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Supplementary information

Environmental performance of blue foods

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Supplementary information: Environmental performance of blue foods

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S1 Methods overview

We draw on life cycle inventory data (i.e., material and energy input and farm-level performance data) from studies that collectively report data from over 1690 farms and 1000 unique fishery records to inform standardized estimates of GHG (kg CO_2-eq), N (kg N-eq), P (kg P-eq), water (m^3), and land (m^2a) stressors. GHG represents the potential contributions to climate change via radiative forcing, N and P represent the emissions of biologically available nitrogen and phosphorus to water bodies contributing to marine and freshwater eutrophication, water represents consumption of fresh water, and land represents annual crop-equivalent occupation of terrestrial land area.

Data from published seafood LCA studies, additional data (detailed below), and background data from the ecoinvent v3.6 LCI database, were used to aggregate environmental stressors (see Fig S1). We produced a series of hierarchical Bayesian models to estimate the off-farm (i.e., feed-associated) and on-farm stressor values at the species level and use global production volumes to produce weighted means for each taxonomic group. Any environmental assessment also varies based on a series of methodological decisions, notably the allocation method and functional unit. We use mass allocation and edible portion as the functional unit in the main text, but also express the aquaculture stressor results in terms of economic and energy allocation (Fig S11–12) and live weight (Fig S10). Additionally, our simplified model stops at the farmgate (Fig S2) or at landing. Some systems with low stressor values within these boundaries may have non-trivial stressors outside these boundaries, such as those associated with processing or transportation.

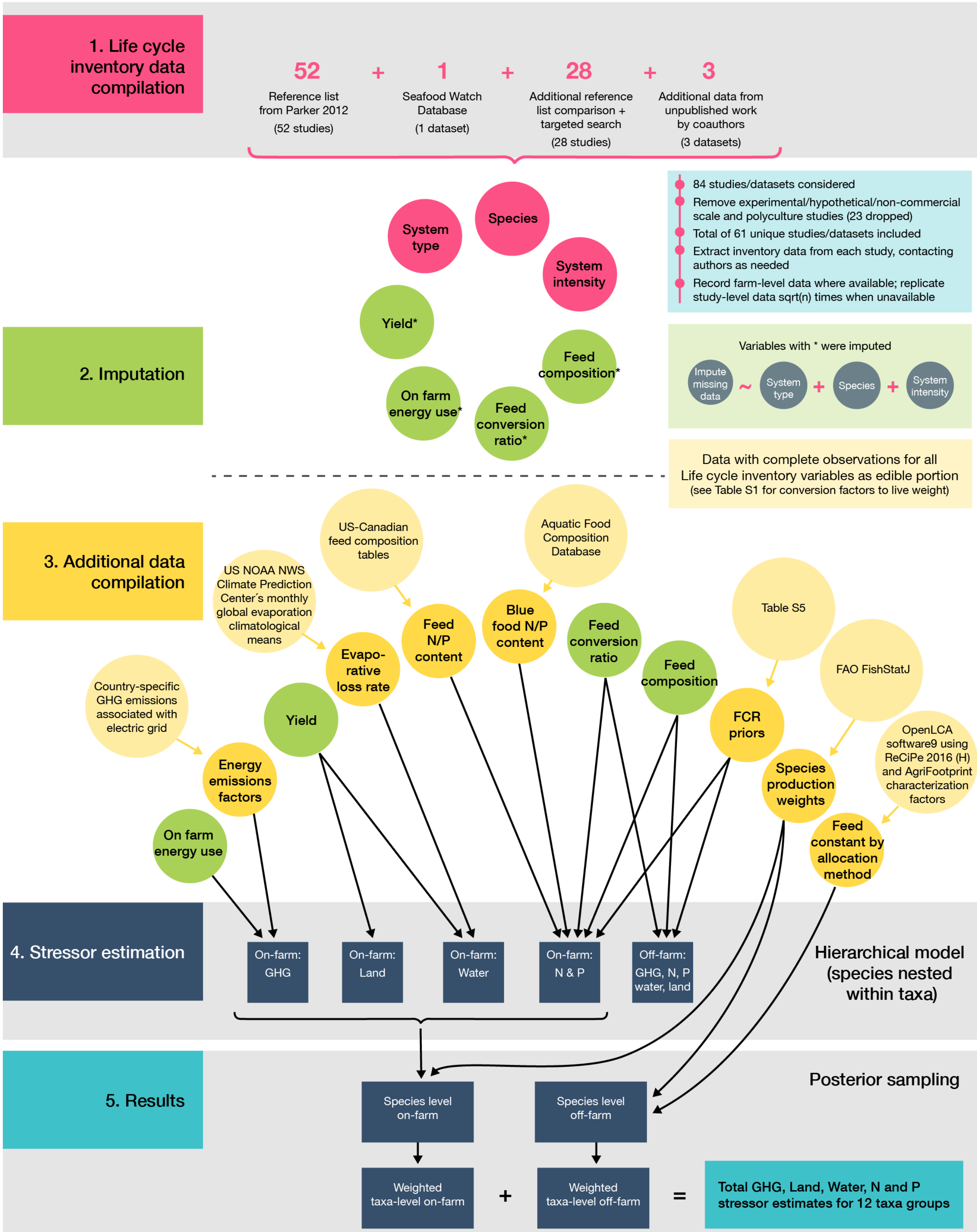

Fig S1 | Methods flow chart. Summary of methodological steps, including data collection and preprocessing, as well as a summary of the variables in each model. Asterisks on compiled life cycle inventory variables indicate variables estimated at the imputation stage for missing values.

S1.1 Goal of the study

The current research builds upon a simplified LCA approach, developed to allow for broader and more rapid environmental assessments of aquaculture systems, using a harmonized approach. We carried out this research to provide an overview of the current environmental impacts of the most farmed aquaculture species worldwide. By using life cycle inventory (LCI) data, rather than characterised life cycle impact assessment (LCIA) results, we allow production systems to be compared using a harmonised approach. Earlier comparisons of the environmental performance of aquaculture either limit themselves to a geographical region, rely upon already characterized LCIA data, limit themselves to aquaculture systems, or only evaluate global warming impacts[1–3]. In response, we recalculate greenhouse gas emissions, nitrogen emissions, phosphorus emissions, terrestrial land occupation, and consumptive freshwater use for aquaculture systems using inventory data (e.g., feed use, feed composition, on-farm energy use, etc.) from existing LCA studies and related literature. In the process, we aim to improve data for systems of high importance for global aquaculture production, in terms of production volumes, but that have been scarcely described in aquaculture LCA literature to date (e.g., carp farming).

The results generated are aimed to inform the scientific community, policy makers, and consumers about the diversity of environmental impacts related to global aquaculture and wild-caught fish. Blue foods are often treated as a homogenous group among these communities, but in this study, we detailed the diversity among individual species and systems. The results are published alongside several other academic publications, as part of the Blue Food Assessment (https://www.bluefood.earth/).

S1.2 Scope of the study

We build our analysis on inventory data from existing LCA literature, and supplement this with additional data sources from production descriptions of species and systems that are deemed important for the global aquaculture sector (Fig S1). The focus of our simplified LCA approach is the grow-out phase, as this is the denominator for most inputs that drive environmental impacts, including use of feed, land, and freshwater.

