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Perspective

Integrating Life Cycle and Impact Assessments to Map Food's Cumulative Environmental Footprint

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Feeding a growing, increasingly affluent population while limiting environmental pressures of food production is a central challenge for society. Understanding the location and magnitude of food production is key to addressing this challenge because pressures vary substantially across food production types. Applying data and models from life cycle assessment with the methodologies for mapping cumulative environmental impacts of human activities (hereafter cumulative impact mapping) provides a powerful approach to spatially map the cumulative environmental pressure of food production in a way that is consistent and comprehensive across food types. However, these methodologies have yet to be combined. By synthesizing life cycle assessment and cumulative impact mapping methodologies, we provide guidance for comprehensively and cumulatively mapping the environmental pressures (e.g., greenhouse gas emissions, spatial occupancy, and freshwater use) associated with food production systems. This spatial approach enables quantification of current and potential future environmental pressures, which is needed for decision makers to create more sustainable food policies and practices.

Introduction

The global food system imposes significant pressure on our environment. These pressures are generated by the inputs, processes, and outputs required to produce different food types and are associated with every stage of production, processing, distribution, consumption, and wastage.[1] Currently, food production uses around 50% of habitable land[2] and 4% of sea area,[3] accounts for about 70% of global freshwater withdrawal,[4] and is responsible for 26% of all anthropogenic greenhouse gas (GHG) emissions.[1] These pressures lead to impacts on natural ecosystems, degrading and destroying habitats that drive biodiversity declines[5] and undercutting the sustainability and production potential of the entire food production system.[6,7] These effects are expected to intensify as the human population and per capita consumption continue to grow.[8]

Both reducing food's environmental footprint and providing safe, nutritious, and sufficient food to humanity are central components of the United Nations Sustainable Development Goals[9] and require comprehensive and spatially explicit understanding of the cumulative pressures and impacts of all food types across the production process. Maps of individual environmental pressures from specific food sectors exist,[10,11] but cumulative maps are currently lacking.[12] Mapping the location and magnitude of the cumulative environmental footprint of food production is needed to identify hotspots of environmental pressures and potential inefficiencies (i.e., environmental pressure per unit

Box 1. Glossary

As in many disciplines, numerous terminologies—often conflicting or interchangeable—have been used in the context of environmental impacts. Here, we suggest a four-step structure, based on the terminology described by Judd et al.:[13] pressures, pathways, impacts, and pressures per unit production.

Environmental pressures (Figure 1, step 1), "life cycle inventory (LCI) results" in LCA[14] and "stressors" or "anthropogenic drivers" in cumulative impact assessments,[15,16] are the consumptive inputs (e.g., land, water), processes and outputs (e.g., excess nutrients, GHG emissions) associated with producing food. Pressures can be highly variable across space and time and depend on the type of food being produced and the method of production. For example, fertilization contributes to the environmental pressure of eutrophication potential and nitrous oxide emissions, but the magnitude of the contribution will depend on the type of fertilizer and the timing and method of application.[17]

Environmental pathways (Figure 1, step 2) refer to the mechanisms through which pressures contribute to resulting impacts and are not necessarily constrained to the site of production. In LCAs, pathways are often referred to as the "midpoint impact category."[14] For example, fertilization results in the environmental pressures (Figure 1, step 1) of phosphorus and nitrogen inputs into the environment that, in turn, might cause the environmental pathway (Figure 1, step 2) of eutrophication (i.e., increased nutrient pollution) at the farm level, or perhaps much further downstream through infiltration into waterways.[18] Importantly, although the conversion between pressures and pathways is typically assumed to be linear, these relationships could be highly complex and exhibit both positive and negative feedbacks.[13,19]

Environmental impacts of food production, or "endpoint impact category" in LCA terminology, depend on the environmental pathways and the sensitivity (i.e., vulnerability) of an environmental or societal receptor to a given pathway (e.g., population, habitat, or other entity(ies) that would be affected if exposed to the given pressure(s)).[14,15,16] Thus, the product of these factors describes the expected consequence(s) of a pressure for people and/or nature (Figure 1, step 3). For example, the abstraction of large amounts of groundwater (higher environmental pressure) from a heavily modified, species-poor river in a wet climate (lower sensitivity), might have relatively lower environmental impacts than smaller abstraction (lower environmental pressure) from an unmodified, species-rich river in a relatively dry climate (higher sensitivity). Notably, impacts on humans can be measured by using the same overall approach by considering the social or health vulnerability of a human population to an environmental pathway based on intrinsic (e.g., age, existing health conditions, genetics) and extrinsic (e.g., socioeconomic vulnerability, access to health care) variables.[20,21] Importantly, there might be temporal delays in impacts (decades or longer) because of legacies of historical accumulation (e.g., delayed release by aquifers and sediments).

Finally, environmental pressures, pathways, or impacts per unit production (Figure 1, step 4) can be calculated by standardizing environmental pressures, pathways, or impacts by a common unit of food system production (e.g., calories, grams of protein, or servings). Standardization allows meaningful comparisons between locations and across food types in relation to production levels (Box 3). Without considering production levels, low overall environmental pressures because of low production levels can appear to be less environmentally damaging within the context of the global food system than high-production, high-pressure systems. However, the environmental pressures per unit production might be higher. Calculating and spatially mapping pressures per unit production helps to uncover practices that are relatively more efficient and elucidate where specific policies and regulations can produce the biggest benefits through reducing the environmental pressure per unit production. Importantly, both pressures and pressures per unit production should be considered together to account for these potential trade-offs.

production, Box 1) to inform sustainable policies and practices. Further, accounting for cumulative pressures arising from food production allows evaluation of the most problematic pressures, including those that could lead to unacceptable or avoidable environmental outcomes.

A key reason for this knowledge gap is the boundaries between academic disciplines that have developed methodologies for different aspects of comprehensive impact assessments: life cycle assessment (LCA) and cumulative impact mapping. LCA aims to understand the environmental aspects and potential impacts throughout a product's complete life cycle (i.e., cradle to grave)[22] from an industrial ecology perspective. Recent LCA meta-analyses have clearly demonstrated that not all food is equivalent in terms of environmental pressure per unit production, providing insight into the opportunities and risks within the global food system and allowing for the development of generalized recommendations for more sustainable diets.[1,23,24] Methods for conducting regionalized LCAs have recently been proposed,[25] but most LCAs do not describe the fine-scale spatial distribution of environmental pressures (total and per unit production),[26–28] which is critical for predicting impacts on ecosystems and improving sustainability. Furthermore, most food LCAs have focused on one or a few relatively well-studied production types and environmental pressures[12] and usually report results per individual pressure at global or national scales. Results from LCAs that use spatially disaggregated input data, such as land-use change, soil erosion, and/or water scarcity, often differ sharply from non-spatially explicit examples,[14,29–33] highlighting the importance of considering environmental pressures at finer scales.

Largely independent of the LCA literature, conservation scientists have also improved our ability to combine and map pressures and impacts of human activities on the environment across spatial scales.[12,15,16] Similar to LCA, a well-documented set of best practices and assumptions for spatial accounting that combine multiple sources of pressure have emerged, including

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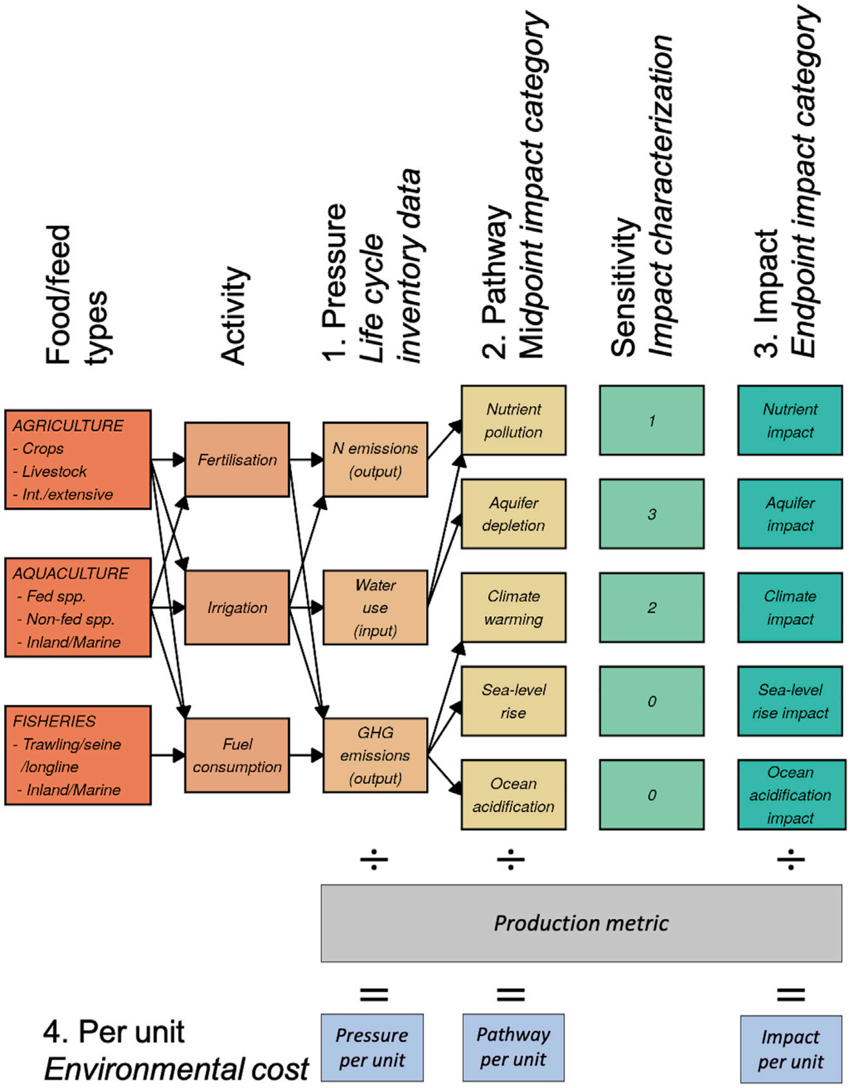


