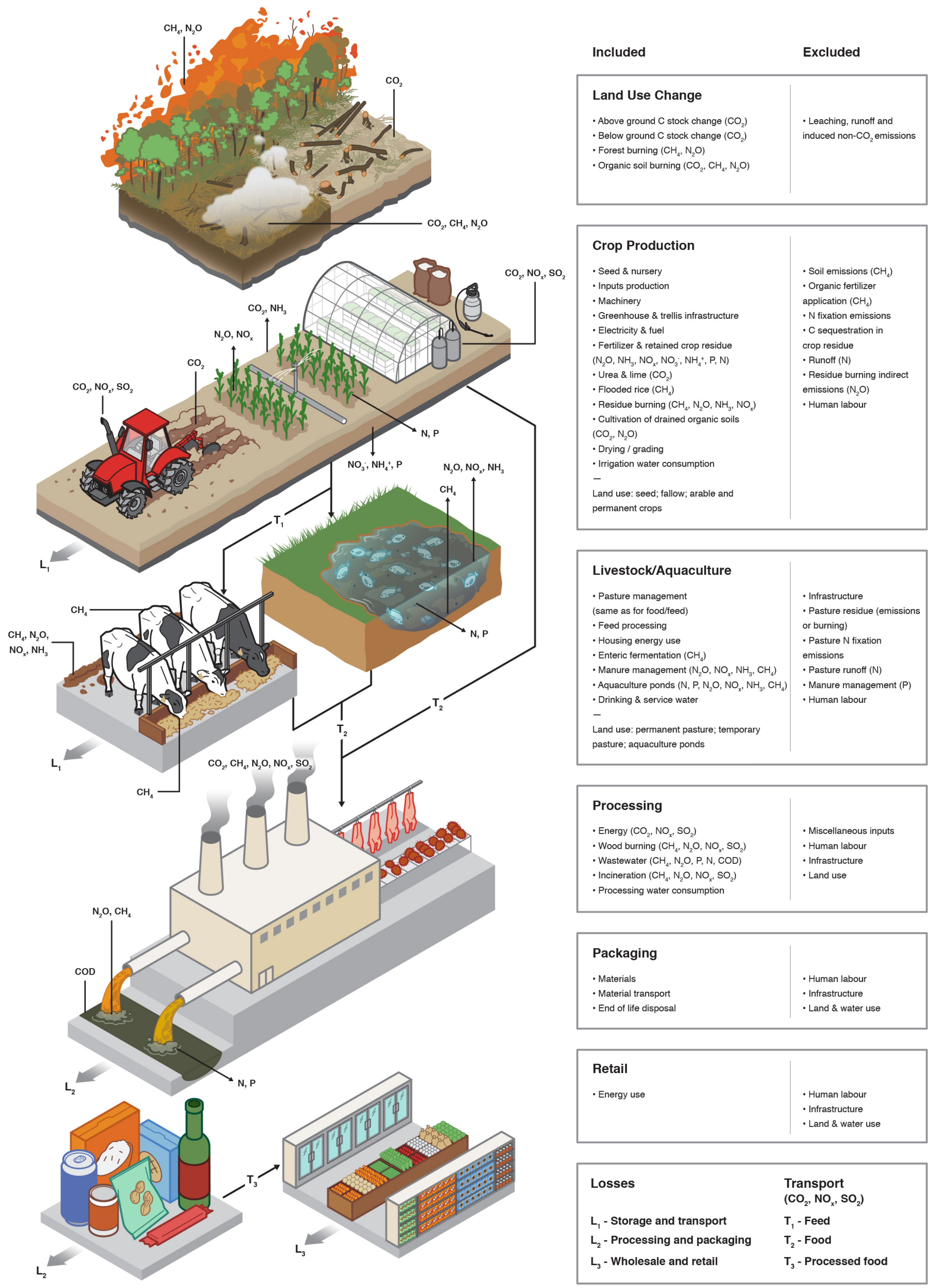


Fig. S1. Emissions and resource uses included or excluded by supply chain stage.

d. Functional Units Used and Products Included

Co-products with similar nutritional roles, despite differences in value or desirability, were not differentiated. Nutrient densities were derived from food balance sheets (*FAOSTAT*, 2021).

Table S2. Functional units (FUs) used.

	Mass / Volume FU	Nutrition FU	Nutrient Density
Starch-Rich			
Wheat & Rye	1 kg of bread (variable protein wheat)	1000 kcal energy	2695 $kcal\ kg^{-1}$
Maize	1 kg of meal (for polenta)		4165 $kcal\ kg^{-1}$
Oats	1 kg of rolled oats		2605 $kcal\ kg^{-1}$
Rice	1 kg of full grain white or brown rice		3685 $kcal\ kg^{-1}$
Potatoes	1 kg of soil free tuber		730 $kcal\ kg^{-1}$
Cassava	1 kg of soil free tuber		975 $kcal\ kg^{-1}$
Protein-Rich			
Peas	1 kg of dry pea without pod	100 g protein	215 $g\ kg^{-1}$
Other Pulses	1 kg of dry pulse without pod		220 $g\ kg^{-1}$
Nuts	1 kg of shell free, dry nut		160 $g\ kg^{-1}$
Groundnuts	1 kg of shell free, roasted nut		260 $g\ kg^{-1}$
Soybeans	1 kg of tofu (~16% protein)		160 $g\ kg^{-1}$
Cheese	1 kg of cheese		225 $g\ kg^{-1}$
Eggs	1 kg of eggs		110 $g\ kg^{-1}$
Poultry Meat	1 kg of fat and bone-free meat and edible offal		175 $g\ kg^{-1}$
Pig Meat			160 $g\ kg^{-1}$
Lamb & Mutton			200 $g\ kg^{-1}$
Beef			200 $g\ kg^{-1}$
Fish	1 kg of edible fish		230 $g\ kg^{-1}$
Crustaceans	1 kg of head-free meat (shell-free for large shrimp)		150 $g\ kg^{-1}$
Alcoholic Beverages			
Barley	1 litre of beer	1 unit (10ml alcohol)	5 units
Wine grapes	1 litre of wine		12.5 units
Other			
Milk	1 litre of pasteurised milk (4% fat, 3.3% protein)	-	-
Soybeans	1 litre of soymilk (~3.3% protein)	-	-
Root Vegetables	1 kg of soil free tuber	-	-
Fruit & Veg.	1 kg of fresh fruit or vegetable	-	-
Cocoa	1 kg of dark chocolate	-	-
Coffee	1 kg of ground, roasted beans	-	-
Oil crops	1 litre of refined/filtered oil	-	-
Sugar crops	1 kg of raw/refined sugar	-	-

e. Allocation

Economic allocation between co-products reflects the rationale for which producers create environmental burdens (Ponsioen & van der Werf, 2017) and is used here. The method is also practical and widely used.

f. Characterisation

Table S3. Indicators and characterisations used.

Indicator	Characterisation	Emissions / Uses Characterised
Land Use * Occupation Time	None	Seed, on- and off-farm arable and permanent crops, fallow land, temporary pasture, permanent pasture
Greenhouse Gas Emissions	IPCC (IPCC, 2013) AR5 100-year factors with climate-carbon feedbacks	CO_2, CH_4, N_2O to air
Acidification	CML2 Baseline (CML, 2001)	SO_2, NH_3, NO_x to air
Eutrophication	CML2 Baseline (CML, 2001)	NH_3, NO_x to air, NO_3^-, NH_4^+, P, N to water
Freshwater Withdrawals	None	Irrigation, drinking, pond, and processing water
Scarcity-Weighted Freshwater Withdrawals	AWARE (Boulay et al., 2018)	Irrigation, drinking, pond, and processing water

For greenhouse gas (GHG) emissions, IPCC (IPCC, 2007b) AR4 characterisation factors (CFs) included climate-carbon feedbacks in CO_2 only, but inconsistently not in other GHGs (IPCC, 2013). The AR5 factors with feedbacks are both more complete (by including the direct and indirect impacts of GHGs) and consistent, and were used here despite higher uncertainty in feedback magnitude. Results under AR4 CFs are presented for comparability (Data S2). 100-year CFs were used, the most common indicator of the impact of mixed gases on the mid- to long-term climate.

2) Meta-Analysis Approach

a. Study Inclusion Criteria

Based on the above, the following criteria were used to identify studies that:

1. Are included in peer-reviewed journals, or are PhD theses, ISO compliant reports, LCA databases, or conference proceedings with clear data and methods
2. Are published in print or online between 2000 and June 2016
3. Report results not presented in another included study
4. Assess commercially farmed products
5. For crops, report real, not simulated yield and inventory data, from specific farms, regions, or countries
6. Use LCA or similar methodology
7. Calculate according to our system boundary or provide sufficient inventory data to recalculate
8. Calculate according to our functional units, or make recalculation possible
9. Use attributional modelling and economic allocation, or make recalculation possible
10. Calculate GHG emissions, characterised under IPCC AR5 100-year factors with climate-carbon feedbacks, or make recharacterisation possible
11. Calculate on- and off-farm land use, or make calculation possible.

b. Aggregating Results

Results were included as a separate observation (line of the database) when they:

1. Represented different systems or practices, e.g., input level, rotation, cultivar
2. Represented significantly different geographies, e.g., regions or countries.

Otherwise, results were averaged into a single observation with standard deviations calculated across farms. Results were averaged across years to ensure independence of observations.

c. *Literature Search*

A comprehensive approach was used by: searching for publications using the terms "life cycle assessment" OR "life cycle analysis" OR "GHG emissions" AND the relevant product name, in Google Scholar; following references within publications and citations to publications; identifying LCA conference proceedings; and identifying online LCA datasets. This resulted in 1530 studies for potential inclusion. Where data were unavailable in the publication, 346 authors were contacted directly. Of these studies, 570, supplemented with additional data provided by 139 authors, met our criteria. This resulted in 2278 unique observations, covering ~38,700 regional or farm level inventories in 119 countries (fig. S2). Observations are concentrated in Europe, North America, Oceania, Brazil, and China, but limited in Africa and Central Asia, demonstrating the need for study weights that allow one geography to represent another (Materials and Methods, Section 8).

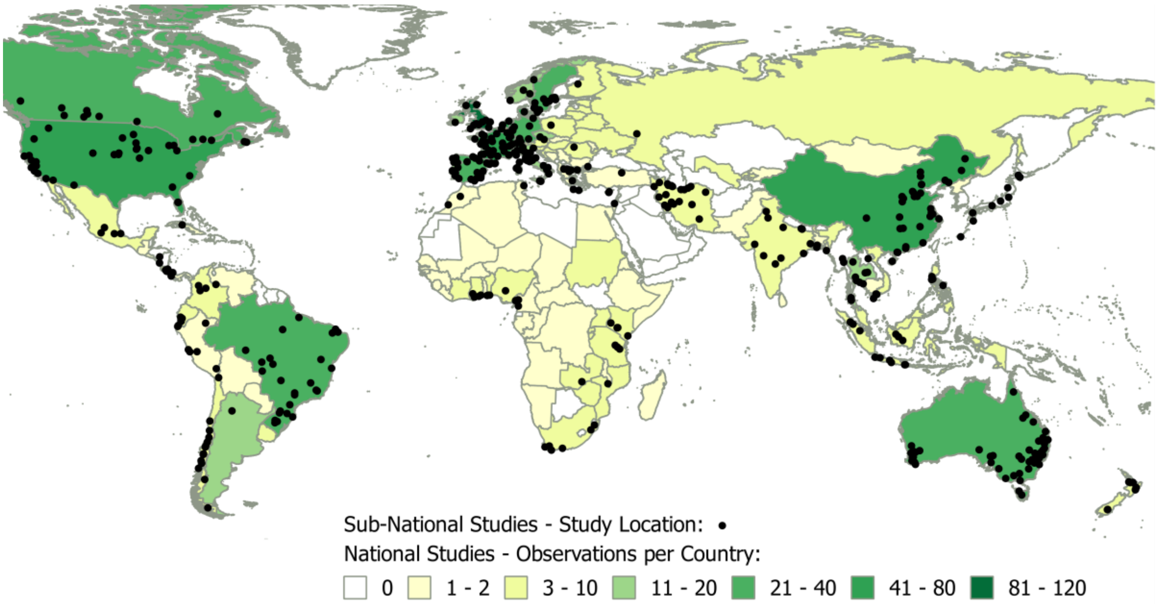


Fig. S2. Map of study locations for all products. Black circles represent locations of subnational studies (*n* observations = 1160); country shading represents the number of national-level studies per country (*n* observations = 1118).

3) Building and Standardizing the Inputs and Management Inventory

Inventory data were recorded to allow recalculation of missing emission sources. Some inventory items, if missing, could reasonably be estimated from external sources.

a. Data Derived from Study Locations

Studies with co-ordinates were point-sampled. Regional studies were linked to GADM regions (Hijmans et al., 2018), and the mean was taken within that area. For eco-climate zones (discrete), the mode was taken.

Table S4. Sources of spatial data.

Inventory Item	Source
Soil Characteristics	
pH H_2O	HWSD (FAO/IIASA/ISRIC/ISSCAS/JRC, 2012)
Clay Content (% weight, 0-30cm)	HWSD (FAO/IIASA/ISRIC/ISSCAS/JRC, 2012)
Sand Content (% weight, 0-30cm)	HWSD (FAO/IIASA/ISRIC/ISSCAS/JRC, 2012)
Organic Carbon (% weight, 0-30cm)	HWSD (FAO/IIASA/ISRIC/ISSCAS/JRC, 2012)
Total Nitrogen (kg N t^{-1}, 0-50cm)	ISRIC/WDC-Soils (Batjes, 2015)
Phosphorus (kg P t^{-1}, 0-50cm)	Scherer and Pfister (Scherer & Pfister, 2015)
Drainage (6 classes)	HWSD (FAO/IIASA/ISRIC/ISSCAS/JRC, 2012)
Erodibility (t h MJ^{-1} mm^{-1})	Scherer and Pfister (Scherer & Pfister, 2015)
Geography	
Slope Length (dimensionless)	GMTED (Danielson & Gesch, 2008; Scherer & Pfister, 2015)
Slope (%)	GMTED (Danielson & Gesch, 2008; Scherer & Pfister, 2015)
Phosphorus reaching aquatic environment (%)	Scherer and Pfister (Scherer & Pfister, 2015)
Climate	
Precipitation (mm $year^{-1}$)	WorldClim (Hijmans et al., 2005)
Winter-type Precipitation Correction	WorldClim (Hijmans et al., 2005)
Average Temperature (°C)	WorldClim (Hijmans et al., 2005)
Potential Evapotranspiration (mm)	Zomer *et al.* (Zomer et al., 2006)
Eco-Climate Zones (12 classes)	Hiederer *et al.* (Hiederer et al., 2010)
Other	
Irrigated Water Applied (m^3 ha^{-1})	Pfister and Bayer (Pfister et al., 2011)
CF_{AWARE} (water scarcity for each basin, relative to global water scarcity) (m^3_{world} m^{-3})	Boulay *et al.* (Boulay et al., 2018)
Cropping Intensity	MIRCA2000 (Portmann et al., 2010)

i. Irrigation Water Applied

Evapotranspiration from irrigation was drawn from a basin-level dataset of 160 crops (Pfister et al., 2011). For flooded rice, data including flood water evaporation were used (Chapagain & Hoekstra, 2011). To convert from evapotranspiration to field applied water, application efficiency factors (Nemecek, Bengoa, et al., 2015), weighted by country shares of irrigation system (FAO, 2017), were applied.

ii. Aquaculture Water Requirements

Evaporation from aquaculture ponds was estimated from potential evapotranspiration (PET) (Zomer et al., 2006) and factors converting PET to open water evaporation (Allen et al., 1998).

iii. Multiple Cropping and Fallow

Land use was calculated from inverse yield and occupation time. Occupation time is reduced by multiple cropping but increased by fallow requirements. Many studies did not provide crop timetables, and derivation was required.

From MIRCA2000 (Portmann et al., 2010), minimum crop fallow requirements were calculated as cropland extent (CE_{MIRCA}) over maximum monthly growing area (MMGA) (Stefan Siebert et al., 2010). MMGA is the maximum area required for the crop rotation in that location. CE_{MIRCA} is the area used for arable crops including fallow (Ramankutty et al., 2008). Fallow land was treated as insignificant for greenhouse crops, vineyards, and bananas. Given the large variation in orchard lifecycles, fallow requirements were set based on commercial lifespans using literature data. Longer fallow requirements for some practices (e.g., organic) were not considered.

Multiple cropping was calculated from the ratio of MMGA to area harvested (AH) (Stefan Siebert et al., 2010). AH is counted each time a crop is harvested in a year (e.g., for double cropping, MMGA/AH = 2). Land use, calculated from yield, can be multiplied by each of these ratios in turn, to reconcile to global cropland extent from FAOSTAT (Materials and Methods, Section 6a).

b. Data Derived from External Datasets

Table S5. External datasets used.

Inventory Item	Source / Methodology
Seed (kg ha^{-1})	Food Balance Sheets (*FAOSTAT*, 2021)
Nursery Land Use (m^2·year m^2·year^{-1})	Literature sources
Nutrient Composition of Org. Fert. (kg ha^{-1})	Webb *et al.* (Webb et al., 2012); Sintermann *et al.* (Sintermann et al., 2012); AGRIBALYSE (Colomb et al., 2014)
Nutrient Content of Excreta (kg ha^{-1})	ASAE (ASAE, 2005); EEA (EEA, 2013)
Synthetic Fertilizer Composition (%)	FeedPrint (Vellinga et al., 2013)
Fuel & Machinery Use (kg ha^{-1})	AGRIBALYSE (Colomb et al., 2014)
Energy for Irrigation (kWh ha^{-1})	WFLDB (Nemecek, Bengoa, et al., 2015)
Dry Matter (%) & Crop Composition	Feedipedia (Feedipedia et al., 2015); other sources
Share of Residue Removed and Burnt (%)	GNOC (Köble, 2014); other sources
Residue Remaining (kg DM ha^{-1}; kg N ha^{-1})	IPCC (IPCC, 2006); other sources
Infrastructure (kg ha^{-1} year^{-1})	Kowata *et al.* (Kowata et al., 2008)
Water Use by Feed Crops (L kg^{-1})	Pfister *et al.* (Pfister et al., 2011)
Animal Drinking & Service Water (L kg LW^{-1})	Mekonnen and Hoekstra (Mekonnen & Hoekstra, 2010)

i. Nutrient Composition Content of Organic Fertilizer

The nitrogen (N), phosphorus (P), and total ammoniacal nitrogen (TAN) content of manure at the point of application, not excretion, was used here, given differing mineral loss rates in housing and storage. No data were collected on the storage method prior to application, and a range was drawn from literature sources to reflect this variation.

For solid manure the meta-analysis of Webb *et al.* (Webb et al., 2012) was used, which included 266 observations by animal. For liquid manure, data from Sintermann *et al.* (Sintermann et al., 2012) were used which included 345 observations by animal, supplemented with data from AGRIBALYSE (Colomb et al., 2014). For compost, TAN was taken from AGRIBALYSE. Green manure was taken to have no NH_3 emissions, and TAN was set to 0.

ii. Fuel and Machinery Use

Most studies did not account for the impact of machinery production and delivery to farm. From 139 processes in AGRIBALYSE, the ratio of machinery depreciated per unit of fuel consumed (kg machinery kg diesel^{-1}) was established. Recognizing that farms in less developed countries have poorer access to capital and maintain farm machinery for longer, the machinery-to-diesel ratio was doubled in countries with a Human Development Index (UNDP et al., 2014) less than 0.8.

c. Allocation and Conversion Factors

For allocation between beef and milk, and lamb and wool, economic allocation factors were recalculated where required, using national price data and the yield of each product. For grain and straw, roots and feed grade roots, and nut kernels and hulls, global allocation factors were taken from literature sources.

4) Standardizing the Impact / Resource Use Indicators

For studies consistent with our system boundary, impact and resource use indicators were recorded directly.

Where the system boundary was consistent, but indicators were provided under a different characterisation, direct conversion was possible if major emissions were reported for each gas or liquid separately.

Where different characterisations were used, and gas and liquid emissions were not reported separately, recalculation was still possible in some cases:

- **GHG emissions:** Most studies included use AR4 characterisation factors (CFs). Only separately reported CH_4 emissions are required for recalculation under AR5 CFs with climate-carbon feedbacks, given the same CF is used for N_2O.
- **Acidification:** NH_3 is the dominant acidifying emission in agriculture, and the characterisation was converted based on the ratio between the CML2 baseline CF and the studies CF for this gas. SO_2 was used as the dominant gas for post-farm processes.
- **Eutrophication:** EDIP2003 (Hauschild & Potting, 2005) and ReCiPe (Goedkoop et al., 2009) split emissions into P and N equivalents. P emissions were directly recharacterised under CML2 Baseline. For N emissions, we weighted CFs by global agricultural N emissions (EC-JRC/PBL, 2013) by type to derive a conversion factor.

5) *Standardizing the Functional Unit*

i. *Arable and Permanent Crops*

For grains, oilseeds, pulses, and soybeans, where studies presented results in fresh weight, mass change from drying was included by using dry matter shares at harvest and storage (Feedipedia et al., 2015). For nuts, standard kernel weights (*FAOSTAT*, 2021) were used for conversions.

ii. *Meat, Fish, and Crustaceans*

Weight definitions for meat and fish vary by animal and country. The following definitions were standardised to as much as possible:

- Liveweight (LW): weight of the living animal leaving the farm.

  <u>*Meat:*</u>

- Hot standard carcass weight (HSCW): weight at slaughter, after removal of hides, head, feet, tail, and inedible offal. For poultry, also after removal of feathers. For pigs, also after removal of skin. Includes bones.
- Retail weight (RW): weight after removal of bones and excess fat.
- Edible offal (EO): non-muscle parts considered edible, variable by country.

  <u>*Fish:*</u>

- Filleted weight: weight after removal of head, fins, skin, bones, and organs.
- Edible weight: weight excluding large bones and inedible organs.

Data were collected from literature sources. A carcass weight adjustment of -2% was made for dairy breeds. For fish, data by species were used (FAO, 1989).

Table S6. Meat processing conversions used.

	HSCW / LW			RW+EO / HSCW			By Product Value		
Product	**Avg.**	**SD**	**n**	**Avg.**	**SD**	**n**	**Avg.**	**SD**	**n**
Beef	52%	3%	101	72%	2%	4	7%	5%	13
Mutton	47%	3%	27	71%	1%	2	7%	5%	7
Pork	75%	3%	12	68%	2%	3	5%	3%	8
Poultry	72%	2%	2	72%	4%	2	2%	2%	5

iii. Milk, Soymilk, and Tofu

Animal milk purchase prices are largely determined on fat and protein content. During processing, milk is standardised by removing and adding back solids to form grades of milk. The relevant functional unit for milk is therefore one that controls for fat and protein, and here milk was standardised to 4% fat and 3.3% protein (IDF, 2010) for all ruminants (Opio et al., 2013).

For soy products, protein is lost during processing as by-products or waste. Data were collected on the protein conversion from beans to soymilk or tofu, and then standardised to 3.3% and 16% protein respectively. This ensures nutritional unit results are robust to changes in processed-product protein content.

6) Filling Gaps in the System Boundary or Recalculating Indicators

Land use was split into five types (table S2). Farm-stage GHG emissions were split into 20 sources, gaps filled, and the total recalculated. For land use, acidification, and eutrophication, the entire indicator was recalculated from the inventory if calculated inconsistently with our system boundary (except aquaculture, where NO_x and NH_3 emissions were added to existing values otherwise consistent with our system boundary).

a. Land Use

i. Temporary and Permanent Crops

$$\boldsymbol{Land\ Use} = \frac{\mathbf{10,000}}{\boldsymbol{Yield}} \cdot \frac{\boldsymbol{Seed + Yield}}{\boldsymbol{Yield}} \cdot \frac{\boldsymbol{Crop\ Duration}}{\mathbf{365}} \cdot \frac{\boldsymbol{Rotation\ Duration}}{\boldsymbol{Cultivated\ Duration}}$$

where $Land\ Use$ is the area occupied to produce 1 kg of product, in m^2·year, $Yield$ and $Seed$ are in kg ha^{-1} and are on the same marketable weight basis (e.g., 15% moisture post field losses), and the $Duration$ terms are in days.

For temporary crops, yields for all studies included here, and in most statistical datasets (*FAOSTAT*, 2021), represent output per harvest, not output per year. Where multiple cropping occurs, a time-based allocation was used to apportion land use between crops in the rotation, as $Crop\ Dur/365$ where $Crop\ Dur \leq 365$ represents the time from crop preparation to the beginning of preparation for the next crop (Nemecek, Hayer, et al., 2015). For permanent crops, excluding orchard crops, yield represents life-cycle yield from establishment to eradication, and $Crop\ Dur$ was set to 365. No allocation was used for intercropping.

$Rotation\ Duration$ is the duration of the whole rotation including marketed crops and fallow, and $Cultivated\ Duration$ is the period cultivated with marketed crops. The difference between these terms is the fallow period. Including fallow allows for a reconciliation to the FAOSTAT (*FAOSTAT*, 2021) term “Arable land and permanent crops”.

ii. Orchard Crops

$$\boldsymbol{Land\ Use} = \frac{\mathbf{10,000}}{\boldsymbol{Yield}} \cdot \frac{\boldsymbol{Cultivated\ Duration}}{\boldsymbol{Bearing\ Duration}} \cdot \boldsymbol{Nursery} \cdot \frac{\boldsymbol{Rotation\ Duration}}{\boldsymbol{Cultivated\ Duration}}$$

where $Yield$ represents the period when the orchard is bearing marketed fruit ($Bearing\ Duration$), consistent with FAOSTAT (Statistics et al., 2011). $Cultivated\ Duration$ represents the period from orchard establishment to removal. The difference between $Bearing\ Duration$ and $Cultivated\ Duration$ is the non-bearing period after establishment, typically 1-4 years. The fallow period after orchard removal and before replanting is $Rotation\ Duration/Cultivated\ Duration$.

For orchard crops seed is not significant, but the nursery period is. The additional area required for the nursery stage per kilogram of product was calculated as:

$$\boldsymbol{Nursery} = \mathbf{1} + \frac{\boldsymbol{Nursery\ Duration/365}}{\boldsymbol{Sapling\ Yield}} \cdot \frac{\boldsymbol{Orchard\ Density}}{\boldsymbol{Cultivated\ Duration}}$$

where $Nursery\ Duration$ is the time from planting seedlings to the sale of marketable trees (in days); $Sapling\ Yield$ is the number of marketable saplings produced per hectare per year; and $Orchard\ Density$ is the number of trees required for 1 ha of mature orchard.

iii. Animal Products

For animal products, land used for feed was further disaggregated into the five feed crops that used most land. For each feed, the crop, geographic origin, and land use share were recorded. Fallow land and seed requirements were then recalculated for each crop-geography. Where feed originated from the farm, and temporary pasture was recorded on that farm, on-farm fallow was taken to be used as temporary pasture, and fallow was set to 0.

b. Freshwater Withdrawals and Scarcity-Weighted Freshwater Withdrawals

Freshwater withdrawals were calculated directly from inventory items: irrigation withdrawals; irrigation withdrawals embedded in feed; drinking water for livestock; water for aquaculture ponds; and processing water. For irrigation withdrawals embedded in feed, we recorded the feed crop type and its country of origin.

To calculate scarcity-weighted freshwater withdrawals, we assumed that all irrigation water is evapo-transpired or embedded in the product, and none is returned to the watershed through percolation. This is sometimes true and sometimes an overestimation, depending on the need of the crop and the irrigation technique, but good data are lacking here, and we leave assessment of freshwater returns to further research. We therefore directly multiplied freshwater withdrawals by the spatially explicit AWARE (Boulay et al., 2018) characterisation factors by basin and/or country. We differentiated the location of each feed crop and the location of post-farm water use.

c. Production and Transport of Farm Inputs

Inputs required on-farm were grouped as: seed and nursery; fertilizers, pesticides, and lime; fuel and machinery; infrastructure; and electricity. For seed and nursery, emissions were calculated based on a closed-loop as for land use. For the remaining inputs, two consistent sources, ecoinvent (Weidema et al., 2013) and AGRIBALYSE (Colomb et al., 2014), were used to derive global average emissions and standard deviations.

d. On-Farm Emissions

Table S7. On-farm emissions and methodology to fill gaps.

Source	Emission	Methodology
Fuel use	CO_2, SO_2, and NO_x to air	ecoinvent (Weidema et al., 2013)
Fertilizer application on mineral soils and excretion on pasture	N_2O to air	Stehfest and Bouwman (Stehfest & Bouwman, 2006); IPCC (IPCC, 2006) Tier 1
Crop residues left on field	N_2O to air	IPCC (IPCC, 2006) Tier 1
Flooded rice cultivation	CH_4 to air	*Recalculation not required*
Urea application	CO_2 to air	IPCC (IPCC, 2006) Tier 1
Lime application	CO_2 to air	IPCC (IPCC, 2006) Tier 1
Synthetic fertilizer application	NH_3 to air	EEA (EEA, 2013) Tier 2
Organic fertilizer application	NH_3 to air	Webb *et al.* (Webb et al., 2012); Sintermann *et al.* (Sintermann et al., 2012)
Excretion on pasture	NH_3 to air	EEA (EEA, 2013) Tier 2
Crop residues left on field	NH_3 to air	de Ruijter *et al.* (Ruijter et al., 2010)
Fertilizer application, excretion on pasture and crop residues left on field	NO_x to air	Stehfest and Bouwman (Stehfest & Bouwman, 2006)
Fertilizer application and site conditions	NO_3^- and N to water	Meta-analysis; Scherer and Pfister (Scherer & Pfister, 2015)
Crop residues left on field	NO_3^- to water	IPCC (IPCC, 2006) Tier 1
Fertilizer application and site conditions	P to water	Scherer and Pfister (Scherer & Pfister, 2015)
Fertilizer and crop residue leaching, runoff, and volatilisation	N_2O indirect to air	IPCC (IPCC, 2006)
Crop residue burning	CH_4, N_2O, NH_3, and NO_x to air	Akagi *et al.* (Akagi et al., 2011); IPCC (IPCC, 2006) Tier 1
Cultivated organic soils	N_2O and CO_2 to air	IPCC (Tubiello et al., 2016) Tier 1 country-level data
Enteric fermentation	CH_4 to air	IPCC (IPCC, 2006) Tier 2; WFLDB (Nemecek, Bengoa, et al., 2015)
Aquaculture	N_2O, NH_3 to air	Literature sources
Aquaculture	N and P to water	*Recalculation not required*
Aquaculture	CH_4 to air	Model; Literature review
Manure management	N_2O, NO_x, NH_3, and CH_4 to air	EEA (EEA, 2013) Tier 2; IPCC (IPCC, 2006) Tier 2

i. Direct N_2O and NO_x emissions to air from fertilizer applied on mineral soils, excretion on pasture (and crop residues left on field)

Fertilizer-induced direct N_2O and NO_x emissions on mineral soils were calculated using a global model (Stehfest & Bouwman, 2006), derived from a meta-analysis of 1008 and 189 field observations respectively (Smeets et al., 2009) as:

$$N_2O - N = \exp(c + 0.0038 \cdot (F_{SN} + F_{ON} + F_{PRP}) + \sum_{i=1}^{n} E_i) - \exp(c + \sum_{i=1}^{n} E_i)$$

$$0 \leq N_2O - N/(F_{SN} + F_{ON} + F_{PRP}) < 7.2\%$$

$$NO_x - N = \exp(c + 0.0061 \cdot (F_{SN} + F_{ON} + F_{PRP} + F_{CR}) + \textstyle\sum_{i=1}^{n} E_i) - \exp(c + \textstyle\sum_{i=1}^{n} E_i)$$

$$0 \leq NO_x - N/(F_{SN} + F_{ON} + F_{PRP}) < 2.5\%$$

where c is the regression constant; F_{SN}, F_{ON}, and F_{PRP} are synthetic fertilizer, organic fertilizer, and excreta respectively in kg N ha^{-1}; and E_i denotes the effect values of the remaining i significant effects from Stehfest and Bouwman (Stehfest & Bouwman, 2006). This specification isolates the fertilizer-induced effect. Here, the function is constrained to the 95th-percentile induced effect from the original study dataset. For NO_x, crop residues (F_{CR}) were included in this function, given the lack of other models.

The N_2O model relies on geographically specific inputs, and for country-level studies, IPCC (IPCC, 2006) Tier 1 emissions factors were used. For NO_x experimentally-grounded Tier 1 factors are not available. Here, we implemented the NO_x model at a global level, using spatial data specified in table S4. We then averaged within countries to derive country average emission factors. This avoids problems with nonlinearity of the exponential function.

Emissions for synthetic fertilizer, organic fertilizer, and excreta were then allocated by share of N applied. Crops grown in substrates lacking nitrifying and denitrifying bacteria (e.g., rock wool) were taken to have no emissions.

ii. Direct N_2O emissions to air from crop residues left on field

Experimental results are uncertain, suggesting both no significant net N_2O emission (Shan & Yan, 2013) and significant net N_2O emissions determined by multiple factors (Bureau et al., 2013). Given this, IPCC (IPCC, 2006) Tier 1 values were used.

iii. NH_3 emissions to air from organic fertilizer application

For solid manure, the same dataset as for TAN content was used (Webb et al., 2012). This provided 215 observations, covering different animals, practices, and measurement/ experimental techniques, which were aggregated into a single EF with standard deviation of 0.56±0.34 kg NH_3-N kg TAN^{-1}.

For liquid manure, the same dataset as for TAN slurry content was used (Sintermann et al., 2012), but based on the discussion in that study about significant changes in practice after the year 2000, we excluded studies before that date. This provided 109 observations, with no significant difference between animal type or land use, and gave an EF of 0.25±0.16 kg NH_3-N kg TAN^{-1}.

iv. NH_3 emissions to air from crop residues left on field

NH_3 emissions from residue vary by crop and management practice (Ruijter et al., 2010). Research in this area is scarce, and here a linear model of N in above-ground crop residues (N_{AG}) in kg and total above-ground residue dry matter (AG_{DM}) in kg (Ruijter et al., 2010) was used:

$$NH_3 - N = a \cdot N_{AG}\ ,\ \ a = (0.38 \cdot N_{AG} \cdot 1000/AG_{DM} - 5.44)\ /100\ ,\ 0 \le a < 17\%$$

where 0% and 17% are the bounds of observations in the study. The model therefore predicts no volatilisation when the N content is less than 14.3g N kg DM^{-1} (e.g., cereal straw).

v. N leaching, erosion, and runoff from fertilizer application, excretion, and crop residues left on field

The IPCC (IPCC, 2006) Tier 1 approach can be decomposed into $FRAC_{LEACH}$ (N lost below the root zone to nearby or distant rivers and streams), $FRAC_{EROSION}$ (loss of surface N contained in eroded soil), and $FRAC_{RUNOFF}$ (loss of residual surface N in runoff water).

After an extensive search, no reliable N leaching models were identified that would work with typical LCA inventory data, and we developed a model to estimate this. For leaching, background losses are non-negligible given leaching of mineralised soil organic N and atmospherically deposited N among other sources. The interest here is only in assessing the observed anthropogenic N_2O source (Nevison, 2000) in relation to the observed atmospheric N_2O increase, as well as anthropogenically induced eutrophication. Therefore, induced leaching has to be isolated from background leaching. This can be estimated from experimental leaching studies that measure leaching L of mineral N (kg NO_3-N or NH_4-N ha^{-1}) under two or more fertilizer levels $F_1 > F_0$ (kg N ha^{-1}) for the same crop, site, and year, assuming linearity, as:

$$FRAC_{LEACH} = \frac{L_1 - L_0}{F_1 - F_0}$$

To control data quality, above-ground biomass uptake U (kg N ha^{-1}) was also recorded, and results were treated as erroneous where $(L_1 - L_0) + (U_1 - U_0) > (F_1 - F_0)$.

To ascertain these data, a literature review was conducted. The search terms “nitrate leaching” AND “uptake” AND “experiment” were used in Google Scholar, and any studies cited in or citing these studies were also selected, until 1000 studies were identified. Experiments using lysimeters, suction cups with water balances, or tile drains were included. From these studies, 91 included treatments with multiple fertilizer levels and provided leaching in kg N ha^{-1}. This yielded 417 observation pairs, of which 53 were excluded based on the uptake criterion or other factors that made fertilizer treatments incomparable.