Our simplified LCA approach allows us to generate standardized stressor estimates that are comparable across studies, enabling us to generalize the patterns in stressors across the main blue food taxa groups. Taking this approach allows us to capture the major sources of stressors in blue food production, yet there are some processes that are potentially important that we were not able to include within our system boundaries (Fig S2) due to limitations in available data and/or processes that are highly context dependent. As aquaculture system mapping and documentation improves, many of these represent important areas for improving stressor models. Feed resources were simplified into four categories: Fish-derived products, livestock byproduct meals, agricultural products (excl. soybean), and soybean-meal and oil. Soybeans were specified separately given their strong association with land-use and land-use change (LULUC) in Brazil[4]. Emissions from feed resources were sourced from[5,6], and weighted based on country exports for crops, soy and animal byproducts, and by production for fishery products. Electricity use was specified on a country basis, using data from IEA.org (accessed 12-May-2020), detailing sources of electricity generation, energy use by the sector, and losses across the grid. Proxies for all emissions related to electricity generation were derived from the ecoinvent 3.6 APOS database[7].

Additionally, our on-farm greenhouse gas emissions do not include emissions from the decomposition of organic matter in ponds. Standing water bodies will result in hypoxic conditions and methanogenesis, and nitrogen will volatilise form the surface. This can result in substantial emissions of methane, nitrous oxide, nitrogen dioxide, ammonia, and other gases[8]. Of these methane and nitrous oxides are potent greenhouse gases and can result exaggerate carbon footprints. MacLeod et al.[3] for example, identified nitrous oxide emissions as a major source of GHGs for bivalves and some finfish systems, while Astudillo et al.[9] attributed 97% of GHG emissions from extensive carp systems to methane from ponds. While we acknowledge that these emissions are highly relevant when accounting GHG emissions from aquaculture, large uncertainties exist, especially when estimating blue foods at a global scale, as was done in the current study. Both the formation of methane and nitrous oxide are dependent upon temperature, salinity, aeration, pond depth, grow-out period, and other biotic and abiotic factors. In-situ and ex-situ empirical measurements subsequently range over an order of magnitude per tonne fish produced[8]. Since our study includes a global mix of systems and regions for each species, with a mix of farming in aerated and non-aerated systems, reservoirs, ponds, and cages, these estimates would become extremely crude. We subsequently do not integrate methane emissions from ponds or nitrous oxide volatilisation in our models. Nonetheless, we encourage more data to be collected and improvement of models to capture these sources of GHGs. We also encourage better accounting of blue food production by systems and aeration at national levels. Nitrous oxide emissions would also better be estimated based upon nitrogen inputs into systems, rather than generically across systems[10]. This as, for example, bivalves are generally net nitrogen extractors, rather than nitrogen emitters.

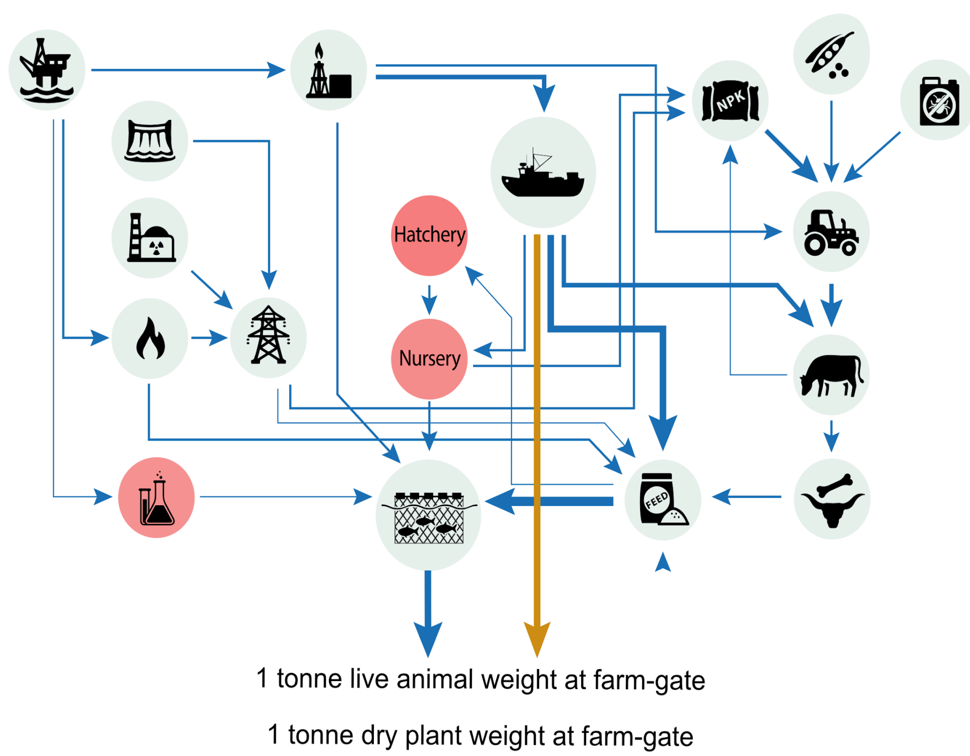

Fig S2 | Study system boundaries. System boundaries for fisheries (orange arrow) and aquaculture (blue arrow) with inputs in red indicating components excluded from the study. This figure is modified from[11].

The goal and scope of our study sets out to define the current environmental impact of different blue foods globally. Thus, our simplified modeling approach adopts an attributional LCA approach whereas consequential LCA modeling warrants an understanding of substituting food products that would need to be grossly simplified at the global scale and broad taxa groups within our study. Even at a regional level it is hard to predict which food commodities blue foods substitute, and preference for different blue foods is in rapid transition[12]. Market substitutions will be further influenced by realities such as: not all fish species can be farmed; wild and domesticated fish can have different fillet yields; consumer perceptions of wild and farmed fish differ, and, maybe most importantly, price remains the main determinant for food procurement choices[13]. Subsequently, system substitution (system expansion), was not a viable option for our model. A result of this decision is that our scenarios modeled represent a snapshot in time and do not speak to future changes in prices or demand.

Co-product allocation is the division of impacts among products originating from the same process (e.g., livestock meat and by-products). Allocation is an artificial problem and can therefore only be solved in artificial ways[14]. One should, however, seek to maintain a consistent allocation strategy throughout the modeling and try to adhere to well justified allocation strategies[14]. In attributional LCAs, as in this case, the most common allocation strategies include: cut-off, where all impacts are attributed to the main product; allocation based upon mass; allocation based upon economic value; and allocation based on gross energy content.

Our global scope complicates economic allocation due to regional price differences and price fluctuations over time. In terms of edible yields, cultural preferences strongly influence the market price. Fish heads or racks are, for example, more expensive than the fillets in some markets. We consequently choose to use mass allocation for our primary results, as it is simple to understand, can be consistently applied to all regions, and remains static over time. It is also the only allocation option possible for capture fisheries, as details on all types and prices of fish landed were limited[6].

To test the robustness of our conclusions, we recalculated the aquaculture results using allocation based on monetary value (economic allocation) and gross energy content (Fig S11-S12). These results landed in slightly different absolute impacts, but their relative ranking remained largely consistent. Thus, we argue that in the realm of relative LCA results, changing allocation strategy does not undermine our study's conclusions.

Choice of allocation can strongly influence the environmental burdens associated with certain products, such as animal byproducts. For example, mass allocation dictates that the overall environmental costs are divided between meat and its by-products based on the differences in mass, but if these by-products have low economic value, their environmental cost will be low. This implies that caution is required when comparing different product stressors[15,16] and the reason why we tested how the allocation factor affects the results below[17]. While ISO 14044 gives some guidance in choosing an allocation factor (e.g. that it should have a physical relationship if possible), the crude guidance provided leaves many options for interpretation[18,19]. In reality, each allocation choice has its strengths and weaknesses and the final choice often comes down to the worldview of the modeler. This is evident in previous LCAs of blue foods that have used all of the aforementioned allocation methods, or a mix of them, depending on the modeled process[14,20].