Figure 1. Conceptual Diagram of the Four Steps in Environmental Impact Assessment of Food Production

These include (1) pressures, (2) pathways, (3) impacts, and (4) pressures per unit production. Sensitivity scores represent exemplary low (0) to high (3) sensitivity values in relation to each pathway. Boxes represent examples and are thus not comprehensive. Italicized words represent the corresponding terminology in LCA analyses.

methods to translate these pressures into impacts.[19,34,35] However, unlike LCAs, these mapping assessments rarely account for the cumulative environmental footprint across multiple steps of a production cycle (e.g., processing, transportation, and packaging), which is essential in the context of food production where each stage of the process can impose different environmental pressures with unique footprints (e.g., through feed linkages; see Note S1). In addition, estimates of the environmental pressures of food production need to be scaled by a production metric (per unit) to assess efficiency, a standardizing step in LCAs that is less common in cumulative impact mapping. Thus, to ensure that food production policies are sensitive to location-specific contexts, it is necessary to merge the spatially explicit nature of cumulative impact mapping with the standardization and life stage approach of LCAs.

The ultimate goal of LCA and cumulative impact mapping methodologies is to measure the environmental pressures and associated pathways of food production to better understand resulting impacts on the environment and society (Box 1 and Figure 1). The challenges of validating and harmonizing data across vastly different production systems and spatiotemporal scales requires a method for spatially quantifying pressures and translating them to pathways and finally impacts. Here, we introduce an approach for assessing and mapping the cumulative environmental pressures (total and per unit of production) of the global food production system by integrating LCA and cumulative impact mapping methodologies. We outline the overall process, quantitative tools, and key considerations necessary for defining and incorporating multiple food production categories and environmental pressures. These include accounting for linkages between food systems (e.g., through feed), filling data gaps, and spatially reporting comparative and cumulative results. To advance potential applications of this approach to food systems, we also suggest appropriate methods for translating pressures into impacts. To illustrate our proposed methodology, we present an example using simulated data for three environmental pressures and four food types drawn from both land and sea.

Mapping Environmental Pressures

We describe the steps necessary for quantifying and spatially mapping the comparative and cumulative pressures (total and per unit production) of food production per grid cell. In practice, implementation of these steps is complex, requiring numerous decisions and assumptions,[19] particularly in the context of food systems and spatially explicit analyses (see Accounting for Uncertainty section).

Definition of Goal and Scope

The goal and scope of an assessment influences the comparisons that can be made among food systems and dictates the data needs. Defining the goal helps determine the breadth and intended use of an analysis, whereas the scope determines the system boundary and level of detail,[22] which will vary among practitioners on the basis of geographic location and food types of interest. We recommend viewing this as an iterative process where data availability feeds back into study design.

A hierarchical system (Figure S1) provides flexibility when categorizing food types and pressures that allows for analyses at various classification scales: among sectors (e.g., mariculture versus fisheries versus beef), or among practices within sectors, which can be highly variable. For example, the relative water use of beef varies considerably between grazing and feedlot raised animals[36] and the environmental pressures of aquaculture vary greatly among fed and unfed cultivated species.[24,37] As a consequence, comparing the impact of producing aquaculture, wild fish, and beef is only meaningful if these differences in pressures among and within sectors are accounted for.

Similarly, environmental pressures can be categorized in a variety of ways that can alter assessment outcomes and reduce comparability between assessments. For example, atmospheric emissions can be combined into a single pressure (i.e., measured according to their GHG effect by converting various gases to units of CO_2-equivalent by using global warming potential) or kept separated as individual gases to track other aspects of their impact. A hierarchical approach can be helpful in identifying pressures that are shared across food production types, but it is important to select a consistent level of subdivision to avoid overemphasis of certain production types when cumulative pressures are calculated. For food production types and pressures, creating comprehensive lists permits explicit reporting on what has and has not been used in an analysis and why (e.g., data limitations, see section on Accounting for Uncertainty).

Inventory Analysis

Once the focal food production types and pressures have been identified, there are three types of data needed to cumulatively map food production pressures: (1) spatial occupancy, (2) pressure values, and (3) production levels (to calculate pressures per unit production).

Mapping pressures requires knowledge of where the identified focal food types are produced (i.e., determining their spatial occupancy). International organizations (e.g., FAO) and research initiatives (e.g., MapSPAM) now provide spatial data for many food production types, particularly terrestrial foods. The geographic detail of terrestrial agricultural systems (e.g., crop and domesticated livestock production) and commercial marine fisheries is not perfect but is constantly improving due to technological innovations, satellite imagery, and spatial models.[38,39] Knowledge of the spatial distribution of less visible and/or studied systems (e.g., artisanal fishing, aquaculture, and bushmeat hunting[12]) is markedly less comprehensive.

In the absence of spatial occupancy data, many efforts to date have relied on an environmental suitability approach to predict where food production is most likely to occur in relation to environmental and economic proxies.[16,40,41] Suitability mapping can significantly increase the scope of an assessment by increasing the types of foods that can be included. However, combining suitability maps with production footprint information will inevitably introduce error into the results: environmental pressures will be diluted or extended where suitability maps overestimate spatial extent of production and concentrated where underestimated. To minimize the potential for false-positive and false-negative errors misdirecting policy actions or limited funds,[42] the use of suitability maps in this context requires careful thought and transparent reporting (see Accounting for Uncertainty section).

The next step is determining the environmental pressure values for each food type. LCA or environmental assessment models often provide data and methods for quantifying individual pressure data (e.g., the Global Livestock Environmental Assessment Model[32]), supplemented with modeling based on data from the primary scientific literature. Understanding the characteristics of these diverse data sources is critical for aggregating data and avoiding double counting of pressures. For example, LCA results are often ''cradle to grave'', whereas the desired goal and scope of a study might only be ''cradle to farm gate'' or some other variation. It might be possible to disaggregate LCA results into different stages of production, and the ability to do this, alongside the goals and scope of a study, will determine the usability and comparability of different data sources. Importantly, to integrate LCA and cumulative impact mapping, synthesis of farm-level LCAs is necessary for aggregating production types to comparable scales and spatially mapping results. This can be difficult because LCAs often address the same products in different ways. However, these data are becoming increasingly available,[1,24,32] making it possible to combine these two approaches.

The comparability of individual environmental pressures among different food production types and practices is also important. Land use, for example, has a relatively stationary and defined distribution that results in some level of ''exclusion'' of natural landscapes in terrestrial systems. In aquatic systems, on the other hand, food production practices (e.g., fishing and fish farming) can be more dynamic and mobile. This leads to fluctuating and evolving levels of habitat modification pressures on the environment on a spectrum from ''subtraction'' of resources (e.g., selective removal of species) to ''exclusion'' of a natural habitat, which is more similar to land use in terrestrial systems.[15,43] In these instances, production methods can be weighted based on relative disturbance to obtain occupancy and disturbance pressure values that reflect these differences. In the case that LCA data or environmental models are not available for a given pressure, the feasibility of modeling that pressure must be carefully evaluated (see Accounting for Uncertainty section).

Determining cumulative environmental pressures per unit production is important to be able to holistically and fairly compare across food production types and locations. To do this, some measure of production is required. Various production metrics have been used to calculate pressures per unit production in the context of LCA, including measures of weight (per tonne, kilogram, etc.), nutritional content (e.g., per kilocalorie, per gram protein, potential number of people fed per hectare[44]), or portion size (100 g, serving size, typical unit of product such as a loaf of bread, etc.). Given that comparative results can vary significantly on the basis of the chosen production metric, careful consideration of the scope, scale, and intended goal of the assessment is critical to determine which metric of production is best suited for any given analysis. For example, an analysis aimed at informing socioeconomic policies or dietary recommendations might choose production metrics in relation to the potential number of people fed per hectare or portion size.[44] In contrast, those aimed at developing understanding within the production sector (e.g., farmers, harvesters, governments) might focus on metrics commonly used in regional or national statistics, such as tonnes or kilograms.[2]

As with the spatial extent of production, fine-scale data on production levels are often lacking but are important for targeting management and policy recommendations. This is particularly the case for diverse food production systems, like fisheries, which contain thousands of different species that vary in time and space.[45] In most cases, production statistics are spatially and/or taxonomically aggregated at the regional or national level, providing useful insight into broad patterns.[11] However, for these purposes, production data need to be distributed at a finer scale.