Site-specific conditions are major determinants in N leaching (van Drecht et al., 2003). In very low-permeability soils, in areas with low water input, or under deep-rooted crops, leaching will be low (Burns, 1975). Equally, under highly permeable soils, in areas with high water input, or under shallow-rooted crops, leaching will be high. $FRAC_{LEACH}$ was therefore estimated for different rooting depths, soil textures (sand and clay fraction), water input (only precipitation was used here, which is more subject to leaching given higher variability), and water table height (flooded or non-flooded crops). Cut-off levels for each factor were based on visual inspection of the data and sample size. Four groups were then created (Kruskal-Wallis test, $p < 0.001$; Dunn’s post hoc tests, $p < 0.05$).

Table S8. Fraction of fertilizer leached as mineral nitrogen.

	FRAC$_{LEACH}$ (kg NO_3-N kg N^{-1} unless stated)					
	Avg.	**SD**	**Obs. Pairs**	**Avg.**	**SD**	**Obs. Pairs**
Low Leaching Conditions*, at least one of:*						
Max. Root Depth > 1.3m	6.5%	5.2%	23	6.7%	5.1%	45
Clay > 50%	7.8%	5.8%	11			
Precipitation < 500mm	5.8%	4.5%	11			
High Leaching Conditions*, at least one of:*						
Max. Root Depth < 0.5m	28.0%	13.0%	8	23%	14%	42
Sand > 85%	21.6%	15.7%	26			
Precipitation > 1300mm	26.8%	13.6%	10			
Other Conditions *(or both high and low leaching conditions):*						
All Other Conditions				12%	10%	252
Flooded Rice						
Flooded Rice (NO_3-N)	2.8%	3.4%	25	3.5%	3.1%	22
Flooded Rice (NH_4-N)	1.3%	1.3%	22			

Given the small number of LCA studies where recalculation of leaching on pasture was required, a value of 7±2% was used, based on the average value for pasture-dominant New Zealand (Thomas et al., 2005).

Surface runoff requires simultaneously occurring factors: water input greater than evapotranspiration and infiltration, causing surface accumulation; slope or ditches so water runs-off rather than puddles; field outlets; and residual N on the surface at the time of runoff. Additional information on the quantity of N that reaches rivers or streams, as opposed to neighbouring terrestrial areas, is also required. These data requirements make runoff difficult to model with available LCA inventory data. Further, most global studies do not model this flow (J. Liu et al., 2010; van Drecht et al., 2003). The data requirements, and more limited set of conditions that this flow occurs in, make it reasonable not to consider it here.

$FRAC_{EROSION}$ was estimated following Scherer and Pfister (Scherer & Pfister, 2015), replacing soil P with soil N derived from the HWSD (FAO/IIASA/ISRIC/ISSCAS/JRC, 2012). $FRAC_{EROSION}$ is a total N flow and is only included in eutrophication calculations.

vi. Indirect N_2O emissions to air from fertilizer and crop residues left on field, from leaching, runoff, and volatilisation

Indirect N_2O emissions were then calculated as (IPCC, 2006):

$$N_2O - N = 0.01 \cdot (NH_3 - N + NO_x - N) + 0.0075 \cdot NO_3 - N$$

For some studies that did not provide sufficient information to calculate NH_3 or NO_x, the default fraction volatilised from IPCC (IPCC, 2006) was used.

vii. P loss to water from fertilizer application and site conditions

The model of Scherer and Pfister (Scherer & Pfister, 2015) estimates P loss to water from four mechanisms: soil erosion, runoff, drainage, and leaching. Their original specification was modified by setting maximum field slope to 5% for flooded rice, where terracing or other mechanisms are used to prevent water loss.

viii. N_2O and NH_3 emissions to air from aquaculture

The difference between N inputs as feed and fertilizer (N_{IN}) and N outputs in liveweight (N_{OUT}) is subject to gaseous losses during the aqueous phase. N consumed but not assimilated is excreted by aquatic animals with approximately 80% TAN (Papatryphon et al., 2005). To allow for feed not consumed, excreted TAN was estimated as the minimum of $(N_{IN} - N_{OUT}) \cdot 0.8$, or $3.31 \cdot N_{OUT} \cdot 0.8$, where the coefficient in the latter is based on 23% of feed N converted to fish biomass N (IPCC, 2014). Emissions of N_2O are likely higher from the TAN component of excreta, and an emissions factor of 1.8±0.7% N_2O-N kg TAN^{-1} was used (IPCC, 2014). N_2O emissions from unconsumed feed and solid excreta are likely lower, and an emissions factor of 0.5±6.2% N_2O-N kg N^{-1} was used (IPCC, 2006). N_2 and NO_x emissions were calculated from nitrification/ denitrification ratios proposed by Dämmgen (Dämmgen, 2009). NH_3-N volatilised was estimated from data on freshwater ponds as 0.3·TAN (Gross et al., 2000), constrained to a maximum of 50 mg m^{-2} day^{-1} in systems where the surface area for diffusion is limited (Schroeder, 1987). Emissions from pond drainage and refilling (EEA, 2013) were not considered.

ix. CH_4 emissions to air from aquaculture

Organic carbon (OC) in excreta, unconsumed feed, fertilizer, and net primary production (NPP) can mineralise to CH_4 when they accumulate in anoxic sediments with low sulphate and nitrate levels. These conditions allow methanogenesis to become a significant source of mineralization, as sulphate reduction, nitrification and aerobic mineralization become less dominant pathways (Biology & Fry, 1987). Here, we develop an initial model for these emissions that are included in few LCAs or climate models.

To estimate OC sedimentation, a carbon balance was used. OC input from feed and fertilizer (C_{IN}) was estimated from feed energy contents, more widely reported than carbon contents as 21 g C MJ^{-1} based on typical feeds. OC input from NPP was estimated based on temperature (Lewis Jr, 2011; Schroeder, 1978). The dominant OC outputs are respiration by fish (C_{RESP}), carbon removed in fish biomass at harvest (C_{FISH}), and mineralization in the dissolved OC pool. We assumed the ratio of fish biomass to respiration to excretion was 40:40:20 (Wang et al., 2013), which we calculated from liveweight (LW) and expressed in kg C kg LW^{-1}. Taking aqueous OC outflow to be 0, OC available for sedimentation C_S was calculated as:

$$C_S = \max(C_{IN} + C_{NPP} \cdot Cycle\,Time/Stocking\,Density - C_{FISH} - C_{RESP}\,, C_{EXCR}) \cdot S$$

where C_{IN} and C_S are in kg C kg liveweight^{-1} (LW) produced, C_{NPP} is in kg C m^{-2} day^{-1}, $Cycle\,Time$ is in days and $Stocking\,Density$ is in kg LW m^{-2} cycle^{-1}. S is a constant reflecting the share of the carbon pool deposited as sediment, influenced by a large range of factors. We set S within the range of literature sources as 35±5% for freshwater (Kuivilal et al., 1988; Millero et al., 1980; Schroeder, 1987) and 55±10% for marine (Alongi et al., 2009; Hall, 1990).

CH_4-C emissions were then calculated as:

$$CH_4 - C = \min\,(C_S \cdot M \cdot M_{CH_4} \cdot R,$$
$$CH_4 - C_{max} \cdot Cycle\,Time/Stocking\,Density)$$

where M is total mineralization of sedimented OC, M_{CH_4} is the share mineralized as CH_4-C, and R is the share of CH_4 not oxidised at the sediment/water interface or in the water column, and instead released by diffusion or ebullition into the atmosphere. $CH_4 - C_{max}$ is the maximum observed methane flux (0.5 g CH_4-C m^{-2} day^{-1}) from a meta-analysis of 474 methane emission estimates from freshwater bodies (Bastviken et al., 2011). R varies by depth, and here we set it to 61±22% for shallow systems (<2m) (Bastviken et al., 2008; Detweiler et al., 2014) and 22±20% (≥2m) (Bastviken et al., 2008).

Experimental data (Bastviken et al., 2008) shows that temperature limits M_{CH_4}. Here, we estimate M_{CH_4} by using our previous formula for $CH_4 - C$, substituting in known values of the variables from global data. C_S was calculated by latitude using NPP data for lakes. M was set to 100% as a long-term value without sediment removal. R was set to the average of shallow and deep water (41.5%). Resultant $CH_4 - C$ values were taken from the methane flux meta-analysis (Bastviken et al., 2011). M_{CH_4} was then calculated. In marine environments, higher sulphate concentrations favour sulphate reduction and M_{CH_4} was determined from literature sources (Alongi et al., 2009; Hall, 1990).

Table S9. Share of mineralized carbon mineralized as methane.

	% Mineralized C as CH_4-C (M_{CH_4})
Freshwater: fast flowing	0%
Freshwater: slow flowing (<23.5°C surface temperature)	20±20%
Freshwater: slow flowing (≥23.5°C surface temperature)	45±20%
Marine: flow-through	0%
Marine: sea cages/ponds	4±4%

Because in aquaculture, sediment is often removed and mineralization rates differ with temperature, we calibrated mineralization (M) based on observed sediment C:N ratios. To do this we used observations in our meta-analysis where sufficient data were available to calculate C_S, and where we had observations for sediment N. We found M values of 60% and 30% for warm (average annual temperature ≥23.5°C) and cool climates respectively yielded C:N sediment ratios in line with literature values. These M values were used here.

x. N_2O, NO_x, NH_3, and CH_4 emissions to air from manure management

For livestock, the EEA (EEA, 2013) mass balance approach was used, with adjustments to emissions factors based on EPA (EPA, 2016) Annex 3, IPCC (IPCC, 2006) and other literature sources.

For aquaculture sediment, N was calculated as unconsumed feed and solid excreta less gaseous losses (Materials and Methods, Section 6c. viii). Liquid N excreta was assumed to be lost from the system (e.g., in drainage water). Sediment OC was calculated as deposited OC after mineralization ($C_S \cdot M$). OC was multiplied by 2.05 to estimate volatile solids, a value that was derived from a linear regression on aquaculture residue composition (Holmer et al., 2005). A maximum methane potential (B_0) of 0.31 was used (Suhr et al., 2015). The fate of sediments was taken from details in each study. Fates typically included field application, pumping/release into other water bodies, or storage in anaerobic sediment ponds or stockpiles. The first two have no emissions, and for the latter, emissions were based on slurry in uncovered anaerobic lagoons (IPCC, 2006).

7) Filling Gaps in The Rest of the Supply Chain

a. Land Use Change

To estimate CO_2 emissions and sequestration from carbon stock change, we used a model consistent with PAS2050-1 (Blonk Consultants, 2013). The model uses above- and below-ground carbon pools (IPCC, 2006) by country and accounts for multiple climates and soil types (JRC, 2010). It then uses agricultural land expansion by country (*FAOSTAT*, 2021) to estimate emissions. Emissions are amortized over 20 years (The British Standards Institution, 2011). We also estimated CH_4 and N_2O emissions from forest burning, and CO_2, CH_4 and N_2O emissions from peat burning, using country forest and peat burning extent (Rossi et al., 2016). Country data, as opposed to farm or sub-regional data, better reflect the drivers of land use change which cover multiple actors (Ponsioen & van der Werf, 2017).

We adapted the model by defining when a specific crop's expansion translates into losses from another land class. First, arable crops were taken to expand into existing arable area first, and permanent crops into existing permanent crop area first. Second, where the sum of expansion and contraction of all crops (net expansion) was positive, arable cropland was assumed to expand into permanent cropland if a negative balance existed in the other, and vice versa. Third, both arable crops, permanent crops, and permanent pasture were taken to expand proportionately into deforested area. Fourth, any remaining cropland not accounted for was taken to expand into pasture or vice versa if a negative balance existed in the other. Finally, any remaining agricultural area expansion was allocated to the 'other land' category (which includes degraded land).

Under this approach, 61% of 1990-2010 forest loss was attributable to commercial agriculture (excluding shifting cultivation). This value reconciles to survey data (Hosonuma et al., 2012). We used FAO data (*FAOSTAT*, 2021) as a consistent annual inventory of multiple land classes, but recognise that total deforestation in the Forest Resources

Assessment (*FAOSTAT*, 2021) is below remote sensing estimates (M. C. C. Hansen et al., 2013). Our approach likely underestimates agriculturally induced land use change, but benefits by reconciling to FAO data.

b. Transport

Distances, modes, and emissions were adapted from ecoinvent (ecoinvent, 2013). The ecoinvent methodology took annual global transport volumes by mode (Fulton et al., 2009; International Civil Aviation Organization, 2017; UNCTAD, 2015) and allocated these between different products and transport modes using data from US freight surveys of 42 goods, and EU-27 freight surveys of 20 goods. Here, we estimated the chilled transport share from UK data (James & James, 2010). We drew emissions from a dataset considering average load factors and the full transport life-cycle (Wernet et al., 2016).

c. Processing

Data from 117 LCA studies provided 232 observations on GHG emissions, acidification and eutrophication, and processing conversions across ~495 processes. The data were consolidated into averages and standard deviations, weighted by the number of processing plants assessed per observation.

d. Packaging

Data from previously used studies and an additional 34 LCA studies provided 171 observations. Studies were included that assessed end-of-life disposal and calculated at least GHG emissions. The observations were consolidated into 11 product groups with similar pack types.

e. Retail

Data from a further two LCA studies, combined with studies previously used, provided 58 observations across three groups: fresh, chilled, and ambient.

f. Losses

Following the FAO (FAO et al., 2011), food losses occur at five stages, during: harvest and pre-harvest operations (L_0); storage and transport between farm and distribution (L_1); processing and packaging (L_2); wholesale and retail distribution (L_3); and consumption (L_4). Consumption losses are not included in this study.

Production and yield in FAOSTAT and the food balance sheets (FBS) are net of harvest and pre-harvest losses (L_0) (FAO, 2001). Here, all yield data collected from LCA studies were entered in the database net of harvest and pre-harvest losses to ensure reconciliation. Storage and transport losses (L_1) were occasionally reported by LCAs, and if missing this gap was filled. Estimates of losses at this stage were taken from the FBSs, following Gustavsson *et al.* (Gustavsson et al., 2013). Processing and packaging (L_2), and wholesale and retail (L_3) losses were taken from Gustavsson *et al.* (Gustavsson et al., 2013). Losses at these stages represent an average for the crop/geography, not necessarily the consumption mode in this study.

Losses were calculated as the additional food required to deliver one functional unit to the consumer as:

$$T = \frac{\left[\frac{\left[\frac{(LUC + Feed + Farm)}{(1 - L_1)} + Proc\right]}{(1 - L_2)} + Trans + Pack + Rtl\right]}{(1 + L_3)}$$

$$L = T - (LUC + Feed + Farm + Proc + Trans + Pack + Rtl)$$

where T represents the total mass flow including losses, and L represents losses. If by-products are marketed (e.g., feed-grade vegetables), allocation means that the mass flow does not equal the environmental flow.

8) *Weights*

a. *Within-Country Weights*

Study representativeness within a country was determined first, either based on values reported by the author, or by derivation from global datasets on tillage (FAO, 2016a), irrigation (S. Siebert et al., 2010), organic farming (FiBL and IFOAM, 2014), and/or sub-national production censuses.

b. *Between-Country Weights*

i. *Temporary and Permanent Crops*

Where ≥75% of global production was represented by observations, countries were weighted by production (eight crops).

Where <75% of global production was represented, agro-ecological suitability (IIASA/FAO, 2012) and macro-nutrient input levels (West et al., 2014), were used to group countries by similarity. HDI was used as a proxy for macro-nutrient input if not available (UNDP et al., 2014). This created a 2×2 high-low suitability-input matrix of countries for 21 crops. The production weights of all countries in each quadrant were scaled up to the share of global production represented by each quadrant.

For the remaining four crops, weights were based on the share of each country's production.

ii. *Animal Products*

For milk, countries were split into three groups (low, medium, and high yield per cow) (*FAOSTAT*, 2021) where boundaries between each group split global production in thirds. For fish, shares of production by species were taken from FishStatJ (FAO, 2016b). For other animal products, weights were based on country production (FAO, 2016c; *FAOSTAT*, 2021).

9) Randomization and Resampling

Some studies group farms into a single observation and provide an average mid-point impact and associated standard deviation. When we fill gaps in the supply chain, variance is also associated with: emissions factors (but here not characterisation factors); processing, packaging, retail, and transport impacts; processing conversions; and other conversions (e.g., dry matter weights).

To include all these sources of variance, as well as the variance among observations, we re-specified all values associated with variance as normally distributed variables. A random number was then generated, creating a new value for each observation. For each product one observation was randomly recorded, with likelihood based on the observation weights. A new random number was generated, and the process repeated creating 10,000 observations for each product.

This approach has limitations if studies did not report standard deviations, or remodelling from inventory data were used to fill different emissions gaps for each study. Nevertheless, it was the best way identified to effectively incorporate these multiple sources of variance.

Supplementary Text

Reconciliation of values from this meta-analysis to independent estimates

Table S10. Weighted average global yields for this study vs. FAO global average yields.

Crop (*n* = observations)	**FAO Yield** (t ha^{-1}, '09-11 avg.)		**This Study Yield** (t ha^{-1}, ~2010)		**Bias** (Study - FAO Yield) / FAO Yield	
	Mean	**90th-pctl**	**Mean**	**90th-pctl**	**Mean**	**90th-pctl**
Wheat & Rye (*n* = 261)	3.1	6.4	3.2	7.1	6%	11%
Maize (152)	5.2	9.7	5.3	10.0	3%	4%
Barley (93)	2.7	6.1	2.7	6.4	-2%	6%
Oats (17)	2.3	4.6	2.4	3.2	8%	-30%
Rice (flooded) (65)	4.4	6.6	4.5	7.2	2%	9%
Potatoes (91)	16.6	41.1	19.8	41.0	19%	0%
Cassava (52)	11.4	20.1	11.2	23.7	-1%	18%
Sugar Cane (53)	71.0	78.5	73.0	85.0	3%	8%
Sugar Beet (36)	51.4	90.0	49.9	75.6	-3%	-16%
Other Pulses (44)	0.8	1.7	1.0	1.3	25%	-22%
Peas (33)	1.6	3.0	2.0	4.4	23%	47%
Nuts (23)	1.4	4.3	1.4	3.8	2%	-12%
Groundnuts (24)	1.6	3.4	2.1	3.6	27%	4%
Soybeans (49)	2.5	2.9	2.3	3.0	-5%	3%
Palm (30)	14.2	20.9	19.4	23.0	37%	10%
Sunflower (31)	1.4	2.3	1.4	2.4	-2%	5%
Rapeseed (77)	1.9	3.6	2.1	3.6	8%	1%
Olives (24)	2.0	2.9	2.0	9.9	0%	238%
Tomatoes (82)	33.6	81.5	30.3	198.5	-10%	144%
Onions & Leeks (29)	18.4	45.4	24.5	47.2	33%	4%
Root Vegetables (30)	29.8	54.1	40.3	80.2	35%	48%
Brassicas (32)	24.9	34.5	24.1	57.1	-3%	65%
Citrus Fruit (30)	14.4	31.1	16.8	36.9	17%	19%
Bananas (23)	20.7	41.6	28.2	45.9	36%	11%
Apples (66)	15.0	38.8	24.4	42.9	62%	11%
Berries (40)	13.6	29.7	13.5	72.8	-1%	145%
Coffee (28)	0.8	2.0	1.0	2.2	26%	12%
Cocoa (19)	0.5	0.6	0.5	0.7	9%	21%

Comparing mean yields to FAOSTAT (*FAOSTAT*, 2021), 17 of 28 crops reconcile to within ±10% (table S10). For pulses, peas, potatoes, and groundnuts, we have low representation in low-yielding African and Asian countries, and our yield estimates are on average 24% higher than FAOSTAT. The remaining crops that did not reconcile are primarily trees and vegetables.

For the former, FAOSTAT data include trees in residential areas or small orchards (Statistics et al., 2011), not captured in this dataset. Further, the distinction between bearing and non-bearing periods is inexact and has likely reduced comparability. For palm, data for Nigeria, a country with high production volume and low yields, are missing from the LCA literature and therefore this meta-analysis, with a significant effect on the yield reconciliation. In summary, this dataset overestimates yield for some tree crops. For vegetable crops, many countries group multiple crops into 'Vegetables, fresh nes' for FAOSTAT reporting. Equally, values in this meta-analysis for China (the largest producer) do not reconcile to FAOSTAT, although they do reconcile to Chinese economic census data (National Development and Reform Commission of China, 2013). It is unclear whether vegetable crop yields in this meta-analysis represents an under- or over-estimate.

We also calculated weighted 90th-percentile yields between countries from FAOSTAT. For 24 of 28 crops, 90th-percentile yield is higher in this dataset than FAOSTAT, which would be expected as this dataset captures both within- and between-country variation.

Table S11. Global land for this study vs. FAO.

Land Use (Mha)	**FAO** (2009-11 avg.)	**This Study** (~2010)	**Bias** (Study - FAO) / FAO
Arable Land & Permanent Crops	1535	1415	-7.8%
Area Harvested	1284	1096	-14.6%
Feed	-	422	-
Food	-	547	-
Non-Food*	-	127	-
Fallow	251	319	27.1%
Feed	-	116	-
Food	-	157	-
Non-Food*	-	46	-
Fibre Crops, Rubber & Tobacco	16	-	-
Permanent Meadows & Pasture	3322	1761	-47.0%
Feed	-	1534	-
Non-Food*	-	227	-

* Includes biofuels, leather, wool, processing by-products, and other non-food products derived from products assessed in this study.

We converted land use for each observation from Retail Weight (table S2) to the functional units used by the FBSs (e.g., from 'fat and bone-free meat and edible offal' to 'carcass weight'), and extrapolated globally with weights using FBS consumption, losses, and non-food uses (table S11). Arable land and permanent crops reconcile to -7.8% of FAOSTAT. Of this, we estimate that 538 Mha (38%) was used for feed, 6% lower than Mottet *et al.*'s (Mottet et al., 2017) estimate of 570 Mha, but 53% larger than Foley *et al.*'s (Foley et al., 2011) estimate of 350 Mha. This difference is primarily because our study and Mottet *et al.* economically allocated between crops and crop by-products (such as straw or palm kernel expeller) used as feed or bedding in animal production. These by-products represent ~150 Mha of arable land.

Our non-food arable land estimate is 12%, close to the 10% non-food mass flow in the FBSs. In this study, non-food uses are excluded by using economic allocation and by considering food mass flows only.

For permanent meadows and pasture, we have limited observations on ruminants in Africa, representing 27% of global pasture area, and no observations in Saudi Arabia, Kazakhstan, or Mongolia, representing 14% (*FAOSTAT*, 2021). From FAOSTAT data, pasture area is 1010 m^2 kg $carcass^{-1}$ and 5330 m^2 kg $carcass^{-1}$ respectively in these areas, well above the global average (*FAOSTAT*, 2021). While FAOSTAT data may be overestimated (Ramankutty et al., 2008), missing LCAs in these regions puts a strong downward bias on our estimate of ruminant land use. This also puts a downward bias on our estimate of emissions from cultivated organic soils. It has a smaller effect on our land use change estimates, which are driven by countries where pasture area reconciles. For our global land use totals and diet change estimates, we correct by the difference in our estimate and FAOSTAT to bring the total global pasture value to 3322 Mha. While we are unable to reconcile to FAOSTAT, our estimate is just 10% lower than that of Mottet *et al.* (Mottet et al., 2017) who used a similar modelling approach.

Areas under permanent ice and deserts are generally unsuitable for agriculture. In 2000, 0.8% of desert was cropland and 16.5% was extensive rangelands (extensive rangelands are not recorded as pasture in many countries) (Ellis et al., 2010). Using an ice-, and desert-free area of 11,250 Mha (Ellis et al., 2010), agriculture occupies ~43% of the world's land.

Table S12. Global CH_4 emissions for this study (~2010) vs. estimates drawn from the literature (~2005-2011).

Emissions Source (Mt CH_4)	**Literature** Min - Max	n	**This Study** Average
Flooded Rice	20.0 - 37.5	4	32.6
Enteric Fermentation	76.2 - 105.6	7	78.3
Manure Management	9.1 - 12.7	7	10.7

Our estimates of agricultural methane reconcile to literature sources for flooded rice and manure management (table S12). For enteric fermentation, our estimate is closest to the lowest value we identify, a Tier 2/3 estimate by Herrero *et al.* (Herrero et al., 2013). For N_2O, not all LCAs included break out these emissions, meaning we cannot perform a reconciliation.

For land use change, we estimate that 61% of 1990-2010 forest loss was attributable to commercial agriculture (Materials and Methods, Section 7a), and that agriculturally induced land use change emissions from carbon stock changes and fires are 2.9 Gt CO_2eq year^{-1} (this includes food and non-food). Approximating total land use change emissions by dividing 2.9 by 61% yields 4.7 Gt CO_2eq year^{-1}, close to Houghton *et al.*'s (Houghton et al., 2012) roughly comparable inventory based estimate for the same period of 4.2±0.7 Gt CO_2eq year^{-1}, and within the range of a separate estimate of 3.3±1.8 Gt CO_2eq year^{-1} for 2004-13 (Friedlingstein et al., 2014).

AQUASTAT (FAO, 2017) reports irrigation withdrawals of 2770 km^3 year^{-1}, close to our food and non-food estimate of 2430 km^3 year^{-1}, which unlike AQUASTAT, excludes fibbers, rubber, and tobacco. Industrial and municipal withdrawals are 1230 km^3 year^{-1} (FAO, 2017).

Agriculture's share is therefore ~66%. Using withdrawals and marginal AWARE CFs, scarcity-weighted withdrawals are 74,300 km^3eq $year^{-1}$ for food and 81,200 km^3eq $year^{-1}$ for agriculture.

Boulay *et al*. (Boulay et al., 2018) report consumptive water use, which accounts for water returned to rivers and groundwater, putting agricultures share at 90%. Using consumptive water use and marginal AWARE CFs, agriculture contributes 95% of scarcity-weighted water use. For global analysis, many researchers suggest using average CFs (Boulay et al., 2018), which are unpublished. At the margin, irrigation typically drives basin stress, meaning differences between average CFs for irrigation and other uses should be smaller. We therefore report the range 90-95%.

Variance decomposition

Variance-based sensitivity analysis allocates a portion of the variance in the output of a model to each input. When inputs are statistically dependent, commonly used Sobol' or R^2 decompositions are difficult to interpret and often do not sum to total variance. Recently introduced Shapley effects, under the methodology proposed by Song *et al.* (Song et al., 2016), allow for nonlinear models with dependent inputs, and sum to the total variance of the output. From our sample, we calculated covariance matrices and means of model inputs, and used the Shapley effects implementation in R (Pujol et al., 2017). See fig. S10 for further results.

Table S13. Variance-based sensitivity analysis of CH_4 emissions model for freshwater aquaculture ponds. Shading indicates temperature-determined inputs. *n*=39 observations.

Model Input	Model Input Formula	Contribution to Output Variance
Carbon input as NPP per m^2 of pond	C_{NPP}	23%
Conversion of C_{NPP} per m^2 to kg liveweight	$Cycle\ Time/Stocking\ Density$	32%
Other carbon additions to pond	$C_{IN} + C_{FISH} - C_{RESP}$	8%
Mineralization of sedimented carbon	M	10%
Share of M mineralized as methane	M_{CH_4}	15%
- Temperature	M_{CH_4}	*4%*
- Flow	M_{CH_4}	*11%*
Methane released to atmosphere	R	12%
Contribution of Temperature to Variance		**37%**

Table S14. Variance-based sensitivity analysis of reactive N loss models, assessing the fraction of N lost. Shading indicates geographically determined inputs. For these sensitivity analyses, performed across multiple products, we calculated weighted covariance matrices and weighted means of model inputs. 'Total' is an average of effects by row, weighted by the share of each emission in total volatile N emissions from crops. Fert = synthetic (syn) and organic (org) fertilizer. Res = crop residue.

Model Input	N_2O Fert	N_2O Resid.	NO_x	NH_3 Syn	NH_3 Org	NH_3 Res	NO_3^-	Total
***n* = observations**	**674**	**1397**	**620**	**1134**	**632**	**993**	**783**	**-**
N per hectare	13%	-	41%	-	-	-	-	2%
Crop/Fertilizer type	35%	100%	-	85%	100%	100%	32%	56%
Soil organic carbon	5%	-	-	-	-	-	-	-
Soil nitrogen	-	-	36%	-	-	-	-	-
Soil pH	3%	-	-	11%	-	-	-	-
Soil texture	3%	-	-	-	-	-	27%	-
Temp/Precipitation	41%	-	23%	4%	-	-	41%	-
Contrib. of Geog.	**52%**	**0%**	**59%**	**15%**	**0%**	**0%**	**68%**	**42%**

Diet change estimates

Current diets are taken from FBSs (*3*). The mix of protein sources in the 'No animal products' diet is taken from survey data (*n* = 120) reported in Haddad and Tanzman (Haddad & Tanzman, 2003). Fruit and vegetable consumption increases by 20% under the 'No animal products' diet based on survey data (*n* = 2041) reported in Springmann *et al.* (Springmann, Godfray, et al., 2016).

Table S15. Per capita composition of global diets. FBS weight is 'Food supply quantity' in the FAO food balance sheets. It is in the units used in the FBSs (e.g., carcass weight) and includes storage and transport losses only (Materials and Methods Section 7f). Retail Weight includes losses between distribution and retail, but not consumer losses, and is expressed in Retail Weight functional units (e.g., fat and bone-free meat, table S2). Calories and protein are in Retail Weight. On a Retail Weight basis, farmed animal products provide 18% of calories and 37% of protein.

	Current Diet (2009-11 avg.)				**No Animal Products**		
	FBS Weight (g/d)	Retail Wt. (g/d)	Calories (kcal/d)	Protein (g/d)	Retail Wt. (g/d)	Calories (kcal/d)	Protein (g/d)
Beef (beef herd)	16	10	22	2.1	0	0	0
Lamb & Mutton	5.7	3.7	11	0.7	0	0	0
Beef (dairy herd)	13	8.6	18	1.7	0	0	0
Buffalo	2.7	1.8	2.8	0.4	0	0	0
Crustaceans (farmed)	4.3	2.1	1.1	0.2	0	0	0
Cheese	8.3	8.0	27	1.7	0	0	0
Pig Meat	45	28	112	4.5	0	0	0
Fish (farmed)	18	7.4	12	1.7	0	0	0
Poultry Meat	39	26	51	4.5	0	0	0
Eggs	24	24	34	2.6	0	0	0
Fish (capture)	21	8.4	13	1.9	0	0	0
Crustaceans (capture)	8.5	4.2	2.1	0.4	0	0	0
Tofu	3.5	3.2	2.5	0.5	53	40	8.4
Groundnuts	4.3	3.5	21	0.9	5.9	36	1.6
Other Pulses	16	15	51	3.1	55	188	12
Nuts	6.0	2.7	16	0.5	4.7	28	0.8
Peas	2.3	2.1	7.2	0.5	7.9	27	1.8
Milk	185	171	105	6.1	0	0	0
Butter, Cream & Ghee	4.8	4.6	29	0.1	0	0	0
Soymilk	10	9.1	5.1	0.3	185	104	6.1
Cassava	55	45	44	0.4	45	44	0.4
Rice	148	134	494	9.3	146	538	10
Oatmeal	1.6	1.0	2.6	0.1	1.1	2.9	0.1
Potatoes	115	90	66	1.3	90	66	1.3
Wheat & Rye (Bread)	182	166	471	14	181	513	15
Maize (Meal)	47	28	127	3.1	31	138	3.3
Cereals & Oilcr. Misc.	39	34	93	3.2	37	101	3.5
Palm Oil	6.6	6.7	52	0	7.5	59	0
Soybean Oil	10	10	77	0	11	87	0
Olive Oil	1.2	1.3	10	0	1.5	11	0
Rapeseed Oil	4.0	4.1	33	0	4.7	37	0

Sunflower Oil	3.8	3.8	31	0	4.3	35	0
Oils Misc.	5.1	4.7	41	0	5.2	47	0
Animal Fats	4.2	3.8	27	0	0	0	0
Tomatoes	55	37	6.7	0.4	44	8.0	0.4
Brassicas	28	25	6.2	0.3	30	7.5	0.4
Onions & Leeks	29	23	8.7	0.3	28	10	0.4
Root Vegetables	13	11	2.8	0.2	14	3.4	0.2
Other Vegetables	241	213	53	2.9	256	64	3.4
Aquatic Plants	5.0	4.4	1.8	0.1	5.3	2.1	0.1
Berries	11	7.5	4.3	0	9.0	5.1	0.1
Bananas	42	29	19	0.2	35	23	0.3
Apples	25	22	9.2	0.1	27	11	0.1
Citrus	48	40	11	0.2	47	13	0.2
Other Fruit	77	58	26	0.3	69	32	0.4
Cane Sugar	50	41	145	0	41	145	0
Beet Sugar	10	7.9	28	0	7.9	28	0
Sweeteners & Honey	8.3	6.7	20	0	6.7	20	0
Beer	72	63	28	0.3	63	28	0.3
Wine	9.1	8.0	5.3	0	8.0	5.3	0
Dark Chocolate	1.7	0.6	3.0	0.1	0.6	3.0	0.1
Coffee	3.1	1.7	0.7	0.1	1.7	0.7	0.1
Stimul. & Spices Misc.	5.3	3.5	6.8	0.4	3.5	6.8	0.4
Total	**1792**	**1480**	**2494**	**72**	**1573**	**2516**	**72**

For the USA, the share of imported and domestic food was estimated from the FBSs. Global impacts were used for imported food. For domestic consumption, environmental impacts were recalculated using observations from the USA and Canada.

Table S16. Per capita mass and nutritional composition for diets in the USA. FBS weight is 'Food supply quantity' in the FAO food balance sheets. It is in the units used in the FBSs (e.g., carcass weight) and includes storage and transport losses only (Materials and Methods Section 7f). Retail Weight includes losses between distribution and retail, but not consumer losses, and is expressed in Retail Weight functional units (e.g., fat and bone-free meat, table S2). Calories and protein are in Retail Weight.