Stressor estimates can be expressed in terms of different functional units such as live weight or edible portion at the farm gate. Stressor estimates expressed in terms of live weight equivalent enable the data to be easily connected to production data, which is also typically expressed in terms of live weight, while the edible portion is more relevant to blue food demand and the role of blue foods in diets. As a result, we calculate the stressors in terms of both edible portion (Fig 1) and live weight equivalent (Fig S10). Edible portions as a fraction of the live weight can vary substantially due to differences in anatomy (Table S1). Further, edible yields are also influenced by cultural preferences and processing efficiencies. Fish heads, for example, are a delicacy throughout most of Asia, while they are discarded in Europe and North America. Other edible parts, such as swim bladders from Pangasius catfish, can yield much higher values than the fillets[21]. While these result in higher utilization, in other cases, inefficiencies in processing can result in a lower percentage of the live weight mass being utilized. Other byproducts are also often utilized for other processes, such as raw materials for fishmeal and fish oil production, but details on these utilization rates are incomplete. Moreover, these efficiencies vary across space and time. To standardize the definition of edible at the global level, we use the muscle fraction to represent the edible portion. Note that in both cases plants are expressed in terms of dry weight due to the fact that water loss varies substantially after harvest up to the farm gate, even pre-processing. In our analysis, all impacts reside in the edible portion. As utilization approaches 100%, the stressor estimates would approach the estimates expressed in terms of live weight. Even though the two allocation methods result in different stressor estimates, the relative performance of the blue food groups is generally robust to the choice of functional unit.

Table S1 | Edible portions for farmed and capture taxa groups. Edible portions represent the average muscle fraction (% live weight) for species within each taxa group derived from the indicated references.

Taxa group	Production source	Edible portion (%)
Milkfish	Aquaculture	61.00
Salmon	Aquaculture	58.50
Trout	Aquaculture	58.50
Shrimp	Aquaculture	57.00
Silver and bighead carp	Aquaculture	54.00
Other carp	Aquaculture	54.00
Catfish	Aquaculture	53.05
Misc. diadromous	Aquaculture	53.05
Misc. marine	Aquaculture	51.00
Tilapia	Aquaculture	37.00
Bivalves	Aquaculture	20.33
Cephalopods	Capture	66.67
Large pelagic fishes	Capture	61.74
Small pelagic fishes	Capture	60.19
Salmonids	Capture	59.33
Shrimps	Capture	58.00
Jacks, mullets, sauries	Capture	54.09
Flatfishes	Capture	52.75
Gadiformes	Capture	49.62
Redfishes, basses, congers	Capture	47.26
Lobsters	Capture	30.00
Bivalves	Capture	17.89

S2 Data characterization

This section summarizes the data inputs used in the aquaculture and capture fishery models. All data and code is publicly available on Github and archived[22].

S2.1 Aquaculture inventory data

Aquaculture inventory data were extracted from a database of aquaculture life cycle assessments initially compiled by[23] and updated with more recent studies by comparing the reference list to other published reviews and conducting targeted searches for underrepresented taxa groups and geographies (Fig S3; Fig S4; Table S9). Published LCAs were supplemented with FCR and feed composition data from Monterey Bay Aquarium's Seafood Watch program[24] and farm-level data collected for a range of systems in southeast Asia[25] to improve geographic representativeness (Fig S4). Studies were systematically filtered to exclude those assessing experimental or hypothetical systems, agri-aquaculture systems, polyculture systems producing species in more than one taxa group, and those for which no inventory data were reported, resulting in a dataset of 61 studies and datasets published between 1995 and 2020 (Table S9). For each study, where available, we compiled inventory data on economic feed conversion ratios, general feed composition (soy, other crop, fishery, and livestock-derived ingredients), electricity use, inputs of diesel and other energy carriers, and data relating to stocking densities and annual yields (t m^{-2}) (Table S10). All inventory data were converted to edible portion (Table S1) and live weight farm-gate values.

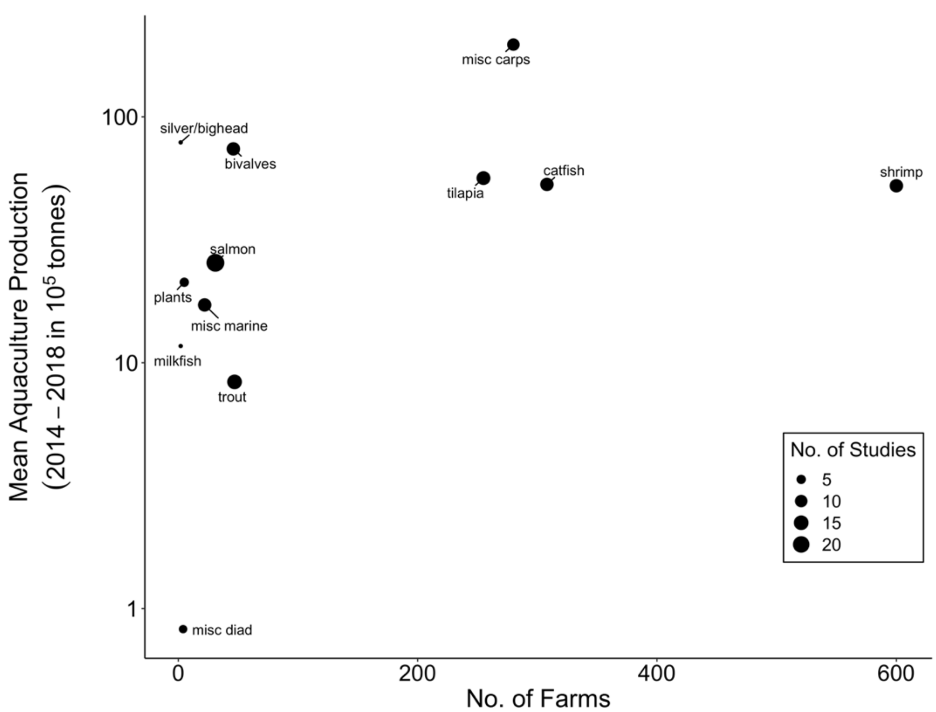

Fig S3 | Representativeness of observations by taxa group. Number of farm-level observations from which life cycle inventory data was recorded for each taxa group compared to total global production (2014–2018). Points are scaled by the number of studies from which the observations are recorded. Farm-level production volumes varied substantially but were not consistently available across source studies.

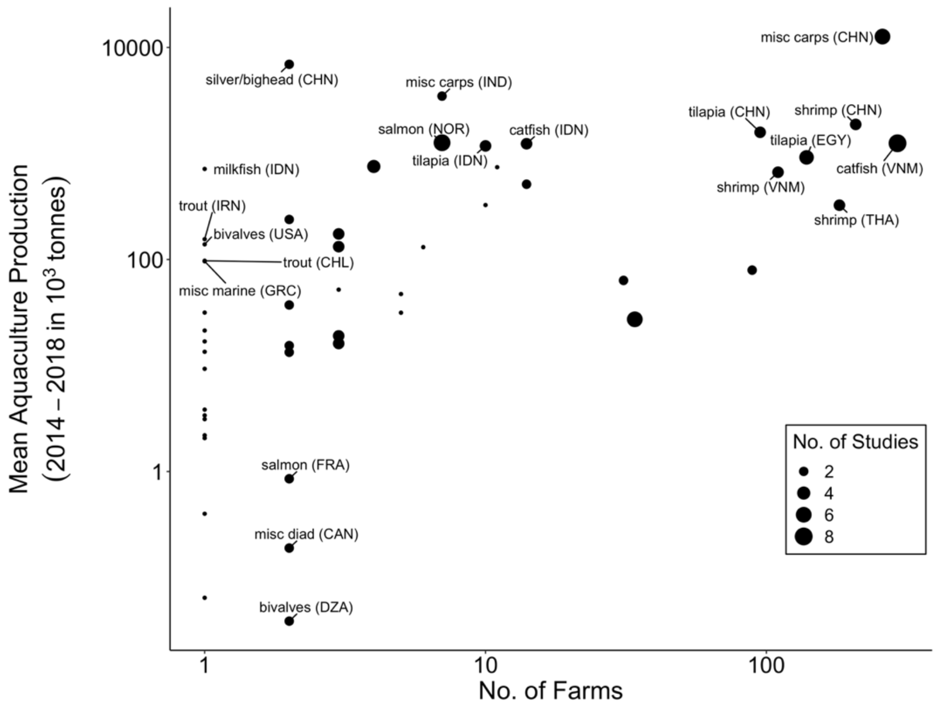

Fig S4 | Geographic representativeness of data. Number of farm-level observations from which life cycle inventory data was recorded for each observation from each country compared to national production by taxa group (2014–2018). Points are scaled by the number of studies from which the observations are recorded. Farm-level production volumes varied substantially but were not consistently available across source studies.