The simplest approach for allocating production when the actual distribution is unknown is to distribute national-level production data evenly across the total extent of production. This can help capture spatial variation between, but not within, the original reporting units (e.g., countries). This renders estimates of environmental pressures per unit production at national scales largely uninformative and hinders policy decisions at more localized scales. A more nuanced approach is to combine a modified species distribution modeling approach coupled with spatial production allocation models.[39,46,47] If data are available, production can be distributed in relation to farm distribution, yields, and/or stocking rates while accounting for any confounding factors (e.g., the higher mortality that can accompany higher stocking densities[48]). Alternatively, production can be distributed proportionally to environmental variables, using simple rules such as higher river discharge corresponding to more freshwater aquaculture,[16] or through more complex predictive modeling approaches.[39] Such models are invaluable, but can require significant effort to produce and validate.

Mapping Cumulative Environmental Pressures

To enable cumulative mapping, environmental pressure data from different food systems must be integrated into a common framework and scale. There are complex, system-specific considerations for doing this (as discussed above), but the assumptions and methodology for bringing together disparate and complex sources of data for cumulative spatial analyses have been discussed in the cumulative impact mapping literature and are largely transferable to food system analysis.[15,16,19,49] The most notable difference for adapting previous cumulative impact mapping techniques to food systems is combining data not only across various sources of environmental pressure but also different production types and stages and translating cumulative environmental pressures to pressures per unit production (e.g., tonnes, nutritional content, etc.).

Spatializing environmental pressures can be done by using several approaches: pressures can be assigned to (1) the site at which they are incurred, (2) the site at which the final food product is produced, or (3) the site of consumption. Mapping environmental pressures to the site where they are incurred (i.e., spatially distinguishing between pressures exerted at the site of feed production and on-farm pressures arising from production of the final animal product) allows local or regional decision makers to more directly track and account for both the localized and global context of production processes. For example, water limitation could be a constraint where feed crops are grown but not where livestock are produced, and this distinction could be lost if feed and on-farm livestock pressures are mapped together at the livestock production site. At the farm level (i.e., combining on-farm and feed pressures for animal production to the final animal production site), farmers, consumers, and policy makers can better understand the combined footprint of the food produced in that location, allowing for the identification of specific farm practices that have relatively higher or lower environmental pressures. Finally, mapping pressures to the place of consumption allows for the assessment of how resource demand drives environmental pressures (i.e., mapping on-farm and feed pressures to the place of consumption). Such an approach could reveal solutions that do not fall solely on producers (supply-side approach), but on those creating demand for production, and potential inequities associated with pressures and products arising from the production of certain foods (e.g., distribution mode and distance[50]).

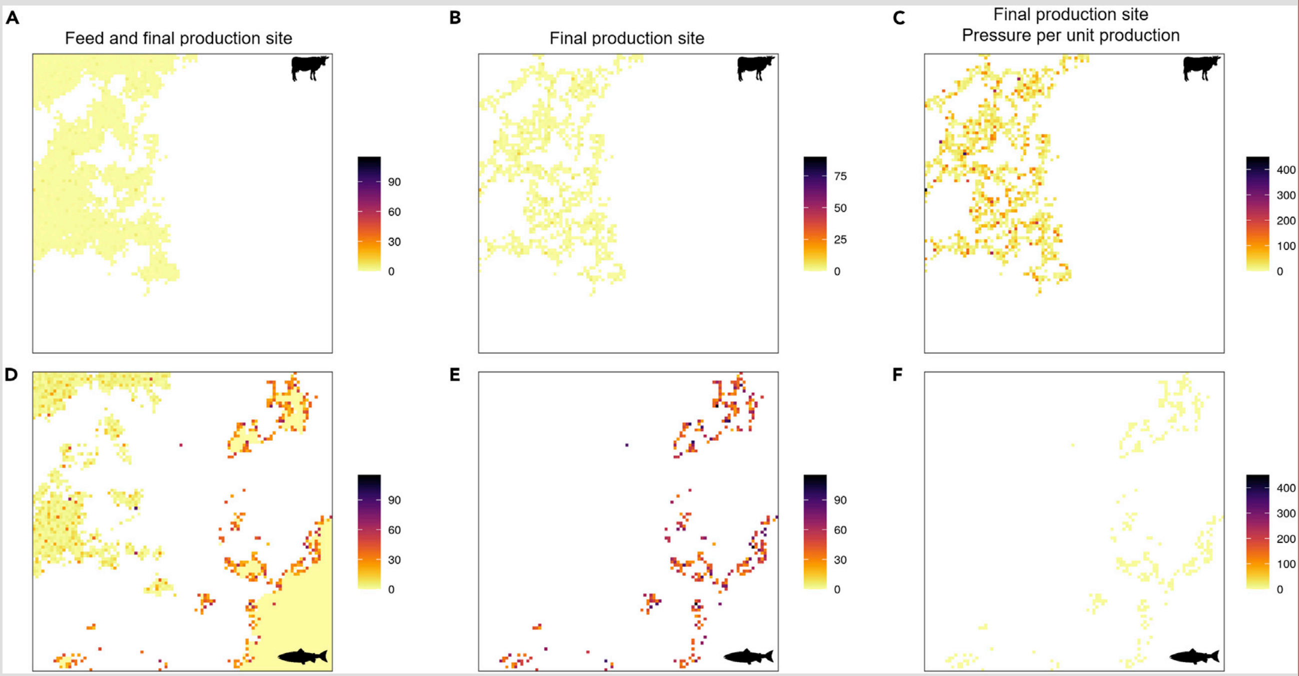
Although each of these approaches tell useful narratives, complex feed and trade dynamics make robust fine-scale spatial accounting difficult (Note S1). For example, it is currently not possible to explicitly link feed production in a specific cell to animal production in another cell, largely because commodities are typically pooled before they are traded. Establishing such links is only currently possible at the national level. We demonstrate mapping GHG emissions (total and per unit production) for beef and salmon aquaculture across a theoretical landscape (discussed below) at both the site at which they are incurred and the site at which the final food product is produced in Box 2. We recognize the need to further develop alternative approaches (e.g., at the site of consumption) for a holistic understanding of complex food networks.

Exploring a Hypothetical Case

We present a general framework for standardizing and combining multiple environmental pressures and production types into a single cumulative environmental pressure (total and per unit production) metric below, with an illustrative example in Box 3 and the Supplemental Information (Experimental Procedures and Tables S1–S6). The data and code to reproduce our example can be found at https://knb.

Box 2. Allocating Pressures between Animal and Feed Production Sites

Comprehensive and fair comparisons of the environmental footprint of food requires mapping environmental pressures, which can take different forms depending on the location where pressures are mapped (e.g., at the site where pressures are incurred, mapping feed and on-farm animal pressures separately to their respective production sites; figure panels A and D below) or at the farm level (mapping feed and on-farm pressures together to the final animal production site; figure panels B and E below). Further, environmental pressures per unit production depict the relative efficiency of different production types based on production levels, and thus all pressures must be accounted for and mapped to the final animal production site and standardized by a production metric (figure panels C and F below).



Examples of Mapping GHG Emissions

Thousands of kg CO_2 equivalents for beef (A–C) and salmon aquaculture (D–F). We present three approaches: (1) mapping feed and on-farm pressures separately to the site of feed production and the site of animal production (A and D), (2) mapping feed and on-farm pressures together to the final sites of animal production (B and E), and (3) mapping pressures per unit production to the final sites of animal production (C and F). The higher density of salmon production per cell results in higher GHG emission values per cell for salmon than beef (B and E). However, beef has higher GHG emissions per kilogram of production than salmon across the hypothetical landscape (C and F).

We demonstrate how to account for feed and on-farm environmental pressures by using GHG emissions from beef and salmon aquaculture (see Experimental Procedures and Tables S1–S5). In this example, beef is fed maize and salmon aquaculture is fed both maize and fish meal/oil from a small pelagic fishery (see Experimental Procedures and Table S4).