		Current Diet (2009-11 avg.)				**No Animal Products**		
	Share Imported	FBS Weight (g/d)	Retail Wt. (g/d)	Calories (kcal/d)	Protein (g/d)	Retail Wt. (g/d)	Calories (kcal/d)	Protein (g/d)
Beef (beef herd)	10%	79	51	72	8.9	0	0	0
Lamb & Mutton	55%	1.2	0.8	2.7	0.1	0	0	0
Beef (dairy herd)	10%	26	18	25	3.1	0	0	0
Buffalo	3%	2.2	1.5	1.8	0.4	0	0	0
Crustaceans (farmed)	85%	3.2	1.6	0.9	0.2	0	0	0
Cheese	4%	45	43	172	11	0	0	0
Pig Meat	5%	77	47	112	6.8	0	0	0
Fish (farmed)	61%	1.3	0.5	0.9	0.1	0	0	0
Poultry Meat	1%	138	92	182	17	0	0	0
Eggs	0%	38	37	52	4.0	0	0	0
Fish (capture)	61%	31	12	20	2.6	0	0	0
Crustaceans (capture)	85%	24	12	6.4	1.2	0	0	0
Tofu	1%	2.2	2.0	1.6	0.3	104	79	17
Groundnuts	4%	8.4	6.8	47	2.1	23	159	7.2
Other Pulses	20%	9.2	8.4	29	1.9	108	366	24
Nuts	46%	11	5.1	30	0.9	17	102	2.9
Peas	32%	1.3	1.2	4.1	0.3	16	52	3.8
Milk	4%	373	346	183	10	0	0	0
Butter, Cream & Ghee	3%	5.6	5.4	38	0	0	0	0
Soymilk	1%	6.2	5.7	3.1	0.2	357	191	12
Cassava	100%	2.7	2.2	0.8	0	2.2	0.8	0
Rice	23%	19	17	66	1.2	20	75	1.4
Oatmeal	66%	11	7.2	17	0.7	8.2	20	0.8
Potatoes	15%	152	119	72	1.9	119	72	1.9
Wheat & Rye (Bread)	13%	221	202	531	17	232	610	20
Maize (Meal)	0%	35	20	84	1.5	23	97	1.7
Cereals Misc.	13%	11	10	27	0.7	11	31	0.8
Palm Oil	100%	0.2	0.2	1.5	0	0.2	1.7	0
Soybean Oil	2%	63	63	478	0.2	70	528	0.2
Olive Oil	100%	2.5	2.7	20	0	3.0	23	0
Rapeseed Oil	84%	5.1	5.2	41	0	5.8	46	0
Sunflower Oil	23%	0.6	0.7	5.0	0	0.7	5.5	0
Oils Misc.	45%	4.0	3.7	30	0	4.1	34	0
Animal Fats	2%	8.8	8.0	55	0	0	0	0

Tomatoes	11%	111	74	13	0.6	88	15	0.7
Brassicas	26%	5.9	5.2	1.2	0.1	6.3	1.5	0.1
Onions & Leeks	11%	28	22	7.1	0.2	27	8.6	0.3
Root Vegetables	26%	7.3	6.4	1.5	0.1	7.7	1.8	0.1
Other Vegetables	26%	175	155	37	1.7	186	44	2.1
Berries	14%	20	15	8.1	0.1	17	10	0.1
Bananas	93%	31	21	13	0.2	26	16	0.2
Apples	54%	59	52	18	0	63	22	0
Citrus	39%	103	86	23	0.4	103	28	0.5
Other Fruit	60%	70	53	26	0.3	63	31	0.4
Cane Sugar	31%	69	56	208	0	56	208	0
Beet Sugar	31%	13	10	37	0	10	37	0
Sweeteners & Honey	7%	86	70	222	0.1	70	222	0.1
Beer	12%	224	197	83	0.6	197	83	0.6
Wine	30%	20	17	12	0	17	12	0
Dark Chocolate	100%	7.5	2.7	10	0.4	2.7	10	0.4
Coffee	100%	11	6.1	3.4	0.5	6.1	3.4	0.5
Stimul. & Spices Misc.	86%	3.9	2.6	5.1	0.3	2.6	5.1	0.3
Total	**-**	**2463**	**2011**	**3138**	**100**	**2074**	**3249**	**100**

Diet change carbon sink

If farmland, no longer required for food production, reverts to natural vegetation, it can remove carbon dioxide from the atmosphere. Schmidinger and Stehfest (*146*) report how much carbon would be removed by natural vegetation for scenarios of less animal product consumption, broken down for five animal products and five geographic regions. These potentials are based on simulations in the IMAGE integrated assessment model, which uses 13 potential vegetation types and a spatially explicit economic land use allocation model.

Under the 'No Animal Products' scenario, 809 Gt of CO_2 would be removed by re-growing vegetation from the atmosphere over 100 years, with continued but lower uptake after that. 74% is uptake by above- and below-ground vegetation biomass and 26% is soil carbon accumulation. This sink is additional to the annual avoided agricultural CO_2eq emissions. Under the second scenario of a 50% reduction in animal products targeting the highest impact producers, 551 Gt of CO_2 would be removed from the atmosphere over 100 years.

Sensitivity Analysis

Here, we report four sensitivities to the diet change scenarios. These are not reflected in the reported confidence intervals.

1. Oil production creates meals that are primarily fed to animals. For sunflower, palm, and rapeseed, 10-30% of the environmental impact is apportioned to animal products using economic allocation, increasing to ~60% for soy. Here, we assume 100% is apportioned to oil. This is a worst-case scenario: meal is a food (e.g., soy flour), and it can fertilize crops, suppress weeds, and build soil fertility (Darby et al., 2010).
2. We estimate the change in emissions from replacing manure and slurry with synthetic fertilizer. We include emissions from fertilizer production and all N losses. We use studies with full inventory data on N flows only. We do not account for lower nutrient availability of organic fertilizer to plants.
3. At CO_2 concentrations of 990ppm by 2100, CO_2 fertilization could increase the 'No animal products' scenario carbon sink. We approximate this by multiplying the additional sink from Strassmann *et al.* (*151*) by the 76% reduction in farmland.
4. Consumer waste, not assessed elsewhere in this study, is 2.5-9% higher in animal than vegetable proteins, but is also high in fresh fruit and vegetables which increase in the 'No animal products' diet. We quantify this using estimated consumer wastage values from Gustavsson *et al.* (Gustavsson et al., 2013).

Table S17. Sensitivity of the 'No animal products' scenario. Showing absolute change in impact, and in parentheses, the percentage change in impact (e.g., for Scenario 1, +2.8% means food's annual GHG emissions are reduced by ~46% instead of 49%).

Scenario	**Land Use** (Mha)	**GHG** (Gt CO_2eq)	**Acid.** (Kt SO_2eq)	**Eutr.** (Kt PO_4^{3-}eq)	**Sct. Wtr.** (km^3eq)
1. Oilseed meals not utilised	+63 (+1.5%)	+0.38 (+2.8%)	+1110 (+1.3%)	+870 (+1.3%)	+970 (+1.3%)
2. Manure replaced with synthetic fertilizer	-	+0.06 (+0.4%)	+1150 (+1.3%)	+490 (+0.8%)	-
3. Carbon sequestration per year at 990ppm	-	-3.20	-	-	-
4. Lower consumer waste of veg. proteins	-12 (-0.3%)	-0.04 (-0.3%)	-220 (-0.2%)	-160 (-0.2%)	-310 (-0.4%)

Table S18. Global GHG emissions, acidification, and eutrophication by stage of the supply chain for the year ~2010. GHG emissions from savannah burning are taken from FAOSTAT (*FAOSTAT*, 2021). Acidification and eutrophication from land use change and savannah burning are taken from EDGAR (EC-JRC/PBL, 2013). GHG emissions from capture fisheries are from Parker *et al.* (Parker et al., 2018), and acidifying and eutrophying emissions are calculated based on fuel use. Global total GHG emissions are taken from EDGAR, replacing emissions from organic soils, savannah burning, land use change, enteric fermentation, methane emissions from rice, and methane from manure management with values from this study. Total acidifying and eutrophying emissions to air are taken from EDGAR. Non-agricultural phosphorus emissions are taken from Cordell *et al.* (Cordell et al., 2011).

	GHG Emissions		**Terrestrial Acidification** (Mt SO_2eq)	**Freshwater & Marine Eutr.** (Mt PO_4^{3-}eq)
Emissions Source	Gt CO_2eq	% Share		
Land Use Change	2.38	17%	2.5	0.5
Food	0.78	6%	0.8	0.2
Feed	1.60	12%	1.7	0.3
Savannah Burning	0.29	2%	0.8	0.2
Cultivated Org. Soils	0.55	4%	-	-
Food	0.27	2%	-	-
Feed	0.28	2%	-	-
Crop Production	3.68	27%	45.9	45.4
Food	2.87	21%	24.6	25.1
Feed	0.81	6%	21.3	20.3
Livestock/Aquaculture	4.14	30%	23.5	15.9
Capture Fisheries	0.18	1%	2.9	0.3
Processing	0.60	4%	2.2	1.1
Transport	0.80	6%	7.3	0.8
Packaging	0.63	5%	3.5	0.6
Retail	0.39	3%	3.7	0.5
Total	**13.7**	-	**92.4**	**65.3**
Food Waste	2.05	-	14.1	11.6
All Sector Total	**52.3**	-	**290.5**	**84.2**
Food Share	**26%**		**32%**	**78%**

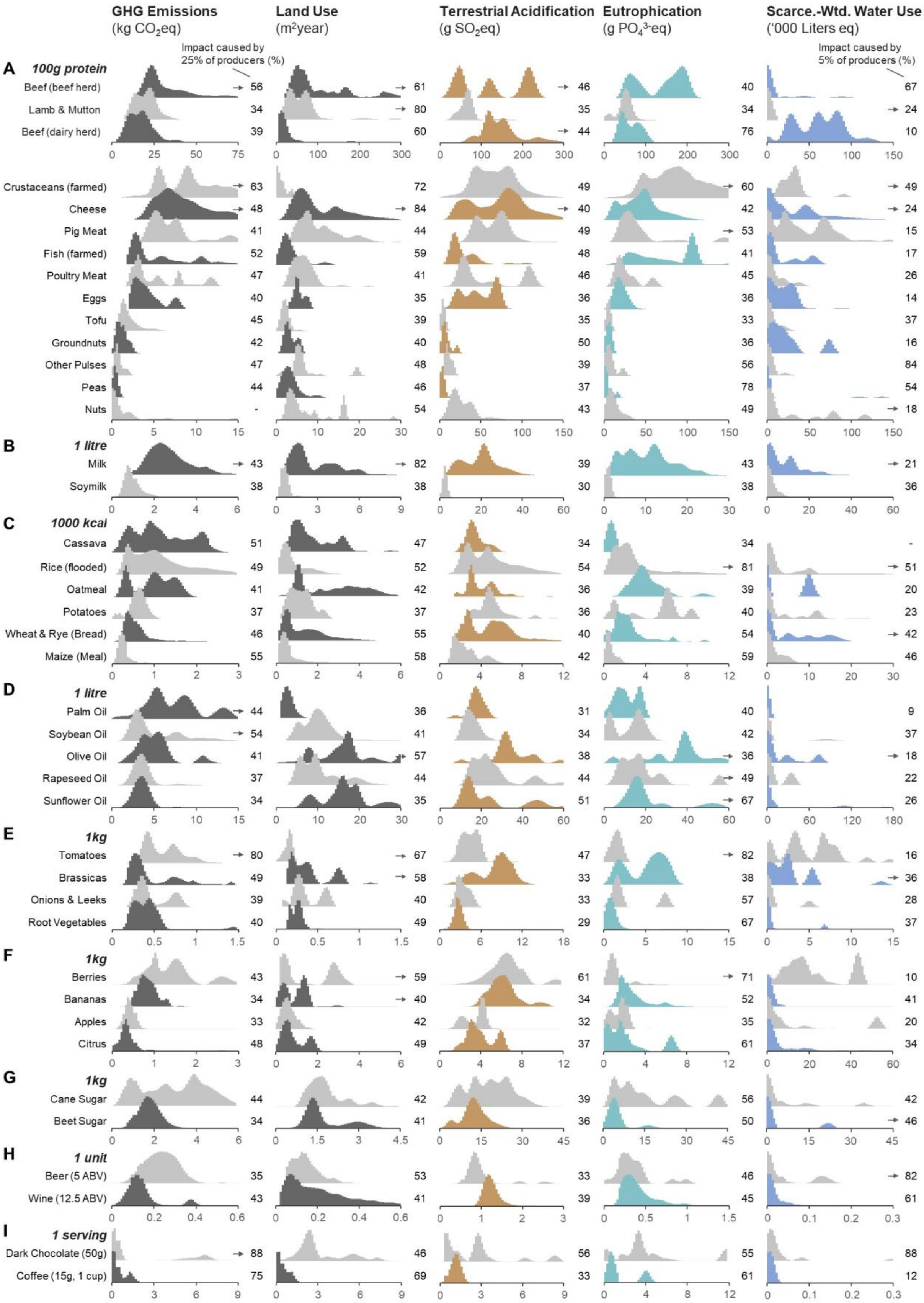
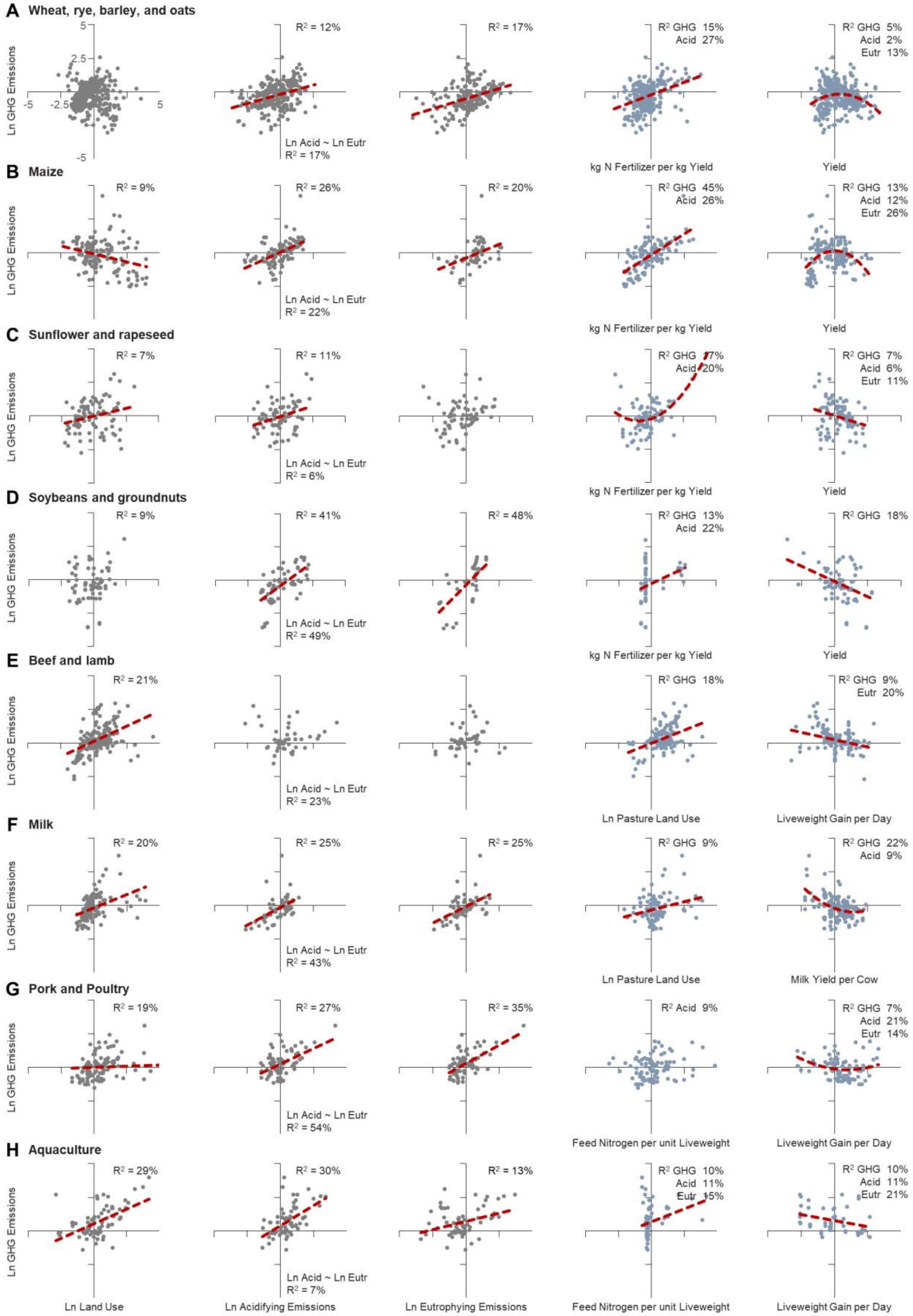
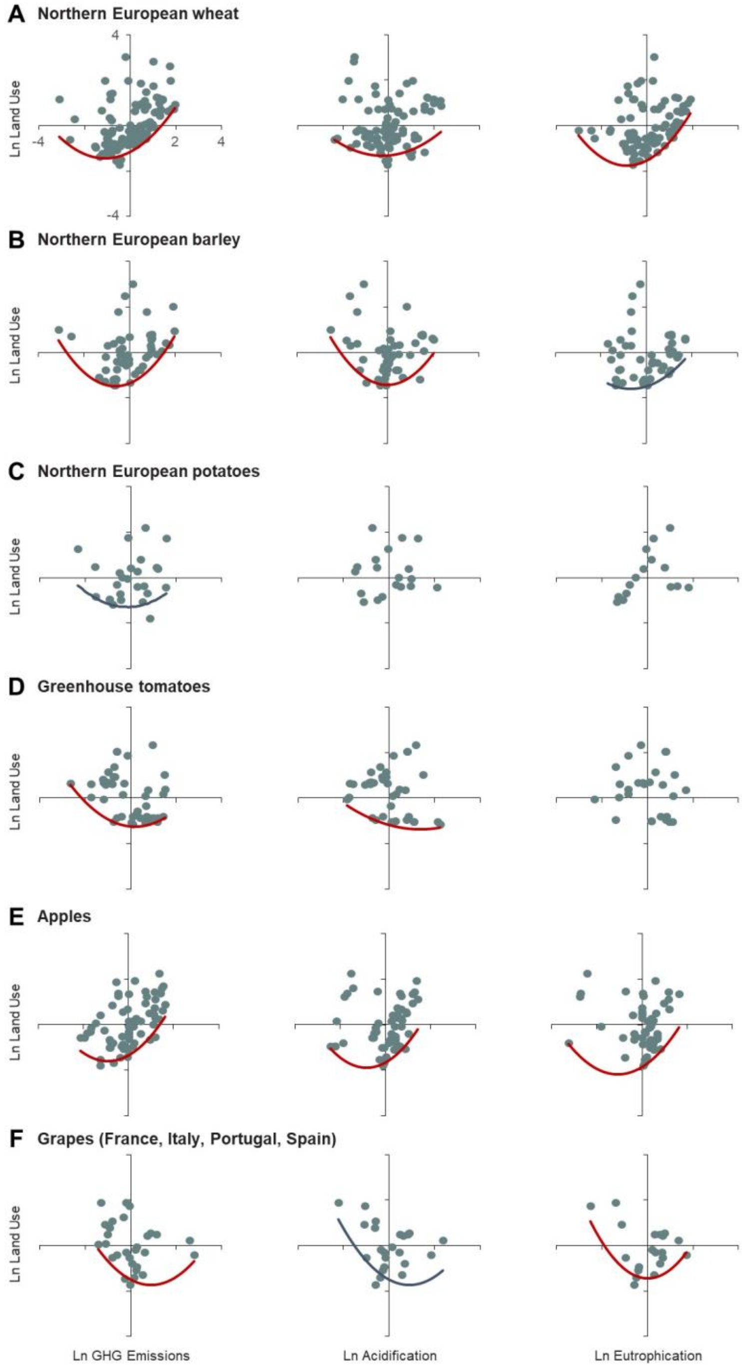

GHG Emissions (kg CO_2eq)
Land Use (m^2year)
Terrestrial Acidification (g SO_2eq)
Eutrophication (g PO_4^{3-}eq)
Scarce.-Wtd. Water Use ('000 Liters eq)
Impact caused by 25% of producers (%)
Impact caused by 5% of producers (%)
A 100g protein
Beef (beef herd) 56 61 46 40 67
Lamb & Mutton 34 80 35 34 24
Beef (dairy herd) 39 60 44 76 10
0 25 50 75 | 0 100 200 300 | 0 100 200 300 | 0 100 200 300 | 0 50 100 150
Crustaceans (farmed) 63 72 49 60 49
Cheese 48 84 40 42 24
Pig Meat 41 44 49 53 15
Fish (farmed) 52 59 48 41 17
Poultry Meat 47 41 46 45 26
Eggs 40 35 36 36 14
Tofu 45 39 35 33 37
Groundnuts 42 40 50 36 16
Other Pulses 47 48 39 56 84
Peas 44 46 37 78 54
Nuts - 54 43 49 18
0 5 10 15 | 0 10 20 30 | 0 50 100 150 | 0 50 100 150 | 0 50 100 150
B 1 litre
Milk 43 82 39 43 21
Soymilk 38 38 30 38 36
0 2 4 6 | 0 3 6 9 | 0 20 40 60 | 0 10 20 30 | 0 20 40 60
C 1000 kcal
Cassava 51 47 34 34 -
Rice (flooded) 49 52 54 81 51
Oatmeal 41 42 36 39 20
Potatoes 37 37 36 40 23
Wheat & Rye (Bread) 46 55 40 54 42
Maize (Meal) 55 58 42 59 46
0 1 2 3 | 0 2 4 6 | 0 4 8 12 | 0 4 8 12 | 0 10 20 30
D 1 litre
Palm Oil 44 36 31 40 9
Soybean Oil 54 41 34 42 37
Olive Oil 41 57 38 36 18
Rapeseed Oil 37 44 44 49 22
Sunflower Oil 34 35 51 67 26
0 5 10 15 | 0 10 20 30 | 0 20 40 60 | 0 20 40 60 | 0 60 120 180
E 1kg
Tomatoes 80 67 47 82 16
Brassicas 49 58 33 38 36
Onions & Leeks 39 40 33 57 28
Root Vegetables 40 49 29 67 37
0 0.5 1 1.5 | 0 0.5 1 1.5 | 0 6 12 18 | 0 5 10 15 | 0 5 10 15
F 1kg
Berries 43 59 61 71 10
Bananas 34 40 34 52 41
Apples 33 42 32 35 20
Citrus 48 49 37 61 34
0 1 2 3 | 0 2 4 6 | 0 4 8 12 | 0 4 8 12 | 0 20 40 60
G 1kg
Cane Sugar 44 42 39 56 42
Beet Sugar 34 41 36 50 46
0 2 4 6 | 0 1.5 3 4.5 | 0 15 30 45 | 0 15 30 45 | 0 15 30 45
H 1 unit
Beer (5 ABV) 35 53 33 46 82
Wine (12.5 ABV) 43 41 39 45 61
0 0.2 0.4 0.6 | 0 0.2 0.4 0.6 | 0 1 2 3 | 0 0.5 1 1.5 | 0 0.1 0.2 0.3
I 1 serving
Dark Chocolate (50g) 88 46 56 55 88
Coffee (15g, 1 cup) 75 69 33 61 12
0 3 6 9 | 0 3 6 9 | 0 3 6 9 | 0 4 8 12 | 0 0.1 0.2 0.3

Fig. S3. Distributions of environmental impacts by product. Histograms are normalized and smoothed using a Gaussian kernel, and then rescaled for display to set the largest bin count equal to one. Black arrows indicate that >5% of the data lie outside the plot. Shown to the right of each histogram is the percentage of global environmental impact caused by 25% of production (or by 5% of production for scarcity-weighted freshwater withdrawals). (**A**) Protein-rich products. (**B**) Milks. (**C**) Starch-rich products. (**D**) Oils. (**E**) Vegetables. (**F**) Fruits. (**G**) Sugars. (**H**) Alcoholic beverages (1 unit = 10 ml of alcohol; ABV, alcohol by volume). (**I**) Stimulants. Fisher-Pearson coefficients of skew are provided in Data S2.



A Wheat, rye, barley, and oats
R² = 12%
R² = 17%
R² GHG 15% Acid 27%
R² GHG 5% Acid 2% Eutr 13%
Ln Acid ~ Ln Eutr R² = 17%
kg N Fertilizer per kg Yield
Yield
B Maize
R² = 9%
R² = 26%
R² = 20%
R² GHG 45% Acid 26%
R² GHG 13% Acid 12% Eutr 26%
Ln Acid ~ Ln Eutr R² = 22%
C Sunflower and rapeseed
R² = 7%
R² = 11%
R² GHG 77% Acid 20%
R² GHG 7% Acid 6% Eutr 11%
Ln Acid ~ Ln Eutr R² = 6%
D Soybeans and groundnuts
R² = 9%
R² = 41%
R² = 48%
R² GHG 13% Acid 22%
R² GHG 18%
Ln Acid ~ Ln Eutr R² = 49%
E Beef and lamb
R² = 21%
R² GHG 18%
R² GHG 9% Eutr 20%
Ln Acid ~ Ln Eutr R² = 23%
Ln Pasture Land Use
Liveweight Gain per Day
F Milk
R² = 20%
R² = 25%
R² = 25%
R² GHG 9%
R² GHG 22% Acid 9%
Ln Acid ~ Ln Eutr R² = 43%
Milk Yield per Cow
G Pork and Poultry
R² = 19%
R² = 27%
R² = 35%
R² Acid 9%
R² GHG 7% Acid 21% Eutr 14%
Ln Acid ~ Ln Eutr R² = 54%
Feed Nitrogen per unit Liveweight
H Aquaculture
R² = 29%
R² = 30%
R² = 13%
R² GHG 10% Acid 11% Eutr 15%
R² GHG 10% Acid 11% Eutr 21%
Ln Acid ~ Ln Eutr R² = 7%
Ln GHG Emissions
Ln Land Use
Ln Acidifying Emissions
Ln Eutrophying Emissions

Fig. S4. Correlations between greenhouse gas emissions and land use (first column), greenhouse gas emissions and acidifying emissions (second column), and greenhouse gas emissions and eutrophying emissions (third column), and correlations between environmental impacts and proxies (last two columns), for all producers globally. R^2 is shown when $p \leq 0.05$ on the regression coefficient. In the second column, R^2 values are also shown for correlations between acidifying emissions and eutrophying emissions. Emissions for crops exclude land use change and cultivated organic soils that are calculated at the country level and cannot be changed directly by individual farmers. We do not assess indirect land use change in this study but including it would increase correlations with yield. Emissions for animal products include land use change and cultivated organic soils caused by feed. LCA modelling means variance in environmental impact accumulates multiplicatively, and impacts are log-transformed to control for this. Proxies are not log-transformed, and relationships are fitted by including a quadratic term if significant at $p \leq 0.05$. Observations are normalized by subtracting the weighted mean and dividing by the weighted standard deviation of each crop or animal product, allowing similarly produced products to be compared together. Observations with values on any indicator or proxy greater than ±5 SD are excluded ($n = 9$). (**A**) Wheat, rye, barley, and oats. (**B**) Maize. (**C**) Sunflower and rapeseed. (**D**) Soybeans and groundnuts. (**E**) Beef and lamb. (**F**) Milk. (**G**). Pork and poultry. (**H**) Aquaculture (fish and crustaceans). Sample sizes, R^2 and p-values are provided for all regressions in Data S2.



A Northern European wheat

Correlation between indicators (R^2)	Land Use	GHG Emissions	Acidification
GHG Emissions	18%	-	-
Acidification	0.9%	19%	-
Eutrophication	6.3%	24%	35%

B Northern European barley

Correlation between indicators (R^2)	Land Use	GHG Emissions	Acidification
GHG Emissions	6.4%	-	-
Acidification	0.8%	40%	-
Eutrophication	0.7%	43%	49%

C Northern European potatoes

Correlation between indicators (R^2)	Land Use	GHG Emissions	Acidification
GHG Emissions	0.8%	-	-
Acidification	0.5%	11%	-
Eutrophication	16%	23%	33%

D Greenhouse tomatoes

Correlation between indicators (R^2)	Land Use	GHG Emissions	Acidification
GHG Emissions	19%	-	-
Acidification	3.0%	42%	-
Eutrophication	1.1%	15%	43%

E Apples

Correlation between indicators (R^2)	Land Use	GHG Emissions	Acidification
GHG Emissions	25%	-	-
Acidification	1.8%	0.8%	-
Eutrophication	1.5%	2.8%	65%

F Grapes (France, Italy, Portugal, Spain)

Correlation between indicators (R^2)	Land Use	GHG Emissions	Acidification
GHG Emissions	5.2%	-	-
Acidification	6.9%	74%	-
Eutrophication	9.5%	47%	74%

Fig. S5. Trade-offs and correlations between environmental impacts for products in similar geographies or systems. Only emissions that producers can control (fertilizer, pesticide, crop residue, lime, machinery, fuel) are included. Emissions that are largely fixed per hectare and cannot be controlled directly by an individual producer (land use change and emissions from organic soils) are excluded; greater fixed emissions will make yield increases more beneficial. Observations are normalized by subtracting the weighted mean and dividing by the weighted standard deviation. We assume we have sufficient observations of input optimizing producers, and fit the frontier of lowest land use and emissions using maximum likelihood estimation of the stochastic frontier (Coelli & Henningsen, 2017). The red line represents significance at $p \leq 0.05$ on the quadratic term, and the grey line represents a positive but insignificant quadratic term. We also show R^2 values for the linear regression of log-transformed land use on log-transformed emissions (same as fig. S4, but for crops in similar geographies and systems). (**A**) Northern European (Denmark, Finland, France, Germany, Ireland, Netherlands, Poland, Sweden, Switzerland, and United Kingdom) wheat. (**B**) Northern European barley. (**C**) Northern European potatoes. (**D**) Greenhouse tomatoes. (**E**) Apples. (**F**) Grapes cultivated in France, Italy, Portugal, and Spain. Sample sizes and *p*-values are provided in Data S2.

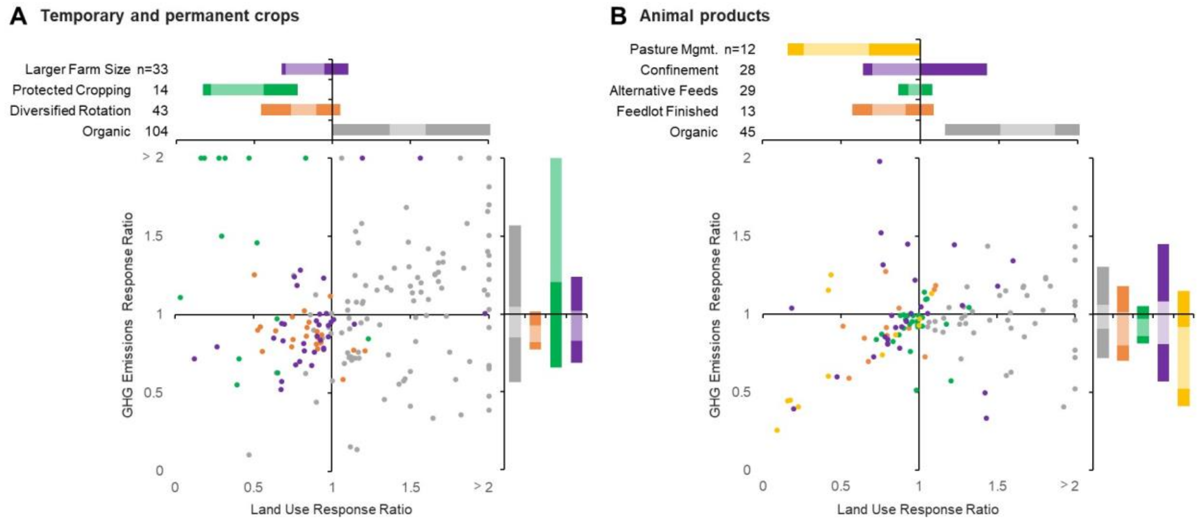


Fig. S6. Effect of practice changes on environmental impact. (**A**) Effect of four commercially viable practice changes for crops (larger vs. smaller farms; protected vs. open-field cropping; diversified rotation vs. monoculture; organic vs. conventional). Studies are included only if they assess specific farms in the same location and year. Dark shaded bars represent the 10th- and 90th-percentiles. Light shaded bars represent the 95% confidence interval of the logged and back-transformed response ratio. *n* = observation pairs. (**B**) Same as (A) but for animal products (improved vs. unmanaged or degraded pasture; confinement vs. grazing or free-range; alternative feed vs. current feed (e.g., European legumes vs. imported soy); feedlot finished vs. grass finished beef; organic vs. conventional). For animal products, GHG emissions include land use change and cultivated organic soils associated with feed.

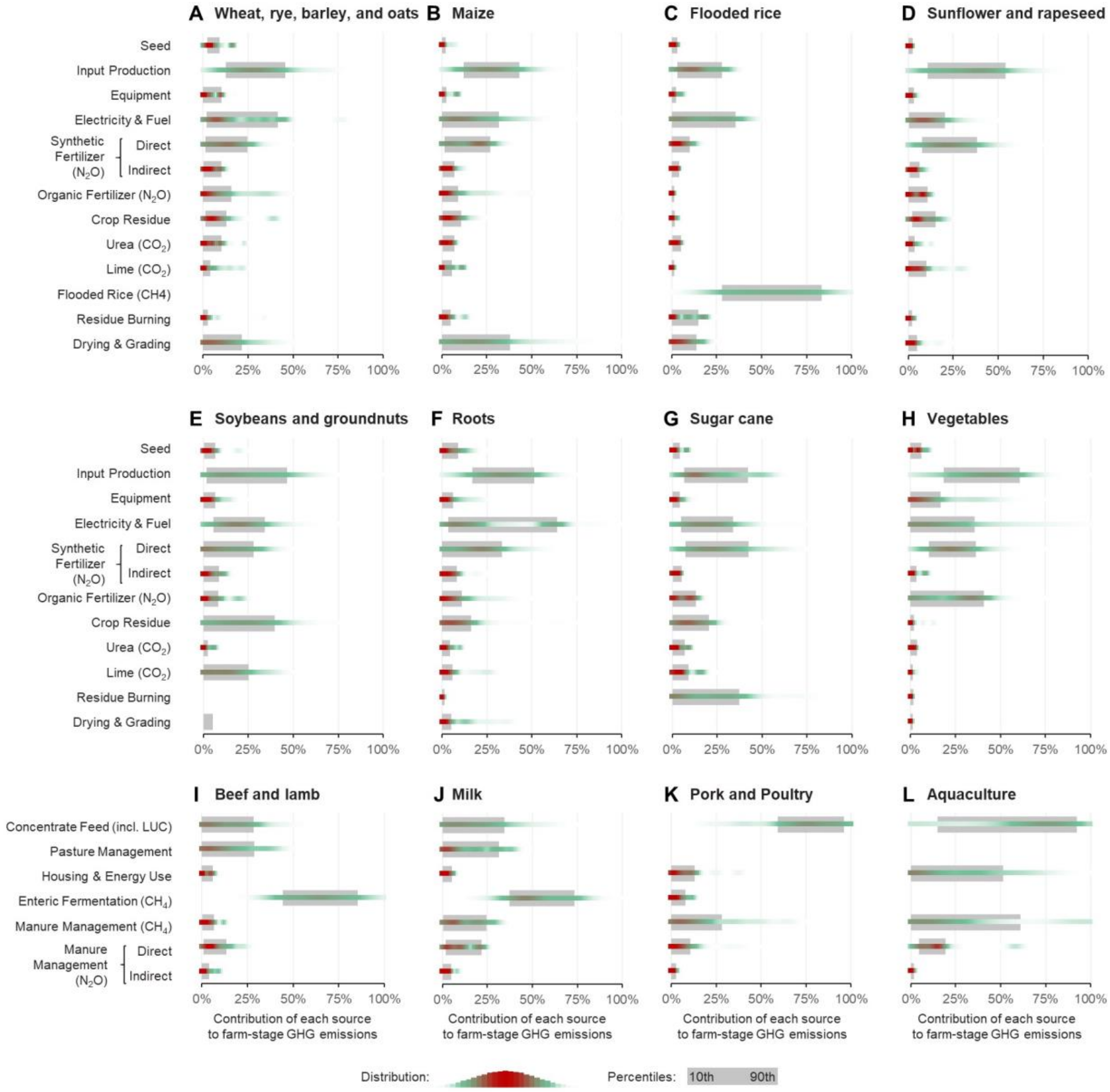


Fig. S7. Contributions of emission sources to total farm-stage GHG emissions. Grey bars show 10th- and 90th-percentile contributions. Shaded bars represent the distribution. Density is estimated using a Gaussian kernel with bandwidth selection performed by biased cross-validation. (**A**) Wheat, rye, barley, and oats. (**B**) Maize. (**C**) Flooded rice. (**D**) Sunflower and rapeseed. (**E**) Soybeans and groundnuts. (**F**) Roots (potatoes, sugar beet, and root vegetables). (**G**) Sugar cane. (**H**) Vegetables (tomatoes, lettuce, cucumber, green beans, and green peas). (**I**) Beef and lamb. (**J**) Milk. (**K**) Pork and poultry. (**L**) Aquaculture (fish and crustaceans), where manure management includes emissions from ponds.