Table S2 | Species representation within each aquaculture taxa group included in this study. The number of studies and number of farms (N) represented by each study are detailed.

Taxa Group	Species or scientific name	N farms	N studies
Aquatic plants	*Gracilaria chilensis*	1	1
Aquatic plants	*Laminaria digitata*	1	1
Aquatic plants	*Macrocystis pyrifera*	1	1
Aquatic plants	*Saccharina latissima*	2	2
Bivalves	*Crassostrea gigas*	2	2
Bivalves	*Mytilus edulis*	10	5
Bivalves	*Mytilus galloprovincialis*	34	5
Catfish	*Clarias batrachus*	5	1
Catfish	*Clarias gariepinus*	1	1
Catfish	*Pangasianodon hypophthalmus*	231	6
Catfish	*Pangasius spp*	71	4
Milkfish	*Chanos chanos*	2	2
Miscellaneous diadromous fishes	*Lates calcarifer*	1	1
Miscellaneous diadromous fishes	*Salvelinus alpinus*	2	2
Miscellaneous marine fishes	*Anoplopoma fimbria*	1	1
Miscellaneous marine fishes	*Cynoscion spp*	8	2
Miscellaneous marine fishes	*Dicentrarchus labrax*	3	3
Miscellaneous marine fishes	*Epinephelus spp*	5	1
Miscellaneous marine fishes	*Scophthalmidae*	2	2
Miscellaneous marine fishes	*Seriola rivoliana*	1	1
Miscellaneous marine fishes	*Sparus aurata*	2	2
Other carps, barbels and cyprinids	*Carassius carassius*	1	1
Other carps, barbels and cyprinids	*Ctenopharyngodon idella*	1	1
Other carps, barbels and cyprinids	*Cyprinidae*	264	6
Other carps, barbels and cyprinids	*Cyprinus carpio*	14	2
Salmon	*Oncorhynchus kisutch*	1	1
Salmon	*Oncorhynchus tshawytscha*	1	1
Salmon	*Salmo salar*	20	13
Salmon	*Salmonidae*	2	2
Shrimps, prawns	*Litopenaeus vannamei*	430	7
Shrimps, prawns	*Penaeus monodon*	170	5
Silver and bighead carp	*Hypophthalmichthys molitrix*	1	1
Silver and bighead carp	*Mixed H. molitrix and H. nobilis*	1	1
Tilapias and other cichlids	*Oreochromis niloticus*	255	13
Trout	*Oncorhynchus mykiss*	44	12

S2.2 Capture fuel use data

Emissions data for wild capture fisheries were calculated based on fishing vessel fuel consumption. Fuel use intensity (liters of fuel consumed per tonne of round weight landings) data were extracted from the Fisheries Energy Use Database, which consists of both published and non-published fuel use observations and calculations from academic, industry, and government-derived sources[26]. A fishery record refers to a vessel or multiple vessels for which a species, gear, and fishing country can be associated. After calculating fuel-related emissions for each fuel use observation, an average of 25% additional emissions was assumed to account for non-fuel sources such as refrigerant loss and manufacture of gear, following[6]. For each fuel use record, several weightings were also estimated to reflect representativeness of observations within the industry. These weightings included species-specific landings within each ISSCAAP group and gear-specific landings within each species[27] and estimated rates at which each species was destined for human consumption as opposed to industrial use for fish meal and fish oil[28,29].

S2.3 Emission and resource use factors

Life cycle emission factors and resource use rates were calculated for all included feed inputs using characterization factors from ReCiPe 2016 Hierarchist method as implemented in the OpenLCA LCIA methods v2.0.5 by GreenDelta[31]. Soy- and other crop-derived feed inputs were modelled using the Agri-footprint 5.0 life cycle inventory database[5]. Fishery-derived inputs were modelled based on species-specific fuel use intensities of various reduction fisheries[26], species-specific yields of meal and oil[28], and energy inputs to meal and oil processing included in Agri-footprint 5.0 datasets. Livestock-derived feed inputs were modelled by adapting animal by-product processes in Agri-footprint 5.0 with inventory data from poultry LCAs undertaken in the United States[32] and Europe[33,34]. Impact factors for energy carriers were modelled using the ecoinvent 3.6 life cycle inventory database from the Swiss Center for Life Cycle Inventories, accounting for national grid mixes[7].

Average feed component stressors were weighted based on the country of origin and the proportion of exports of that feed component originating from that country for crop and livestock products based on FAO commodity flows tables[35]. Fishery products were weighted based on national production data[36].

S2.4 Evaporative loss

For evaporative water loss (mm/year), we use climatology data maintained by the U.S. NOAA National Weather Service's Climate Prediction Center[37]. We downloaded global climatological monthly means from 1981–2010 and used the *stars* package[38] in *R* to compute the annual mean for each pixel. We then spatially-joined these data with a map of country borders and extract country-level means using the rnaturalearth[39] and sf[40] packages, respectively, in *R*.

S2.5 N and P contents

Nitrogen and phosphorus content of blue foods were derived from a new comprehensive database of food composition focused on aquatic foods[41]. Wherever direct N and P values for specific species were unavailable we calculated these values based on carbon and lipid concentrations using regression coefficients[42]. When species-specific data were unavailable, data for species in the same genus, family, or order were substituted. We used N and P values of feeds from the United States-Canadian tables of feed composition[43]. We averaged the relevant values for each feed component group.

S2.6 Production

Aquatic food production by species/taxa group comes from the FAO[36] capture and aquaculture production data. Aquaculture production in 2018 was used to calculate the proportion of production by each species within each taxa group. All taxa-level estimates represent a production-weighted average of the species-level stressors. Calculations of the representativeness of the aquaculture and capture data is based on 2012–2018 averages. For aquaculture, aquatic plants were reduced to 6.8% to discount algae produced for industrial purposes[44]. After this adjustment, we calculated that the taxa groups in our study are representative of 76% of global aquaculture production (or 82% without the adjustment). Since global data on production method or intensity is not available, we cannot ensure that the studies are representative of these attributes. Further, while we have both small- and large-scale aquaculture producers represented in the data, we do not have complete data on the size of all farms or the size distribution of farms globally, so we cannot compare the representativeness with respect to producer size. However, all studies included do represent commercial-scale operations. Similarly, for wild capture, small pelagic fishes (herrings, sardines, anchovies) were reduced to 63.8% to discount catch destined for non-human consumption[45]. Some taxa are also reported with the generic term, "osteichthyes". When all "osteichthyes" are removed from the data and after small pelagics are adjusted, the taxa groups used in our study account for 65% of global capture fisheries production. The 23 taxa groups then collectively cover over 70% of blue food production.