Calculating Feed Pressures from Animal Production

To calculate the pressure from feed inputs, we first calculate the amount of each feed crop in our landscape that is needed (maize and fish meal/oil from the small pelagic fishery) to produce the amount of the final animal food product (beef and salmon). We calculate the amount of feed type, $B_{c,a}$, needed to produce the amount of fed animal production type a across all cells in our landscape n as

$$B_{c,a} = \alpha_{c,a} \mathrm{FCR}_a \sum\nolimits_{i=1}^{n} K_{i,a} , \qquad \text{(Equation 1)}$$

where $K_{i,a}$ is the production (weight) of each fed animal type a in cell i, FCR_a is the feed conversion ratio, and α is the proportion of feed composed of each crop c for animal a (Table S4). We then determine the proportion of total feed crop needed to meet this demand, $D_{c,a}$, as

$$D_{c,a} = \frac{B_{c,a}}{T_c}, \qquad \text{(Equation 2)}$$

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Box 2. *Continued*

where T_c is the total production of crop c. We assume that the proportion of each pressure attributed to feed is equal to the proportion of each crop needed for feed (i.e., if 1% of total maize production is used in beef feed, 1% of maize GHG emissions need to be accounted for in beef GHG emission values). The allocation is done on a mass (kg) basis. The total amount of each pressure resulting from feed use $F_{s,a}$ is then

$$F_{s,a} = P_{s,c}D_{c,a}, \quad \text{(Equation 3)}$$

where $P_{s,c}$ is the total amount of pressure s for feed crop c. In our example, pressure data are already mapped to the origin of production (feed and on-farm animal pressures accounted for separately) and thus can be directly used to calculate cumulative pressures. However, to calculate pressures per unit, feed pressures for beef and salmon must be allocated to the site of animal production and crop pressures must be adjusted accordingly. Aggregated feed and on-farm stressors at the animal production site are calculated as

$$A_{s,a,i} = S_{a,i}\frac{P_{s,a}+F_{s,a}}{P_{s,a}}, \quad \text{(Equation 4)}$$

where $S_{a,i}$ is the on-farm pressure S for animal type a in cell i, which is multiplied by the ratio of total feed $F_{s,a}$ and on-farm pressure, $P_{s,a}$, to on-farm pressure for each pressure and animal production type. Feed crop cells must also be adjusted to account for pressures being mapped to the final site of animal production based on the amount of crop needed:

$$A_{s,c,i} = S_{c,i}(1-D_{c,a}), \quad \text{(Equation 5)}$$

where $S_{c,i}$ is the on-farm pressure S for feed type c in cell i. See the Experimental Procedures regarding separating feed from on-farm pressures when a single combined value is reported.

ecoinformatics.org/view/doi:10.5063/F1PZ575B. We created a simulated landscape with four food production types (maize, beef raised on a combination of grass and maize, salmon aquaculture, and a small pelagic fishery) and two natural habitat types (forest and water) (Figure 2A), and considered three pressures (area occupancy and disturbance, Figure 2B; GHG emissions, Figure 2C; and freshwater withdrawal, Figure 2D). We chose to use a theoretical dataset based on realistic values from Poore and Nemecek[1] to explicitly demonstrate several of the key and complex considerations in a single example, such as the need to account for differences in the disturbance associated with terrestrial agriculture and mobile fisheries in occupancy measures (Experimental Procedures). We map environmental pressures to the site where they are incurred and environmental pressures per unit production to the final site of animal production so that production (kg) can be easily linked with pressure values. Our hypothetical example helps to (1) create focus and transparency of the process and (2) allow better interpretation and identification of flexibility in our assumptions for the ultimate application to real world data.

Once cumulative pressures (total and per unit production) are spatially assessed, pressure drivers and their spatial and temporal trends can be explored to reveal environmental footprints and linkages that are both intuitive and unexpected, and ultimately reduce the environmental demands of food production. For instance, in our example, maize has the highest total environmental pressures across GHG emissions and freshwater use because of its high total production (Table S6). A significant portion of maize production is used for beef and salmon feed in our example (Table S4). The feed pressures become clear when exploring the differences of mapping pressures to where they are incurred versus the final animal production site (Box 2, figure panel A versus B and D versus E). In another example, although salmon aquaculture is known to have relatively low environmental pressures per unit production compared with that of beef,[1,24] when assessed spatially, salmon aquaculture has higher total GHG and freshwater withdrawal per grid cell. This is because salmon has an average yield of 12,840 kg per ha, nearly 400 times higher than beef (average yield of 33 kg per ha) (Table S6). These differences in yield lead to a higher cumulative pressure for salmon aquaculture (an average of 1.16 per ha) compared with beef (1.0) despite the far higher average cumulative pressure per unit production for beef than salmon (0.27 and 0.01 per kg, respectively) across our example landscape. In other words, because it is possible to produce a lot more salmon in a single grid cell, the total pressure within that cell is greater for salmon but still more efficient per kilogram of production than beef.

Translated to the real world, these differences have enormous implications for sustainable food policies: although shifts to more efficient foods and production means are vital for overall sustainability, localized pressures can be high even from these more efficient systems. Further, low production systems might look promising in terms of total cumulative environmental pressures but could result in a larger overall footprint (i.e., displacement of food production) in order to meet production demands.[53] Considering environmental pressures in both total and per unit production is critical for a comprehensive understanding of the food landscape.

Although our hypothetical example cannot be used to inform policy, several patterns emerge that exemplify the potential of our approach for policy development. For example, by quantifying and mapping cumulative environmental pressures, hotspots of environmental pressures can be identified (darker colors

Box 3. Calculating Cumulative Pressures (Total and per Unit)

Here, we demonstrate the general approach of calculating cumulative pressures across multiple production and pressure types by using the theoretical example described in Box 2 and the Supplemental Information (Experimental Procedures, Figure S2, and Tables S1–S5). We include three pressures: GHG emissions, spatial occupancy and disturbance, and freshwater withdrawal.

Once data on all available and relevant pressures have been collected, it is necessary to aggregate individual pressures within each grid cell. Importantly, at this stage, raster data of each environmental pressure are rescaled from native units to values on a common scale (usually [0 … 1]). For calculating environmental pressures per unit, environmental pressure data are first divided by total production from all food types within a cell and then rescaled by a scaling value.

Many potential rescaling functions exist (e.g., MinMax observed, MinMax possible, MinMax log transform), but global cumulative mapping assessments have largely rescaled data using a quantile approach.[15] Rescaling by the upper quantile of the data distribution reduces the effect of outliers (which can drive patterns in MinMax transformations). The specific quantile should be based on the sample size, but the 99.99th percentile has been used in other cumulative mapping approaches with a large amount of cells (e.g., global, ~1 km resolution).[15] In using this approach, all rescaled values > 1 should be adjusted to equal 1.

Once the environmental pressure data have been rescaled, they can then be summed within each cell to produce a cumulative pressure, $I_{C,i}$, or pressure per unit production, $E_{C,i}$, value (Figures 3A and 3B):

$$I_{C,i} = \sum_{s=1}^{m} R_{s,i}, \qquad \text{(Equation 6)}$$

$$E_{C,i} = \sum_{s=1}^{m} G_{c,i}, \qquad \text{(Equation 7)}$$

where $R_{s,i}$ and $G_{c,i}$ are the rescaled values (between 0 and 1) of food production pressure, s, or pressures per unit production, c, in cell i. Cumulative pressure scores should range between 0 and m (the total number of pressures being summed). Optionally, pressures can be weighted relative to their perceived importance before they are summed. Notably, ISO LCIA standards and cumulative mapping exercises consider normalization and weighting of pressures as "optional" components, because they are not objective. It is important to consider whether normalization and/or weighting are necessary in a given analysis (e.g., if there are expected trade-offs between scores[51]) and explicitly state the effects that they might have on conclusions being drawn. These issues have been discussed extensively elsewhere.[27,19,51,52]

Figure 3A). Regions of particularly severe cumulative environmental pressures represent areas where mitigation could be essential to avoid transgressing environmental boundaries, which could involve shifting to more sustainable production practices (e.g., resulting in relatively lower cumulative pressures (total and/or per unit production)) or food types.[53] High cumulative pressures per unit production (dark colors Figure 3B) represent potentially less efficient production practices or environments and should be explored in further detail to determine the source of these relative inefficiencies. Areas with lower cumulative pressure per unit production help identify more sustainable policies, practices or environmental conditions that can be applied to other regions. Again, considering environmental pressures and pressures per unit production together can reveal trade-offs in production practices to help improve sustainability of the food system as a whole.

Mapping environmental pressures is the first step toward mapping environmental impacts—the level at which policy decisions should ultimately be made (Box 4). The cumulative impact of food production is calculated by summing across impacts from each combination of pressures, pathways, and sensitivities (Figure 1). To make this spatially explicit, the intensity of each pressure is mapped, while the pathways and sensitivities are generally treated as either invariant or can be specific to a particular type of environment, where that typology is also mapped comprehensively. Accounting for the distribution of environmental entities that differ in sensitivity to a pressure enables the cumulative impact map to capture local and regional differences in species and habitats. Altogether, these steps allow diverse impacts operating through a range of environmental pathways to be quantified in a common way across pressures with regard to their impact on particular environmental or societal outcomes. Although calculating cumulative impacts specific to food systems remains an unresolved challenge, we provide a more detailed roadmap for translating cumulative environmental pressures to impacts in Box 4 and highlight it as an area in need of further development and research for food systems.

Accounting for Uncertainty

Uncertainty can arise from many sources, in particular through the underlying data used in calculations and the varying accuracy and robustness of the models. Indeed, data gaps still exist that hinder cumulative mapping for some food production systems. However, the urgency and importance of addressing the sustainability of food mean it is essential that transparent and repeatable practices are developed now that will help make results more rigorous and amenable to updates from improved data and models in the future.