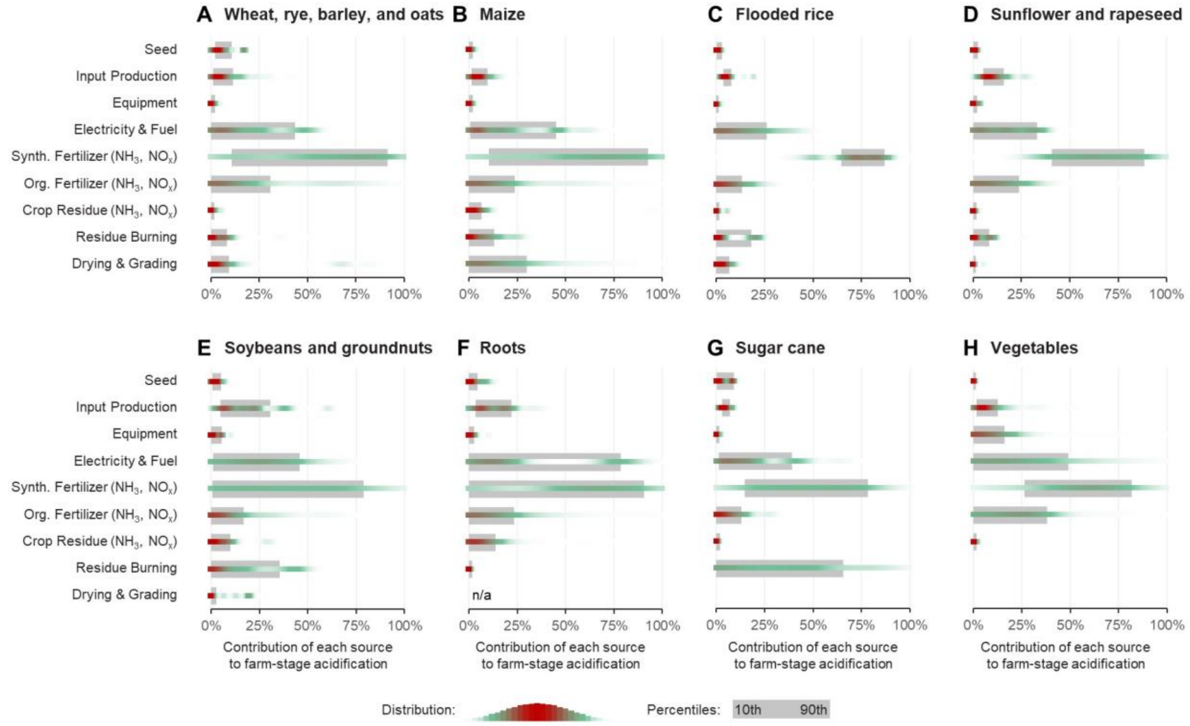


Fig. S8. Contributions of emission sources to total farm-stage acidification. Grey bars show 10th- and 90th-percentile contributions. Shaded bars represent the distribution. Density is estimated using a Gaussian kernel with bandwidth selection performed by biased cross-validation. (**A**) Wheat, rye, barley, and oats. (**B**) Maize. (**C**) Flooded rice. (**D**) Sunflower and rapeseed. (**E**) Soybeans and groundnuts. (**F**) Roots (potatoes, sugar beet, and root vegetables). (**G**) Sugar cane. (**H**) Vegetables (tomatoes, lettuce, cucumber, green beans, and green peas).

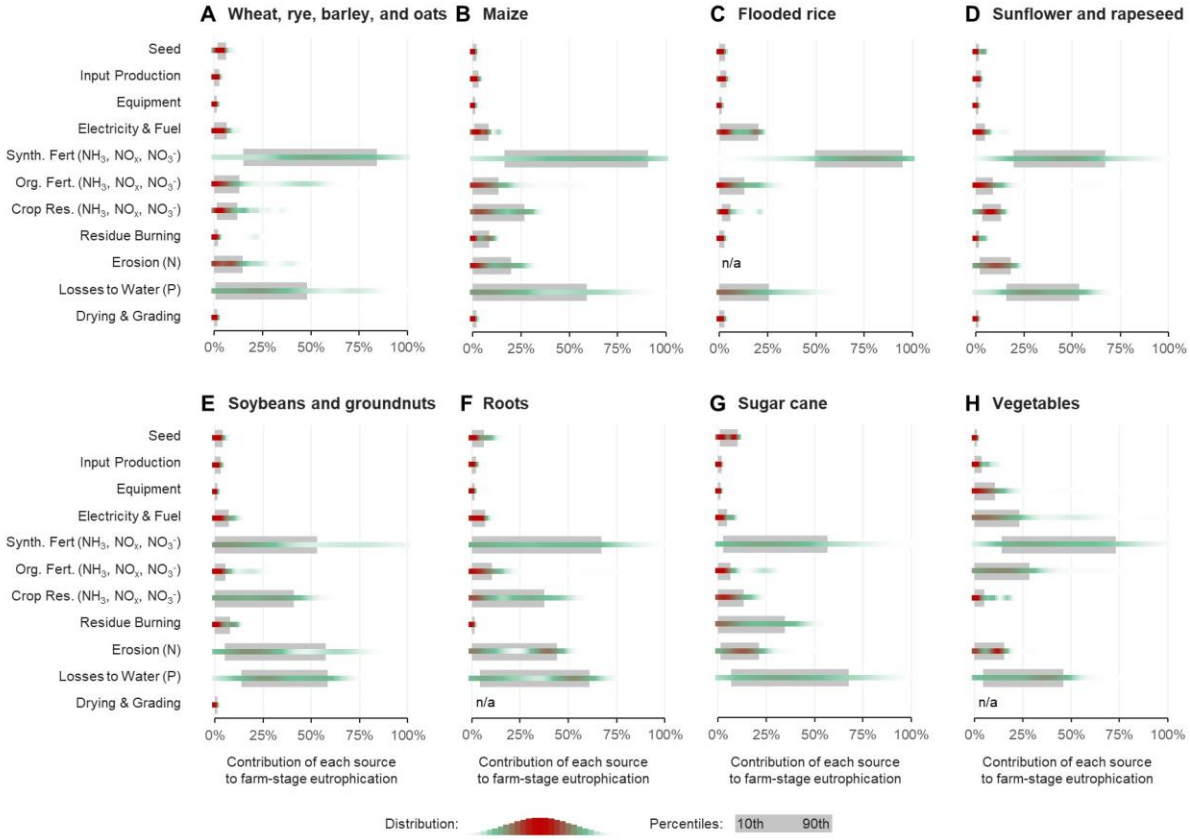


Fig. S9. Contributions of emission sources to total farm-stage eutrophication. Grey bars show 10th- and 90th-percentile contributions. Shaded bars represent the distribution. Density is estimated using a Gaussian kernel with bandwidth selection performed by biased cross-validation. (**A**) Wheat, rye, barley, and oats. (**B**) Maize. (**C**) Flooded rice. (**D**) Sunflower and rapeseed. (**E**) Soybeans and groundnuts. (**F**) Roots (potatoes, sugar beet, and root vegetables). (**G**) Sugar cane. (**H**) Vegetables (tomatoes, lettuce, cucumber, green beans, and green peas).

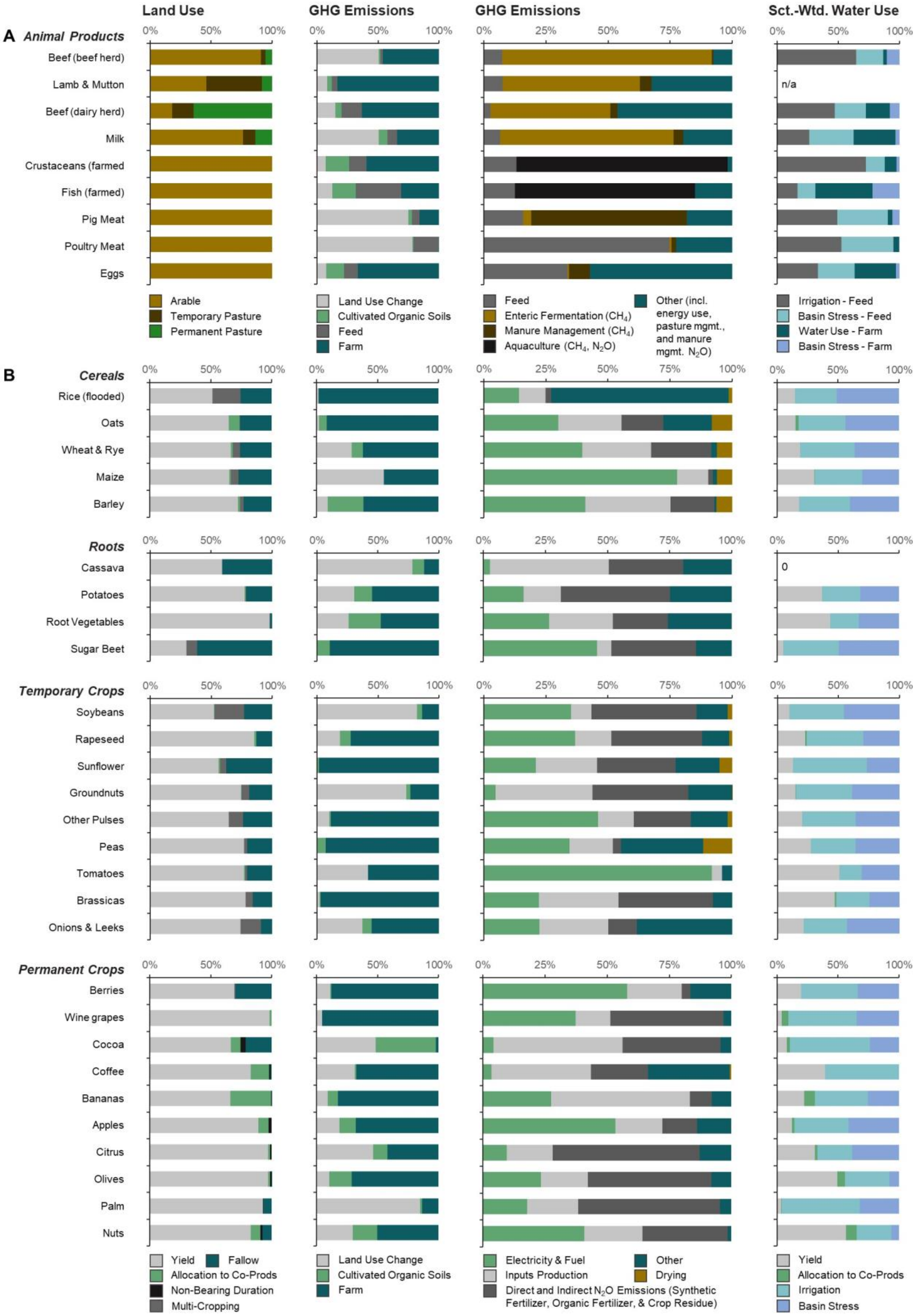

Land Use
GHG Emissions
GHG Emissions
Sct.-Wtd. Water Use
A Animal Products
Beef (beef herd)
Lamb & Mutton
Beef (dairy herd)
Milk
Crustaceans (farmed
Fish (farmed)
Pig Meat
Poultry Meat
Eggs
n/a
Arable
Temporary Pasture
Permanent Pasture
Land Use Change
Cultivated Organic Soils
Feed
Farm
Feed
Enteric Fermentation (CH_4)
Manure Management (CH_4)
Aquaculture (CH_4, N_2O)
Other (incl. energy use, pasture mgmt., and manure mgmt. N_2O)
Irrigation - Feed
Basin Stress - Feed
Water Use - Farm
Basin Stress - Farm
B Cereals
Rice (flooded)
Oats
Wheat & Rye
Maize
Barley
Roots
Cassava
Potatoes
Root Vegetables
Sugar Beet
Temporary Crops
Soybeans
Rapeseed
Sunflower
Groundnuts
Other Pulses
Peas
Tomatoes
Brassicas
Onions & Leeks
Permanent Crops
Berries
Wine grapes
Cocoa
Coffee
Bananas
Apples
Citrus
Olives
Palm
Nuts
Yield
Fallow
Allocation to Co-Prods
Non-Bearing Duration
Multi-Cropping
Land Use Change
Cultivated Organic Soils
Farm
Electricity & Fuel
Inputs Production
Direct and Indirect N_2O Emissions (Synthetic Fertilizer, Organic Fertilizer, & Crop Residue)
Other
Drying
Yield
Allocation to Co-Prods
Irrigation
Basin Stress

Fig. S10. Contribution of each impact source to variance among producers for the same product. Contributions are calculated using variance-based sensitivity analysis (supplementary text). (**A**) Animal products. 'Water Use – Farm' includes drinking water, service water, and pasture irrigation. (**B**) Crops.

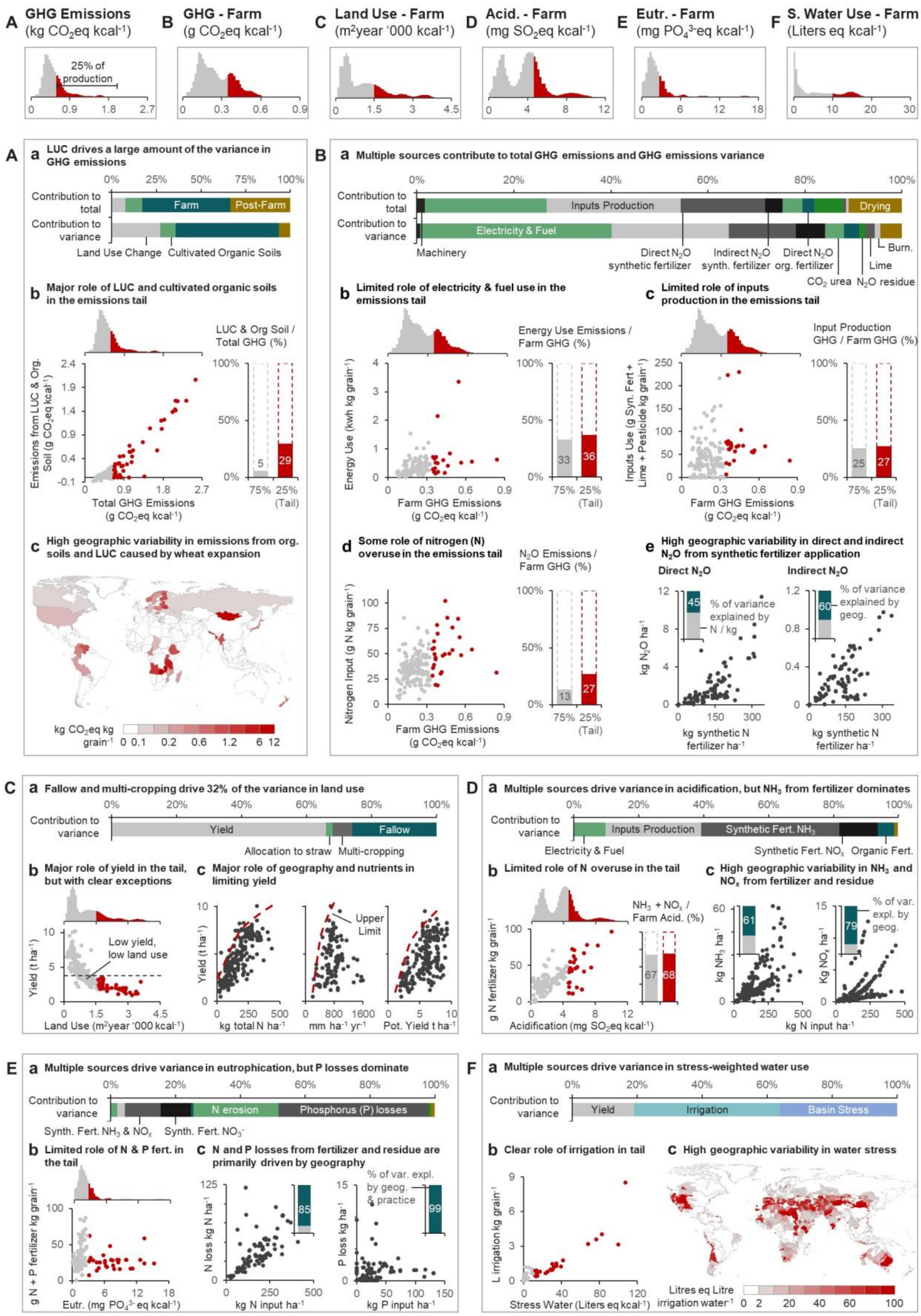
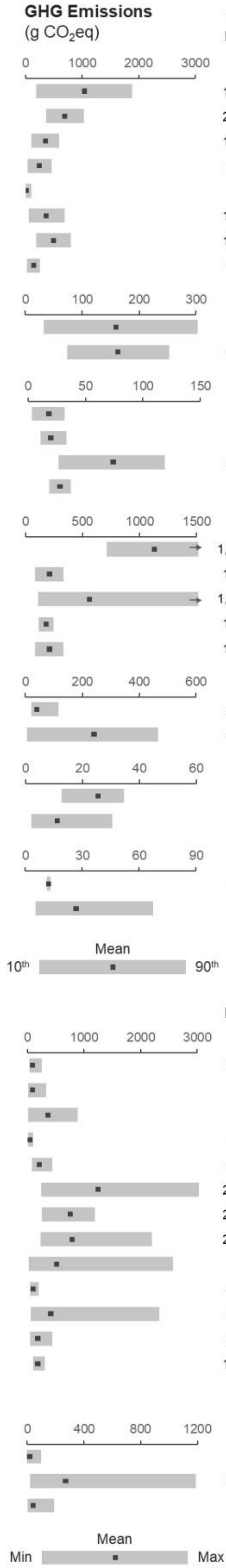

A GHG Emissions (kg CO2eq kcal-1)
25% of production
B GHG - Farm (g CO2eq kcal-1)
C Land Use - Farm (m2year '000 kcal-1)
D Acid. - Farm (mg SO2eq kcal-1)
E Eutr. - Farm (mg PO43-eq kcal-1)
F S. Water Use - Farm (Liters eq kcal-1)
A a LUC drives a large amount of the variance in GHG emissions
Contribution to total
Contribution to variance
Farm
Post-Farm
Land Use Change
Cultivated Organic Soils
b Major role of LUC and cultivated organic soils in the emissions tail
LUC & Org Soil / Total GHG (%)
Emissions from LUC & Org. Soil (g CO2eq kcal-1)
Total GHG Emissions (g CO2eq kcal-1)
75% 25% (Tail)
c High geographic variability in emissions from org. soils and LUC caused by wheat expansion
kg CO2eq kg grain-1
B a Multiple sources contribute to total GHG emissions and GHG emissions variance
Inputs Production
Drying
Electricity & Fuel
Machinery
Direct N2O synthetic fertilizer
Indirect N2O synth. fertilizer
Direct N2O org. fertilizer
CO2 urea
N2O residue
Lime
Burn.
b Limited role of electricity & fuel use in the emissions tail
Energy Use Emissions / Farm GHG (%)
Energy Use (kwh kg grain-1)
Farm GHG Emissions (g CO2eq kcal-1)
c Limited role of inputs production in the emissions tail
Input Production GHG / Farm GHG (%)
Inputs Use (g Syn. Fert + Lime + Pesticide kg grain-1)
d Some role of nitrogen (N) overuse in the emissions tail
N2O Emissions / Farm GHG (%)
Nitrogen Input (g N kg grain-1)
e High geographic variability in direct and indirect N2O from synthetic fertilizer application
Direct N2O
Indirect N2O
% of variance explained by N / kg
% of variance explained by geog.
kg N2O ha-1
kg synthetic N fertilizer ha-1
C a Fallow and multi-cropping drive 32% of the variance in land use
Yield
Fallow
Allocation to straw
Multi-cropping
b Major role of yield in the tail, but with clear exceptions
Low yield, low land use
Yield (t ha-1)
Land Use (m2year '000 kcal-1)
c Major role of geography and nutrients in limiting yield
Upper Limit
kg total N ha-1
mm ha-1 yr-1
Pot. Yield t ha-1
D a Multiple sources drive variance in acidification, but NH3 from fertilizer dominates
Inputs Production
Synthetic Fert. NH3
Electricity & Fuel
Synthetic Fert. NOx
Organic Fert.
b Limited role of N overuse in the tail
NH3 + NOx / Farm Acid. (%)
g N fertilizer kg grain-1
Acidification (mg SO2eq kcal-1)
c High geographic variability in NH3 and NOx from fertilizer and residue
% of var. expl. by geog.
kg NH3 ha-1
Kg NOx ha-1
kg N input ha-1
E a Multiple sources drive variance in eutrophication, but P losses dominate
N erosion
Phosphorus (P) losses
Synth. Fert. NH3 & NOx
Synth. Fert. NO3-
b Limited role of N & P fert. in the tail
g N + P fertilizer kg grain-1
Eutr. (mg PO43- eq kcal-1)
c N and P losses from fertilizer and residue are primarily driven by geography
% of var. expl. by geog. & practice
N loss kg N ha-1
P loss kg ha-1
kg N input ha-1
kg P input ha-1
F a Multiple sources drive variance in stress-weighted water use
Yield
Irrigation
Basin Stress
b Clear role of irrigation in tail
L irrigation kg grain-1
Stress Water (Liters eq kcal-1)
c High geographic variability in water stress
Litres eq Litre irrigation water-1

Fig. S11. Detailed case-study of wheat, showing: contributions to variance of each impact source; drivers of the impact distribution; and the role of geography in impacts. Here, contributions of geography/practice to variance in emissions represent the variance not explained by fertilizer quantity using linear regression. (**A**) Full supply chain GHG emissions. (**B**) Farm-stage GHG emissions. (**C**) Farm-stage land use. (**D**) Farm-stage acidifying emissions. (**E**) Farm-stage eutrophying emissions. (**F**) Farm-stage scarcity-weighted freshwater withdrawals.



Processing

			n	10th pctl	Mean	90th pctl
A	***100g of protein***					
	Beef	Slaughter	25	110	1,120	2,550
	Mutton & Lamb	Slaughter	11	280	710	1,120
	Cheese	Caseiculture	20	100	340	840
	Pig Meat	Slaughter	27	31	300	610
	Fish	Processing	14	1	60	210
	Poultry Meat	Slaughter	17	140	450	800
	Tofu	Production	3	180	490	700
	Groundnuts	Deshelling, Roasting	7	60	170	270
B	***1 litre***					
	Milk	Pasteurisation, Sterilisation	77	9	87	290
	Soymilk	Production	2	69	160	260
C	***1000 kcal***					
	Rice	Dehulling, Milling, Polishing	10	7	16	41
	Oatmeal	Peeling, Rolling	6	13	22	34
	Wheat & Rye	Milling, Bread Making	24	50	77	130
	Maize (Meal)	Dry Milling	4	17	28	32
D	***1 litre***					
	Palm Oil	Milling & Refining	36	1,050	-	-
	Soybean Oil	Crushing & Refining	15	120	200	340
	Olive Oil	Pressing	16	1,280	-	-
	Rapeseed Oil	Milling & Refining	17	140	190	260
	Sunflower Oil	Milling & Refining	15	120	200	340
E	***1kg***					
	Cane Sugar	Milling	25	24	26	27
	Beet Sugar	Milling	14	66	280	440
F	***1 unit***					
	Beer (5% ABV)	Malting, Mashing, Brewing	16	15	23	36
	Wine (12.5% ABV)	Vinification	42	3	5	12
G	***1 serving***					
	Dark Chocolate (50g)	Roasting, Grinding, Blending	5	11	12	13
	Coffee (15g, 1 cup)	Wet/Dry Proc., Grind., Roast.	4	5	27	68

Packaging

		n	Min	Mean	Max
H	***1 kg / litre of retail weight***				
	Bread	8	28	84	250
	Oatmeal, Nuts, Rice, Sugar, Other	8	7	90	330
	Beans, Pulses	6	7	360	890
	Fresh Fruit, Vegetables, Roots (Durable)	9	10	45	92
	Fresh Fruit, Vegetables, Roots (Delicate)	12	80	210	440
	Coffee	3	240	1,250	3,230
	Chocolate	3	250	750	1,190
	Oil, Wine	15	230	790	2,200
	Beer	27	19	510	2,570
	Milk	38	44	100	200
	Meat, Fish, Crustaceans	26	58	410	2,330
	Cheese, Tofu	13	38	180	440
	Eggs	3	100	180	300

Retail

		n	Min	Mean	Max
I	***1 kg / litre of retail weight***				
	Fresh: Fruit and Vegetables	24	0	17	100
	Chilled: Meat, Fish, Cheese, Tofu, Beer	22	20	270	1,190
	Ambient: Bread, Nuts, Roots, Eggs, Oils, Other	12	1	40	190

Fig. S12. Variation in GHG emissions for different post-farm processes, pack types, and retail types. Not shown: post-farm processes with negligible emissions. Bars represent 10th- and 90th-percentiles for processing, and the minimum and maximum for packaging and retail. (**A**) Processing emissions of protein-rich products. (**B**) Milk processing. (**C**) Starch-rich product processing. (**D**) Oil processing. (**E**) Sugar processing. (**F**) Alcoholic beverage processing (1 unit = 10 ml alcohol; ABV, alcohol by volume). (**G**) Stimulant processing. (**H**) Packaging. (**I**) Retail.

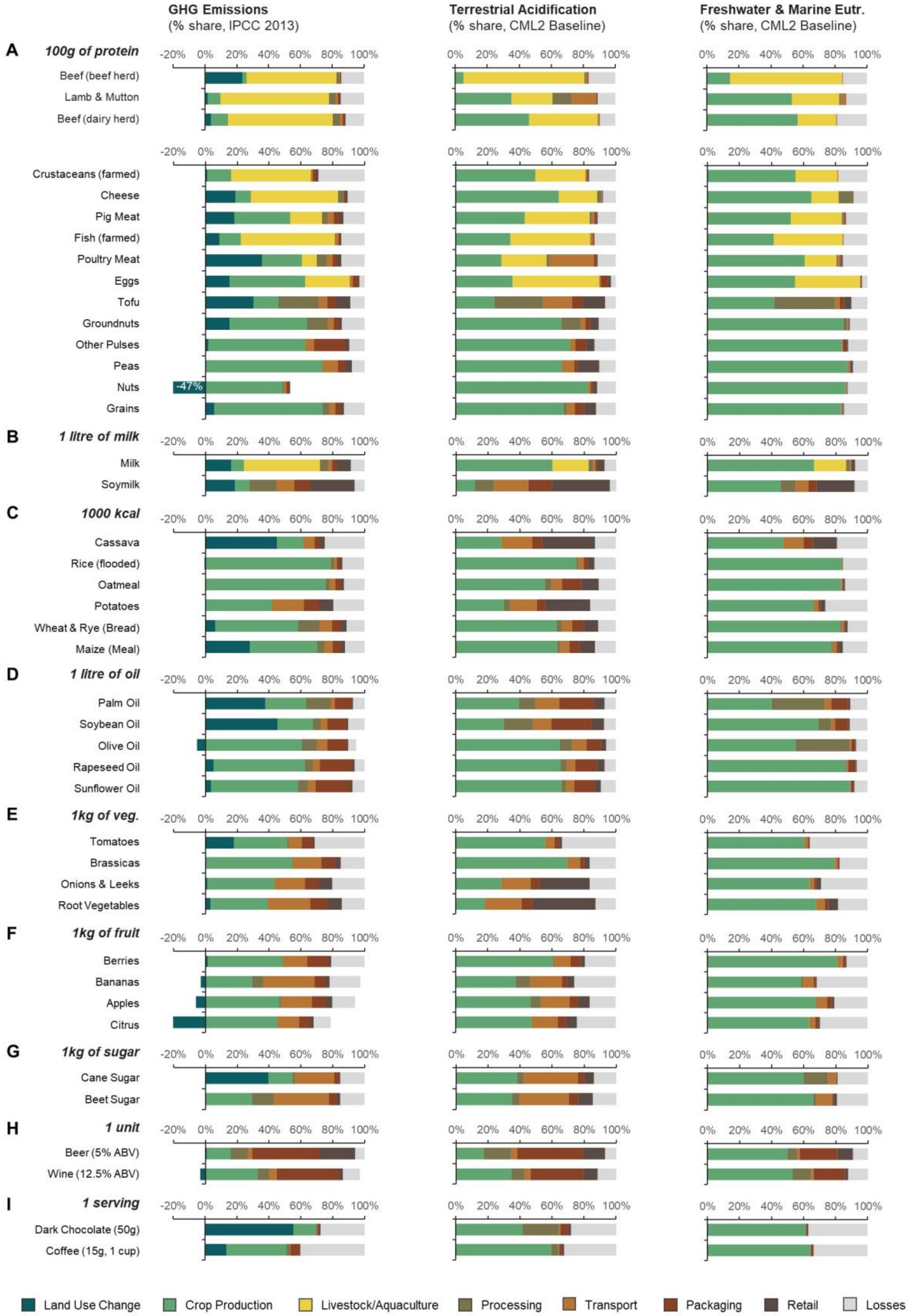
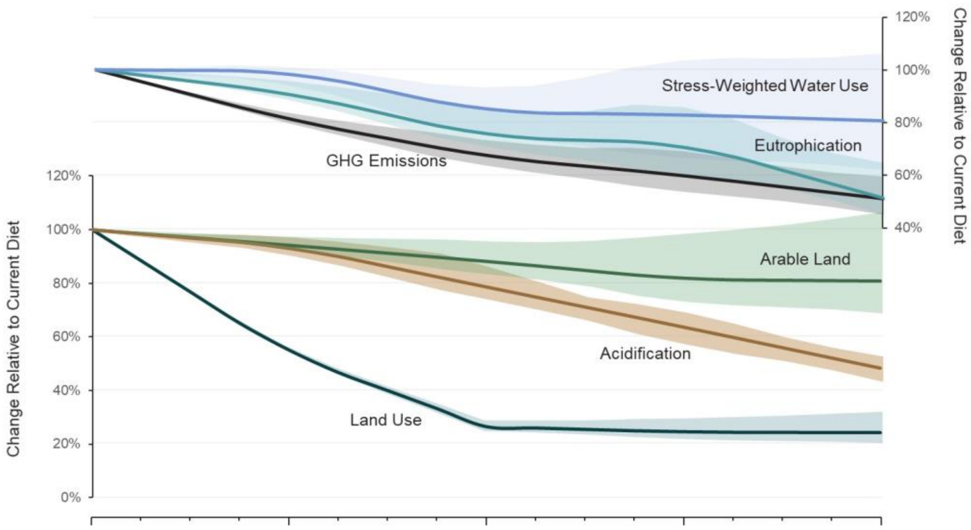

GHG Emissions
(% share, IPCC 2013)
Terrestrial Acidification
(% share, CML2 Baseline)
Freshwater & Marine Eutr.
(% share, CML2 Baseline)
A 100g of protein
Beef (beef herd)
Lamb & Mutton
Beef (dairy herd)
Crustaceans (farmed)
Cheese
Pig Meat
Fish (farmed)
Poultry Meat
Eggs
Tofu
Groundnuts
Other Pulses
Peas
Nuts
-47%
Grains
B 1 litre of milk
Milk
Soymilk
C 1000 kcal
Cassava
Rice (flooded)
Oatmeal
Potatoes
Wheat & Rye (Bread)
Maize (Meal)
D 1 litre of oil
Palm Oil
Soybean Oil
Olive Oil
Rapeseed Oil
Sunflower Oil
E 1kg of veg.
Tomatoes
Brassicas
Onions & Leeks
Root Vegetables
F 1kg of fruit
Berries
Bananas
Apples
Citrus
G 1kg of sugar
Cane Sugar
Beet Sugar
H 1 unit
Beer (5% ABV)
Wine (12.5% ABV)
I 1 serving
Dark Chocolate (50g)
Coffee (15g, 1 cup)
-20% 0% 20% 40% 60% 80% 100%
Land Use Change
Crop Production
Livestock/Aquaculture
Processing
Transport
Packaging
Retail
Losses

Fig. S13. GHG emissions, acidification, and eutrophication by stage of the supply chain by product. Emission contributions are shown for the eight supply chain stages: 1) land use change (burning, above and below ground carbon stock change, amortized over 20 years from conversion, excluding savannah burning for management), which can be negative from carbon sequestration; 2) crop production (inputs production, field emissions, drying and grading) and for feed crops, transport; 3) livestock/aquaculture (pasture irrigation and fertilization, manure management, aquaculture emissions, enteric fermentation and energy use); 4) processing; 5) transport (farm to processor, processor to retailer); 6) packaging; 7) retail; 8) losses (storage and transport, processing and packaging, wholesale and retail). (**A**) Protein-rich products. Grains are an average of wheat, maize, oats, and flooded rice, and are included under protein-rich products given their high contribution to global protein intake, despite their lower protein content per kilogram. (**B**) Milks. (**C**) Starch-rich products. (**D**) Oils. (**E**) Vegetables. (**F**) Fruits. (**G**) Sugars. (**H**) Alcoholic beverages. (**I**) Stimulants.



	Current (~2010) Diet	No Beef (beef herd) or Mutton	No Beef (dairy herd), Milk, or Cheese	No Pork or Poultry (Eggs and Fish only)	No Animal Products
Land Use (million ha)	**4,130**	**2,210**	**1,100**	**1,010**	**1,010**
Arable Land	1,240	1,170	1,100	1,010	1,010
Permanent Pasture	2,890	1,040	0	0	0
GHG Emiss. (Gt CO_2eq)	**13.79**	**11.11**	**9.21**	**8.26**	**7.05**
Land Use Change	2.67	1.84	1.54	1.05	1.02
Feed Production	1.10	1.09	0.98	0.52	0.00
Food Production	7.60	5.82	4.34	4.54	3.70
Processing	0.60	0.55	0.52	0.44	0.55
Packaging	0.80	0.79	0.80	0.74	0.78
Transport	0.63	0.63	0.63	0.61	0.62
Retail	0.39	0.39	0.40	0.36	0.38
Acidification (Mt SO_2eq)	**91.5**	**85.9**	**72.0**	**58.3**	**44.2**
Farm	74.8	69.3	54.9	44.2	29.5
Post-Farm	16.7	16.6	17.1	14.1	14.7
Eutr. (Mt PO_4^{3-}eq)	**64.3**	**58.6**	**48.0**	**46.3**	**33.2**
Farm	61.2	55.5	45.1	43.6	29.8
Post-Farm	3.1	3.1	2.9	2.7	3.4
Freshwater Withdr. (km^3)	**2,200**	**2,200**	**1,900**	**1,900**	**1,700**
Stress-Wtd. Wtr. (km^3eq)	**74,300**	**73,800**	**62,300**	**61,600**	**59,900**
Food Losses (%)	**26.7%**	**26.6%**	**26.6%**	**26.4%**	**26.8%**
Farm to Distribution	4.9%	4.9%	4.8%	4.6%	4.8%
Distribution to Retail	13.8%	13.8%	14.2%	14.2%	14.4%
Consumer (not incl.)	10.5%	10.5%	10.2%	10.0%	10.2%
Food Miles (million tkm, farm to consumer)	**9,395**	**9,395**	**9,385**	**9,385**	**9,375**
Road	2,910	2,900	2,890	2,880	2,870
Rail	930	930	930	930	930
Water	5,540	5,550	5,550	5,560	5,560
Air	15	15	15	15	15

Stimulants 17%
Sugar Cane 17%
Palm 7%
Cereals 12%
Cassava 10%
Soy 33%

Reduction in food waste and food miles associated with changing from animal to vegetable proteins is offset by higher consumption of fresh fruit and veg.

Fig. S14. Impacts of alternative diet change scenarios. Shading indicates total global impacts, assuming new production is produced with impacts at the 10th- and 90th-percentiles of existing production. Non-food agricultural impacts are excluded (e.g., textiles, processing co-products). Land use change in the ‘No animal products’ scenario reflects historical land use change from soy and other crops. Acidification and eutrophication do not include forest or savannah burning. Scarcity-weighted freshwater withdrawals are calculated using marginal characterisation factors and current crop footprints. Consumer food losses are not included in totals but are shown here for reference and are included as a sensitivity (table S17). Food miles are based on current crop footprints and do not include transport of feed to farm.

Data S1. Additional reference lists.

Available at: science.org/doi/suppl/10.1126/science.aaq0216/suppl_file/aaq0216_datas1.xls

This file contains references for all studies used in the meta-analysis, all studies not used with justifications based on inclusion criteria, and the list of authors who contributed additional data to this study. Detailed notes on locations of data within each published study, how study data were supplemented with data provided by authors, and details of the recalculations performed, are provided in the 'Notes' column in the original model. This model is freely available for download from the link in this study.

Data S2. Data in spreadsheet format.