Table S3 | Definitions of abbreviated taxa names

Taxa group name	Definition
silver/bighead	silver or bighead carp
cod, etc	cods, hakes, haddocks
flounder, etc	flounders, halibuts, soles
herring, etc	herrings, sardines, anchovies
jack, etc	jacks, mullets, sauries
misc diad	miscellaneous diadromous fishes
misc marine	miscellaneous marine fishes
redfish, etc	redfishes, basses, congers
salmon, etc	salmons, trouts, smelts
squid, etc	squid, cuttlefishes, octopuses
tuna, etc	tunas, bonitos, billfishes

S2.7 Ecological risk assessment

The number of marine mammal species assessed as being at different levels of risk (high, medium, low) in Fig 3 were extracted from two studies assessing multiple gear types in different regions of the world[46,47]. To calculate the risk index, we multiplied the number of species at high risk by three, the number of species at medium risk by two and the number of species at low risk by 1 and summed. This data was matched with data from FEUD[26] for the same gear types and region, and closest match available for target species.

S3 Model

We used a hierarchical framework to estimate Bayesian means of total emissions and resource use across five stressors (greenhouse gas [kg CO_2-eq], nitrogen [kg N-eq], phosphorus [kg P-eq], land [m^2a] and water [m^3]). We do this for all unique scientific names (e.g., Cyprinidae, *Cyprinus carpio*) found in our compiled LCA data as well as for aggregated groups of taxa (e.g., miscellaneous carps). Specifically, our model structure has study i, nested in scientific name j, nested in taxa group k. To give additional weight to studies with multiple observations, but for with individual farm-level data or variance around the mean was not reported, study-level data was replicated to the farm-level as the square root of the number of farms. All Bayesian models were run using Markov Chain Monte Carlo (MCMC) algorithms in Stan[48] and called from R[49] using the R package, $rstan$ [50]. All models converged (i.e., diagnostics for all parameters showed $0.99 < \hat{R} < 1.01$, $n_{eff}/N > 0.1$, and no divergent transitions) after 2500 iterations run on 4 chains. For each stressor, we calculate total emissions and resource use as the sum of their off-farm (feed-associated) and on-farm components as described below.

S3.1 Off-farm (feed-associated) stressors

For off-farm stressors, we modelled the dry weight feed conversion ratio of study i, FCR_i, as:

$$FCR_i \sim normal(\mu_{FCR_{j[i]}}, \sigma_{FCR_{j[i]}})$$

$$\mu_{FCR_{j[i]}} \sim normal(\mu_{FCR_{k[j]}}, \sigma_{FCR_{k[j]}})$$

$$\sigma_{FCR_{j[i]}}, \sigma_{FCR_{k[j]}} \sim halfCauchy(0,1)$$

such that $\mu_{FCR_{j[i]}}$ and $\mu_{FCR_{k[j]}}$ are the mean FCR for scientific name j and and taxa group k, respectively, and $\sigma_{FCR_{j[i]}}$ and $\sigma_{FCR_{k[j]}}$ are their respective standard deviations. To help with convergence we apply weakly-informative half-Cauchy priors on the scientific name and taxa group level σ's.

For off-farm stressors, we also modelled the proportions of feed originating from soy, crops, livestock, and fisheries. For each study i, Xi is a vector of feed proportions that sums to 1. We modelled this vector as:

$$X_i = (X_{soy}, X_{crops}, X_{livestock}, X_{fisheries}) \sim Dirichlet(\alpha_{j[i]})$$

such that $\alpha_{j[i]}$ is a shape parameter describing the distribution (uniform or degenerate) of the feed proportions for scientific name j. We then reparameterized $\alpha_{j[i]}$ as:

$$\alpha_{j[i]} = K_{j[i]} * \theta_{j[i]}$$

such that $\theta_{j[i]}$ is the vector of estimated feed proportions of scientific name j and $K_{j[i]}$ is the sample size (number of studies) for scientific name j (Stan Development Team, 2020). To obtain our taxa group estimates, we modelled the estimated scientific name feed proportions $\theta_{j[i]}$ as Dirichlet distributed, and reparameterized this as above to obtain a vector of estimated feed proportions for taxa group k:

$$\theta_{j[i]} \sim Dirichlet(\alpha_{k[j]})$$

$$\alpha_{k[j]} = K_{k[j]} * \theta_{k[j]}$$

Finally, we calculated the species and taxa group level off-farm (i.e., feed-associated) stress ($S_{feed[stressor]}$) for each stressor (GHG, N, P, land, and water) by multiplying the feed requirements by the associated stressors of the feed, weighted by the feed composition:

$$S_{feed[stressor]} = FCR \sum_{f=1}^{4} S_f \, p_f$$

Here, f indexes the four feed ingredients (soy, other crops, fishmeal and fish oil, and livestock byproducts). S_f is a constant that quantifies the stressors of each feed ingredient f, while FCR and p_f are the posterior distributions of the estimated dry weight feed conversion ratio and the proportion of each feed component f.

S3.2 On-farm stressors

On-farm nitrogen and phosphorus stressors are calculated from the same species and taxa-level means of FCR and feed proportions, p_f, described above for off-farm stressors. Here, on-farm N and P stress are estimated as the difference between the N and P content of each feed component and the species-specific N and P contents of each blue food product such that:

$$S_{nonfeed[nitrogen]} = FCR \sum_{f=1}^{4} N_f \, p_f - N_{fish}$$

$$S_{nonfeed[phosphorus]} = FCR \sum_{f=1}^{4} P_f \, p_f - P_{fish}$$

where N_f and P_f represent the nitrogen and phosphorus content of feed component f and N_{fish} and P_{fish} represent the species-specific nitrogen and phosphorus content of a unit of fish, shellfish, or seaweed. While on-farm stress, $S_{nonfeed}$, for N and P are both derived from the Bayesian means of FCR and the feed proportions, the other stressors, land, GHG, and water, are derived from nested means of the calculated stressor as described below. The non-feed associated land use refers to the land area allocated to the growth of a unit of output which applies to aquaculture systems that are ponds, recirculating systems and tanks. We calculated land stress ($S_{nonfeed[land]}$; m^2 a t^{-1}) as the reciprocal of annual yield (Y; t m^{-2}):

$$S_{nonfeed[land]} = \frac{1}{Y}$$

The on-farm greenhouse gas emissions ($S_{nonfeed[GHG]}$) are calculated as the electricity use times the country-specific GHG emissions, plus the diesel, petrol, and natural gas use times each of their GHG stressor factors:

$$S_{nonfeed[GHG]} = \sum_{q=1}^{4} G_q \, E_q$$

Here, q indexes the four energy sources (electricity, diesel, petrol, and natural gas), G_q represents the GHG emissions of energy source q, and E_q represents the energy use of source q. While energy use does contribute to the other stressors, we only include it in the GHG stressor since the contribution to the other stressors is negligible. To calculate the on-farm water use, we estimated the evaporative losses over the surface area allocated to the unit of production as:

$$S_{nonfeed[water]} = VTS_{nonfeed[land]}$$

where V represents the country-specific average surface evaporation rate and T represents the grow-out period. Evaporative loss was only included for freshwater systems. We then model the Bayesian means for on-farm land, GHG, and water stressors with study i nested in scientific name j, nested in taxa group k as shown below:

$$S_{nonfeed[stressor]} \sim normal(\mu_{Stressor_{j[i]}}, \sigma_{Stressor_{j[i]}})$$

$$\mu_{Stressor_{j[i]}} \sim normal(\mu_{Stressor_{k[j]}}, \sigma_{Stressor_{k[j]}})$$

To help with convergence, we apply the following hyperpriors on all ’s at the scientific name and taxa group level. Specifically,

$$\sigma_{GHG_{j[i]}}, \sigma_{GHG_{k[j]}} \sim halfCauchy(0{,}1000)$$

$$\sigma_{Land_{k[j]}}, \sigma_{Land_{k[j]}} \sim halfCauchy(0{,}10000)$$

$$\sigma_{Water_{k[j]}}, \sigma_{Water_{k[j]}} \sim halfCauchy(0{,}100)$$

Finally, we apply priors on mean FCR at the taxa-level for all taxa groups except “miscellaneous diadromous fishes”:

$$\mu_{FCR_{k[j]}} \sim normal(prior, 1)$$

We focus on FCR because it is a parameter found in all of our stressor models for which there is considerable information. Priors were derived from[51] and updated by expert judgement. Re-running the models with vs without these priors caused slight shifts in the posterior, but the major results (i.e., ordering of taxa results from highest to lowest stress) did not change (Fig S13).