The validity and repeatability of the results arising from this framework first depend upon using the best available data and models. For example, the Intergovernmental Panel on Climate Change (IPCC) provides guidance on calculating GHG emissions from agricultural activities.[56] When available, published models and open source data should be used. In addition, it is ideal to provide full access to the scripts and data used to calculate results. This provides full transparency

CellPress
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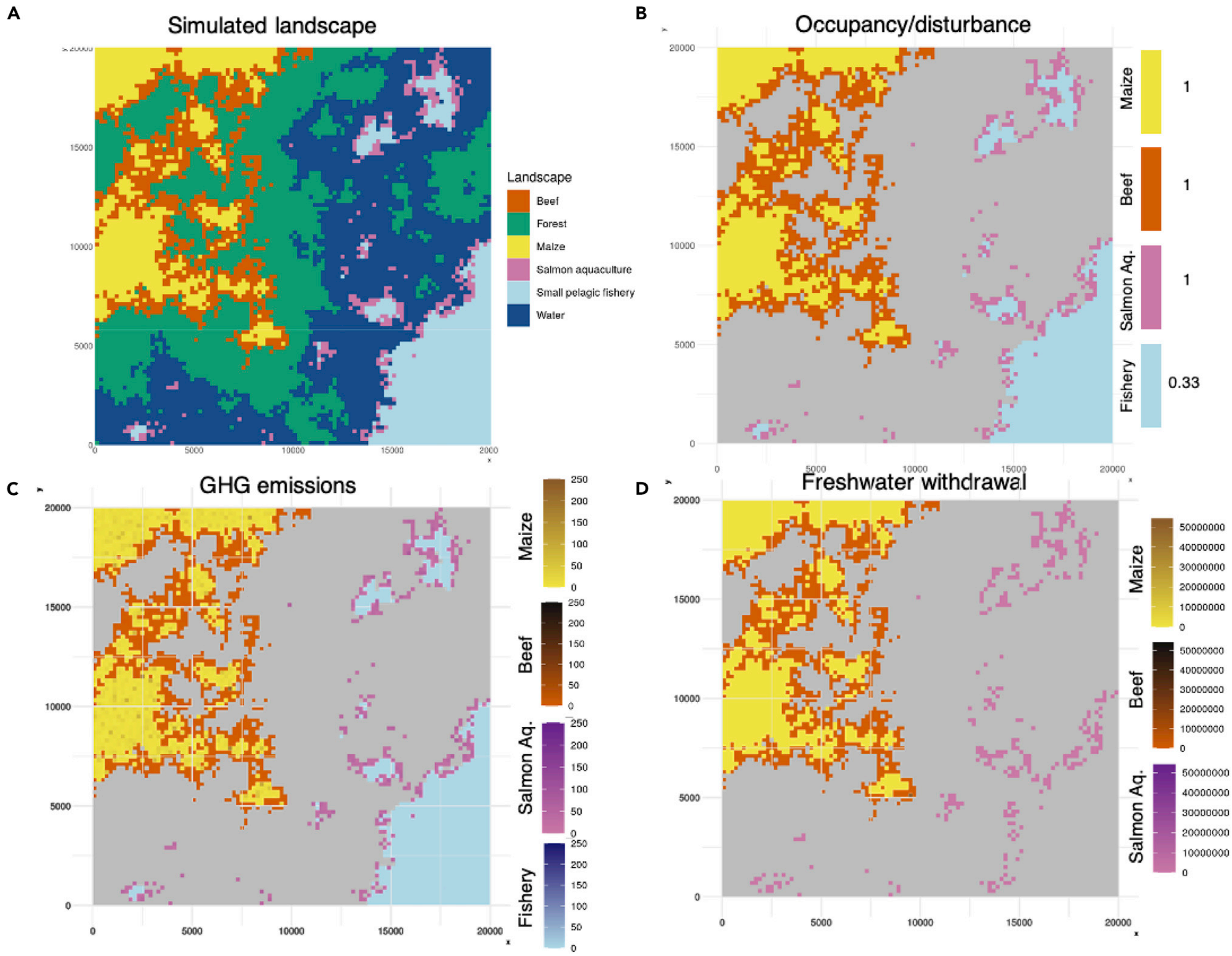

Figure 2. Landscape and Environmental Pressures Depicted in Our Hypothetical Example
Our hypothetical example includes (A) a landscape containing four food production types (beef, maize, salmon aquaculture, small pelagic fishery) and two natural habitat types (forest, water), and environmental pressures from (B) area occupancy and disturbance (hectares), (C) greenhouse gas emissions (kg CO_2 equivalents (log + 1 transformed)), and (D) freshwater withdrawal (liters (log + 1 transformed)) from each food production type within the landscape.

of the methods, makes results repeatable, and allows for the revision of results when improved data and models become available[57] (https://knb.ecoinformatics.org/view/doi:10.5063/F1PZ575B).

Next, clear documentation of high-level decisions (e.g., which pressure sources and food production types are included or excluded and why), models, coefficients used in models, data sources, and known weaknesses of each aspect of the analysis increases transparency, identifies important research gaps, and helps to improve assessments in the future.[12] Judging the quality and comprehensiveness of existing data (e.g., spatial resolution and gaps) should be guided by the decisions and/or actions that the work is intended to inform and should reflect the resolution of available data as well as the availability of suitable proxies that could fill data gaps. This level of transparency allows for the identification of the source of potential differences between analyses and can help pinpoint important assumptions and parameters that will improve reliability and accuracy of modeling approaches in the future.

Finally, it is critical to develop effective methods of tracking, quantifying, and communicating approaches to dealing with missing data. Estimating missing data, or gap filling, is critical because it leads to less biased and more accurate results and provides a measure of the reliability of the results for different regions and pressure sources.[58] For example, available regional or national-level data can be used to ground-truth production suitability mapping approaches and provide a measure of error,[59] but error measurements based on a subset of places cannot be considered globally representative. A systematic, hierarchical approach for determining pressures provides information on sources of uncertainty: if fine-scale data are not available for a given region or production type, a national average can be used, or to fill gaps in national data, a regional average could be applied. Weighting schemes based on production types (e.g., intensive versus extensive)

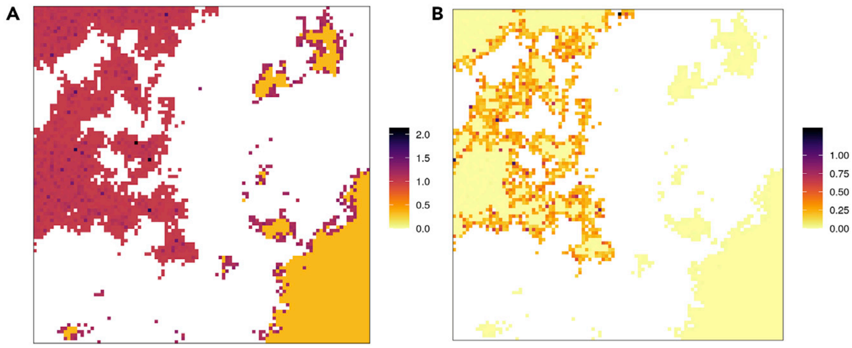

Figure 3. Resulting Spatially Explicit Cumulative Pressure (Total and per Unit Production) from Our Hypothetical Example
Mapped (A) cumulative pressure values at the site where pressures are incurred and (B) cumulative pressures per unit production values (mapped to the final site of animal production) within the theoretical landscape.

or levels (e.g., low versus high) can add further refinement to these data-filling approaches, noting an equal weight is still an assumed weighting scheme.[60] All else being equal, however, the most detailed data should be used when possible, and it is usually preferable to fill data gaps through estimation than to not account for a known pressure.[58] There are many approaches to estimating missing data, and using cross-validation methods to estimate error can be used to inform the best approach for gap filling and estimating uncertainty in models.

Ultimately, the pressures and impacts reported for food production studies should include a description of the range of plausible values (i.e., confidence intervals) given errors in the model and data as well as natural variation. For example, values describing the conversion of feed into animal products are highly variable. Some of this variation is due to measurement error, but much can be attributed to differences in temperature, animal breed, feed components, as well as other variables that are not controlled in agricultural systems and expected to vary. Confidence intervals can be estimated by bootstrapping.[61] Alternatively, values can be randomly sampled from a probability distribution (e.g., normal distribution) based on the population parameters derived from the data (e.g., mean and standard deviation of feed conversion ratios). A full estimate of uncertainty is impossible because many sources of uncertainty are unknowable or difficult to measure. However, substantive improvements can be iteratively made over time to achieve a more comprehensive assessment of uncertainty.

Conclusions

As the human population races toward 10 billion people, the need to rapidly develop effective policies to guide sustainable food production is critical. Such policies must be rooted in understanding where, how, and to what extent different foods are affecting the environment. At present, knowledge gaps limit our understanding of the spatial distribution of pressures (total and per unit production) and impacts of food production, potentially resulting in food production policies that fail to protect the interests of both people and nature.