Available at: science.org/doi/suppl/10.1126/science.aaq0216/suppl_file/aaq0216_datas2.xls

This file contains randomized and resampled data by product at the 5th-, 10th-, 90th-, and 95th-percentiles, mean and median; data without randomisation at the minimum and maximum; and GHG emissions under IPCC AR4 and AR5 characterisations. Data are provided under different functional units: Retail Weight; Nutritional Units (table S2); and food balance sheet equivalent weights (ref. 129). Sample sizes are provided for each indicator by n = observations and n = farm/regional inventories, where one observation is a line in the database and can represent multiple similar farms. This file also includes measures of skew by product, and R^2, p-values, and sample sizes from the regressions in figs. S4, and S5.

SUPPLEMENTARY MATERIALS FOR:

Chapter 3: HESTIA: A harmonised way to represent and share agri-environmental data

Contains:

Supplementary Text

Figs. S15 to S16

Supplementary Text

Examples of converting data into the HESTIA format

a. A survey of Myanmar arable farms

Dataset: 935 farms in the Southern Shan region of Myanmar were surveyed in June-October 2018 (Food Security Policy Project, 2020). The farms cultivated maize and/or pigeon peas, often using intercropping. 99 enumeration areas were selected based on areas where maize or pigeon pea cultivation was known to occur, followed by stratification based on the size of the areas. Data were captured by interviewing farmers and asking them to recall information about the prior production cycle(s). Further information on survey design is documented elsewhere (Fang & Belton, 2020). Data items included the township where the farm was located, the quantities of agricultural inputs (e.g., seeds, fertilizers), input costs, hours of labour and machinery, quantities produced, and sale prices. Data were stored in an Excel spreadsheet after removing personally identifying information such as coordinates.

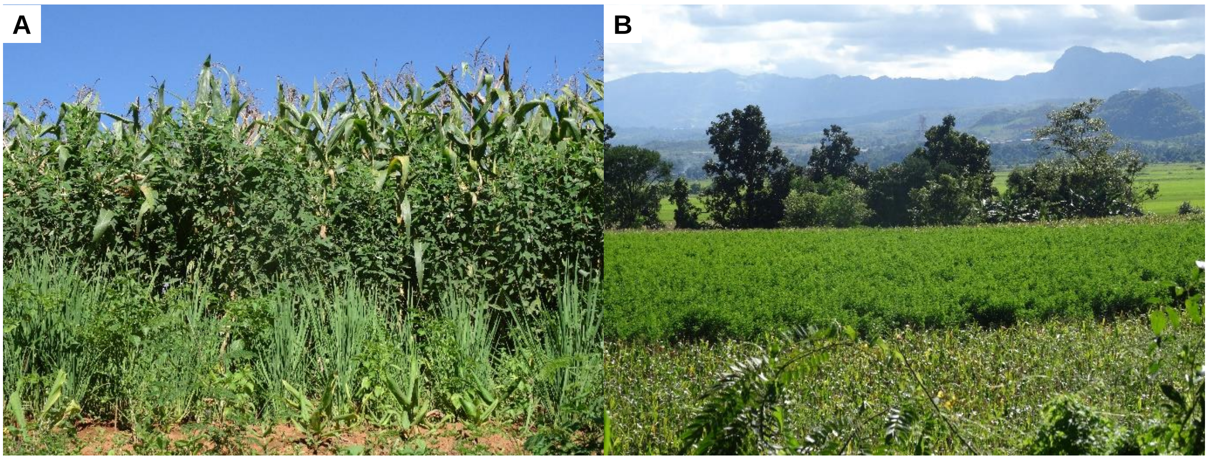


Fig. S15. Photographs from Southern Shan, Myanmar. (**A**) Intercropping with natural vegetation in foreground, followed by a row of pigeon peas, followed by maize. (**B**) Single-cropped maize in the foreground and single-cropped pigeon peas in the background. Credit: Ben Belton.

Conversion:

1. Added a new row below the existing column headers. In this row, we added field names from the schema.
2. We restructured the dataset so each row represents one Cycle. Cycles where maize and pigeon peas were intercropped had two Products.
3. The surveyed farms had already been given a unique identifier, and we used these for `site.id` and `cycle.id`. We then linked cycles to the sites they occurred on using `cycle.site.id`.
4. Added new columns for the data Source and added bibliographic information to it. Set this as the `defaultSource` for all Cycles and Sites.
5. Added the required fields for Cycles and Sites which were not included in the original spreadsheet. Specifically, we added `endDate` and `functionalUnitMeasure` to the Cycle, and country.name and `siteType` to the Site.
6. Added a new column called `site.region.name` and matched each of the townships surveyed with the most specific geographical region in the HESTIA Glossary.
7. For each Input and Product, converted the units to those defined in the Hestia glossary (e.g., `kg`), and then expressed them per functional unit defined by the schema (here `1 ha`).
8. Requested new Terms were added to the Glossary to allow better representation of the data (e.g., `Family labour`, and `Hired labour`).

9. Added the Measurement `Fallow correction`, which represents the number of years fallow relative to the total rotation period. We calculated this based on the prior land use averaged across all Sites.
10. Added columns for the data Completeness assessment and filled them in based on the rules defined at https://hestia.earth/schema/Completeness.
11. Initially we set `dataPrivate` to true for all nodes, so we could check the data on the HESTIA platform first without it becoming public. When we were ready to share the data publicly, we reuploaded with `dataPrivate` set to false.

Validation: On initial upload to the HESTIA platform, the validation engine detected errors. Some fields and terms had typos in which were identified and corrected. A full stop symbol (`.`) was mistakenly used to mark data as not available, and we changed this to a dash (`-`) which represents no data in HESTIA along with blank cells.

Links: Original dataset (xlsx); dataset in HESTIA format (xlsx); dataset on the HESTIA platform.

b. A nitrogen leaching meta-analysis

Dataset: A meta-analysis consolidated data from 91 studies representing 559 observation of nitrate and ammonium leaching under cropland (Chapter 2). The Excel file includes possible covariates of leaching such as rainfall and crop yield.

Conversion: We used the steps as described in example (a), with the following additional steps. With these steps we were able to represent all of the data in the Excel file.

1. To each Source, we only added the title of the article (`bibliography.title`) and/or the DOI (`bibliography.documentDOI`) and let the HESTIA pipeline add the rest of the bibliographic items automatically from the Mendeley library.
2. To each Source, we also added a `metaAnalysisBibliography`.
3. In the meta-analysis, crop yield was expressed as kilograms of dry matter, however in the HESTIA Glossary, we defined crops to be expressed in kilograms of marketable weight (e.g., `Maize, grain` has a default dry matter of 85.8%). Therefore, to each crop Product we added the Property `Dry matter` from the Glossary with the value 100%. Adding a Property to a blank node overrides the default Property from the Glossary.
4. Some fertilizers were controlled release, or included nitrification or urease inhibitors, and this was specified by adding a Property to the fertilizer.
5. Soil Measurements had defined depth intervals, and these were added using `depthUpper` and `depthLower`.
6. Some Measurements had different Sources to the `defaultSource` of the Site (e.g., a prior study on the same Site may have reported the soil pH), and these were specified for each Measurement, creating a new `source.id` if necessary.
7. Emissions have required fields for `methodModel` and `methodTier`. The method or model used to quantify emissions can change the result and this is a critical field to record, and we identified the correct `methodModel` in the Glossary for each Emission. Methods and models can also be broadly grouped by their specificity and `methodTier` can take five values and the value for these Emissions is `measured`.

Validation: The bibliographies for seven studies were not available automatically and these were entered manually. Some coordinates were identified as being in the wrong country or region, and these were corrected (either by referring to the original study if the error was in the meta-analysis, or by using other site location data in the original study instead if the error was there). Some more coordinates were identified as erroneous where they did not intersect with known cropland (according to the MODIS land cover map) and some of these were corrected but others were accepted based on visual inspection of high-resolution satellite images. Some estimates of above ground crop residue were automatically identified as too high, were found to include below ground residue, and these were corrected.

Links: Dataset in HESTIA format (xlsx); dataset on the HESTIA platform.

c. A nitrate leaching experiment with time-series data

Dataset: A study reported results from an experimental field trial in Sweden which assessed the effects of different fertilization levels and crop rotations on nitrate leaching (Engström et al., 2011). There were two experiments with nine treatments over two years, resulting in 36 Cycles. Leaching data were provided with monthly frequency. Data were presented in tables and the text.

Conversion: We largely followed the same steps as example (b), with the following additional steps. With these steps, we were able to represent virtually all of the data in the study (with the exception of the results of the statistical analyses the authors performed on the data which are not the focus of the HESTIA data structure).

1. Data for many Measurements, Inputs, and Emissions were provided as arrays where each value represented the date they occurred on. For upload to HESTIA, arrays can be created in Excel or csv files by separating each value with a semicolon (e.g., `0.443;23.461`). Arrays of associated dates are added in the `dates` field using the

ISO 8601 format (e.g., `2004-09;2004-10`, which represent September 2004 and October 2004 respectively). Missing values in arrays can be represented using either a dash or a blank (e.g., `4;-;8`, `4;;8`).

2. Long term rainfall and temperature data were provided as the total or average for each month averaged over the period 1961-1990. To represent these data, the `startDate` and `endDate` of the Measurements were specified as `1961` and `1990` respectively. The monthly rainfall and temperature data were added using an array. Arrays of associated dates were added in the `dates` field using the ISO 8601:2000 format for dates without a year (e.g., `--01;--02;...`, which represent January and February respectively).
3. The values in some arrays are additive (e.g., monthly rainfall sums to annual rainfall), whereas others must be averaged (e.g., the average of the monthly temperature is approximately the average annual temperature). The nitrogen uptake by a plant is an additive array, which means that the value for each date must be the incremental amount of uptake compared to the previous date. The uptake data in the study were already in this format and were entered directly.
4. Some soil measurements were provided per hectare. The Glossary does not allow soil measurement data per hectare because they are meaningless unless the depth interval for the Measurement is also provided. Soil total nitrogen measurements in kilograms of N per hectare in the top 90cm of soil were therefore converted to grams of N per m3 by multiplying by 1000 (which converts from kilograms to grams) and then dividing by 10,000 * 0.9 (which divides by the volume of soil per hectare).

Validation: Soft validation errors were raised for the twelve rapeseed Cycles recommending that the crop yield was provided, however these data were not available in the study and this error was ignored. Soft validation errors were also raised where soil texture ("sandy loam") as provided without a depth interval and based on the article a depth interval of 0-30cm was assigned, and this was corrected.

Links: Dataset in HESTIA format (xlsx); dataset on the HESTIA platform.

d. An environmental LCA of aquaculture in Peru

Dataset: A study (Avadí et al., 2015) assessed the effects of different feeds on the environmental impacts of trout (*Oncorhynchus mykiss*), tilapia (*Oreochromis* spp.) and tambaqui (*Colossoma macropomum*) production in Peru. There was one fish oil and fish meal production Cycle, seven feed blending Cycles, and eight fish production Cycles.

Conversion: We largely followed the same steps as example (a), with the following additional steps. With these steps, we were able to represent all of the data provided in the article the exceptions of six data items that were not clearly defined in the study including "FCR retained" and "ash digestibility".

1. We created six Sites, two for feed processing in Chile and Peru, one for the trout cage systems, one for the tambaqui pond systems, one for the semi-intensive tilapia system, and one for the intensive tilapia system. Because multiple Sites were surveyed and then aggregated, we specified the `numberOfSites`.
2. We added Infrastructure representing the cages or ponds and specified the lifespan of the Infrastructure.

3. We created 16 Cycles, linked them to the Sites, and set the functional unit to `relative`. `Relative` means that the functional unit is defined by the quantity and units of the Products.
4. For the aquaculture Cycles, we specified the Practice `Yield of primary aquaculture product (liveweight per m2)`. During validation, this Practice is automatically recommended for all aquaculture Cycles. This is because Sites can be of any size (e.g., a country, a region, a field, a part of a field), and while the `1 ha` functional unit normalizes for Site size, the `relative` functional unit does not. By adding this Practice, the land use of the Cycle is specified.
5. The fish processing Cycle creates two Products: fish oil and fish meal. These Products are subsequently used as Inputs into the feed blending Cycles. Cycles cannot be directly linked in HESTIA and must be linked via an Impact Assessment. Therefore, we therefore created the fish processing Cycle with multiple Products, and then created two Impact Assessments for the oil and meal.
6. We created the seven feed blending Cycles and added each Input, its quantity, and the country of origin of each Input. For the fish oil and fish meal, we also linked the Input to the Impact Assessment. We specified the Product of these Cycles as `Concentrate feed blend`. We used Properties to specify the nutrient composition of the blended feed. We also created seven Impact Assessments for these feed Cycles. The authors provided substantial data to populate these Impact Assessments (such as GHG emissions, ecotoxicity, land occupation) and we added these data.
7. We created the eight aquaculture Cycles and added the Inputs and Products. We linked the `Concentrate feed blend` Input to the Impact Assessment using `cycle.inputs.0.impactAssessment`.

8. The aquaculture Cycles had two Products: fish and excreta. We added them and also added the split between solid and liquid excreta.

9. Following excretion, microorganisms change the mass and composition of excreta, creating Emissions such as NH_3 and CH_4. A share of that excreta is sedimented at the bottom of the pond and it is often removed and stored in an excreta management system. Here, microorganisms convert it into a different Product again. To represent the transformations of excreta, we added Transformation blank nodes to the Cycles. Specifically, the `name` of the first Transformation is the first excreta management system, `Excretion into water body`, and the Input is `Excreta, solid and liquid, fish/crustaceans (kg N)`. The second excreta management system was not specified in the paper, so a generic term was used which was `Liquid/Slurry`, and we assumed that the amount sedimented was inputted into that system.

Validation: The phosphorus excreted was negative in the study, which was raised as a hard validation error. On inspection of the data the authors were including phosphorus uptake by the fish from sediment and water as a negative amount in the excreta. This should be entered as an Input to the fish, but insufficient data were provided to split the excreta from the uptake, so to resolve this, we simply didn't add the phosphorus content of the excreta.

Links: Dataset in HESTIA format (xlsx); dataset on the HESTIA platform.

e. An LCA on vegetable oil crushing & refining

Dataset: An study conducted an LCA using information from ~20 vegetable oil processing facilities in six countries representing ~70% of European vegetable oil production

(Schneider & Finkbeiner, 2013). All data were provided in a pdf report. Data were extracted from figures using Quintessa Graph Grabber 2.0.2.

Conversion: To upload this study, we began by using the Wizard available in the user submission dashboard at https://hestia.earth. The Wizard allowed us to structure up the first few rows of data into the HESTIA format. We then downloaded the Wizard output as a csv file and finished the process in Excel. A number of additional steps to example (1) were required for this study.

1. In the Source, we specified the ISO14044:2006 reporting requirements for LCAs including the intended audience of the study, the intended application, the study reasons, and whether the study was to be used for comparative assertions.
2. We used the converter in the Wizard – which uses the default Properties of the Terms – to convert to the correct units specified in the Term (e.g., from mass to volume based).
3. As with example (4) we used a `relative` functional unit.
4. Most of the emissions data were provided as characterised impact indicators (e.g., `GWP100` in kg CO_2eq) and were not broken down into each gas (e.g., CO_2). The characterised impacts also largely related to the production of Inputs. Emissions related to the production of Inputs, resource uses, and characterised indicators, should generally be entered in an Impact Assessment node and that Impact Assessment linked should be linked to the Inputs of the Cycle. However, that would be time consuming for this study, so we used the shortcut method, added the emissions related to Input production as Emission to the Cycle, split them out based on the Input they related to, and specified the input using (`emission.inputs.0.term.name`, etc.).

Validation: `IPCC (2006)` was stated in the report as a characterisation method for greenhouse gas emissions, which was detected as an error, and was corrected to `IPCC (2007)`.

Links: [Dataset in HESTIA format] (xlsx); [dataset on the HESTIA platform].

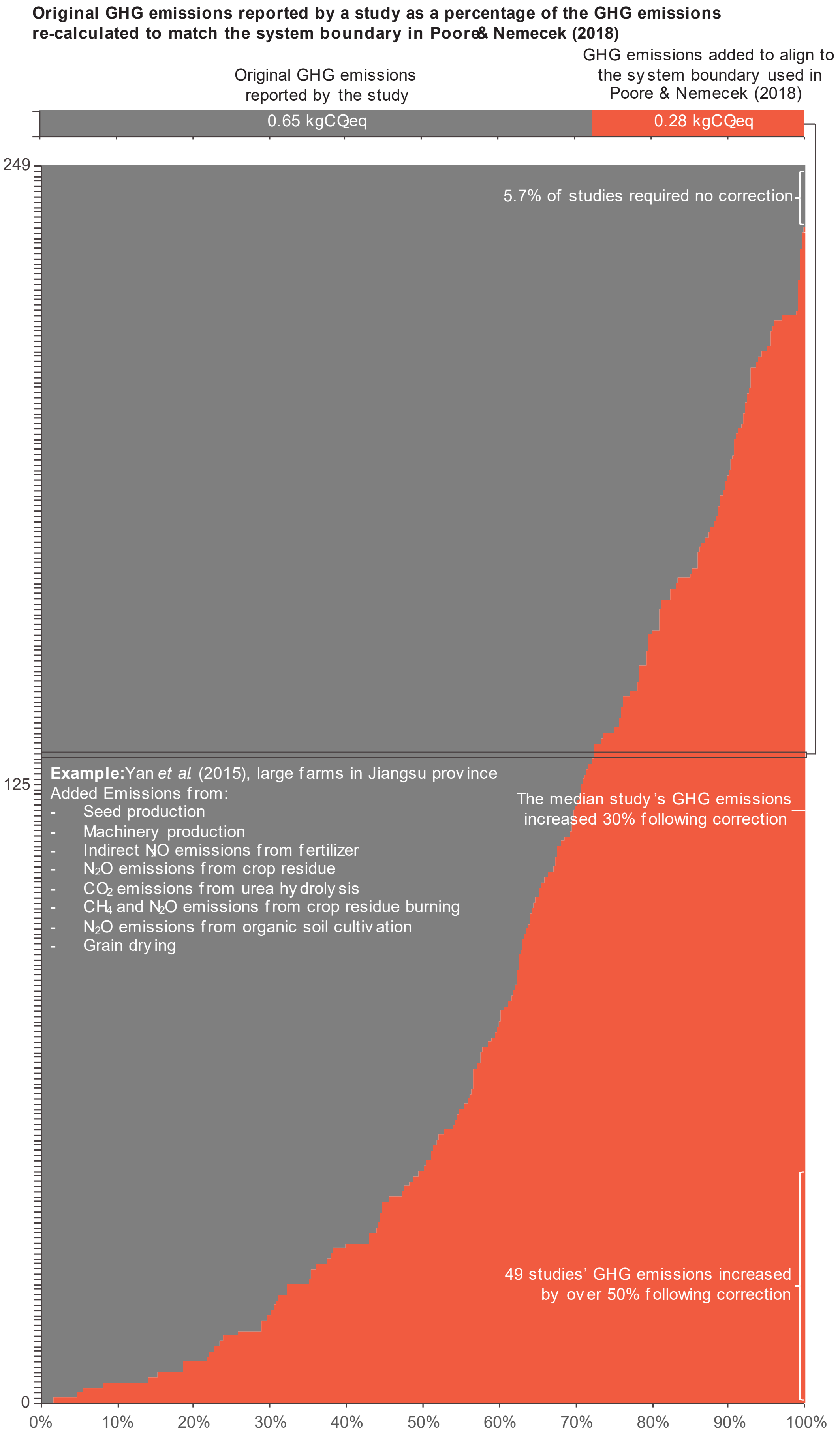

Original GHG emissions reported by a study as a percentage of the GHG emissions re-calculated to match the system boundary in Poore & Nemecek (2018)
Original GHG emissions reported by the study
GHG emissions added to align to the system boundary used in Poore & Nemecek (2018)
0.65 kgCO2eq
0.28 kgCO2eq
249
125
0
5.7% of studies required no correction
Example: Yan et al. (2015), large farms in Jiangsu province
Added Emissions from:
- Seed production
- Machinery production
- Indirect N2O emissions from fertilizer
- N2O emissions from crop residue
- CO2 emissions from urea hydrolysis
- CH4 and N2O emissions from crop residue burning
- N2O emissions from organic soil cultivation
- Grain drying
The median study's GHG emissions increased 30% following correction
49 studies' GHG emissions increased by over 50% following correction
0%
10%
20%
30%
40%
50%
60%
70%
80%
90%
100%

Fig. S16. The GHG original emissions per kilogram of wheat reported by 249 studies included in a global meta-analysis of LCAs (Chapter 2) compared to the GHG emissions following gap-filling and recalculation to match the system boundary of Chapter 2. For example, Yan et al. (2015) reported farm-stage GHG emissions of 0.65 kg CO_2eq / kg grain. Following align to the system boundary in Chapter 2, by including emissions related to seed production, machinery manufacture, indirect N_2O emissions from fertilizer, direct and indirect N_2O emissions from crop residue decomposition, emissions from crop residue burning, N_2O emissions from organic soil cultivation, and emissions from grain drying, farm-stage emissions increase to 0.93 kg CO_2eq / kg dry grain.

BIBLIOGRAPHY

AgGateway. (2022). *ADAPT*. https://adaptframework.org/

AgMIP. (2022). *Agricultural Research Data Network (ARDN)*. https://agmip.github.io/ARDN/

Aguilar, J., Gramig, G. G., Hendrickson, J. R., Archer, D. W., Forcella, F., & Liebig, M. A. (2015). Crop species diversity changes in the United States: 1978-2012. *PLoS ONE*, *10*(8), 1–14. https://doi.org/10.1371/journal.pone.0136580

Akagi, S. K., Yokelson, R. J., Wiedinmyer, C., Alvarado, M. J., Reid, J. S., Karl, T., Crounse, J. D., & Wennberg, P. O. (2011). Emission factors for open and domestic biomass burning for use in atmospheric models. *Atmospheric Chemistry and Physics*, *11*(9), 4039–4072. https://doi.org/10.5194/acp-11-4039-2011

Alkemade, R., Oorschot, M., Miles, L., Nellemann, C., Bakkenes, M., & ten Brink, B. (2009). GLOBIO3: A Framework to Investigate Options for Reducing Global Terrestrial Biodiversity Loss. *Ecosystems*, *12*(3), 374–390. https://doi.org/10.1007/s10021-009-9229-5

Allen, R. G., Pereira, L. S., Raes, D., & Smith, M. (1998). Crop evapotranspiration: Guidelines for computing crop requirements. *Irrigation and Drainage Paper*, *56*, 300. https://doi.org/10.1016/j.eja.2010.12.001

Alliance Europe. (2019). *Evaluation of the impacts of the CAP on habitats, landscape, biodiversity*. https://ec.europa.eu/info/sites/default/files/food-farming-fisheries/key_policies/documents/ext-eval-biodiversity-final-report_2020_en.pdf

Alliance for an Energy Efficient Economy (AEEE). (2015). *Evaluating Market Response to the Appliance Standards and Labelling Programme - A Status Report*. http://www.aeee.in/wp-content/uploads/2016/11/SL-Mkt-Evaluation-Final-Report.pdf

Alongi, D. M., McKinnon, A. D., Brinkman, R., Trott, L. A., Undu, M. C., Muawanah, & Rachmansyah. (2009). The fate of organic matter derived from small-scale fish cage aquaculture in coastal waters of Sulawesi and Sumatra, Indonesia. *Aquaculture*, *295*(1–2), 60–75. https://doi.org/10.1016/j.aquaculture.2009.06.025

Andor, M. A., Frondel, M., Gerster, A., & Sommer, S. (2019). Cognitive reflection and the valuation of energy efficiency. *Energy Economics*, *84*, 104527. https://doi.org/10.1016/j.eneco.2019.104527

Andor, M. A., Gerster, A., & Sommer, S. (2020). Consumer Inattention, Heuristic Thinking and the Role of Energy Labels. *Energy Journal*, *41*(January), 83–112. https://doi.org/10.5547/01956574.41.1.mand

Annan, K., Conway, G., & Dryden, S. (2016). African farmers in the digital age: How digital solutions can enable rural development. *Foreign Affairs*.

APPLiA. (2021). *APPLiA Database*. https://www.applia-europe.eu/

Arouna, A., Michler, J. D., Yergo, W. G., & Saito, K. (2021). One Size Fits All? Experimental Evidence on the Digital Delivery of Personalized Extension Advice in Nigeria. *American Journal of Agricultural Economics*, *103*(2), 596–619. https://doi.org/10.1111/ajae.12151

ASAE. (2005). *Manure Production and Characteristics*.

Atwood, L. W., & Wood, S. A. (2020). *AgEvidence: Agro-environmental responses of* *conservation agricultural practices in the US Midwest published from 1980 to 2017*. Knowledge Network for Biocomplexity. https://doi.org/10.5063/F1W37TQJ

Aung, S. M. (2018). Burma - Union of Grain and Feed 2018 Annual Report. *USDA, Foreign Agricultural Service*, *BM 8003*, 12. http://gain.fas.usda.gov/Recent GAIN Publications/Grain and Feed Annual_Rangoon_Burma - Union of_4-28-2015.pdf

Avadí, A., Pelletier, N., Aubin, J., Ralite, S., Núñez, J., & Fréon, P. (2015). Comparative environmental performance of artisanal and commercial feed use in Peruvian freshwater aquaculture. *Aquaculture*, *435*, 52–66. https://doi.org/10.1016/j.aquaculture.2014.08.001

Banerjee, A., & Solomon, B. D. (2003). Eco-labeling for energy efficiency and sustainability: A meta-evaluation of US programs. *Energy Policy*, *31*(2), 109–123. https://doi.org/10.1016/S0301-4215(02)00012-5

Bartholomé, E., & Belward, A. S. (2005). GLC 2000: a new approach to global land cover mapping from Earth observation data. *International Journal of Remo*, *26*(9), 1959–1977.

Bastounis, A., Buckell, J., Hartmann-boyce, J., Cook, B., King, S., Potter, C., Bianchi, F., Rayner, M., & Jebb, S. A. (2021). The impact of environmental sustainability labels on willingness-to-pay for foods: A systematic review and meta-analysis of discrete choice experiments. *Nutrients*, *13*(8). https://doi.org/10.3390/nu13082677

Bastviken, D., Cole, J. J., Pace, M. L., & Van de-Bogert, M. C. (2008). Fates of methane from different lake habitats: Connecting whole-lake budgets and CH4 emissions. *Journal of Geophysical Research: Biogeosciences*, *113*. https://doi.org/10.1029/2007JG000608

Bastviken, D., Tranvik, L. J., Downing, J. A., Crill, J. A., & Enrich-Prast, A. (2011). Freshwater Methane Emissions Offset the Continental Carbon Sink. *Science*, *331*, 50. https://doi.org/10.1126/science.1196808

Batjes, N. H. (2015). *World soil property estimates for broad-scale modelling (WISE30sec)*.

Benton, T. G., Vickery, J. A., & Wilson, J. D. (2003). Farmland biodiversity: Is habitat heterogeneity the key? *Trends in Ecology and Evolution*, *18*(4), 182–188. https://doi.org/10.1016/S0169-5347(03)00011-9

Beza, E., Silva, J. V., Kooistra, L., & Reidsma, P. (2017). Review of yield gap explaining factors and opportunities for alternative data collection approaches. *European Journal of Agronomy*, *82*, 206–222. https://doi.org/10.1016/j.eja.2016.06.016

Biology, D. A., & Fry, J. C. (1987). Functional roles of the major groups of bacteria associated with detritus. In D. J. W. Moriarty & R. S. V. Pullin (Eds.), *Detritus and microbial ecology in aquaculture* (pp. 83–122). ICLARM.

Biradar, C. M., Thenkabail, P. S., Noojipady, P., Li, Y., Dheeravath, V., Turral, H., Velpuri, M., Gumma, M. K., Gangalakunta, O. R. P., Cai, X. L., Xiao, X., Schull, M. A., Alankara, R. D., Gunasinghe, S., & Mohideen, S. (2009). A global map of rainfed cropland areas (GMRCA) at the end of last millennium using remote sensing. *International Journal of Applied Earth Observation and Geoinformation*, *11*(2), 114–129. https://doi.org/10.1016/j.jag.2008.11.002

Bleda, M., & Valente, M. (2009). Graded eco-labels: A demand-oriented approach to reduce pollution. *Technological Forecasting and Social Change*, *76*(4), 512–524. https://doi.org/10.1016/j.techfore.2008.05.003

Blonk Consultants. (2013). *Direct Land Use Change Assessment Tool v2014.1*. http://www.blonkconsultants.nl/direct-land-use-change-assessment-tool/?lang=en

Bontemps, S., Defourny, P., Bogaert, E. Van, Kalogirou, V., & Perez, J. R. (2011). GLOBCOVER 2009 Products Description and Validation Report. *ESA Bulletin*, *136*, 53. https://doi.org/10013/epic.39884.d016

Bossio, D., Obersteiner, M., Wironen, M., Jung, M., Wood, S., Folberth, C., Boucher, T., Alleway, H., Simons, R., Bucien, K., Dowell, L., Cleary, D., Jones, R., Burns, C., Phang, S. C., Cisse, M., Doane, M., Fernandez-, M., Kariuki, A., … Masuda, Y. J. (2021). *Foodscapes: Towards food system transition*.

Boulay, A. M., Bare, J., Benini, L., Berger, M., Lathuillière, M. J., Manzardo, A., Margni, M., Motoshita, M., Núñez, M., Pastor, A. V., Ridoutt, B., Oki, T., Worbe, S., & Pfister, S. (2018). The WULCA consensus characterization model for water scarcity footprints: assessing impacts of water consumption based on available water remaining (AWARE). *International Journal of Life Cycle Assessment*, *23*, 368–378. https://doi.org/10.1007/s11367-017-1333-8

Bouwman, A. F., Van Vuuren, D. P., Derwent, R. G., & Posch, M. (2002). A global analysis of acidification and eutrophication of terrestrial ecosystems. *Water, Air, and Soil Pollution*, *141*(1–4), 349–382. https://doi.org/10.1023/A:1021398008726

Brunner, F., Kurz, V., Bryngelsson, D., & Hedenus, F. (2018). Carbon Label at a University Restaurant – Label Implementation and Evaluation. *Ecological Economics*, *146*(August 2017), 658–667. https://doi.org/10.1016/j.ecolecon.2017.12.012

Buchholz, M., & Musshoff, O. (2021). Tax or green nudge? An experimental analysis of pesticide policies in Germany. *European Review of Agricultural Economics*, *48*(4), 940–982. https://doi.org/10.1093/erae/jbab019

Buchhorn, M., Lesiv, M., Tsendbazar, N. E., Herold, M., Bertels, L., & Smets, B. (2020). Copernicus global land cover layers-collection 2. *Remote Sensing*, *12*(6), 1–14. https://doi.org/10.3390/rs12061044

Bureau of Energy Efficiency (BEE). (2021). *Impact of Energy Efficiency Measures for the Year 2019-20*. https://beeindia.gov.in/sites/default/files/BEE_Final Report_Website version.pdf

Bureau, P., Chen, H., Li, X., Hu, F., & Shi, W. (2013). Soil nitrous oxide emissions following crop residue addition: A meta-analysis. *Global Change Biology*, *19*(10), 2956–2964. https://doi.org/10.1111/gcb.12274

Burgass, M. J., Halpern, B. S., Nicholson, E., & Milner-Gulland, E. J. (2017). Navigating uncertainty in environmental composite indicators. *Ecological Indicators*, *75*, 268–278. https://doi.org/10.1016/j.ecolind.2016.12.034

Burney, J. A., Davis, S. J., & Lobell, D. B. (2010). Greenhouse gas mitigation by agricultural intensification. *Proceedings of the National Academy of Sciences*, *107*(26), 12052–12057. https://doi.org/10.1073/pnas.0914216107

Burns, I. G. (1975). An equation to predict the leaching of surface-applied nitrate. *J. Agric. Sci., Camb*, *85*, 443–454.

Campbell, B. M., Beare, D. J., Bennett, E. M., Hall-Spencer, J. M., Ingram, J. S. I., Jaramillo, F., Ortiz, R., Ramankutty, N., Sayer, J. A., & Shindell, D. (2017). Agriculture production as a major driver of the earth system exceeding planetary boundaries. *Ecology and Society*, *22*(4). https://doi.org/10.5751/ES-09595-220408

Carlson, K. M., Gerber, J. S., Mueller, N. D., Herrero, M., Macdonald, G. K., Brauman, K. A., Havlik, P., O'Connell, C. S., Johnson, J. A., Saatchi, S., West, P. C., Connell, C. S. O., Johnson, J. A., Saatchi, S., & West, P. C. (2016). Greenhouse gas emissions intensity of global croplands. *Nature Climate Change*, *7*(21 November), 63–68. https://doi.org/10.1038/NCLIMATE3158

Carrero, I., Valor, C., Díaz, E., & Labajo, V. (2021). Designed to be noticed: A reconceptualization of carbon food labels as warning labels. *Sustainability*, *13*(3), 1–14. https://doi.org/10.3390/su13031581

Cassidy, E. S., West, P. C., Gerber, J. S., & Foley, J. A. (2013). Redefining agricultural yields: from tonnes to people nourished per hectare. *Environmental Research Letters*, *8*(3), 034015. https://doi.org/10.1088/1748-9326/8/3/034015

CDP. (2021). *CDP Database*. https://www.cdp.net/

Certified California Sustainable Winegrowing. (2020). *Annual Report 2020*. https://www.sustainablewinegrowing.org/

CGIAR. (2022a). *Agronomy Ontology*. https://bigdata.cgiar.org/resources/agronomy-ontology/

CGIAR. (2022b). *Crop Ontology*. https://www.cropontology.org/

CGIAR. (2022c). *GARDIAN*. https://gardian.bigdata.cgiar.org/

CGIAR. (2022d). *Global N2O Dashboard*. https://samples.ccafs.cgiar.org/n2o-dashboard/

Chapagain, A. K., & Hoekstra, A. Y. (2011). The blue, green and grey water footprint of rice from production and consumption perspectives. *Ecological Economics*, *70*(4), 749–758. https://doi.org/10.1016/j.ecolecon.2010.11.012

Chaudhary, A., & Tremorin, D. (2020). Nutritional and environmental sustainability of lentil reformulated beef burger. *Sustainability (Switzerland)*, *12*(17), 1–18. https://doi.org/10.3390/SU12176712

Chen, J. J. J., Chen, J. J. J., Liao, A., Cao, X., Chen, L., Chen, X., He, C., Han, G., Peng, S., Lu, M., Zhang, W., Tong, X., & Mills, J. (2014). Global land cover mapping at 30 m resolution: A POK-based operational approach. *ISPRS Journal of Photogrammetry and Remote Sensing*, *103*, 7–27. https://doi.org/10.1016/j.isprsjprs.2014.09.002

Chen, X. P., Cui, Z. L., Vitousek, P. M., Cassman, K. G., Matson, P. A., Bai, J. S., Meng, Q. F., Hou, P., Yue, S. C., Römheld, V., & Zhang, F. S. (2011). Integrated soil-crop system management for food security. *Proceedings of the National Academy of Sciences of the United States of America*, *108*(16), 6399–6404. https://doi.org/10.1073/pnas.1101419108

Chiron, F., Chargé, R., Julliard, R., Jiguet, F., & Muratet, A. (2014). Pesticide doses, landscape structure and their relative effects on farmland birds. *Agriculture, Ecosystems and Environment*, *185*, 153–160. https://doi.org/10.1016/j.agee.2013.12.013

Chunekar, A., Kelkar, M., & Mulay, S. (2019). Impact of India's large-scale LED bulb program. *ECEEE Summer Study Proceedings*, 735–744.

Clark, M. A., Springmann, M., Hill, J., & Tilman, D. (2019). Multiple health and environmental impacts of foods. *Proceedings of the National Academy of Sciences of the United States of America*, *12*(116 (46)), 23357–23362. https://doi.org/10.1073/pnas.1906908116

Clark, M., & Tilman, D. (2017). Comparative analysis of environmental impacts of agricultural production systems, agricultural input efficiency, and food choice. *Environmental Research Letters*, *12*(6), 064016. https://doi.org/10.1088/1748-9326/aa6cd5

CLASP. (2021). *CLASP Policy Resource Center*. https://cprc-clasp.ngo/

Clune, S., Crossin, E., & Verghese, K. (2017). Systematic review of greenhouse gas emissions for different fresh food categories. *Journal of Cleaner Production*, *140*, 766–783. https://doi.org/10.1016/j.jclepro.2016.04.082

CML. (2001). *CML2 Baseline Method 2000*.