S3.3 Missing Data Imputation

Missing data for FCR, feed proportions, yield, and all energy inputs (electricity, petrol, diesel, and natural gas) were imputed using taxa group as a categorical predictor and intensity and system type as ordinal predictors. In other words, the predicted value for missing data is pulled to the mean of other LCA studies of the same taxa group, intensity, and system type. For the feed proportions we used a Bayesian Dirichlet regression and for all other variables we used a Bayesian gamma regression with log link to estimate the effects of all predictors on each variable. For each missing data point, we used the median of their predicted posterior distribution as the imputed value for all subsequent analyses. All predictor variables are centered and scaled by two standard deviations. All models were fitted using Stan and implemented with brms in R. All models converged (i.e., diagnostics for all parameters showed $0.99 < \hat{R} < 1.01$, $n_{eff}/N > 0.1$, and no divergent transitions) after 5000 iterations run on 4 chains. For the gamma regressions, the following hyperpriors were implemented on the coefficients (m_i), intercept (b), and shape (α) parameter for the gamma:

$$m_i \sim normal(0{,}2.5)$$

$$b \sim normal(0{,}5)$$

$$\alpha \sim exponential(1)$$

All stressor estimates are provided in Table S11.

S3.4 Poultry estimates

To draw comparisons with poultry, often used as a relatively low-impact benchmark for animal protein, we re-modelled three chicken LCAs following the same impact assessment methods applied here. These systems were also the basis for our chicken by-product feed inputs. Inputs of electricity and energy carriers were extracted from Agri-footprint 5.0 processes. Feed compositions and FCRs were derived directly from poultry LCAs in the United States[32], Italy[33], and France[34]. Our poultry estimates therefore represent industrial poultry production in the US and Europe. Cases were run using the same model developed for aquaculture and were checked against GHG ranges from LCAs as reported by[52]. Poultry estimates are presented in Fig S14 and Table S7.

S3.5 Modelled scenarios

We first tested the influence of model parameters on estimated stressors by reducing each parameter by 10%, holding all other parameters constant, and computing the difference between the baseline and perturbed stressor. In the case of feed composition, when one feed component is decreased, the others are increased proportionally such that the proportions still sum to one.

To test the result of more realistic scenarios, we developed a series of intervention scenarios that shift parameters or constants, described in Table S8. We also ran the scenarios using economic allocation estimates for comparison (Fig S17–S18).

S4 Stressor estimates

S4.1 Aquaculture stressor estimate trade-offs

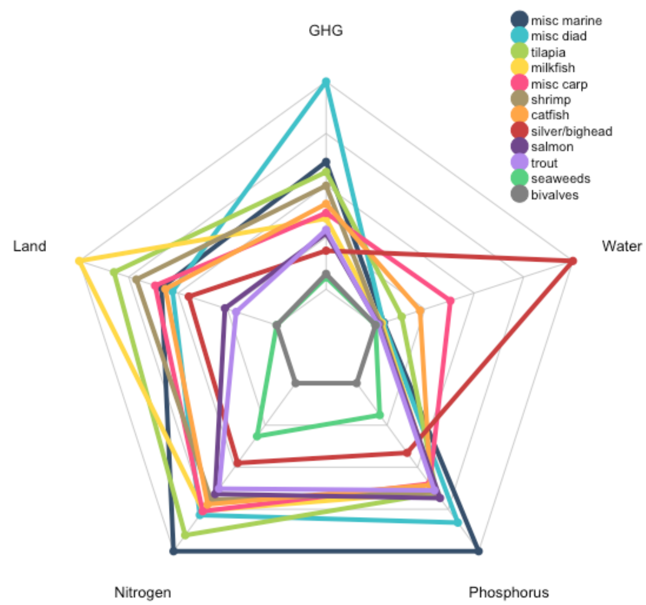

Fig S5 | Spider diagram of mean stressor estimates for aquaculture taxa groups. Mean stressor estimates are displayed along each spoke to illustrate the trade-offs across stressors among the taxa groups. Values represent normalized stressors from 0 to 1 calculated as stressor / max(stressor). In the case of N and P, which include negative values, we normalize the min/max values. Capture taxa groups are not displayed since the non-GHG stressors are all zero in our simplified model.

S4.2 Aquaculture stressor estimates by source

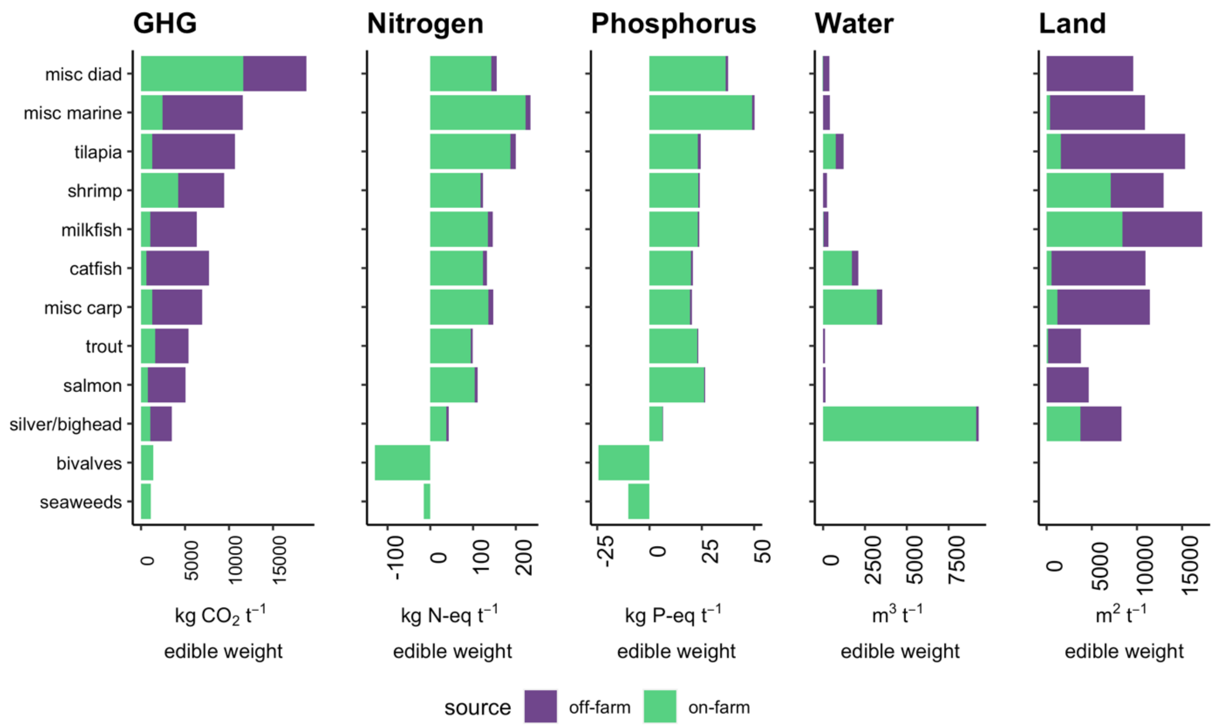

Fig S6 | Stressor estimates by feed-associated versus on-farm component. Units: GHG emissions (kg CO2-eq t^{-1}); Land use (m^2a t^{-1}); Water use (m^3 t^{-1}); N (kg N-eq t^{-1}); P (kg P-eq t^{-1}).