Combining data and methodologies from LCA with cumulative impact mapping provides an important step in filling this knowledge gap and increasing our understanding of the environmental footprint of food production. Doing so requires comprehensive, standardized, and fine-scale mapping of pressure and production data. We have provided an overview of how these data can be merged to understand cumulative pressures and eventually impacts. Together, these integrative spatial analyses can reveal patterns in the underlying pressures, which can help guide development of better models and food production policies now and into the future. This information is requisite to achieving fair comparisons among components of the food system[12] and identifying opportunities to reduce the net impact of feeding humanity. Adopting the approaches and many complexities outlined herein will offer the food system and environmental science community abundant opportunities to enhance understanding of pressures of food production across diverse spatial scales and food types.

EXPERIMENTAL PROCEDURES

Resource Availability

Lead Contact

Further information and requests for resources and reagents should be directed to and will be fulfilled by the Lead Contact, Caitlin D. Kuempel (c.kuempel@uq.edu.au).

Materials Availability

This study did not generate new unique materials.

Data and Code Availability

The data and code to recreate the results and figures associated with the paper can be found on the KNB data repository at https://doi.org/10.5063/F1PZ575B (https://knb.ecoinformatics.org/view/doi:10.5063/F1PZ575B). Some additional processing of figures was undertaken in Microsoft PowerPoint, as noted in the relevant codes. This work is dedicated to the public domain under the Creative Commons Universal 1.0 Public Domain Dedication. To view a copy of this dedication, visit https://creativecommons.org/publicdomain/zero/1.0/.

Methods for Developing Our Hypothetical Example

Our hypothetical example demonstrates the general approach for mapping cumulative environmental pressures (total and per unit production) of food production for beef, maize, salmon aquaculture and a small pelagic fishery from “cradle to gate” (Figures 3A and 3B). Reproducible code to recreate this example can be found on the KNB data repository (https://knb.ecoinformatics.org/view/doi:10.5063/F1PZ575B). Although we endeavored to base our example on realistic data, our intention is to demonstrate the implementation of the methodology, and thus the values are illustrative only.

Hypothetical Landscape

We created a theoretical landscape (Figure 2A) with four food production types (beef, maize, salmon aquaculture, small pelagic fishery) and two natural habitat types (forest, water) based on a two-dimensional fractional Brownian motion neutral landscape model using the nlm_fbm function in the NLMR package[62] in R v3.6.1.[63] We assumed the spatial resolution of

Box 4. Mapping Environmental Pathways and Impacts

The ultimate goal of LCA and cumulative impact mapping methodologies is to measure the environmental pressures and associated pathways of food production to better understand resulting impacts on the environment and society. Thus, a method for translating pressures to pathways and finally impacts is needed.

Linking environmental pressures to pathways is difficult, because it requires full accounting of the sources and sinks of environmental changes. The easiest case is when a pressure is considered to be diffuse and contribute to the same generic receiving environment (site generic[26]), such as GHG emissions. Since GHG emissions have an impact on the entire world, this allows for attribution of the ~26% of global GHG emissions from terrestrial food production[1] to resultant pathways of sea level rise, ocean acidification, or change in sea surface temperature. Nutrient pollution, on the other hand, is intermediate and spatial occupancy and disturbance is non-diffuse, acting at local and regional scales, and thus require careful modeling and accounting of temporal and spatial dynamics that influence where and how much each pressure travels across the land and/or seascape (site-dependent and site-specific pressures). Notably, only cumulative environmental pressures mapped to the place where pressures are incurred should be translated to impacts as impacts are in relation to the underlying human and environmental entities in an area.

Once the contribution of each pressure to each pathway has been allocated, there are five key sub-steps in translating these environmental pathways (Figure 1, step 2) to impacts (Figure 1, step 3):

1. Determine and map the intensity of the environmental pathways across the study area.
2. Determine and map the "entity" that is being impacted. This entity can be species or habitats for biodiversity outcomes andhuman populations of different demographic and socioeconomic status or ecosystem services for social outcomes.
3. Determine the sensitivity of these entities to each pressure.
4. Multiply the presence of the entity in a given area by its sensitivity to the pathway and the pathway intensity for each combination of entity and pathway.
5. Combine spatial intensity and sensitivity values to form a final cumulative impact map (similar to in Box 3). If the resolution is fine enough that any given pixel has only one entity (habitat or population), then the spatial impact values (pressure intensity and entity vulnerability) can be summed. However, if any given pixel has more than one entity, the values should be averaged.

Determining the sensitivity of different entities (sub-step 3 from above) is arguably the most challenging step in this process and entails considerable complexity, often relying on subjective weighting variables derived from expert surveys.[54] Notably, methodologies to assess and incorporate the uncertainty in these approaches have recently been developed, such as using a range (e.g., worst case, most likely, best case) of sensitivity values.[55] LCIA analyses have derived habitat sensitivity based on species richness to quantify "potentially disappeared fraction of species" (i.e., the number of species, or fraction thereof, which might disappear as a result of the cumulative impacts of the action under study), and measured sensitivity of human health in terms of disability-adjusted life-years (DALYs).[14] Cumulative assessments that are focused on impacts on humans largely quantify sensitivity based on demographics and/or socioeconomic variables,[20,21] but could also consider the sensitivity of ecosystem services to environmental pathways (which in turn might have an impact on biodiversity and/or human well-being). Further, although there is a great need to combine terrestrial and aquatic impact mapping, especially for food production, this further complicates the development of sensitivity measures given varying baselines (e.g., the land has been in a relatively degraded state for hundreds to thousands of years because of human activity, compared with the relatively recent large-scale anthropogenic impacts to the ocean). These and other caveats need to be carefully considered to determine relevant baselines and approaches for calculating entity sensitivity.

our example was 1 ha. For simplicity, we assumed that each grid cell in the landscape was fully occupied by a single food production type. In reality, and dependent on the spatial resolution of the analysis, multiple production types might overlap within a cell or only partially cover cells. However, this difference does not impact the described methodology.

Production Data

We randomly sampled yield data (kilograms live weight per hectare) based on high and low yield estimates (Table S1). We assumed the high and low yield estimates were 95th and 5th quantiles of the yield distributions and randomly sampled yields for each production type assuming a uniform distribution. Yield samples were then randomly assigned to grid cells of the corresponding food production type within the theoretical landscape (Figure S2).

On-Farm Pressure Data

We considered three pressures in our example: occupancy/disturbance (hectares), GHG emissions (kilograms CO_2 equivalent) and freshwater withdrawal (liters). Pressure data for GHG emissions and freshwater withdrawal for beef, maize, and salmon aquaculture were modeled based on farm pressure data reported in Poore and Nemecek.[1] Due to our cradle-to-gate study design, we excluded pressures attributed to processing, packaging, transporting, storing, retail, and loss. Poore and Nemecek[1] values were converted from the reported retail weight to kilograms of live weight by removing the conversion from live weight to retail weight for all production types and removing or reversing the economic allocation to secondary by-products for beef production (Poore, personal communication).

Pressure data for the small pelagic fishery was sourced from Hilborn et al.[24] and was converted to kilograms of live weight from the reported functional unit of 40 g of protein assuming a conversion factor of 180 g of edible protein per filet (herring[24]). These values only included pressures up to the vessel landing site, and thus were already consistent with the cradle-to-gate scope of our example. Freshwater withdrawal was not considered as a pressure for wild fisheries as wild fish are not fed and freshwater use is minimal up to the vessel landing site.

Reported GHG emissions and freshwater withdrawal values had varying sample sizes for each pressure and production type (Table S2). A log-normal distribution was fit to these values for each food production type and pressure by using the fitdist function in the fitdistrplus package[64] in R v3.6.1.[63] To incorporate zero pressure data for some production types, a value of 0.00001 was added to all pressure values. Modeled samples were produced, equal to the number of cells of each food production type in our theoretical landscape, using the resulting model fit estimates (Table S3).

Area occupancy/disturbance, the final pressure in our analysis, was calculated based on the expected disturbance of each production type in each cell. We assumed that maize, beef, and salmon production would result in 100% disturbance of the underlying environment because of the relatively more stationary and intensive nature of these production types. We assumed the small pelagic fishery would cause one-third of this disturbance. This value is arbitrary but reflects lower disturbance that is expected due to the use of targeted fishing gear that generally has very low environmental impact. More refined estimates and/or sensitivity tests to explore how changes in these values impact results should be employed when using this approach.

The calculated sampled pressure values represent the on-farm pressure from each production type per kilogram live weight. Thus, to calculate the total on-farm pressure, we multiplied the sampled pressure values for GHG emissions and freshwater withdrawals by the production (i.e., yield) estimates in each cell. For simplicity, we assumed that occupancy/disturbance was not impacted by production level and thus did not adjust these values by production values. When considering animal production types, another approach to calculating pressures per cell would be to calculate individual pressures per animal and multiplying by the number of reared animals occupying each cell.