Coelli, T., & Henningsen, A. (2017). *frontier: Stochastic Frontier Analysis. R package version 1.1-2*.

Collins, S. J., & Fahrig, L. (2017). Responses of anurans to composition and configuration of agricultural landscapes. *Agriculture, Ecosystems and Environment*, *239*, 399–409. https://doi.org/10.1016/j.agee.2016.12.038

Colomb, V., Amar, S. A., Mens, C. B., Gac, A., Gaillard, G., Koch, P., Mousset, J., & Salou, T. (2014). *AGRIBALYSE®: the French LCI Database for agricultural products: high quality data for producers and environmental labelling*.

Conway, G. (1999). *The Doubly Green Revolution: Food for All in the Twenty-First Century*. Cornell University Press.

Cool Farm Alliance. (2020). *Cool Farm Impact Report*. https://coolfarmtool.org/wp-content/uploads/2020/10/Cool-Farm-Impact-Report-2020.pdf

Cordell, D., Rosemarin, A., Schröder, J. J., & Smit, A. L. (2011). Towards global phosphorus security: A systems framework for phosphorus recovery and reuse options. *Chemosphere*, *84*(6), 747–758. https://doi.org/10.1016/j.chemosphere.2011.02.032

Crippa, M., Solazzo, E., Guizzardi, D., Monforti-Ferrario, F., Tubiello, F. N., & Leip, A. (2021). Food systems are responsible for a third of global anthropogenic GHG emissions. *Nature Food*, *2*(3), 198–209. https://doi.org/10.1038/s43016-021-00225-9

Cronin, J., Zabel, F., Dessens, O., & Anandarajah, G. (2020). Land suitability for energy crops under scenarios of climate change and land-use. *GCB Bioenergy*, *12*(8), 648–665. https://doi.org/10.1111/gcbb.12697

CTA. (2019). *The Digitalisation of African Agriculture Report 2018-19*. https://www.cta.int/en/digitalisation/issue/the-digitalisation-of-african-agriculture-report-2018-2019-sid0d88610e2-d24e-4d6a-8257-455b43cf5ed6

Cucurachi, S., Scherer, L., Guinée, J., & Tukker, A. (2019). Life Cycle Assessment of Food Systems. *One Earth*, *1*(3), 292–297. https://doi.org/10.1016/j.oneear.2019.10.014

Cui, Z., Wu, L., Ye, Y. L., Ma, W. Q., Chen, X. P., & Zhang, F. S. (2014). Trade-offs between high yields and greenhouse gas emissions in irrigation wheat cropland in China.

Biogeosciences, *11*(8), 2287–2294. https://doi.org/10.5194/bg-11-2287-2014

Cui, Z., Zhang, H., Chen, X., Zhang, C., Ma, W., Huang, C., Zhang, W., Mi, G., Miao, Y., Li, X., Gao, Q., Yang, J., Wang, Z., Ye, Y., Guo, S., Lu, J., Huang, J., Lv, S., Sun, Y., … Dou, Z. (2018). Pursuing sustainable productivity with millions of smallholder farmers. *Nature*, *555*, 363–366. https://doi.org/10.1038/nature25785

Curtis, P. G., Slay, C. M., Harris, N. L., Tyukavina, A., & Hansen, M. C. (2018). Classifying drivers of global forest loss. *Science*, *361*(6407), 1108–1111. https://doi.org/10.1126/science.aau3445

D'Haultfœuille, X., Durrmeyer, I., & Février, P. (2016). Disentangling sources of vehicle emissions reduction in France: 2003-2008. *International Journal of Industrial Organization*, *47*, 186–229. https://doi.org/10.1016/j.ijindorg.2016.05.002

Dämmgen, U. (2009). *Calculations of emission from German agriculture - National Emission Inventory Report 2009 for 2007*.

Danielson, J., & Gesch, D. (2008). An enhanced global elevation model generalized from multiple higher resolution source dataets. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XXXVII*(B4), 1857–1864.

Danish Crown. (2020). *Sustainability Report*. https://www.danishcrown.com/en-gb/about-us/annual-reports-csr-and-key-figures/sustainability-reports/

Darby, H., Hills, K., Cummings, E., & Madden, R. (2010). *Assessing the value of oilseed meals for soil fertility and weed suppression*.

Daum, T., & Birner, R. (2020). Agricultural mechanization in Africa: Myths, realities and an emerging research agenda. *Global Food Security*, *26*, 100393. https://doi.org/10.1016/j.gfs.2020.100393

Davis, K., Babu, S. C., & Ragasa, C. (2020). *Agricultural Extension: Global Status and Performance in Selected Countries* (Vol. 38). IFPRI.

Dayanidhi, V. K., Hedge, S. P., Chendrashekaran, P., & Begum, K. (2016). A Cross-Sectional Survey on the Awareness of Pesticide Labels and Pesticide Safety Pictograms Among Paddy Farming In South India. *J Heath Sci Surveillance Sys*, *4*(4), 158–166.

de Baan, L., Alkemade, R., & Koellner, T. (2012). Land use impacts on biodiversity in LCA: a global approach. *The International Journal of Life Cycle Assessment*, *18*(6), 1216–1230. https://doi.org/10.1007/s11367-012-0412-0

de Baan, L., Mutel, C. L., Curran, M., Hellweg, S., Koellner, T., Baan, L. De, Mutel, C. L., Curran, M., Hellweg, S., & Koellner, T. (2013). Land use in life cycle assessment: global characterization factors based on regional and global potential species extinction. *Environmental Science & Technology*, *47*(16), 9281–9290. https://doi.org/10.1021/es400592q

De Beenhouwer, M., Aerts, R., & Honnay, O. (2013). A global meta-analysis of the biodiversity and ecosystem service benefits of coffee and cacao agroforestry. *Agriculture, Ecosystems and Environment*, *175*, 1–7. https://doi.org/10.1016/j.agee.2013.05.003

de Vries, M., de Boer, I. J. M. J. M., Vries, M. De, Boer, I. J. M. De, de Vries, M., & de Boer,

I. J. M. J. M. (2010). Comparing environmental impacts for livestock products: A review of life cycle assessments. *Livestock Science*, *128*(1–3), 1–11. https://doi.org/10.1016/j.livsci.2009.11.007

DeFries, R. S., Fanzo, J., Mondal, P., Remans, R., & Wood, S. A. (2017). Is voluntary certification of tropical agricultural commodities achieving sustainability goals for small-scale producers? A review of the evidence. *Environmental Research Letters*, *12*(3). https://doi.org/10.1088/1748-9326/aa625e

Del Grosso, S. J., Gollany, H. T., & Reyes-Fox, M. (2016). Simulating Soil Organic Carbon Stock Changes in Agroecosystems using CQESTR, DayCent, and IPCC Tier 1 Methods. In S. Del Grosso, L. Ahuja, & W. Parton (Eds.), *Synthesis and Modeling of Greenhouse Gas Emissions and Carbon Storage in Agricultural and Forest Systems to Guide Mitigation and Adaptation* (Vol. 6, pp. 89–110). https://doi.org/10.2134/advagricsystmodel6.2013.0001.5

Delang, C. O., & Yuan, Z. (2015). China's Grain for Green Program. In *China's Grain for Green Program*. https://doi.org/10.1007/978-3-319-11505-4

Dendler, L. (2014). Sustainability Meta Labelling: An effective measure to facilitate more sustainable consumption and production? *Journal of Cleaner Production*, *63*, 74–83. https://doi.org/10.1016/j.jclepro.2013.04.037

Denef, K., Paustian, K., Archibeque, S., Biggar, S., & Pape, D. (2012). *Report of Greenhouse Gas Accounting Tools for Agriculture and Forestry Sectors*.

Detweiler, A. M., Bebout, B. M., Frisbee, A. E., Kelley, C. A., Chanton, J. P., & Prufert-Bebout, L. E. (2014). Characterization of methane flux from photosynthetic oxidation ponds in a wastewater treatment plant. *Water Science and Technology*, *70*(6), 980–989. https://doi.org/10.2166/wst.2014.317

Dieu-Hang, T., Grafton, R. Q., Martínez-Espiñeira, R., & Garcia-Valiñas, M. (2017). Household adoption of energy and water-efficient appliances: An analysis of attitudes, labelling and complementary green behaviours in selected OECD countries. *Journal of Environmental Management*, *197*, 140–150. https://doi.org/10.1016/j.jenvman.2017.03.070

Dimitri, C., Effland, A., & Conklin, N. (2005). The 20th century transformation of U.S. agriculture and farm policy. *USDA Economic Information Bulletin*, *3*, 17. http://proxyiub.uits.iu.edu/login?url=http://search.ebscohost.com/login.aspx?direct=true&db=edswao&AN=edswao.389725811&site=eds-live&scope=site

DKE-Data. (2022). *agrirouter*. https://my-agrirouter.com/

Dolan, P., Hallsworth, M., Halpern, D., King, D., Metcalfe, R., & Vlaev, I. (2012). Influencing behaviour: The mindspace way. *Journal of Economic Psychology*, *33*(1), 264–277. https://doi.org/10.1016/j.joep.2011.10.009

Downar, B., Ernstberger, J., Reichelstein, S. J., Schwenen, S., & Zaklan, A. (2020). The Impact of Carbon Disclosure Mandates on Emissions and Financial Operating Performance. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3693670

EC-JRC/PBL. (2013). *EDGAR v4.2 FT2010*. http://edgar.jrc.ec.europa.eu/

ecoinvent. (2013). *Background data for transport*.

http://www.ecoinvent.org/files/transport_default_20130722.xls

Ecoinvent. (2022). *ecoSpold2*. https://www.ecoinvent.org/data-provider/data-provider-toolkit/ecospold2/ecospold2.html

EcoLabel Index. (2021). *Food Ecolabels*. http://www.ecolabelindex.com/ecolabels/?st=category,food

EEA. (2013). *EMEP/EEA air pollutant emission inventory guidebook 2013: Technical guidance to prepare national emission inventories*.

efeca. (2020). *Palm Oil Certification Schemes: MSPO*. https://www.efeca.com/wp-content/uploads/2020/03/Certification-Scheme-MSPO-Infobriefing-5-Part-3-Final.pdf

Ekroos, J., Tiainen, J., Seimola, T., & Herzon, I. (2019). Weak effects of farming practices corresponding to agricultural greening measures on farmland bird diversity in boreal landscapes. *Landscape Ecology*, *34*(2), 389–402. https://doi.org/10.1007/s10980-019-00779-x

Ellis, E. C., Beusen, A. H. W., & Goldewijk, K. K. (2020). Anthropogenic biomes: 10,000 BCE to 2015 CE. *Land*, *9*(5), 8–10. https://doi.org/10.3390/LAND9050129

Ellis, E. C., Klein Goldewijk, K., Siebert, S., Lightman, D., & Ramankutty, N. (2010). Anthropogenic transformation of the biomes, 1700 to 2000. *Global Ecology and Biogeography*, *19*, 589–606. https://doi.org/10.1111/j.1466-8238.2010.00540.x

Engström, L., Stenberg, M., Aronsson, H., & Lindén, B. (2011). Reducing nitrate leaching after winter oilseed rape and peas in mild and cold winters. *Agronomy for Sustainable Development*, *31*(2), 337–347. https://doi.org/10.1051/agro/2010035

Environmental Investigation Agency (EIA). (2020). *A False Hope? An analysis of the new draft Indonesia Sustainable Palm Oil (ISPO) regulations*. https://eia-international.org/report/a-false-hope-an-analysis-of-the-new-draft-indonesia-sustainable-palm-oil-ispo-regulations/

EPA. (2016). *Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2014*.

Ericksen, P. J. (2008). Conceptualizing food systems for global environmental change research. *Global Environmental Change*, *18*(1), 234–245. https://doi.org/10.1016/j.gloenvcha.2007.09.002

Euromonitor. (2018). http://www.portal.euromonitor.com

Recommendation 2013/179/EU on the use of common methods to measure and communicate the life cycle environmental performance of products and organisations, Official Journal of European Union 210 (2013). https://doi.org/doi:10.3000/19770677.L_2013.124.eng

Commission Delegated Regulation (EU) 2019/2016 of 11 March 2019 supplementing Regulation (EU) 2017/1369 of the European Parliament and of the Council with regard to energy labelling of refrigerating appliances and repealing Commission Delegated Regulation, (2019).

European Commission. (2021). *Life Cycle Data Network (LCDN)*. https://eplca.jrc.ec.europa.eu/LCDN/index.xhtml

European Commission. (2022). *ILCD International Life Cycle Data system*.

https://eplca.jrc.ec.europa.eu/ilcd.html

European Commisson. (2018). Commission Implementing Regulation (EU) 2018/746. *Official Journal of the European Union*.

European Environment Agency (EEA). (2019). EMEP/EEA air pollutant emission inventory guidebook 2019: Technical guidance to prepare national emission inventories. *EEA Technical Report*. https://www.eea.europa.eu/publications/emep-eea-guidebook-2019

Regulation (EU) No 1308/2013: establishing a common organization of the markets in agricultural products, Official Journal of the European Union 671 (2013).

European Space Agency (ESA) Climate Change Initiative (CCI). (2017). *Land Cover Map 1992-2015*. https://www.esa-landcover-cci.org/

Ewers, R. M., Scharlemann, J. P. W., Balmford, A., Green, R. E., St, D., Lodge, T., Ewers, R. M., Scharlemann, J. P. W., Balmford, A., & Green, R. E. (2009). Do increases in agricultural yield spare land for nature? *Global Change Biology*, *15*(7), 1716–1726. https://doi.org/10.1111/j.1365-2486.2009.01849.x

EY, Cambridge Econometrics, & Arcadia International. (2014). *The economic impact of modern retail on choice and innovation in the EU food sector*. https://ec.europa.eu/competition/publications/KD0214955ENN.pdf

Faccioli, M., Law, C., Caine, C. A., Berger, N., Yan, X., Weninger, F., Guell, C., Day, B., Smith, R. D., & Bateman, I. J. (2022). Combined carbon and health taxes outperform single-purpose information or fiscal measures in designing sustainable food policies. *Nature Food*, *3*, 331–340. https://doi.org/10.1038/s43016-022-00482-2

Fahrig, L., Baudry, J., Brotons, L., Burel, F. G., Crist, T. O., Fuller, R. J., Sirami, C., Siriwardena, G. M., & Martin, J. L. (2011). Functional landscape heterogeneity and animal biodiversity in agricultural landscapes. *Ecology Letters*, *14*(2), 101–112. https://doi.org/10.1111/j.1461-0248.2010.01559.x

Fahrig, L., Girard, J., Duro, D., Pasher, J., Smith, A., Javorek, S., King, D., Lindsay, K. F., Mitchell, S., & Tischendorf, L. (2015). Farmlands with smaller crop fields have higher within-field biodiversity. *Agriculture, Ecosystems and Environment*, *200*, 219–234. https://doi.org/10.1016/j.agee.2014.11.018

Fan, M. S., Zhao, F. J., Fairweather-Tait, S. J., Poulton, P. R., Dunham, S. J., & McGrath, S. P. (2008). Evidence of decreasing mineral density in wheat grain over the last 160 years. *Journal of Trace Elements in Medicine and Biology*, *22*(4), 315–324. https://doi.org/10.1016/j.jtemb.2008.07.002

Fane, S., Grossman, C., & Schlunke, A. (2020). Australia's water efficiency labelling and standards scheme: Summary of an environmental and economic evaluation. *Water Science and Technology: Water Supply*, *20*(1). https://doi.org/10.2166/ws.2019.137

Fane, Simon, Schlunke, A., Falletta, J., Chan, A., & Prentice, E. (2018). *Evaluation of the environmental and economic impacts of the WELS scheme*. https://www.waterrating.gov.au/about/review-evaluation/environmental-effects

Fang, P., & Belton, B. (2020). Maize and pigeon pea production, profitability, and tied credit in southern Shan state. In *Feed the Future Innovation Lab for Food Security Policy* (Issue 173). https://www.canr.msu.edu/resources/maize-and-pigeon-pea-production-profitability-and-tied-credit-in-southern-shan-state

FAO/IIASA/ISRIC/ISSCAS/JRC. (2012). *Harmonized World Soil Database (version 1.2)*.

FAO. (1989). *Yield and nutritional value of the commercially more important fish species*.

FAO. (2001). *Food balance sheets – a handbook.*

FAO. (2005). *A system of integrated agricultural censuses and surveys*. http://www.fao.org/3/a0135e/A0135E00.htm

FAO. (2010a). *Global Livestock Environmental Assessment Model Version 2.0*. *2*, 82. http://www.fao.org/fileadmin/user_upload/gleam/docs/GLEAM_2.0_Model_description.pdf

FAO. (2010b). *The Second Report on the State of the World's Plant Genetic Resources for Food and Agriculture*.

FAO. (2014). *The State of Food and Agriculture*.

FAO. (2016a). *AQUASTAT (Database) - Conservation Agriculture Adoption Worldwide*. http://www.fao.org/nr/water/aquastat/data/query/index.html

FAO. (2016b). *FishStatJ - software for fishery statistical time series*. http://www.fao.org/fishery/statistics/software/fishstatj

FAO. (2016c). *Global Livestock Environmental Assessment Model: Reference Documentation v2.0*.

FAO. (2017). *AQUASTAT (Database)*. http://www.fao.org/nr/water/aquastat

FAO. (2020). *The State of World Fisheries and Aquaculture 2020*. https://doi.org/10.4060/ca9229en

FAO. (2021a). *AGROVOC Multilingual Thesaurus*. https://agrovoc.fao.org/browse/agrovoc/

FAO. (2021b). *Microdata*. https://microdata.fao.org/index.php/catalog

FAO. (2021c). The State of Food Security and Nutrition in the World 2021. In *The State of Food Security and Nutrition in the World 2021*. https://doi.org/10.4060/cb4474en

FAO, Gustavsson, J., Cederberg, C., Sonesson, U., van Otterdijk, R., & Meybeck, A. (2011). *Global food losses and food waste – Extent, causes and prevention*.

FAOSTAT. (2013). *Data Structure, Concepts and Definitions common to FAOSTAT and CountrySTAT framework*. https://www.fao.org/publications/card/fr/c/7a27b523-79a4-4ff9-8c65-f8ba965885dc/

FAOSTAT. (2021). http://www.fao.org/faostat

Feedipedia, Heuzé, V., & Tran, G. (2015). *Feedipedia, a programme by INRA, CIRAD, AFZ and FAO*. http://www.feedipedia.org/

FiBL and IFOAM. (2014). Share of organic agriculture - world: selected crops by country 2004 -2013. In H. Willer & J. Lernoud (Eds.), *The World of Organic Agriculture. Statistics and Emerging Trends 2014.*

Field to Market. (2022). *Fieldprint Platform*. https://fieldtomarket.org/our-programs/fieldprint-platform/

Fischer, J., Brosi, B., Daily, G. C., Ehrlich, P. R., Goldman, R., Goldstein, J., Lindenmayer, D. B., Manning, A. D., Mooney, H. a, Pejchar, L., Ranganathan, J., & Tallis, H. (2008). Should agricultural policies encourage land sparing or wildlife-friendly farming? *Frontiers in Ecology and the Environment*, *6*(7), 380–385. https://doi.org/10.1890/070019

Foley, J., DeFries, R., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., Chapin, F. S., Coe, M. T., Daily, G. C., Gibbs, H. K., Helkowski, J. H., Holloway, T., Howard, E., Kucharik, C. J., Monfreda, C., Patz, J., Prentice, C., Ramankutty, N., & Snyder, P. K. (2005). Global Consequences of Land Use. *Science*, *309*(5734), 570–574. https://doi.org/10.1126/science.1111772

Foley, J., Ramankutty, N., Brauman, K., Cassidy, E., Gerber, J., Johnston, M., Mueller, N., O'Connell, C., Ray, D., West, P. C., Balzer, C., Bennett, E., Carpenter, S., Hill, J., Monfreda, C., Polasky, S., Rockström, J., Sheehan, J., Siebert, S., … O'Connell, C. (2011). Solutions for a cultivated planet. *Nature*, *478*(7369), 337–342. https://doi.org/10.1038/nature10452

Food Security Policy Project. (2020). *Shan Household, Agriculture and Rural Economy: Household Survey – May-October 2018*. Harvard Dataverse. https://doi.org/10.7910/DVN/HLJRHJ

Friedlingstein, P., Andrew, R. M., Rogelj, J., Peters, G. P., Canadell, J. G., Knutti, R., Luderer, G., Raupach, M. R., Schaeffer, M., Van Vuuren, D. P., & Le Quéré, C. (2014). Persistent growth of CO2 emissions and implications for reaching climate targets. In *Nature Geoscience* (Vol. 7, Issue 10, pp. 709–715). Nature Publishing Group. https://doi.org/10.1038/NGEO2248

FrieslandCampina. (2019). *Annual Report 2019*. https://www.frieslandcampina.com/uploads/2020/03/FrieslandCampina-Annual-Report-2019.pdf

Frison, E. (2008). Indispensable resources. *Development and Cooperation*, *5*, 190. https://www.dandc.eu/en/article/green-revolution-africa-will-depend-biodiversity

Fritz, S., See, L., Mccallum, I., You, L., Bun, A., Moltchanova, E., Duerauer, M., Albrecht, F., Schill, C., Perger, C., Havlik, P., Mosnier, A., Thornton, P., Wood-Sichra, U., Herrero, M., Becker-Reshef, I., Justice, C., Hansen, M., Gong, P., … Obersteiner, M. (2015). Mapping global cropland and field size. *Global Change Biology*, *21*(5), 1980–1992. https://doi.org/10.1111/gcb.12838

Fulton, L., Cazzola, P., & Cuenot, F. (2009). IEA Mobility Model (MoMo) and its use in the ETP 2008. *Energy Policy*, *37*(10), 3758–3768. https://doi.org/10.1016/j.enpol.2009.07.065

Garnett, E. E., Marteau, T. M., Sandbrook, C., Pilling, M. A., & Balmford, A. (2020). Order of meals at the counter and distance between options affect student cafeteria vegetarian sales. *Nature Food*, *1*(8), 485–488. https://doi.org/10.1038/s43016-020-0132-8

Garnett, T., Appleby, M. C., Balmford, A., Bateman, I. J., Benton, T. G., Bloomer, P., Burlingame, B., Dawkins, M., Dolan, L., Fraser, D., Herrero, M., Hoffmann, I., Smith, P., Thornton, P. K., Toulmin, C., Vermeulen, S. J., & Godfray, H. C. J. (2013). Sustainable intensification in agriculture: Premises and policies. *Science*, *341*(6141), 33–34. https://doi.org/10.1126/science.1234485

Garrett, R. D., Ryschawy, J., Bell, L. W., Cortner, O., Ferreira, J., Garik, A. V. N., Gil, J. D. B., Klerkx, L., Moraine, M., Peterson, C. A., Dos Reis, J. C., & Valentim, J. F. (2020). Drivers of decoupling and recoupling of crop and livestock systems at farm and territorial scales. *Ecology and Society*, *25*(1). https://doi.org/10.5751/ES-11412-250124

Gaspar, R., & Antunes, D. (2011). Energy efficiency and appliance purchases in Europe: Consumer profiles and choice determinants. *Energy Policy*, *39*(11), 7335–7346. https://doi.org/10.1016/j.enpol.2011.08.057

General Mills. (2020). *Global Responsibility 2020*. https://www.generalmills.com/en/Company/publications/responsibility-reports

Gerbens-Leenes, P. W., Nonhebel, S., & Ivens, W. P. M. F. (2002). A method to determine land requirements relating to food consumption patterns. *Agriculture, Ecosystems & Environment*, *90*(1), 47–58. https://doi.org/10.1016/S0167-8809(01)00169-4

Gerber, P. J., Steinfeld, H., Henderson, B., Mottet, A., Opio, C., Dijkman, J., Falcucci, A., & Tempio, G. (2013). *Tackling Climate through Livestock: A Global Assessment of Emissions and Mitigation Opportunities*.

German, R. N., Thompson, C. E., & Benton, T. G. (2017). Relationships among multiple aspects of agriculture's environmental impact and productivity: a meta-analysis to guide sustainable agriculture. *Biological Reviews*, *92*(2), 716–738. https://doi.org/10.1111/brv.12251

Gilhespy, S. L., Anthony, S., Cardenas, L., Chadwick, D., del Prado, A., Li, C., Misselbrook, T., Rees, R. M., Salas, W., Sanz-Cobena, A., Smith, P., Tilston, E. L., Topp, C. F. E., Vetter, S., & Yeluripati, J. B. (2014). First 20 years of DNDC (DeNitrification DeComposition): Model evolution. In *Ecological Modelling* (Vol. 292, pp. 51–62). Elsevier B.V. https://doi.org/10.1016/j.ecolmodel.2014.09.004

Global Aquaculture Alliance. (2018). *Annual Report 2018*. https://www.aquaculturealliance.org/wp-content/uploads/2020/02/GAA-2018-Annual-Report.pdf

Godfray, H. C. J. (2015). The debate over sustainable intensification. *Food Security*, *7*(2), 199–208. https://doi.org/10.1007/s12571-015-0424-2

Godfray, H. C. J., Aveyard, P., Garnett, T., Hall, J. W., Key, T. J., Lorimer, J., Pierrehumbert, R. T., Scarborough, P., Springmann, M., & Jebb, S. A. (2018). Meat consumption, health, and the environment. *Science*, *361*(6399). https://doi.org/10.1126/science.aam5324

Godfray, H. C. J., Beddington, J. R., Crute, I. R., Haddad, L., Lawrence, D., Muir, J. F., Pretty, J., Robinson, S., Thomas, S. M., & Toulmin, C. (2010). Food security: the challenge of feeding 9 billion people. *Science*, *327*(5967), 812–818. https://doi.org/10.1126/science.1185383

Godfray, H. C. J., & Garnett, T. (2014). Food security and sustainable intensification. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *369*(1639), 6–11. https://doi.org/10.1098/rstb.2012.0273

Goedkoop, M., Heijungs, R., Huijbregts, M., Schryver, A. De, Struijs, J., Zelm, R. Van, Heijungs, R., Huijbregts, M., Schryver, A. De, Struijs, J., & Zelm, R. Van. (2009). *ReCiPe 2008*.

Golan, E., Kuchler, F., & Krissoff, B. (2007). Do Food Labels Make a Difference? ... Sometimes. *Amber Waves (USDA ERS)*, *5*(5). https://www.ers.usda.gov/amber-waves/2007/november/do-food-labels-make-a-difference-sometimes/

Goldewijk, K. K., Beusen, A., Doelman, J., & Stehfest, E. (2017). Anthropogenic land use estimates for the Holocene - HYDE 3.2. *Earth System Science Data*, *9*(2), 927–953. https://doi.org/10.5194/essd-9-927-2017

Gong, P., Wang, J., Yu, L., Zhao, Y., Zhao, Y., Liang, L., Niu, Z., Huang, X., Fu, H., Liu, S., Li, C., Li, X., Fu, W., Liu, C., Xu, Y., Wang, X., Cheng, Q., Hu, L., Yao, W., … Chen, J. (2013). Finer resolution observation and monitoring of global land cover: First mapping results with Landsat TM and ETM+ data. *International Journal of Remote Sensing*, *34*(7), 2607–2654. https://doi.org/10.1080/01431161.2012.748992

Green Food China. (2018). *2018 Statistical Annual Report*. http://www.greenfood.org.cn/ztzl/tjnb/lssp/

Green, R. E., Balmford, A., Cornell, S. J., Scharlemann, J. P. W., & Balmford, A. (2005). Farming and the fate of wild nature. *Science*, *307*(5709), 550–555. https://doi.org/10.1126/science.1106049

Grekousis, G., Mountrakis, G., & Kavouras, M. (2015). An overview of 21 global and 43 regional land-cover mapping products. *International Journal of Remote Sensing*, *36*(21), 5309–5335. https://doi.org/10.1080/01431161.2015.1093195

Grigoriadis, V., Nugent, A., & Brereton, P. (2021). Working towards a combined measure for describing environmental impact and nutritive value of foods: A review. *Trends in Food Science and Technology*, *112*, 298–311. https://doi.org/10.1016/j.tifs.2021.03.047

Groeneveld, L. F., Lenstra, J. A., Eding, H., Toro, M. A., Scherf, B., Pilling, D., Negrini, R., Finlay, E. K., Jianlin, H., Groeneveld, E., & Weigend, S. (2010). Genetic diversity in farm animals - A review. *Animal Genetics*, *41*, 6–31. https://doi.org/10.1111/j.1365-2052.2010.02038.x

Gröfke, N., Duplat, V., Wickert, C., & Tjemkes, B. (2021). A multi-stakeholder perspective on food labelling for environmental sustainability: Attitudes, perceived barriers, and solution approaches towards the "traffic light index." *Sustainability*, *13*(2). https://doi.org/10.3390/su13020933

Gross, A., Boyd, C. E., & Wood, C. W. (2000). Nitrogen transformations and balance in channel catfish ponds. *Aquacultural Engineering*, *24*, 1–14.

Grunert, K. G., Hieke, S., & Wills, J. (2014). Sustainability labels on food products: Consumer motivation, understanding and use. *Food Policy*, *44*, 177–189. https://doi.org/10.1016/j.foodpol.2013.12.001

Grzywacz, D., Stevenson, P. C., Mushobozi, W. L., Belmain, S., & Wilson, K. (2014). The use of indigenous ecological resources for pest control in Africa. *Food Security*, *6*(1), 71–86. https://doi.org/10.1007/s12571-013-0313-5

GSMA. (2017). *Creating scalable, engaging mobile solutions for agriculture*. https://www.gsma.com/mobilefordevelopment/agritech/creating-scalable-mobile-solutions/

GSMA. (2021). *The State of Mobile Internet Connectivity 2021*. https://www.gsma.com/r/wp-content/uploads/2021/09/The-State-of-Mobile-Internet-Connectivity-Report-2021.pdf

Gulbrandsen, L. H. (2006). Creating markets for eco-labelling: Are consumers insignificant? *International Journal of Consumer Studies*, *30*(5), 477–489. https://doi.org/10.1111/j.1470-6431.2006.00534.x

Gustavsson, J., Cederberg, C., Sonesson, U., & Emanuelsson, A. (2013). *The methodology of the FAO study: "Global Food Losses and Food Waste - extent, causes and prevention" - FAO, 2011*.

Haddad, E. H., & Tanzman, J. S. (2003). What do vegetarians in the United States eat. *American Journal of Clinical Nutrition*, *78*, 626S-32S.

Haddaway, N. R., Hedlund, K., Jackson, L. E., Kätterer, T., Lugato, E., Thomsen, I. K., Jørgensen, H. B., & Isberg, P. E. (2017). How does tillage intensity affect soil organic carbon? A systematic review. *Environmental Evidence*, *6*(30), 1–48. https://doi.org/10.1186/s13750-017-0108-9

Hagmann, D., & Siegrist, M. (2020). Nutri-Score, multiple traffic light and incomplete nutrition labelling on food packages: Effects on consumers' accuracy in identifying healthier snack options. *Food Quality and Preference*, *83*(October 2019), 103894. https://doi.org/10.1016/j.foodqual.2020.103894

Hall, O. J. (1990). Chemical flux and mass balances in a marine fish cage farm. I. Carbon. *Marine Ecology Progress Series*, *61*, 61–73.

Halpern, B. S., Cottrell, R. S., Blanchard, J. L., Bouwman, L., Froehlich, H. E., Gephart, J. A., Jacobsen, N. S., Kuempel, C. D., McIntyre, P. B., Metian, M., Moran, D. D., Nash, K. L., Többen, J., & Williams, D. R. (2019). Putting all foods on the same table: Achieving sustainable food systems requires full accounting. *Proceedings of the National Academy of Sciences of the United States of America*, *116*(37), 18152–18156. https://doi.org/10.1073/pnas.1913308116

Handa, M., Jain, S., & Ahuja, P. (2021). Is it cost saving or environmental benefits: Factors influencing energy saving behaviour amongst consumers in India. *International Journal of Indian Culture and Business Management*, *23*(4), 431. https://doi.org/10.1504/ijicbm.2021.117478

Hansen, M. C. C., Potapov, P. V, Moore, R., Hancher, M., Turubanova, S. A. a, Tyukavina, A., Thau, D., Stehman, S. V. V, Goetz, S. J. J., Loveland, T. R. R., Kommareddy, A., Egorov, A., Chini, L., Justice, C. O. O., Townshend, J. R. G. R. G., Patapov, P. V., Moore, R., Hancher, M., Turubanova, S. A. a, … Townshend, J. R. G. R. G. (2013). High-Resolution Global Maps of 21st-Century Forest Cover Change. *Science*, *342*(November), 850–854. https://doi.org/10.1126/science.1244693

Hansen, M. C., Sohlberg, R., DeFries, R. S., & Townshend, J. R. G. (2000). Global land cover classification at 1 km spatial resolution using a classification tree approach. In *International Journal of Remote Sensing* (Vol. 21, Issues 6–7). https://doi.org/10.1080/014311600210209

Hass, A. L., Kormann, U. G., Tscharntke, T., Clough, Y., Baillod, A. B., Sirami, C., Fahrig, L., Martin, J. L., Baudry, J., Bertrand, C., Bosch, J., Brotons, L., Bure, F., Georges, R., Giralt, D., Marcos-García, M., Ricarte, A., Siriwardena, G., & Batáry, P. (2018). Landscape configurational heterogeneity by small-scale agriculture, not crop diversity, maintains pollinators and plant reproduction in western Europe. *Proceedings of the Royal Society B: Biological Sciences*, *285*(1872). https://doi.org/10.1098/rspb.2017.2242

Hauschild, M., & Potting, J. (2005). *Spatial differentiation in Life Cycle impact assessment - The EDIP2003 methodology*.

Heijungs, R., Allacker, K., Benetto, E., Brandão, M., Guinée, J., Schaubroeck, S., Schaubroeck, T., & Zamagni, A. (2021). System Expansion and Substitution in LCA: A Lost Opportunity of ISO 14044 Amendment 2. *Frontiers in Sustainability*, *2*(June), 1–3. https://doi.org/10.3389/frsus.2021.692055

Hellweg, S., Milà i Canals, L., & Canals, L. M. (2014). Emerging approaches, challenges and opportunities in life cycle assessment. *Science*, *344*(6188), 1109–1113. https://doi.org/10.1126/science.1248361

Henger, B. R., Voigtländer, P. M., Der, I., & Köln, W. (2013). Green investments and green mortgages in Germany. *EMF Hypostat*, *December*, 18–21. https://doi.org/10.13140/2.1.1280.5768

Henryson, K., Kätterer, T., Tidåker, P., & Sundberg, C. (2020). Soil N2O emissions, N leaching and marine eutrophication in life cycle assessment – A comparison of modelling approaches. *Science of the Total Environment*, *725*, 138332. https://doi.org/10.1016/j.scitotenv.2020.138332

Hepburn, C., Stern, N., & Stiglitz, J. E. (2020). "Carbon pricing" special issue in the European economic review. *European Economic Review*, *127*(2020), 1–6. https://doi.org/10.1016/j.euroecorev.2020.103440

Herold, M., Mayaux, P., Woodcock, C. E., Baccini, A., & Schmullius, C. (2008). Some challenges in global land cover mapping: An assessment of agreement and accuracy in existing 1 km datasets. *Remote Sensing of Environment*, *112*(5), 2538–2556. https://doi.org/10.1016/j.rse.2007.11.013

Herrero, M., Havlík, P., Valin, H., Notenbaert, A., Rufino, M. C., Thornton, P. K., Blümmel, M., Weiss, F., Grace, D., & Obersteiner, M. (2013). Biomass use, production, feed efficiencies, and greenhouse gas emissions from global livestock systems. *Proceedings of the National Academy of Sciences*, *110*(52), 20888–20893. https://doi.org/10.1073/pnas.1308149110

Hiederer, R., Ramos, F., Capitani, C., Koeble, R., Blujdea, V., Gomez, O., Mulligan, D., & Marelli, L. (2010). *Biofuels: a new methodology to estimate GHG emissions from global land use change*.