S4.3 Stressor estimate distributions

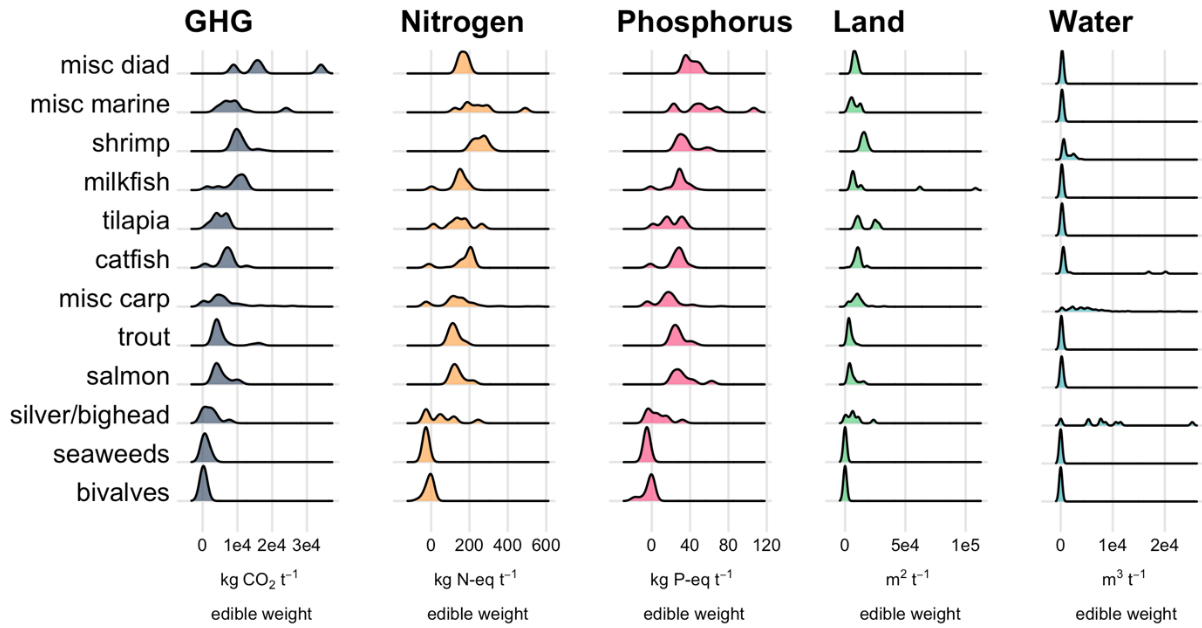

Fig S7 | Stressor estimate distributions by taxa. Within a taxa group, GHG emissions may vary more than 20-fold, N/P emissions vary up to 12-fold, and land and water vary up to 22-fold.

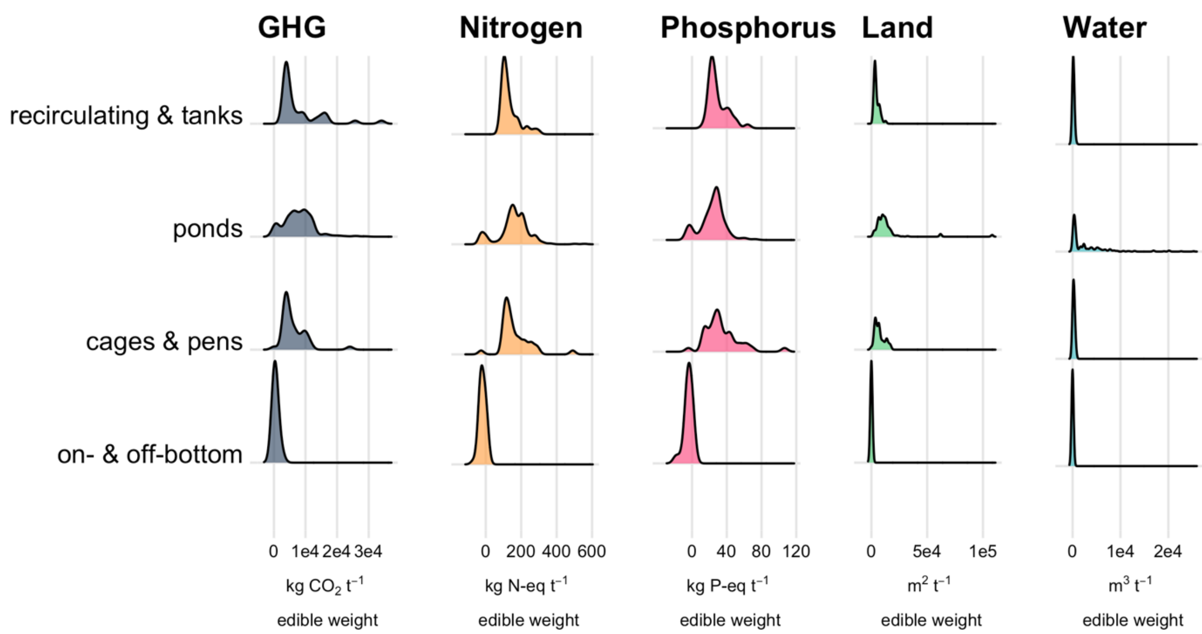

Fig S8 | Stressor estimate distributions by production system

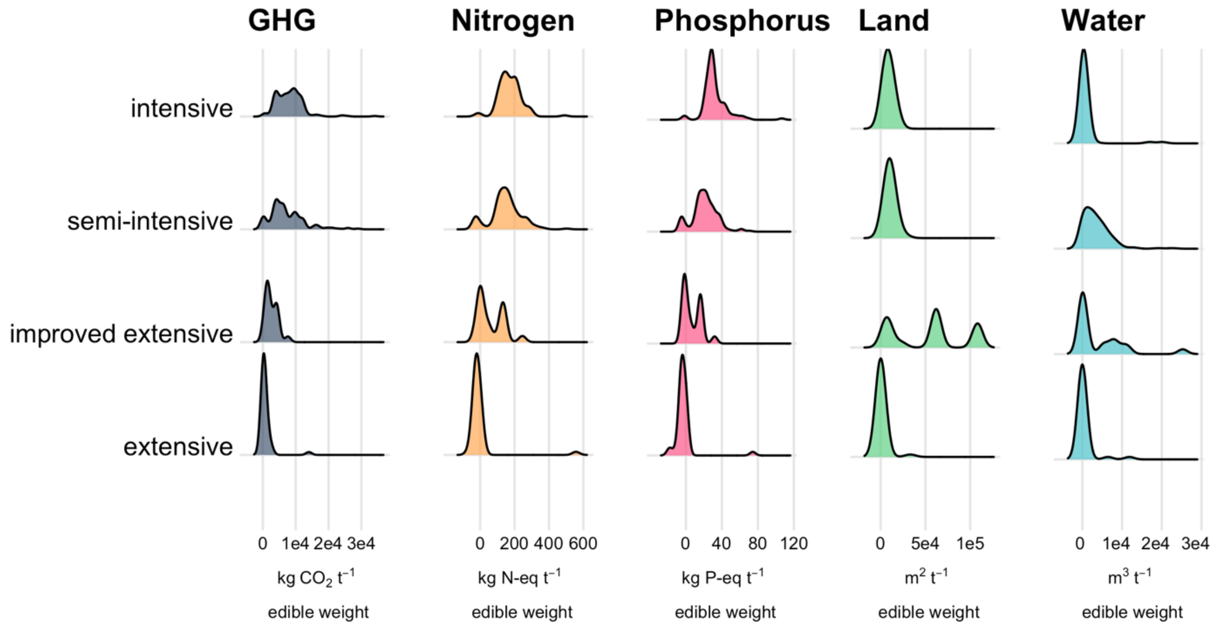

Fig S9 | Stressor estimate distributions by intensity

Table S4 | Correlations among stressors. The correlation matrix among the stressors represents Pearson's correlation coefficient across all stressor observations.