Mapping Pressures

For each food production type, we calculated and mapped pressures in two ways: where pressures are incurred (feed and final animal production site) and the final animal production site (Box 2, figure). To map cumulative pressures, the on-farm pressure values were randomly allocated to cells of each production type as described above (Figures 2B–2D and 3A). In both cases, it is important to be able to account for pressures resulting from feed production and on-farm pressures from final animal production.

To calculate environmental pressure per unit production, environmental pressure from feed (e.g., maize and small pelagic fishery) used to produce beef and salmon aquaculture needed to be accounted for at the site of animal production, and feed crop pressure values needed to be adjusted accordingly. Methods and further discussion for this accounting can be found in the main text and Box 2. Input variables for these calculations are in Table S4. The final proportion of on-farm pressures for beef and salmon aquaculture can be found in Table S5, and summary statistics for environmental pressures for each food production type across the entire landscape in Table S6.

In some cases, tabular pressure data from feed and on-farm activities can be reported as a single pressure attributed to the final product site. To map these pressures to the site they were incurred, they will need to be separated on the basis of feed and on-farm pressures. To separate pressure attributed to feed production from that attributed to the on-farm final animal product, the proportion of total feed crop in the study area needed to meet feed demand of an animal product, $D_{c,a}$, should be calculated as in Box 2.

Given the assumption that the proportion of each pressure (e.g., GHG emissions) attributed to feed would be equal to the proportion of each crop needed for feed (e.g., if 1% of maize production was needed to feed the total amount of beef production, then 1% of maize GHG emissions are assumed to be accounted for within the total beef GHG emission estimates), then the proportion of on-farm pressures, $S_{P,a}$, can be calculated as

$$S_{p,a} = \frac{P_{s,a} - P_{s,c}D_{c,a}}{P_{s,a}}, \quad \text{(Equation 8)}$$

where $P_{s,a}$ is the total amount of pressure, s, from animal type a, and $P_{s,c}$ is the total amount of pressure, s, from feed type c. Assuming cells where feed production occur still include pressures attributed to feed production (e.g., a potential double counting of feed pressures at the feed and final animal production sites), feed production cells (e.g., maize, small pelagic fishery in our example) for each pressure need to be multiplied by the proportion of on-farm feed pressures not attributed to animal feed production, $(1 - D_{c,a})$, and all fed animal production cells by the proportion of on-farm pressure, $S_{p,a}$, to spatially disaggregate on- and off-farm pressures in relation to production level for each production type.

SUPPLEMENTAL INFORMATION

Supplemental Information can be found online at https://doi.org/10.1016/j.oneear.2020.06.014.

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DECLARATION OF INTERESTS

H.E.F. is a member of the Technical Advisory Group for Aquaculture Stewardship Council.

REFERENCES

1. Poore, J., and Nemecek, T. (2018). Reducing food's environmental impacts through producers and consumers. Science *360*, 987–992.
2. FAO (2019). FAOStat (Food and Agriculture Organization of the United Nations). http://www.fao.org/faostat/en/#home.
3. Amoroso, R.O., Parma, A.M., Pitcher, C.R., McConnaughey, R.A., and Jennings, S. (2018). Comment on "Tracking the global footprint of fisheries.". Science *361*, eaat6713.
4. FAO (2017). Water for Sustainable Food and Agriculture: A Report Produced for the G20 Presidency of Germany (Food and Agriculture Organization of the United Nations). http://www.fao.org/3/a-i7959e.pdf.
5. Maxwell, S.L., Fuller, R.A., Brooks, T.M., and Watson, J.E.M. (2016). Biodiversity: the ravages of guns, nets and bulldozers. Nature *536*, 143–145.
6. Dangour, A.D., Mace, G., and Shankar, B. (2017). Food systems, nutrition, health and the environment. Lancet Planet. Health *1*, e8–e9.
7. Benton, T.G., and Bailey, R. (2019). The paradox of productivity: agricultural productivity promotes food system inefficiency. Glob. Sustain. *2*, e6.
8. Motesharrei, S., Rivas, J., Kalnay, E., Asrar, G.R., Busalacchi, A.J., Cahalan, R.F., Cane, M.A., Colwell, R.R., Feng, K., Franklin, R.S., et al. (2016). Modeling sustainability: population, inequality, consumption, and bidirectional coupling of the earth and human systems. Nat. Sci. Rev. *3*, 470–494.
9. United Nations (2017). Transforming Our World: The 2030 Agenda for Sustainable Development (Springer Publishing Company).
10. Mekonnen, M.M., and Hoekstra, A.Y. (2011). The green, blue and grey water footprint of crops and derived crop products. Hydrol. Earth Syst. Sci. *15*, 1577–1600.
11. Herrero, M., Havlik, P., Valin, H., Notenbaert, A., Rufino, M.C., Thornton, P.K., Blummel, M., Weiss, F., Grace, D., and Obersteiner, M. (2013). Biomass use, production, feed efficiencies, and greenhouse gas emissions from global livestock systems. Proc. Natl. Acad. Sci. U S A *110*, 20888–20893.
12. Halpern, B.S., Cottrell, R.S., Blanchard, J.L., Bouwman, L., Froehlich, H.E., Gephart, J.A., Sand Jacobsen, N., Kuempel, C.D., McIntyre, P.B., Metian, M., et al. (2019). Opinion: putting all foods on the same table: achieving sustainable food systems requires full accounting. Proc. Natl. Acad. Sci. U S A *116*, 18152–18156.
13. Judd, A.D., Backhaus, T., and Goodsir, F. (2015). An effective set of principles for practical implementation of marine cumulative effects assessment. Environ. Sci. Policy *54*, 254–262.
14. Verones, F., Bare, J., Bulle, C., Frischknecht, R., Hauschild, M., Hellweg, S., Henderson, A., Jolliet, O., Laurent, A., Liao, X., et al. (2017). LCIA framework and cross-cutting issues guidance within the UNEP-SETAC Life Cycle Initiative. J. Clean. Prod. *161*, 957–967.
15. Halpern, B.S., Walbridge, S., Selkoe, K.A., Kappel, C.V., Micheli, F., D'Agrosa, C., Bruno, J.F., Casey, K.S., Ebert, C., Fox, H.E., et al. (2008). A global map of human impact on marine ecosystems. Science *319*, 948–952.
16. Vörösmarty, C.J., McIntyre, P.B., Gessner, M.O., Dudgeon, D., Prusevich, A., Green, P., Glidden, S., Bunn, S.E., Sullivan, C.A., Liermann, C.R., et al. (2010). Global threats to human water security and river biodiversity. Nature *467*, 555–561.