High Level Panel of Experts on Food Security and Nutrition (HLPE). (2014). *Food Losses and Waste in the Context of Sustainable Food Systems* (Issue June). www.fao.org/cfs/cfs-hlpe%0Ahttp://www.fao.org/3/a-i3901e.pdf

Hijmans, R. J., Cameron, S. E., Parra, J. L., Jones, P. G., & Jarvis, A. (2005). Very high resolution interpolated climate surfaces for global land areas. *International Journal of Climatology*, *25*(15), 1965–1978. https://doi.org/10.1002/joc.1276

Hijmans, R. J., Kapoor, J., Wieczorek, J., Garcia, N., Maunahan, A., Rala, A., & Mandel, A. (2018). *GADM Database of Global Administrative Areas (v. 3.6)*. https://gadm.org/

Hillier, J., Walter, C., Malin, D., Garcia-suarez, T., Mila-i-canals, L., & Smith, P. (2011). A farm-focused calculator for emissions from crop and livestock production. *Environmental Modelling and Software*, *26*(9), 1070–1078. https://doi.org/10.1016/j.envsoft.2011.03.014

Hoekstra, A. Y., Chapagain, A. K., Aldaya, M. M., & Mekonnen. (2011). *The Water Footprint Assessment Manual: Setting the Global Standard*. https://doi.org/10.1080/0969160x.2011.593864

Holmer, M., Wildish, D., & Hargrave, B. (2005). Organic Enrichment from Marine Finfish Aquaculture and Effects on Sediment Biogeochemical Processes. *Environmental Effects of Marine Finfish Aquaculture*, *5*, 181–206. https://doi.org/10.1007/b136010

Hosonuma, N., Herold, M., De Sy, V., DeFries, R. S., De Sy, V., De Fries, R. S., Brockhaus, M., Verchot, L., Angelsen, A., & Romijn, E. (2012). An assessment of deforestation and forest degradation drivers in developing countries. *Environmental Research Letters*, *7*(4). https://doi.org/10.1088/1748-9326/7/4/044009

Houghton, R. A., House, J. I., Pongratz, J., Werf, G. R. Van Der, Defries, R. S., Hansen, M. C., & Qu, C. Le. (2012). *Carbon emissions from land use and land-cover change*. *4*, 5125–5142. https://doi.org/10.5194/bg-9-5125-2012

Hurtt, G. C., Chini, L. P., Frolking, S., Betts, R. A., Feddema, J., & Fischer, G. (2011). *Harmonization of land-use scenarios for the period 1500 – 2100 : 600 years of global gridded annual land-use transitions , wood harvest , and resulting secondary lands*. 117–161. https://doi.org/10.1007/s10584-011-0153-2

IDF. (2010). A common carbon footprint approach for dairy: The IDF guide to standard lifecycle assessment methodology for the dairy sector. *Bulletin of the International Dairy Federation*, *445*.

IEA. (2021). *Achievements of Energy Efficiency Appliance and Equipment Standards and Labelling Programmes*. https://doi.org/10.1787/28f0bb11-en

IFAD. (2014). *Improving nutrition through agriculture*. https://www.ifad.org/documents/38714170/40321578/nutrition_e_web.pdf/9e5dbf15-68c1-4586-b7e6-963b84c169f6

IIASA/FAO. (2012). *Global Agro-ecological Zones (GAEZ v3.0) - User's Guide*.

Ingram, J. (2011). A food systems approach to researching food security and its interactions with global environmental change. *Food Security*, *3*(4), 417–431. https://doi.org/10.1007/s12571-011-0149-9

Inoue, N., & Matsumoto, S. (2019). An examination of losses in energy savings after the Japanese Top Runner Program? *Energy Policy*, *124*, 312–319. https://doi.org/10.1016/j.enpol.2018.09.040

Intergovernmental Panel on Climate Change. (2006). N2O Emissions From Managed Soils, and CO2 Emissions From Lime and Urea application. *2006 IPCC Guidelines for National Greenhouse Gas Inventories*, 11.1-11.54.

Intergovernmental Panel on Climate Change. (2014). *Climate Change 2014: Mitigation of Climate Change* (O. R. Edenhofer, Y. Pichs-Madruga, E. Sokona, S. Farahani, K. Kadner, A. Seyboth, I. Adler, S. Baum, P. Brunner, B. Eickemeier, J. Kriemann, S. Savolainen, C. Schlömer, T. von Stechow, Zwickel, & M. J. C. (Eds.)). Cambridge University Press. https://doi.org/10.1017/CBO9781107415416

International Civil Aviation Organization. (2017). *Civil Aviation Statistics of the World*. http://www.icao.int/sustainability/Pages/Statistics.aspx

International Trade Centre (ITC). (2017). *Social and Environmental Standards: From Fragmentation to Coordination*. https://www.evidensia.eco/resources/226/social-and-environmental-standards-from-fragmentation-to-coordination/

International Trade Centre (ITC). (2021). *Standards Map*. https://standardsmap.org/

IPCC. (2006). *IPCC Guidelines for National Greenhouse Gas Inventories*. IGES.

IPCC. (2007a). 6.8.2.1 Standards and labelling. In *Climate Change 2007: Working Group III: Mitigation of Climate Change*. https://www.ipcc.ch/site/assets/uploads/2018/02/ar4-wg3-chapter6-1.pdf

IPCC. (2007b). *Climate Change 2007: Mitigation of Climate Change*. Cambridge University Press.

IPCC. (2013). *Climate Change 2013: The Physical Science Basis* (T. F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex, & P. M. Midgley (Eds.)). Cambridge University Press.

IPCC. (2014). *2013 Supplement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories: Wetlands* (T. Hiraishi, T. Krug, K. Tanabe, N. Srivastava, B. Jamsranjav, M. Fukuda, & T. Troxler (Eds.)). IPCC.

IPCC. (2018). *Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change,* (V. Masson-Delmotte, P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P. R. Shukla, A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J. B. R. Matthews, Y. Chen, X. Zhou, M. I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, & T. Waterfield (Eds.)). IPCC.

IPCC. (2019). *2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories* (E. Calvo Buendia, K. Tanabe, A. Kranjc, J. Baasansuren, M. Fukuda, S. Ngarize, A. Osako, Y. Pyrozhenko, P. Shermanau, & S. Federici (Eds.); Vol. 4). IPCC.

IPES-Food. (2016). *Uniformity Diversity From Uniformity*. 96. http://www.ipes-food.org/_img/upload/files/UniformityToDiversity_FULL.pdf

IPSOS, & London Economics. (2014). *Study on the impact of the energy label and potential changes to it – on consumer understanding and on purchase decisions*. https://ec.europa.eu/info/sites/default/files/impact_of_energy_labels_on_consumer_behaviour_en.pdf

Isermeyer, F., Heidecke, C., Osterburg, B., Isermeyer, P. F., & Osterburg, B. (2019). *Integrating agriculture into carbon pricing* (No. 136a; Thünen Working Paper).

Jaffe, A. B., Newell, R. G., & Stavins, R. N. (2002). Environmental policy and technological change. *Environmental and Resource Economics*, *22*(1–2), 41–70. https://doi.org/10.1023/A:1015519401088

James, S. J., & James, C. (2010). The food cold-chain and climate change. *Food Research International*, *43*(7), 1944–1956. https://doi.org/10.1016/j.foodres.2010.02.001

Janssens-Maenhout, G., Crippa, M., Guizzardi, D., Muntean, M., Schaaf, E., Dentener, F., Bergamaschi, P., Pagliari, V., Olivier, J. G. J., Peters, J. A. H. W., van Aardenne, J. A., Monni, S., Doering, U., & Petrescu, A. M. R. (2017). EDGAR v4.3.2 Global Atlas of the three major Greenhouse Gas Emissions for the period 1970-2012. *Earth System Science Data Discussions*, *August*, 1–55. https://doi.org/10.5194/essd-2017-79

JoinData. (2022). https://join-data.nl/

JRC. (2010). *Support to Renewable Energy Directive*. http://eusoils.jrc.ec.europa.eu/projects/RenewableEnergy/

Kanay, A., Hilton, D., Charalambides, L., Corrégé, J. B., Inaudi, E., Waroquier, L., & Cézéra, S. (2021). Making the carbon basket count: Goal setting promotes sustainable consumption in a simulated online supermarket. *Journal of Economic Psychology*, *83*. https://doi.org/10.1016/j.joep.2020.102348

Karthikeyan, L., Chawla, I., & Mishra, A. K. (2020). A review of remote sensing applications in agriculture for food security: Crop growth and yield, irrigation, and crop losses. *Journal of Hydrology*, *586*, 124905. https://doi.org/10.1016/j.jhydrol.2020.124905

Khoshbakht, K., & Hammer, K. (2008). How many plant species are cultivated? *Genetic Resources and Crop Evolution*, *55*(7), 925–928. https://doi.org/10.1007/s10722-008-9368-0

Khoury, C. K., Bjorkman, A. D., Dempewolf, H., Ramirez-Villegas, J., Guarino, L., Jarvis, A., Rieseberg, L. H., & Struik, P. C. (2014). Increasing homogeneity in global food supplies and the implications for food security. *Proceedings of the National Academy of Sciences*, *111*(11), 4001–4006. https://doi.org/10.1073/pnas.1313490111

Khoury, C. K., Brush, S., Costich, D. E., Curry, H. A., de Haan, S., Engels, J. M. M., Guarino, L., Hoban, S., Mercer, K. L., Miller, A. J., Nabhan, G. P., Perales, H. R., Richards, C., Riggins, C., & Thormann, I. (2022). Crop genetic erosion: understanding and responding to loss of crop diversity. *New Phytologist*, *233*(1), 84–118. https://doi.org/10.1111/nph.17733

Kirk, D. A., Lindsay, K. E., & Brook, R. W. (2011). Risk of Agricultural Practices and Habitat Change to Farmland Birds. *Avian Conservation and Ecology*, *6*(1). https://doi.org/10.5751/ace-00446-060105

Kobayashi, T., Tateishi, R., Alsaaideh, B., Sharma, R. C., Wakaizumi, T., Miyamoto, D., Bai, X., Long, B. D., Gegentana, G., Maitiniyazi, A., Cahyana, D., Haireti, A., Morifuji, Y., Abake, G., Pratama, R., Zhang, N., Alifu, Z., Shirahata, T., Mi, L., … Phong, D. X. (2017). Production of Global Land Cover Data – GLCNMO2013. *Journal of Geography and Geology*, *9*(3), 1. https://doi.org/10.5539/jgg.v9n3p1

Köble, R. (2014). *The Global Nitrous Oxide Calculator (GNOC) Online Tool Manual v. 1.2.4*. http://gnoc.jrc.ec.europa.eu/

Kowata, H., Moriyama, H., Hayashi, K., Kato, H., & Agricultural, N. (2008). Comparison of air emissions for the construction of various greenhouses. *Proc. of the 6th Int. Conf. on LCA in the Agri-Food Sector, Zurich, November 12–14, 2008*, 49–57.

Kremen, C. (2015). Reframing the land-sparing/land-sharing debate for biodiversity conservation. *Annals of the New York Academy of Sciences*, *1355*(1), 52–76. https://doi.org/10.1111/nyas.12845

Kuivilal, K. M., Devol, A. H., Kuivila, K. M., Murray, J. W., Devol, A. H., Lidstrom, M. E., & Reimers, C. E. (1988). Methane cycling in the sediments of Lake Washington. *Limnology and Oceanography*, *33*(4), 571–581. https://doi.org/10.4319/lo.1988.33.4.0571

Ladha, J. K., Rao, A. N., Raman, A. K., Padre, A. T., Dobermann, A., Gathala, M., Kumar, V., Saharawat, Y., Sharma, S., Piepho, H. P., Alam, M. M., Liak, R., Rajendran, R., Reddy, C. K., Parsad, R., Sharma, P. C., Singh, S. S., Saha, A., & Noor, S. (2016). Agronomic improvements can make future cereal systems in South Asia far more productive and result in a lower environmental footprint. *Global Change Biology*, *22*(3), 1054–1074. https://doi.org/10.1111/gcb.13143

Lal, R. (2018). Digging Deeper: A Holistic Perspective of Factors Affecting Soil Organic Carbon Sequestration in Agroecosystems. *Global Change Biology*. https://doi.org/10.1111/gcb.14054

Lam, W. Y., Sim, S., Kulak, M., van Zelm, R., Schipper, A. M., & Huijbregts, M. A. J. (2021). Drivers of variability in greenhouse gas footprints of crop production. *Journal of Cleaner Production*, *315*(89), 128121. https://doi.org/10.1016/j.jclepro.2021.128121

Lane, K., & Harrington, L. (2010). *Evaluation of Energy Efficiency Policy Measures for Household Refrigeration in Australia*. https://www.energyrating.gov.au/sites/default/files/documents/Report_-_Evaluation_of_Energy_Efficiency_Policy_Measures_for_Household_Refrigeration_in_Australia_1.pdf

Latham, J., Cumani, R., Rosati, I., & Bloise, M. (2014). *Global Land Cover SHARE (GLC-SHARE) database Beta-Release Version 1.0 - 2014*. 39.

LEAF. (2020). *Delivering More Sustainable Food and Farming: LEAF's Global Impacts Report 2020*. https://leaf.eco/about-leaf/our-impacts

Lee, C.-S., & Yang, H.-M. (2021). A Study on Consumers' Purchasing Behavior and Perception of the Low-carbon Certificated Agricultural Products. *Korean Journal of Organic Agriculture*, *29*(3), 333–358. https://doi.org/10.11625/KJOA.2021.29.3.333

Lee, M. B., & Goodale, E. (2018). Crop heterogeneity and non-crop vegetation can enhance avian diversity in a tropical agricultural landscape in southern China. *Agriculture, Ecosystems and Environment*, *265*(February), 254–263. https://doi.org/10.1016/j.agee.2018.06.016

Leinonen, I., Williams, A. G., & Kyriazakis, I. (2014). The effects of welfare-enhancing system changes on the environmental impacts of broiler and egg production. *Poultry Science*, *93*(2), 256–266. https://doi.org/10.3382/ps.2013-03252

Lemken, D., Zühlsdorf, A., & Spiller, A. (2021). Improving Consumers' Understanding and

Use of Carbon Footprint Labels on Food: Proposal for a Climate Score Label. *EuroChoices*, *20*(2), 23–29. https://doi.org/10.1111/1746-692X.12321

Lesiv, M., Laso Bayas, J. C., See, L., Duerauer, M., Dahlia, D., Durando, N., Hazarika, R., Kumar Sahariah, P., Vakolyuk, M., Blyshchyk, V., Bilous, A., Perez-Hoyos, A., Gengler, S., Prestele, R., Bilous, S., Akhtar, I. ul H., Singha, K., Choudhury, S. B., Chetri, T., … Fritz, S. (2019). Estimating the global distribution of field size using crowdsourcing. *Global Change Biology*, *25*(1), 174–186. https://doi.org/10.1111/gcb.14492

Lewis Jr, W. (2011). Global primary production of lakes: 19th Baldi Memorial Lecture. *Inland Waters*, *1*(1), 1–28. https://doi.org/10.5268/IW-1.1.384

Licker, R., Johnston, M., Foley, J. a., Barford, C., Kucharik, C. J., Monfreda, C., & Ramankutty, N. (2010). Mind the gap: How do climate and agricultural management explain the “yield gap” of croplands around the world? *Global Ecology and Biogeography*, *19*(6), 769–782. https://doi.org/10.1111/j.1466-8238.2010.00563.x

Liu, H., Gong, P., Wang, J., Clinton, N., Bai, Y., & Liang, S. (2020). Annual dynamics of global land cover and its long-term changes from 1982 to 2015. *Earth System Science Data*, *12*(2), 1217–1243. https://doi.org/10.5194/essd-12-1217-2020

Liu, J., You, L., Amini, M., Obersteiner, M., Herrero, M., Zehnder, A. J. B., & Yang, H. (2010). A high-resolution assessment on global nitrogen flows in cropland. *Proceedings of the National Academy of Sciences*, *107*(17), 8035–8040. https://doi.org/10.1073/pnas.0913658107

Liu, X., Yu, L., Dong, Q., Peng, D., Wu, W., Yu, Q., Cheng, Y., Xu, Y., Huang, X., Zhou, Z., Wang, D., Fang, L., & Gong, P. (2020). Cropland heterogeneity changes on the Northeast China Plain in the last three decades (1980s–2010s). *PeerJ*, *8*, 1–16. https://doi.org/10.7717/peerj.9835

Loveland, T. R., Reed, B. C., Ohlen, D. O., Brown, J. F., Zhu, Z., Yang, L., & Merchant, J. W. (2000). Development of a global land cover characteristics database and IGBP DISCover from 1 km AVHRR data. *International Journal of Remote Sensing*, *21*(6–7), 1303–1330. https://doi.org/10.1080/014311600210191

Lowder, S. K., Skoet, J., & Raney, T. (2016). The Number, Size, and Distribution of Farms, Smallholder Farms, and Family Farms Worldwide. *World Development*, *87*, 16–29. https://doi.org/10.1016/j.worlddev.2015.10.041

Lucas, S., Soler, L. G., & Revoredo-Giha, C. (2021). Trend analysis of sustainability claims: The European fisheries and aquaculture markets case. *Food Policy*, *104*(July), 102141. https://doi.org/10.1016/j.foodpol.2021.102141

Lupiáñez-Villanueva, F., Tornese, P., Veltri, G. A., & Gaskell, G. (2018). *Assessment of different communication vehicles for providing Environmental Footprint information*. https://ec.europa.eu/environment/eussd/smgp/pdf/2018_pilotphase_commreport.pdf

Macours, K. (2019). Farmers Demand and the Traits and Diffusion of Agricultural Innovations in Developing Countries. *Annual Review of Resource Economics*, *11*, 483–499. https://doi.org/10.1146/annurev-resource-100518-094045

Macsween, K., & Feliciano, D. (2018). *Comparison of online greenhouse gas accounting tools for agriculture* (Issue December).

https://ccafs.cgiar.org/resources/publications/comparison-online-greenhouse-gas-accounting-tools-agriculture

Magruder, J. R. (2018). An Assessment of Experimental Evidence on Agricultural Technology Adoption in Developing Countries. *Annual Review of Resource Economics*, *10*, 299–316. https://doi.org/10.1146/annurev-resource-100517-023202

Marteau, T. M. (2017). Towards environmentally sustainable human behaviour: Targeting non-conscious and conscious processes for effective and acceptable policies. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, *375*(2095). https://doi.org/10.1098/rsta.2016.0371

Martin, A. E., Collins, S. J., Crowe, S., Girard, J., Naujokaitis-Lewis, I., Smith, A. C., Lindsay, K., Mitchell, S., & Fahrig, L. (2020). Effects of farmland heterogeneity on biodiversity are similar to – or even larger than – the effects of farming practices. *Agriculture, Ecosystems and Environment*, *288*(April 2019), 106698. https://doi.org/10.1016/j.agee.2019.106698

Massey, J. H., Walker, T. W., Anders, M. M., Smith, M. C., & Avila, L. A. (2014). Farmer adaptation of intermittent flooding using multiple-inlet rice irrigation in Mississippi. *Agricultural Water Management*, *146*, 297–304. https://doi.org/10.1016/j.agwat.2014.08.023

McAuliffe, G. A., Takahashi, T., & Lee, M. R. F. (2020). Applications of nutritional functional units in commodity-level life cycle assessment (LCA) of agri-food systems. *International Journal of Life Cycle Assessment*, *25*(2), 208–221. https://doi.org/10.1007/s11367-019-01679-7

Meemken, E. M. (2020). Do smallholder farmers benefit from sustainability standards? A systematic review and meta-analysis. *Global Food Security*, *26*(April), 100373. https://doi.org/10.1016/j.gfs.2020.100373

Meier, C., Schlatter, B., Willer, H., Sampson, G., Larrea, C., Bermudez, S., Baliño, S., & Lernoud, J. (2020). *The State of Sustainable Markets 2020: Statistics and Emerging Trends*. ITC. https://www.intracen.org/publication/Sustainable-Markets-2020/

Meijers, M. H. C., Noordewier, M. K., Verlegh, P. W. J., Willems, W., & Smit, E. G. (2019). Paradoxical side effects of green advertising: how purchasing green products may instigate licensing effects for consumers with a weak environmental identity. *International Journal of Advertising*, *38*(8), 1202–1223. https://doi.org/10.1080/02650487.2019.1607450

Mekonnen, M. M., & Hoekstra, A. Y. (2010). The Green, Blue and Grey Water Footprint of Farm Animals and Animal Products. In *Value of Water Research Report Series* (Vol. 48).

Meyerding, S. G. H., Schaffmann, A. L., & Lehberger, M. (2019). Consumer preferences for different designs of carbon footprint labelling on Tomatoes in Germany-Does Design Matter? *Sustainability (Switzerland)*, *11*(6), 1–30. https://doi.org/10.3390/su11061587

Michel, A., Bush, E., & Attali, S. (2015). Household refrigerators: Monitoring efficiency changes in Europe and Australia over the last 10 years. *The 8th International Conference on Energy Efficiency in Domestic Appliances and Lighting*. https://op.europa.eu/en/publication-detail/-/publication/9ffe92c5-d6d4-11e5-8fea-01aa75ed71a1

Miljø-og Fødevareministeriet. (2018). *Evaluering af den differentierede pesticidafgift*. https://www2.mst.dk/Udgiv/publikationer/2018/05/978-87-93710-28-3.pdf

Millero, F. J., Mccarthy, J. J., Stewart, Z. W. E., Fallon, R. D., Harrits, S., Hanson, R. S., & Brock, T. D. (1980). The role of methane in internal carbon cycling in Lake Mendota during summer stratification. *Limnology and Oceanography*, *25*(2), 357–360. https://doi.org/10.4319/lo.1980.25.2.0357

Millie, E., van Giesen, R., van den Akker, K., & Dunne, A. (2019). *Consumer testing of alternatives for communicating the Environmental Footprint profile of products*. https://ec.europa.eu/environment/eussd/smgp/pdf/2019_EF_commtest_report.pdf

Millock, K., & Nauges, C. (2010). Household adoption of water-efficient equipment: The role of socio-economic factors, environmental attitudes and policy. *Environmental and Resource Economics*, *46*(4), 539–565. https://doi.org/10.1007/s10640-010-9360-y

Mills, B., & Schleich, J. (2010). What's driving energy efficient appliance label awareness and purchase propensity? *Energy Policy*, *38*(2), 814–825. https://doi.org/10.1016/j.enpol.2009.10.028

Ministère de l'Agriculture de l'Alimentation. (2020). *Les chiffres clés de la Haute Valeur Environnementale*. https://agriculture.gouv.fr/les-chiffres-cles-de-la-haute-valeur-environnementale-hve

Ministry of Housing Communities and Local Government. (2021). *Energy Performance of Buildings Data*. https://epc.opendatacommunities.org/

Mock, P. (2015). Optimizing to the last digit: How taxes influence vehicle CO2 emission levels. *International Council on Clean Transportation*, *2014*. http://theicct.org/sites/default/files/publications/Tax_Step_Analysis_201510.pdf

Monck-Whipp, L., Martin, A. E., Francis, C. M., & Fahrig, L. (2018). Farmland heterogeneity benefits bats in agricultural landscapes. *Agriculture, Ecosystems and Environment*, *253*(November 2017), 131–139. https://doi.org/10.1016/j.agee.2017.11.001

Mottet, A., de Haan, C., Falcucci, A., Tempio, G., Opio, C., & Gerber, P. (2017). Livestock: On our plates or eating at our table? A new analysis of the feed/food debate. *Global Food Security*, *14*(January), 1–8. https://doi.org/10.1016/j.gfs.2017.01.001

Muller, L., Lacroix, A., & Ruffieux, B. (2019). Environmental Labelling and Consumption Changes: A Food Choice Experiment. *Environmental and Resource Economics*, *73*(3), 871–897. https://doi.org/10.1007/s10640-019-00328-9

Muller, L., & Ruffieux, B. (2020). What makes a front-of-pack nutritional labelling system effective: The impact of key design components on food purchases. *Nutrients*, *12*(9). https://doi.org/10.3390/nu12092870

National Development and Reform Commission of China. (2013). *National Data Compilation of Revenue and Cost of Agricultural Products 2013*. China Statistics Press.

Nemecek, T., Antón, A., Basset-Mens, C., Gentil-Sergent, C., Renaud-Gentié, C., Melero, C., Naviaux, P., Peña, N., Roux, P., & Fantke, P. (2022). Operationalising emission and toxicity modelling of pesticides in LCA: the OLCA-Pest project contribution. *The International Journal of Life Cycle Assessment*, 527–542. https://doi.org/10.1007/s11367-022-02048-7

Nemecek, T., Bengoa, X., Lansche, J., Mouron, P., Riedener, E., Rossi, V., Humbert, S., & Nemecek, T. (2015). *World Food LCA Database: Methodological Guidelines for the Life Cycle Inventory of Agricultural Products. Version 3.0*.

Nemecek, T., Hayer, F., Bonnin, E., Carrouée, B., Schneider, A., & Vivier, C. (2015). Designing eco-efficient crop rotations using life cycle assessment of crop combinations. *European Journal of Agronomy*, *65*, 40–51. https://doi.org/10.1016/j.eja.2015.01.005

Nemecek, T., Huguenin-Elie, O., Gaillard, G., & Dubois, D. (2005). *Okobilanzierung von anbausystemen im schweizerischen acker- und futterbau*. Agroscope FAL Reckenholz.

Nepstad, D., Boyd, W., Stickler, C., Bezerra, T., & Azevedo, A. (2013). Responding to climate change and the global land crisis: REDD+, market transformation and low-emissions rural development. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences*, *368*, 20120167.

Nevison, C. (2000). Review of the IPCC methodology for estimating nitrous oxide emissions associated with agricultural leaching and runoff. *Chemosphere - Global Change Science*, *2*(3–4), 493–500. https://doi.org/10.1016/S1465-9972(00)00013-1

New Zealand Winegrowers. (2016). *Sustainability Report*. https://www.nzwine.com/media/4188/nzw-sustainability-report-2016.pdf

Newbold, T., Hudson, L. N., Hill, S. L. L., Contu, S., Lysenko, I., Senior, R. A., Borger, L., Bennett, D. J., Choimes, A., Collen, B., Day, J., De Palma, A., Diaz, S., Echeverria-Londono, S., Edgar, M. J., Feldman, A., Garon, M., Harrison, M. L. K., Alhusseini, T., … Mace, G. M. (2015). Global effects of land use on local terrestrial biodiversity. *Nature*, *520*(7545), 45–50. https://doi.org/10.1038/nature14324\rhttp://www.nature.com/nature/journal/v520/n7545/abs/nature14324.html#supplementary-information

Newell, R. G., & Siikamäki, J. (2014). Nudging Energy Efficiency Behavior: The Role of Information Labels. *Journal of the Association of Environmental and Resource Economists*, *1*(4), 555–598. https://doi.org/10.1086/679281

Nielsen. (2015). *The sustainability imperative: New insights on consumer expectations*. https://www.nielsen.com/wp-content/uploads/sites/3/2019/04/Global20Sustainability20Report_October202015.pdf

Nijdam, D., Rood, T., & Westhoek, H. (2012). The price of protein: Review of land use and carbon footprints from life cycle assessments. *Food Policy*, *37*(6), 760–770. https://doi.org/10.1016/j.foodpol.2012.08.002

Novotný, D., Zapletal, M., Kepka, P., Beneš, J., & Konvička, M. (2015). Large moths captures by a pest monitoring system depend on farmland heterogeneity. *Journal of Applied Entomology*, *139*(5), 390–400. https://doi.org/10.1111/jen.12185

OECD. (2017). *Agriculture Policy Monitoring and Evaluation 2017*. https://doi.org/10.1787/agr_pol-2017-en

Ogle, S. M., Jay Breidt, F., Easter, M., Williams, S., Killian, K., & Paustian, K. (2010). Scale and uncertainty in modeled soil organic carbon stock changes for US croplands using a process-based model. *Global Change Biology*, *16*(2), 810–822. https://doi.org/10.1111/j.1365-2486.2009.01951.x

Ölander, F., & Thøgersen, J. (2014). Informing Versus Nudging in Environmental Policy. *Journal of Consumer Policy*, *37*(3), 341–356. https://doi.org/10.1007/s10603-014-9256-2

openLCA. (2022). *openLCA Schema*. https://greendelta.github.io/olca-schema/

Opio, C., Gerber, P., Mottet, A., Falculli, A., Tempio, G., MacLeod, M., Vellinga, T., Henderson, B., & Steinfeld, H. (2013). *Greenhouse gas emissions from ruminant supply chains*.

Osman, M., Schwartz, P., & Wodak, S. (2021). Sustainable Consumption: What Works Best, Carbon Taxes, Subsidies and/or Nudges? *Basic and Applied Social Psychology*, *43*(3), 169–194. https://doi.org/10.1080/01973533.2021.1889553

Oya, C., Schaefer, F., & Skalidou, D. (2018). The effectiveness of agricultural certification in developing countries: A systematic review. *World Development*, *112*, 282–312. https://doi.org/10.1016/j.worlddev.2018.08.001

Oyinbo, O., Chamberlin, J., Abdoulaye, T., & Maertens, M. (2022). Digital extension, price risk, and farm performance: experimental evidence from Nigeria. *American Journal of Agricultural Economics*, *104*(2), 831–852. https://doi.org/10.1111/ajae.12242

Palmu, E., Ekroos, J., Hanson, H. I., Smith, H. G., & Hedlund, K. (2014). Landscape-scale crop diversity interacts with local management to determine ground beetle diversity. *Basic and Applied Ecology*, *15*(3), 241–249. https://doi.org/10.1016/j.baae.2014.03.001

Panzone, L., Sniehotta, F. F., Comber, R., & Lemke, F. (2020). The effect of traffic-light labels and time pressure on estimating kilocalories and carbon footprint of food. *Appetite*, *155*(August), 104794. https://doi.org/10.1016/j.appet.2020.104794

Panzone, L., Ulph, A., Hilton, D., Gortemaker, I., & Tajudeen, I. (2021). Sustainable by Design: Choice Architecture and the Carbon Footprint of Grocery Shopping. *Journal of Public Policy & Marketing*, *40*(4), 074391562110088. https://doi.org/10.1177/07439156211008898

Papatryphon, E., Petit, J., Van Der Werf, H. M. G., Sadasivam, K. J., & Claver, K. (2005). Nutrient-balance modeling as a tool for environmental management in aquaculture: the case of trout farming in France. *Environmental Management*, *35*(2), 161–174. https://doi.org/10.1007/s00267-004-4020-z

Parker, R. W. R., Blanchard, J. L., Gardner, C., Green, B. S., Hartmann, K., Tyedmers, P. H., & Watson, R. A. (2018). Fuel use and greenhouse gas emissions of world fisheries. *Nature Climate Change*, *8*, 333–337. https://doi.org/10.1038/s41558-018-0117-x

Paustian, K. (2013). Bridging the data gap: engaging developing country farmers in greenhouse gas accounting. *Environmental Research Letters*, *8*(2), 021001. https://doi.org/10.1088/1748-9326/8/2/021001

Pérez-Hoyos, A., Rembold, F., Kerdiles, H., & Gallego, J. (2017). Comparison of global land cover datasets for cropland monitoring. *Remote Sensing*, *9*(11). https://doi.org/10.3390/rs9111118

Perez, M., & Cole, E. J. (2020). *A Guide to Water Quality, Climate, Social, and Economic Outcomes Estimation Tools*. https://farmlandinfo.org/publications/guide-to-outcomes-estimation-tools/

Perino, G., Panzone, L. A., & Swanson, T. (2014). Motivation crowding in real consumption decisions: Who is messing with my groceries? *Economic Inquiry*, *52*(2), 592–607. https://doi.org/10.1111/ecin.12024

Pfister, S., Bayer, P., Koehler, A., Hellweg, S., Stephan, P., Bayer, P., Koehler, A., & Hellweg, S. (2011). Environmental impacts of water use in global crop production: hotspots and trade-offs with land use. *Environmental Science & Technology*, *45*(13), 5761–5768. https://doi.org/10.1021/es1041755

Pingali, P. L. (2012). Green revolution: Impacts, limits, and the path ahead. *Proceedings of the National Academy of Sciences of the United States of America*, *109*(31), 12302–12308. https://doi.org/10.1073/pnas.0912953109

Pittelkow, C. M., Liang, X., Linquist, B. a., van Groenigen, K. J., Lee, J., Lundy, M. E., van Gestel, N., Six, J., Venterea, R. T., & van Kessel, C. (2014). Productivity limits and potentials of the principles of conservation agriculture. *Nature*, *517*(7534), 365–367. https://doi.org/10.1038/nature13809

Pittman, K., Hansen, M. C., Becker-Reshef, I., Potapov, P. V., & Justice, C. O. (2010). Estimating global cropland extent with multi-year MODIS data. *Remote Sensing*, *2*(7), 1844–1863. https://doi.org/10.3390/rs2071844

Planet Proof. (2021). https://www.planetproof-international.eu/527/home.html

Ponsioen, T. C., & van der Werf, H. M. G. (2017). Five propositions to harmonize environmental footprints of food and beverages. *Journal of Cleaner Production*, *153*, 457–464. https://doi.org/10.1016/j.jclepro.2017.01.131

Poore, J. (2017). Back to the wild. *New Scientist*, *235*(3138), 26–29. https://doi.org/10.1016/S0262-4079(17)31568-3

Poore, J. (2018). We label fridges to show their environmental impact – why not food? *The Guardian*.