17. Han, Z., Walter, M.T., and Drinkwater, L.E. (2017). N_2O emissions from grain cropping systems: a meta-analysis of the impacts of fertilizer-based and ecologically-based nutrient management strategies. Nutr. Cycl. Agroecosys. *107*, 335–355.
18. Bouwman, L., Goldewijk, K.K., Van Der Hoek, K.W., Beusen, A.H.W., Van Vuuren, D.P., Willems, J., Rufino, M.C., and Stehfest, E. (2013). Exploring global changes in nitrogen and phosphorus cycles in agriculture induced by livestock production over the 1900-2050 period. Proc. Natl. Acad. Sci. U S A *110*, 20882–20887.
19. Halpern, B.S., and Fujita, R. (2013). Assumptions, challenges, and future directions in cumulative impact analysis. Ecosphere *4*, art131.
20. Huang, G., and London, J. (2012). Mapping cumulative environmental effects, social vulnerability, and health in the San Joaquin Valley, California. Am. J. Public Health *102*, 830–832.
21. Solomon, G.M., Morello-Frosch, R., Zeise, L., and Faust, J.B. (2016). Cumulative environmental impacts: science and policy to protect communities. Annu. Rev. Public Health *37*, 83–96.
22. ISO (2006). Environmental Management - Life Cycle Assessment - Requirements and Guidelines (International Organization for Standardization). https://www.iso.org/standard/37456.html.
23. Tilman, D., and Clark, M. (2014). Global diets link environmental sustainability and human health. Nature *515*, 518–522.
24. Hilborn, R., Banobi, J., Hall, S.J., Pucylowski, T., and Walsworth, T.E. (2018). The environmental cost of animal source foods. Front. Ecol. Environ. *16*, 329–335.
25. Bulle, C., Margni, M., Patouillard, L., Boulay, A.-M., Bourgault, G., De Bruille, V., Cao, V., Hauschild, M., Henderson, A., Humbert, S., et al. (2019). IMPACT World+: a globally regionalized life cycle impact assessment method. Int. J. Life Cycle Assess. *24*, 1653–1674.
26. Hauschild, M. (2006). Spatial differentiation in life cycle impact assessment: a decade of method development to increase the environmental realism of LCIA. Int. J. Life Cycle Assess. *11*, 11–13.
27. Bare, J.C. (2010). Life cycle impact assessment research developments and needs. Clean. Technol. Environ. Policy *12*, 341–351.
28. Liu, K.F.-R., Hung, M.-J., Yeh, P.-C., and Kuo, J.-Y. (2014). GIS-based regionalization of LCA. J. Geosci. Environ. Protect. *02*, 1–8.
29. Potting, J., Schöpp, W., Blok, K., and Hauschild, M. (1998). Site-dependent life-cycle impact assessment of acidification. J. Ind. Ecol. *2*, 63–87.
30. Boulay, A.-M., Motoshita, M., Pfister, S., Bulle, C., Muñoz, I., Franceschini, H., and Margni, M. (2015). Analysis of water use impact assessment methods (part A): evaluation of modeling choices based on a quantitative comparison of scarcity and human health indicators. Int. J. Life Cycle Assess. *20*, 139–160.
31. Chaplin-Kramer, R., Sim, S., Hamel, P., Bryant, B., Noe, R., Mueller, C., Rigarlsford, G., Kulak, M., Kowal, V., Sharp, R., et al. (2017). Life cycle assessment needs predictive spatial modelling for biodiversity and ecosystem services. Nat. Commun. *8*, 15065.
32. FAO (2018). Global Livestock Environmental Assessment Model (Food and Agriculture Organization of the United Nations). http://www.fao.org/gleam/en/.
33. van Zelm, R., van der Velde, M., Balkovic, J., Čengić, M., Elshout, P.M.F., Koellner, T., Núñez, M., Obersteiner, M., Schmid, E., and Huijbregts, M.A.J. (2018). Spatially explicit life cycle impact assessment for soil erosion from global crop production. Ecosyst. Serv. *30*, 220–227.
34. Korpinen, S., and Andersen, J.H. (2016). A global review of cumulative pressure and impact assessments in marine environments. Front. Mar. Sci. *3*, https://doi.org/10.3389/fmars.2016.00153.
35. Stock, A., and Micheli, F. (2016). Effects of model assumptions and data quality on spatial cumulative human impact assessments: uncertainty in human impact maps. Glob. Ecol. Biogeogr. *25*, 1321–1332.
36. Mekonnen, M.M., and Hoekstra, A.Y. (2012). A global assessment of the water footprint of farm animal products. Ecosystems *15*, 401–415.
37. Froehlich, H.E., Runge, C.A., Gentry, R.R., Gaines, S.D., and Halpern, B.S. (2018). Comparative terrestrial feed and land use of an aquaculture-dominant world. Proc. Natl. Acad. Sci. U S A *115*, 5295–5300.
38. Lee, J., South, A.B., and Jennings, S. (2010). Developing reliable, repeatable, and accessible methods to provide high-resolution estimates of fishing-effort distributions from vessel monitoring system (VMS) data. ICES J. Mar. Sci. *67*, 1260–1271.
39. Gilbert, M., Nicolas, G., Cinardi, G., Van Boeckel, T.P., Vanwambeke, S.O., Wint, G.R.W., and Robinson, T.P. (2018). Global distribution data for cattle, buffaloes, horses, sheep, goats, pigs, chickens and ducks in 2010. Sci. Data *5*, 180227.
40. T.P. Robinson and Food and Agriculture Organization of the United Nations., eds. (2011). Global Livestock Production Systems (Food and Agriculture Organization of the United Nations).
41. Beusen, A.H.W., Van Beek, L.P.H., Bouwman, A.F., Mogollón, J.M., and Middelburg, J.J. (2015). Coupling global models for hydrology and nutrient loading to simulate nitrogen and phosphorus retention in surface water – description of IMAGE-GNM and analysis of performance. Geosci. Model Dev. Discuss. *8*, 7477–7539.
42. Loiselle, B.A., Howell, C.A., Graham, C.H., Goerck, J.M., Brooks, T., Smith, K.G., and Williams, P.H. (2003). Avoiding pitfalls of using species distribution models in conservation planning. Conserv. Biol. *17*, 1591–1600.
43. Kaiser, M., Collie, J., Hall, S., Jennings, S., and Poiner, I. (2003). Impacts of fishing gear on marine benthic habitats. In Responsible Fisheries in the Marine Ecosystem, M. Sinclair and G. Valdimarsson, eds. (FAO and CABI Publishing), pp. 197–216.
44. Cassidy, E.S., West, P.C., Gerber, J.S., and Foley, J.A. (2013). Redefining agricultural yields: from tonnes to people nourished per hectare. Environ. Res. Lett. *8*, 034015.
45. Nash, K.L., Watson, R.A., Halpern, B.S., Fulton, E.A., and Blanchard, J.L. (2017). Improving understanding of the functional diversity of fisheries by exploring the influence of global catch reconstruction. Sci. Rep. *7*, 10746.
46. You, L., and Wood, S. (2006). An entropy approach to spatial disaggregation of agricultural production. Agric. Syst. *90*, 329–347.
47. Fritz, S., See, L., McCallum, I., You, L., Bun, A., Moltchanova, E., Duerauer, M., Albrecht, F., Schill, C., Perger, C., et al. (2015). Mapping global cropland and field size. Glob. Change Biol. *21*, 1980–1992.
48. Schram, E., Van der Heul, J.W., Kamstra, A., and Verdegem, M.C.J. (2006). Stocking density-dependent growth of Dover sole (*Solea solea*). Aquaculture *252*, 339–347.
49. Halpern, B.S., Frazier, M., Afflerbach, J., Lowndes, J.S., Micheli, F., O'Hara, C., Scarborough, C., and Selkoe, K.A. (2019). Recent pace of change in human impact on the world's ocean. Sci. Rep. *9*, 11609.
50. Tlusty, M.F., and Lagueux, K. (2009). Isolines as a new tool to assess the energy costs of the production and distribution of multiple sources of seafood. J. Clean. Prod. *17*, 408–415.
51. Finnveden, G., Hauschild, M.Z., Ekvall, T., Guinée, J., Heijungs, R., Hellweg, S., Koehler, A., Pennington, D., and Suh, S. (2009). Recent developments in life cycle assessment. J. Environ. Manage. *91*, 1–21.
52. Pizzol, M., Laurent, A., Sala, S., Weidema, B., Verones, F., and Koffler, C. (2017). Normalisation and weighting in life cycle assessment: quo vadis? Int. J. Life Cycle Assess. *22*, 853–866.
53. Folberth, C., Khabarov, N., Balkovič, J., Skalský, R., Visconti, P., Ciais, P., Janssens, I.A., Peñuelas, J., and Obersteiner, M. (2020). The global cropland-sparing potential of high-yield farming. Nat. Sustain. *3*, 281–289.
54. Halpern, B.S., Selkoe, K.A., Micheli, F., and Kappel, C.V. (2007). Evaluating and ranking the vulnerability of global marine ecosystems to anthropogenic threats. Conserv. Biol. *21*, 1301–1315.
55. Jones, A.R., Doubleday, Z.A., Prowse, T.A.A., Wiltshire, K.H., Deveney, M.R., Ward, T., Scrivens, S.L., Cassey, P., O'Connell, L.G., and Gillanders, B.M. (2018). Capturing expert uncertainty in spatial cumulative impact assessments. Sci. Rep. *8*, 1469.
56. IPCC (2019). 2019 Refinement to the 2006 IPCC Guidelines for National Greenhouse Gas Inventories (Intergovernmental Panel on Climate Change). https://www.ipcc.ch/report/2019-refinement-to-the-2006-ipcc-guidelines-for-national-greenhouse-gas-inventories/.
57. Lowndes, J.S.S., Best, B.D., Scarborough, C., Afflerbach, J.C., Frazier, M.R., O'Hara, C.C., Jiang, N., and Halpern, B.S. (2017). Our path to better science in less time using open data science tools. Nat. Ecol. Evol. *1*, 0160.
58. Frazier, M., Longo, C., and Halpern, B.S. (2016). Mapping uncertainty due to missing data in the global ocean health index. PLoS One *11*, e0160377.
59. Munene, P., Chabala, L.M., and Mweetwa, A.M. (2017). Land suitability assessment for soybean (*Glycine max* (L.) Merr.) production in Kabwe District, Central Zambia. J. Agric. Sci. *9*, 74.
60. Moriarty, P.E., Hodgson, E.E., Froehlich, H.E., Hennessey, S.M., Marshall, K.N., Oken, K.L., Siple, M.C., Ko, S., Koehn, L.E., Pierce, B.D., et al. (2018). The need for validation of ecological indices. Ecol. Indic. *84*, 546–552.

61. DiCiccio, T.J., and Efron, B. (1996). Bootstrap Confidence Intervals, *11* (Statistical Science), pp. 189–212.
62. Sciaini, M., Fritsch, M., Scherer, C., and Simpkins, C. (2018). NLMR and landscapetools: an integrated environment for simulating and modifying neutral landscape models in R. Methods Ecol. Evol. *9*, 2240–2248.
63. R Core Team (2018). R: A Language and Environment for Statistical Computing (R Foundation for Statistical Computing). https://www.R-project.org/.
64. Delignette-Muller, M.L., and Dutang, C. (2015). fitdistrplus: an R package for fitting DIstributions. J. Stat. Softw. *64*, 1–34.