Poore, J., & Nemecek, T. (2018). Reducing food's environmental impacts through producers and consumers. *Science*, *992*(6392), 987–992. https://doi.org/10.1126/science.aaq0216

Portmann, F. T., Siebert, S., & Döll, P. (2010). MIRCA2000 - Global monthly irrigated and rainfed crop areas around the year 2000: A new high-resolution data set for agricultural and hydrological modeling. *Global Biogeochemical Cycles*, *24*(1). https://doi.org/10.1029/2008GB003435

Potter, C., Bastounis, A., Hartmann-Boyce, J., Stewart, C., Frie, K., Tudor, K., Bianchi, F., Cartwright, E., Cook, B., Rayner, M., & Jebb, S. A. (2021). The Effects of Environmental Sustainability Labels on Selection, Purchase, and Consumption of Food and Drink Products: A Systematic Review. *Environment and Behavior*. https://doi.org/10.1177/0013916521995473

Potter, C., Cook, B., Stewart, C., & Frie, K. (2020). *Environmental Labelling and Food Selection - Study 2*. https://doi.org/10.17605/OSF.IO/RWY4K

Potts, J., Wilkins, A., Lynch, M., & McFatridge, S. (2016). *State of Sustainability Initiatives Review: Standards and the Blue Economy*. https://www.iisd.org/publications/state-sustainability-initiatives-review-standards-and-blue-economy

Precision Agriculture for Development. (2020). *Q3 Quarterly Report*. https://precisionag.org/what-we-do/quarterly-reports/

Prestele, R., Hirsch, A. L., Davin, E. L., Seneviratne, S. I., & Verburg, P. H. (2018). A spatially explicit representation of conservation agriculture for application in global change studies. *Global Change Biology*, *24*(9), 4038–4053. https://doi.org/10.1111/gcb.14307

Priyadarshana, T. S., Lee, M. B., Ascher, J. S., Qiu, L., & Goodale, E. (2021). Crop heterogeneity is positively associated with beneficial insect diversity in subtropical farmlands. *Journal of Applied Ecology*, *58*(12), 2747–2759. https://doi.org/10.1111/1365-2664.14005

Pryshlakivsky, J., & Searcy, C. (2013). Fifteen years of ISO 14040: a review. *Journal of Cleaner Production*, *57*, 115–123. https://doi.org/10.1016/j.jclepro.2013.05.038

Pujol, A. G., Iooss, B., Janon, A., Veiga, D., Delage, T., Fruth, J., Gilquin, L., Guil-, J., Gratiet, L. Le, Lemaitre, P., Nelson, B. L., Oomen, R., Ramos, B., Roustant, O., Staum, J., Touati, T., & Weber, F. (2017). *sensitivity. R package version 1.15.0.*

Quintero, R. R., Garrido, C. V.-A., Moons, H., Caldas, M. G., Wolf, O., Skinner, I., van Grinsven, A., ‘t Hoen, M., & van Essen, H. (2019). *Revision of the EU Green Public Procurement Criteria for Transport*. https://ec.europa.eu/environment/gpp/pdf/criteria/eu_gpp_transport_technical_report_final.pdf

Raderschall, C. A., Bommarco, R., Lindström, S. A. M., & Lundin, O. (2021). Landscape crop diversity and semi-natural habitat affect crop pollinators, pollination benefit and yield. *Agriculture, Ecosystems and Environment*, *306*(February 2020). https://doi.org/10.1016/j.agee.2020.107189

Rajkhowa, P., & Qaim, M. (2021). Personalized digital extension services and agricultural performance: Evidence from smallholder farmers in India. *PLoS ONE*, *16*(10 October), 1–23. https://doi.org/10.1371/journal.pone.0259319

Ramankutty, N., Evan, A. T., Monfreda, C., & Foley, J. (2008). Farming the planet: 1. Geographic distribution of global agricultural lands in the year 2000. *Global Biogeochemical Cycles*, *22*. https://doi.org/10.1029/2007GB002952

Rege, J. E. O., & Mwai, A. O. (2006). Improving our knowledge of tropical indigenous animal genetic resources. *Animal Genetics Training Resource*, *July 2015*, 28. http://192.156.137.192/bitstream/handle/10568/3663/Module2.pdf?sequence=1

LOI n° 2020-105 du 10 février 2020 relative à la lutte contre le gaspillage et à l’économie circulaire, (2021). https://www.legifrance.gouv.fr/jorf/id/JORFTEXT000041553759/

Resare Sahlin, K., Röös, E., & Gordon, L. J. (2020). ‘Less but better’ meat is a sustainability message in need of clarity. *Nature Food*, *1*(9), 520–522. https://doi.org/10.1038/s43016-020-00140-5

Reynolds, C., Fletcher, R. J., Carneiro, C. M., Jennings, N., Ke, A., LaScaleia, M. C., Lukhele, M. B., Mamba, M. L., Sibiya, M. D., Austin, J. D., Magagula, C. N., Mahlaba, T., Monadjem, A., Wisely, S. M., & McCleery, R. A. (2018). Inconsistent effects of landscape heterogeneity and land-use on animal diversity in an agricultural mosaic: a multi-scale and multi-taxon investigation. *Landscape Ecology*, *33*(2), 241–255.

https://doi.org/10.1007/s10980-017-0595-7

Rezare Systems. (2022). *DataLinker*. www.datalinker.org

Ritchie, H., & Roser, M. (2021). *Food Prices*. Our World in Data. https://ourworldindata.org/food-prices

Robinson, R. A., & Sutherland, W. J. (2002). Post-war changes in arable farming and biodiversity in Great Britain. *Journal of Applied Ecology*, *39*(1), 157–176. https://doi.org/10.1046/j.1365-2664.2002.00695.x

Roebuck, K., & Wristen, K. (2018). *Global Review of the Aquaculture Stewardship Council's Salmon Standard: Summary Report*. https://www.seachoice.org/wp-content/uploads/2018/10/SeaChoice-ASC-Salmon-Standard-Global-Review-Oct-15-Online.pdf

Röös, E., Sundberg, C., Tidåker, P., Strid, I., & Hansson, P.-A. (2013). Can carbon footprint serve as an indicator of the environmental impact of meat production? *Ecological Indicators*, *24*, 573–581. https://doi.org/10.1016/j.ecolind.2012.08.004

Rossi, S., Tubiello, F. N., Prosperi, P., Salvatore, M., Jacobs, H., Biancalani, R., House, J. I., & Boschetti, L. (2016). FAOSTAT estimates of greenhouse gas emissions from biomass and peat fires. *Climatic Change*, *135*(3–4), 699–711. https://doi.org/10.1007/s10584-015-1584-y

Rothamsted. (2022). *e-RA*. http://www.era.rothamsted.ac.uk/

Rother, H. A. (2018). Pesticide labels: Protecting liability or health? – Unpacking "misuse" of pesticides. *Current Opinion in Environmental Science and Health*, *4*, 10–15. https://doi.org/10.1016/j.coesh.2018.02.004

RSPO. (2017). *RSPO Code of Conduct for Supply Chain Associates 2017*. http://www.rspo.org/resources/key-documents/membership

RSPO. (2020). *Termination of RSPO Membership of Darrell Lea Confectionery Co Pty Ltd*. https://www.rspo.org/news-and-events/announcements/termination-of-rspo-membership-of-darrell-lea-confectionery-co-pty-ltd

Rubik, F., & Frankl, P. (2005). *The Future of Eco-labelling: Making Environmental Product Information Systems Effective*. Greenleaf Publishing.

Ruby, T. M. (2015). Innovation-enabling policy and regime transformation towards increased energy efficiency: The case of the circulator pump industry in Europe. *Journal of Cleaner Production*, *103*, 574–585. https://doi.org/10.1016/j.jclepro.2015.02.017

Rudel, T. K., Defries, R., Asner, G. P., & Laurance, W. F. (2009). Changing drivers of deforestation and new opportunities for conservation. *Conservation Biology*, *23*(6), 1396–1405. https://doi.org/10.1111/j.1523-1739.2009.01332.x

Ruijter, F. J. De, Huijsmans, J. F. M., Rutgers, B., de Ruijter, F. J., Huijsmans, J. F. M., & Rutgers, B. (2010). Ammonia volatilization from crop residues and frozen green manure crops. *Atmospheric Environment*, *44*(28), 3362–3368. https://doi.org/10.1016/j.atmosenv.2010.06.019

Rutten, M. M. (2013). What economic theory tells us about the impacts of reducing food losses and/or waste: Implications for research, policy and practice. *Agriculture and Food Security*, *2*(1), 1–13. https://doi.org/10.1186/2048-7010-2-13

Sachs, J. D., Mcarthur, J. W., Schmidt-traub, G., Kruk, M., Bahadur, C., Faye, M., Mccord, G., Faye, M., & Mccord, G. (2004). Ending Africa 's Poverty Trap. *Brookings Papers on Economic Activity*, *240*(1), 117–216.

Sadras, V. O., Cassman, K. G. G., Grassini, P., Hall, A. J., Bastiaanssen, W. G. M., Laborte, A. G., Milne, A. E., Sileshi, G., & Steduto, P. (2015). Yield gap analysis of field crops, Methods and case studies. In *FAO Water Reports* (Vol. 41).

SAI Platform. (2021). *Benchmarking Equivalancy Overview*. https://saiplatform.org/resource-centre/fsa/?document-id=11837&document-archive=fsa&document-action=Download&document-source=benchmarking-equivalency-overview-26.03.2021.xlsx

Sala, S., Cerutti, A. K., & Pant, R. (2018). Development of a weighting approach for the Environmental Footprint. In *JRC Technical Reports*. https://ec.europa.eu/environment/eussd/smgp/documents/2018_JRC_Weighting_EF.pdf

Šálek, M., Kalinová, K., Daňková, R., Grill, S., & Żmihorski, M. (2021). Reduced diversity of farmland birds in homogenized agricultural landscape: A cross-border comparison over the former Iron Curtain. *Agriculture, Ecosystems and Environment*, *321*. https://doi.org/10.1016/j.agee.2021.107628

Salleh, S. F., Roslan, M. E. B. M., & Isa, A. M. (2019). Evaluating the impact of implementing Minimum Energy Performance Standards appliance regulation in Malaysia. *International Journal of Environmental Technology and Management*, *22*(4/5), 257. https://doi.org/10.1504/ijetm.2019.10026417

Sanchez, P. A. (2002). Soil fertility and hunger in Africa. *Science*, *295*(5562), 2019–2020. https://doi.org/10.1126/science.1065256

Scherer, L., & Pfister, S. (2015). Modelling spatially explicit impacts from phosphorus emissions in agriculture. *The International Journal of Life Cycle Assessment*, *20*, 785–795. https://doi.org/10.1007/s11367-015-0880-0

Scherer, L., Tomasik, B., Rueda, O., & Pfister, S. (2018). Framework for integrating animal welfare into life cycle sustainability assessment. *International Journal of Life Cycle Assessment*, *23*(7), 1476–1490. https://doi.org/10.1007/s11367-017-1420-x

Schleich, J., Durand, A., & Brugger, H. (2021). How effective are EU minimum energy performance standards and energy labels for cold appliances? *Energy Policy*, *149*(November 2020), 112069. https://doi.org/10.1016/j.enpol.2020.112069

Schneider, L., & Finkbeiner, P. M. (2013). *Life Cycle Assessment of EU Oilseed Crushing and Vegetable Oil Refining*. *May*.

Schroeder, G. L. (1978). Autotrophic and heterotrophic production of micro-organisms in intensely-manured fish ponds, and related fish yields. *Aquaculture*, *14*(4), 303–325. https://doi.org/10.1016/0044-8486(78)90014-5

Schroeder, G. L. (1987). Carbon and Nitrogen Budgets in Manured Fish Ponds on Israel's Coastal Plain. *Aquaculture*, *62*, 259–279.

Schulz, R., Bub, S., Petschick, L. L., Stehle, S., & Wolfram, J. (2021). Applied pesticide toxicity shifts toward plants and invertebrates, even in GM crops. *Science*, *84*, 81–84.

Scrinis, G., Parker, C., & Carey, R. (2017). The Caged Chicken or the Free-Range Egg? The Regulatory and Market Dynamics of Layer-Hen Welfare in the UK, Australia and the USA. *Journal of Agricultural and Environmental Ethics*, *30*(6), 783–808. https://doi.org/10.1007/s10806-017-9699-y

See, L., Schepaschenko, D., Lesiv, M., McCallum, I., Fritz, S., Comber, A., Perger, C., Schill, C., Zhao, Y., Maus, V., Siraj, M. A., Albrecht, F., Cipriani, A., Vakolyuk, M., Garcia, A., Rabia, A. H., Singha, K., Marcarini, A. A., Kattenborn, T., … Obersteiner, M. (2015). Building a hybrid land cover map with crowdsourcing and geographically weighted regression. *ISPRS Journal of Photogrammetry and Remote Sensing*, *103*, 48–56. https://doi.org/10.1016/j.isprsjprs.2014.06.016

Segerson, K. (2013). Voluntary Approaches to Environmental Protection and Resource Management. *Annual Review of Resource Economics*, *5*(1), 161–180. https://doi.org/10.1146/annurev-resource-091912-151945

Seufert, V., & Ramankutty, N. (2017). Many shades of gray—the context-dependent performance of organic agriculture. *Science Advances*, *3*(3). https://doi.org/10.1126/sciadv.1602638

Seufert, V., Ramankutty, N., & Foley, J. a. (2012). Comparing the yields of organic and conventional agriculture. *Nature*, *485*(7397), 229–232. https://doi.org/10.1038/nature11069

Seufert, V., Ramankutty, N., & Mayerhofer, T. (2017). What is this thing called organic? – How organic farming is codified in regulations. *Food Policy*, *68*, 10–20. https://doi.org/10.1016/j.foodpol.2016.12.009

Shan, J., & Yan, X. (2013). Effects of crop residue returning on nitrous oxide emissions in agricultural soils. *Atmospheric Environment*, *71*, 170–175. https://doi.org/10.1016/j.atmosenv.2013.02.009

Shangguan, S., Afshin, A., Shulkin, M., Ma, W., Marsden, D., Smith, J., Saheb-Kashaf, M., Shi, P., Micha, R., Imamura, F., & Mozaffarian, D. (2019). A Meta-Analysis of Food Labeling Effects on Consumer Diet Behaviors and Industry Practices. *American Journal of Preventive Medicine*, *56*(2), 300–314. https://doi.org/10.1016/j.amepre.2018.09.024

Siebert, S., Burke, J., Faures, J. M., Frenken, K., Hoogeveen, J., Döll, P., & Portmann, F. T. (2010). Groundwater use for irrigation – a global inventory. *Hydrology and Earth System Sciences*, *14*(10), 1863–1880. https://doi.org/10.5194/hess-14-1863-2010

Siebert, Stefan, Portmann, F. T., & Doll, P. (2010). Global patterns of cropland use intensity. *Remote Sensing*, *2*(7), 1625–1643. https://doi.org/10.3390/rs2071625

Sims, B., Hilmi, M., & Kienzle, J. (2016). Agricultural mechanization A key input for sub-Saharan African smallholders. In *Integrated Crop Management* (Vol. 23). www.fao.org/publications

Sintermann, J., Neftel, a., Ammann, C., Häni, C., Hensen, a., Loubet, B., & Flechard, C. R. (2012). Are ammonia emissions from field-applied slurry substantially over-estimated in European emission inventories? *Biogeosciences*, *9*(5), 1611–1632.

https://doi.org/10.5194/bg-9-1611-2012

Sirami, C., Gross, N., Baillod, A. B., Bertrand, C., Carrié, R., Hass, A., Henckel, L., Miguet, P., Vuillot, C., Alignier, A., Girard, J., Batáry, P., Clough, Y., Violle, C., Giralt, D., Bota, G., Badenhausser, I., Lefebvre, G., Gauffre, B., … Fahrig, L. (2019). Increasing crop heterogeneity enhances multitrophic diversity across agricultural regions. *Proceedings of the National Academy of Sciences of the United States of America*, *116*(33), 16442–16447. https://doi.org/10.1073/pnas.1906419116

Smeets, E. M. W., Bouwman, L. F., Stehfest, E., van Vuuren, D. P., & Posthuma, A. (2009). Contribution of N2O to the greenhouse gas balance of first-generation biofuels. *Global Change Biology*, *15*, 1–23. https://doi.org/10.1111/j.1365-2486.2008.01704.x

Smith, P., Bustamante, M., Ahammad, H., Clark, H., Dong, H., Elsiddig, E. A., Haber, H., Harper, R., House, J., & Jafari, M. (2014). Agriculture, Forestry and Other Land Use (AFOLU). In *Climate Change 2014: Mitigation of Climate Change*. Cambridge University Press.

Smith, P., Martino, D., Cai, Z., Gwary, D., Janzen, H., Kumar, P., McCarl, B., Ogle, S., O'Mara, F., Rice, C., Scholes, B., Sirotenko, O., Howden, M., McAllister, T., Pan, G., Romanenkov, V., Schneider, U., & Towprayoon, S. (2007). Policy and technological constraints to implementation of greenhouse gas mitigation options in agriculture. *Agriculture, Ecosystems and Environment*, *118*(1–4), 6–28. https://doi.org/10.1016/j.agee.2006.06.006

Song, E., Nelson, B. L., & Straum, J. (2016). Shapley Effects for Global Sensitivity Analysis: Theory and Computation. *SIAM/ASA Journal on Uncertainty Quantification*, *4*, 1060–1083. https://doi.org/10.1137/15M1048070

Sonnenschein, J., Van Buskirk, R., Richter, J. L., & Dalhammar, C. (2019). Minimum energy performance standards for the 1.5 °C target: an effective complement to carbon pricing. *Energy Efficiency*, *12*(2), 387–402. https://doi.org/10.1007/s12053-018-9669-x

Spaargaren, G., van Koppen, C. S. A., Janssen, A. M., Hendriksen, A., & Kolfschoten, C. J. (2013). Consumer Responses to the Carbon Labelling of Food: A Real Life Experiment in a Canteen Practice. *Sociologia Ruralis*, *53*(4), 432–453. https://doi.org/10.1111/soru.12009

Springmann, M., Clark, M., Mason-D'Croz, D., Wiebe, K., Bodirsky, B. L., Lassaletta, L., de Vries, W., Vermeulen, S. J., Herrero, M., Carlson, K. M., Jonell, M., Troell, M., DeClerck, F., Gordon, L. J., Zurayk, R., Scarborough, P., Rayner, M., Loken, B., Fanzo, J., … Willett, W. (2018). Options for keeping the food system within environmental limits. *Nature*, *562*(7728), 519–525. https://doi.org/10.1038/s41586-018-0594-0

Springmann, M., Godfray, H. C. J., Rayner, M., & Scarborough, P. (2016). Analysis and valuation of the health and climate change cobenefits of dietary change. *Proceedings of the National Academy of Sciences*, *113*(15), 4146–4151. https://doi.org/10.1073/pnas.1523119113

Springmann, M., Mason-D'Croz, D., Robinson, S., Wiebe, K. D., Godfray, H. C. J., Rayner, M., Scarborough, P., Springmann, M., Mason-D'Croz, D., Robinson, S., Wiebe, K., Godfray, H. C. J., Rayner, M., & Scarborough, P. (2016). Mitigation potential and global health impacts from emissions pricing of food commodities. *Nature Climate Change*, *7*(1), 69–74. https://doi.org/10.1038/nclimate3155

Statistics, F. A. O., Crops, P., & FAO. (2011). *Tree Crops - Guidelines For Estimating Area Data* (Issue January).

Steffen, W., Richardson, K., Rockström, J., Cornell, S. E., Fetzer, I., Bennett, E. M., Biggs, R., Carpenter, S. R., De Vries, W., De Wit, C. A., Folke, C., Gerten, D., Heinke, J., Mace, G. M., Persson, L. M., Ramanathan, V., Reyers, B., Sörlin, S., Veerabhadran, R., … Sörlin, S. (2015). Planetary boundaries: Guiding human development on a changing planet. *Science*, *347*(6223), 736. https://doi.org/10.1126/science.1259855

Stehfest, E., & Bouwman, L. (2006). N2O and NO emission from agricultural fields and soils under natural vegetation: summarizing available measurement data and modeling of global annual emissions. *Nutrient Cycling in Agroecosystems*, *74*(3), 207–228. https://doi.org/10.1007/s10705-006-9000-7

Steingrímsdóttir, M. M., Petersen, A., & Fantke, P. (2018). A screening framework for pesticide substitution in agriculture. *Journal of Cleaner Production, 192,* 306–315. https://doi.org/10.1016/j.jclepro.2018.04.266

Sterne, J. A. C., White, I. R., Carlin, J. B., Spratt, M., Royston, P., Kenward, M. G., Wood, A. M., & Carpenter, J. R. (2009). Multiple imputation for missing data in epidemiological and clinical research: Potential and pitfalls. *BMJ (Online)*, *339*(7713), 157–160. https://doi.org/10.1136/bmj.b2393

Stevenson, J. R., Villoria, N., Byerlee, D., Kelley, T., & Maredia, M. (2013). Green Revolution research saved an estimated 18 to 27 million hectares from being brought into agricultural production. *Proceedings of the National Academy of Sciences of the United States of America*, *110*(21), 8363–8368. https://doi.org/10.1073/pnas.1208065110

Stolze, M., Sanders, J., Kasperczyk, N., Madsen, G., & Meredith, S. (2016). *CAP 2014-2020: Organic farming and the prospects for stimulating public goods*.

Sturm, R., & An, R. (2014). Obesity and economic environments. *CA: A Cancer Journal for Clinicians*, *64*(5), 337–350. https://doi.org/10.3322/caac.21237

Suhr, K. I., Letelier-Gordo, C. O., & Lund, I. (2015). Anaerobic digestion of solid waste in RAS: effect of reactor type on the biochemical acidogenic potential (BAP) and assessment of the biochemical methane potential (BMP) by a batch assay. *Aquacultural Engineering*, *65*, 65–71. https://doi.org/10.1016/j.aquaeng.2014.12.005

Sulla-Menashe, D., & Friedl, M. A. (2018). *User Guide to Collection 6 MODIS Land Cover (MCD12Q1 and MCD12C1) Product*. https://doi.org/10.5067/MODIS/MCD12Q1

Taufique, K. M. R., Nielsen, K. S., Dietz, T., Shwom, R., Stern, P. C., & Vandenbergh, M. P. (2022). Revisiting the promise of carbon labelling. *Nature Climate Change*, *12*, 132–140. https://doi.org/10.1038/s41558-021-01271-8

Tesfaye, K., Takele, R., Sapkota, T. B., Khatri-Chhetri, A., Solomon, D., Stirling, C., & Albanito, F. (2021). Model comparison and quantification of nitrous oxide emission and mitigation potential from maize and wheat fields at a global scale. *Science of the Total Environment*, *782*, 146696. https://doi.org/10.1016/j.scitotenv.2021.146696

The British Standards Institution. (2011). *Publically Available Specificiation (PAS 2050: 2011)*.

The International Water Association (IWA). (2019). *Review of international water efficiency* *product labelling*. https://iwa-network.org/wp-content/uploads/2019/02/IWA-EUWM-Labelling-Report_Final-002.pdf

Thenkabail, P. S., Biradar, C. M., Noojipady, P., Dheeravath, V., Li, Y., Velpuri, M., Gumma, M., Gangalakunta, O. R. P., Turral, H., Cai, X., Vithanage, J., Schull, M. A., & Dutta, R. (2009). Global irrigated area map (GIAM), derived from remote sensing, for the end of the last millennium. *International Journal of Remote Sensing*, *30*(14), 3679–3733. https://doi.org/10.1080/01431160802698919

Thøgersen, J. (2002). Promoting "Green" Consumer Behavior with Eco-Labels. In T. Dietz & P. C. Stern (Eds.), *New Tools for Environmental Protection* (pp. 83–104). The National Academies Press. https://doi.org/10.17226/10401

Thomas, S. M., Ledgard, S. F., & Francis, G. S. (2005). Improving estimates of nitrate leaching for quantifying New Zealand's indirect nitrous oxide emissions. *Nutrient Cycling in Agroecosystems*, *73*(2–3), 213–226. https://doi.org/10.1007/s10705-005-2476-8

Tilman, D., & Clark, M. (2014). Global diets link environmental sustainability and human health. *Nature*, *515*, 518–522. https://doi.org/10.1038/nature13959

Tuanmu, M. N., & Jetz, W. (2015). A global, remote sensing-based characterization of terrestrial habitat heterogeneity for biodiversity and ecosystem modelling. *Global Ecology and Biogeography*, *24*(11), 1329–1339. https://doi.org/10.1111/geb.12365

Tubiello, F. N., Biancalani, R., Salvatore, M., Rossi, S., & Conchedda, G. (2016). A Worldwide Assessment of Greenhouse Gas Emissions from Drained Organic Soils. *Sustainability*, *8*(371). https://doi.org/10.3390/su8040371

Tuck, S. L., Winqvist, C., Mota, F., Ahnström, J., Turnbull, L. A., & Bengtsson, J. (2014). Land-use intensity and the effects of organic farming on biodiversity: a hierarchical meta-analysis. *Journal of Applied Ecology*, *51*(3), 746–755. https://doi.org/10.1111/1365-2664.12219

Tuomisto, H. L., Hodge, I. D., Riordan, P., & Macdonald, D. W. (2012). Exploring a safe operating approach to weighting in life cycle impact assessment – a case study of organic, conventional and integrated farming systems. *Journal of Cleaner Production*, *37*, 147–153. https://doi.org/10.1016/j.jclepro.2012.06.025

Tyukavina, A., Hansen, M. C., Potapov, P., Parker, D., Okpa, C., Stehman, S. V, Kommareddy, I., & Turubanova, S. (2018). Congo Basin forest loss dominated by increasing smallholder clearing. *Science Advances*, *4*(11). https://doi.org/10.1126/sciadv.aat2993

Food Labelling (Environmental Sustainability) Bill, (2021). https://bills.parliament.uk/bills/2796

UNCTAD. (2015). *Review of Maritime Transport 2015*.

UNDP, Vulnerabilities, R., & Resilience, B. (2014). *Human Development Report 2014*.

UNEP. (2017). *Global review of sustainable public procurement*. https://wedocs.unep.org/bitstream/handle/20.500.11822/20919/GlobalReview_Sust_Procurement.pdf

United Nations Environment Programme (UNEP). (2021). *Global LCA Data Access Network*. https://www.globallcadataaccess.org/

University of Nebraska, & Wageningen. (2022). *Global Yield Gap and Water Productivity Atlas*. www.yieldgap.org

University of New Hampshire. (2012). *User's Guide for the DNDC Model Version 9.5*. https://www.dndc.sr.unh.edu/model/GuideDNDC95.pdf

USDA. (2022a). *Ag Data Commons*. https://data.nal.usda.gov/

USDA. (2022b). *Federal LCA Commons*. https://www.lcacommons.gov/

USDA. (2022c). *Long-Term Agroecology Research (LTAR) Network*. https://ltar.ars.usda.gov/

van der Ven, H., Rothacker, C., & Cashore, B. (2018). Do eco-labels prevent deforestation? Lessons from non-state market driven governance in the soy, palm oil, and cocoa sectors. *Global Environmental Change*, *52*(June), 141–151. https://doi.org/10.1016/j.gloenvcha.2018.07.002

van Drecht, G., Bouwman, A. F., Knoop, J. M., Beusen, A. H. W., Meinardi, C. R., Drecht, G. Van, Bouwman, A. F., Knoop, J. M., Beusen, A. H. W., & Meinardi, C. R. (2003). Global modeling of the fate of nitrogen from point and nonpoint sources in soils, groundwater, and surface water. *Global Biogeochem. Cycles*, *17*(4), 1115. https://doi.org/10.1029/2003gb002060

Vanclay, J. K., Shortiss, J., Aulsebrook, S., Gillespie, A. M., Howell, B. C., Johanni, R., Maher, M. J., Mitchell, K. M., Stewart, M. D., & Yates, J. (2010). Customer Response to Carbon Labelling of Groceries. *Journal of Consumer Policy*, *34*(1), 153–160. https://doi.org/10.1007/s10603-010-9140-7

Vanlauwe, B., Bationo, A., Chianu, J., Giller, K. E., Merckx, R., Mokwunye, U., Ohiokpehai, O., Pypers, P., Tabo, R., Shepherd, K. D., Smaling, E. M. A., Woomer, P. L., & Sanginga, N. (2010). Integrated soil fertility management: Operational definition and consequences for implementation and dissemination. *Outlook on Agriculture*, *39*(1), 17–24. https://doi.org/10.5367/000000010791169998

Vellinga, T. V., Blonk, H., Marinussen, M., van Zeist, W. J., de Boer, I. J. M., & Starmans, D. (2013). *Methodology used in feedprint: a tool quantifying greenhouse gas emissions of feed production and utilization*.

Velte, P., Stawinoga, M., & Lueg, R. (2020). Carbon performance and disclosure: A systematic review of governance-related determinants and financial consequences. *Journal of Cleaner Production*, *254*, 120063. https://doi.org/10.1016/j.jclepro.2020.120063

Vermote, M., Bonnewyn, S., Matthys, C., & Vandevijvere, S. (2020). Nutritional content, labelling and marketing of breakfast cereals on the belgian market and their reformulation in anticipation of the implementation of the nutri-score front-of-pack labelling system. *Nutrients*, *12*(4). https://doi.org/10.3390/nu12040884

Verones, F., Huijbregts, M. A. J., Azevedo, L. B., Chaudhary, A., Baan, L. De, Fantke, P., Hauschild, M., Henderson, A. D., Mutel, C. L., Owsianiak, M., Pfister, S., Preiss, P., Roy, O., Scherer, L., Steinmann, Z., Zelm, R. Van, & Dingenen, R. Van. (2016). *LC-IMPACT Version 1.0*.

Vetter, S. H., Malin, D., Smith, P., & Hillier, J. (2018). The potential to reduce GHG emissions in egg production using a GHG calculator – A Cool Farm Tool case study. *Journal of Cleaner Production*, *202*, 1068–1076. https://doi.org/10.1016/j.jclepro.2018.08.199

Vlaeminck, P., Jiang, T., & Vranken, L. (2014). Food labeling and eco-friendly consumption: Experimental evidence from a Belgian supermarket. *Ecological Economics*, *108*, 180–190. https://doi.org/10.1016/j.ecolecon.2014.10.019

Voora, V., Larrea, C., & Bermudez, S. (2020). *Sustainable Commodities Marketplace Series 2019* (Issue October).

Voortman, R. L. (2013). Why the Green Revolution failed in sub-Saharan Africa. *Rural 21: The International Journal for Rural Development*, *47*(3), 32–33. https://www.rural21.com/fileadmin/downloads/2013/en-03/rural2013_03-S32-33.pdf

Waite, R., Pozzi, G., & Zionts, J. (2021). *2020 Cool Food Pledge Collective Greenhouse Gas Emissions Update*. https://coolfood.org/2020-pledge-data-update/

Waldman, K. B., & Kerr, J. M. (2014). Limitations of Certification and Supply Chain Standards for Environmental Protection in Commodity Crop Production. *Annual Review of Resource Economics*, *6*(1), 429–449. https://doi.org/10.1146/annurev-resource-100913-012432

Waldner, F., Fritz, S., Di Gregorio, A., & Defourny, P. (2015). Mapping priorities to focus cropland mapping activities: Fitness assessment of existing global, regional and national cropland maps. *Remote Sensing*, *7*(6), 7959–7986. https://doi.org/10.3390/rs70607959

Waldner, F., Fritz, S., Di Gregorio, A., Plotnikov, D., Bartalev, S., Kussul, N., Gong, P., Thenkabail, P., Hazeu, G., Klein, I., Löw, F., Miettinen, J., Dadhwal, V., Lamarche, C., Bontemps, S., & Defourny, P. (2016). A Unified Cropland Layer at 250 m for Global Agriculture Monitoring. *Data*, *1*(1), 3. https://doi.org/10.3390/data1010003

Wang, X., Andresen, K., Handa, A., Jensen, B., Reitan, K. I., & Olsen, Y. (2013). Chemical composition and release rate of waste discharge from an Atlantic salmon farm with an evaluation of IMTA feasibility. *Aquaculture Environment Interactions*, *4*(2), 147–162. https://doi.org/10.3354/aei00079

Webb, J., Sommer, S. G., Kupper, T., Groenestein, K., Hutchings, N. J., Eurich-Menden, B., Rodhe, L., Misselbrook, T. H., & Amon, B. (2012). Emissions of Ammonia, Nitrous Oxide and Methane During the Management of Solid Manures. In E. Lichtfouse (Ed.), *Agroecology and Strategies for Climate Change* (8th ed., Vol. 8, pp. 67–107). Springer. https://doi.org/10.1007/978-94-007-1905-7

Weber, A. (2021). Mobile apps as a sustainable shopping guide: The effect of eco-score rankings on sustainable food choice. *Appetite*, *167*(August), 105616. https://doi.org/10.1016/j.appet.2021.105616

Weidema, B. P., Bauer, C., Hischier, R., Mutel, C. L., Nemecek, T., Reinhard, J., Vadenbo, C., & Wernet, G. (2013). *The ecoinvent database: Overview and methodology*. www.ecoinvent.org

Wernet, G., Bauer, C., Steubing, B., Reinhard, J., Moreno-Ruiz, E., & Weidema, B. (2016). The ecoinvent database version 3 (part I): overview and methodology. *International Journal of Life Cycle Assessment*, *21*(9), 1218–1230. https://doi.org/10.1007/s11367-016-1087-8

West, P. C., Gerber, J. S., Engstrom, P. M., Mueller, N. D., Brauman, K. A., Carlson, K. M., Cassidy, E. S., Johnston, M., Macdonald, G. K., Ray, D. K., & Siebert, S. (2014). Leverage points for improving global food security and the environment. *Science*, *345*(6194), 325–328. https://doi.org/10.1126/science.1246067

White, E. V, & Roy, D. P. (2015). A contemporary decennial examination of changing agricultural field sizes using Landsat time series data. *Geo: Geography and Environment*, *2*(1), 33–54. https://doi.org/10.1002/geo2.4

Widi, T. S. M. (2015). *Mapping the impact of crossbreeding in smallholder cattle systems in Indonesia*. Wageningen University.

Wilkinson, M. D., Dumontier, M., Aalbersberg, Ij. J., Appleton, G., Axton, M., Baak, A., Blomberg, N., Boiten, J. W., da Silva Santos, L. B., Bourne, P. E., Bouwman, J., Brookes, A. J., Clark, T., Crosas, M., Dillo, I., Dumon, O., Edmunds, S., Evelo, C. T., Finkers, R., … Mons, B. (2016). The FAIR Guiding Principles for scientific data management and stewardship. *Scientific Data*. https://doi.org/10.1038/sdata.2016.18

Willer, H., Schlatter, B., Trávnícek, J., Kemper, L., & Julia, L. (Eds.). (2020). *The World Of Organic Agriculture Statistics and Emerging Trends 2020*. Research Institute of Organic Agriculture (FiBL), Frick and IFOAM - Organics International. https://www.fibl.org/en/shop-en/5011-organic-world-2020.html

Win, K. Z., & Zu, M. A. (2019). *Food Security Policy Project Research Highlights - Myanmar* (No. 17). https://www.canr.msu.edu/fsp/countries/myanmar/fsp research highlight land 17.pdf

Winter, L., Lehmann, A., Finogenova, N., & Finkbeiner, M. (2017). Including biodiversity in life cycle assessment – State of the art, gaps and research needs. *Environmental Impact Assessment Review*, *67*(October 2016), 88–100. https://doi.org/10.1016/j.eiar.2017.08.006

Wolf, M.-A., Pant, R., Chomkhamsri, K., Sala, S., Pennington, D., Handbook, I., Sala, S., & Pennington, D. (2012). The International Reference Life Cycle Data System (ILCD) Handbook. In *European Commission. JRC references reports*. https://doi.org/10.2788/85727

Woods, K. (2015a). CP maize contract farming in Shan State, Myanmar: A regional case of a place-based corporate agro-feed system. *Land Grabbing, Conflict and Agrarian-environmental Transformations: Perspectives from East and Southeast Asia*. https://www.iss.nl/sites/corporate/files/CMCP_35-_Woods.pdf

Woods, K. (2015b). *Opportunities, Risks and Growing Inequality: The Charoen Pokphand Group and Maize Smallholder Production in Shan State, Myanmar*. https://www.lcgmyanmar.org/publication/opportunities-risks-and-growing-inequality-the-charoen-pokphand-group-and-maize-smallholder-production-in-shan-state-myanmar/

World Bank. (2022). *World Bank Open Data*. https://data.worldbank.org/

WRAP. (2020). *The Food Waste Reduction Roadmap - Progress Report 2020*. https://wrap.org.uk/taking-action/food-drink/initiatives/food-waste-reduction-roadmap

WWF. (2020). *Bending the Curve: the Restorative Planet-Based Diets*. https://www.worldwildlife.org/publications/bending-the-curve-the-restorative-power-of-planet-based-diets

Yan, M., Cheng, K., Luo, T., Yan, Y., Pan, G., & Rees, R. M. (2015). Carbon footprint of grain crop production in China – based on farm survey data. *Journal of Cleaner Production*, *104*, 130–138. https://doi.org/10.1016/j.jclepro.2015.05.058

Young, W., Hwang, K., McDonald, S., & Oates, C. J. (2010). Sustainable consumption: Green consumer behaviour when purchasing products. *Sustainable Development*, *18*(1), 20–31. https://doi.org/10.1002/sd.394

Yu, H.-C. (2014). A Cross-Cultural Analysis of Symbolic Meanings of Color. *Chang Gung Journal of Humanities and Social Sciences*, *7*(1), 49–74. http://www.china.org.cn/e-groups/shaoshu/shao-2-naxi.htm.

Yu, L., Wang, J., Li, X. C., Li, C. C., Zhao, Y. Y., & Gong, P. (2014). A multi-resolution global land cover dataset through multisource data aggregation. *Science China Earth Sciences*, *57*(10), 2317–2329. https://doi.org/10.1007/s11430-014-4919-z

Yu, Q., Wu, W., You, L., Zhu, T., van Vliet, J., Verburg, P. H., Liu, Z., Li, Z., Yang, P., Zhou, Q., & Tang, H. (2017). Assessing the harvested area gap in China. *Agricultural Systems*, *153*, 212–220. https://doi.org/10.1016/j.agsy.2017.02.003

Zhou, W., Lee, M. B., & Goodale, E. (2018). The relationship between the diversity of herbaceous plants and the extent and heterogeneity of croplands in noncrop vegetation in an agricultural landscape of south China. *Global Ecology and Conservation*, *14*, e00399. https://doi.org/10.1016/j.gecco.2018.e00399

Zomer, R. J., Trabucco, A., van Straaten, O., & Bossio, D. A. (2006). *Carbon, Land and Water: A Global Analysis of the Hydrologic Dimensions of Climate Change Mitigation through Afforestation/Reforestation*.