	GHG	N	P	Water	Land
GHG	1.00	0.72	0.77	-0.18	0.57
N	0.72	1.00	0.95	-0.05	0.77
P	0.77	0.95	1.00	-0.12	0.64
Water	-0.18	-0.05	-0.12	1.00	0.12
Land	0.57	0.77	0.64	0.12	1.00

S4.4 Stressor estimates expressed in terms of live weight

In addition to the results expressed in terms of edible portion in the main text, we also provide the estimates in terms of live weight equivalents (Fig S10).

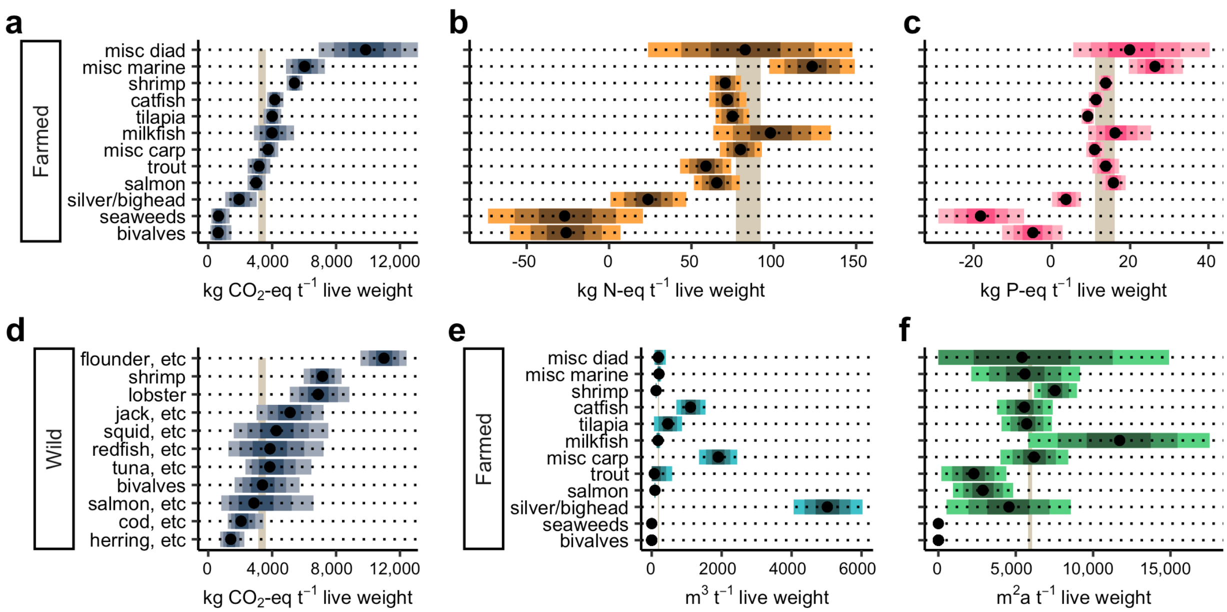

Fig S10 | Stressor posterior distributions. Panels represent a) Aquaculture GHG emissions (kg CO2-eq t-1); b) Aquaculture N (kg N t-1); c) Aquaculture P (kg P t-1); d) Capture GHG emissions (kg CO2-eq t-1); e) Aquaculture Water use (m3 t-1); f) Aquaculture Land use (m2a t-1). Values represent tonnes in live weight equivalents and use mass allocation. Dot indicates the median, colored regions show credible intervals (i.e., range of values that have a 95% (light), 80%, and 50% (dark) probability of containing the true parameter value). Taxa group names are abbreviated ISSCAAP names (e.g., flounder, etc refers to flounders, halibuts, soles; See Table S2 for definitions). Beige bands represent chicken min to max range

S4.5 Aquaculture stressor estimates with economic and energy allocation

We modeled the stressors using economic and energy allocation as a sensitivity analysis and to inform on the possible differences in results using different allocation methods often used in the LCA literature.

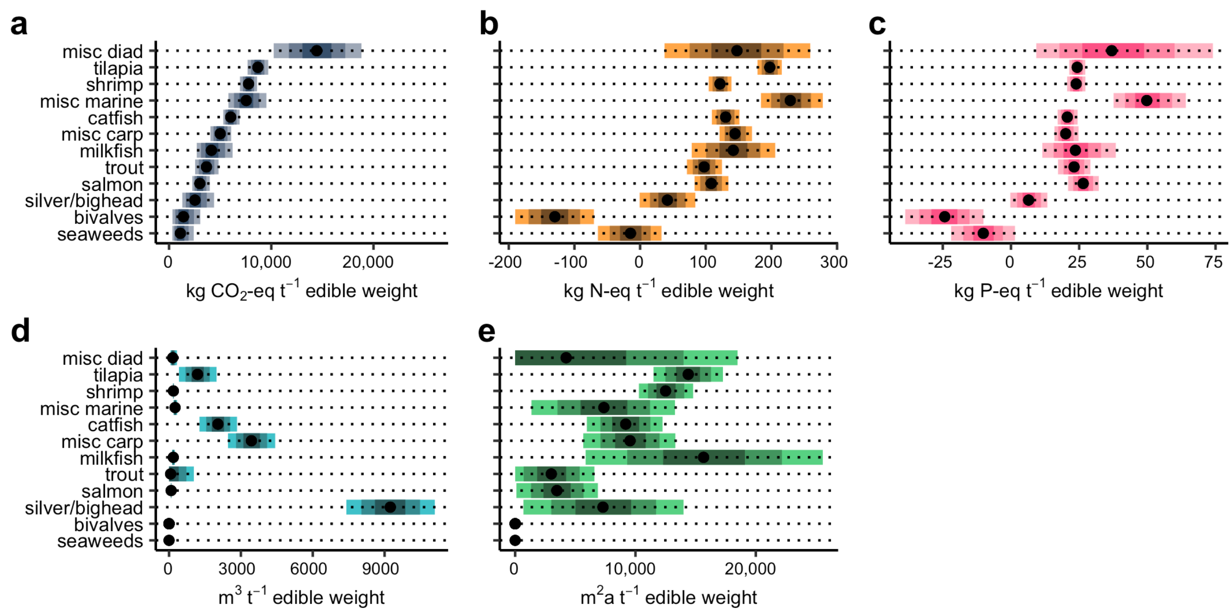

Fig S11 | Total stressor estimates using economic allocation. Posterior distributions by taxa for aquaculture include: a) GHG emissions (kg CO2-eq t^{-1}); b) N (kg N t^{-1}); c) P (kg P t^{-1}); d) Water use (m3 t^{-1}); e) Land use (m^2a t^{-1}). Values represent tonnes in edible portion equivalent and use economic value allocation. Intervals show 95% (light), 80%, and 50% (dark) credible intervals. Dot indicates the median. Taxa groups are abbreviated as follows: silver/bighead = silver or bighead carp; misc diad = miscellaneous diadromous fishes; misc marine = miscellaneous marine fishes. No data was available for wild capture fisheries.

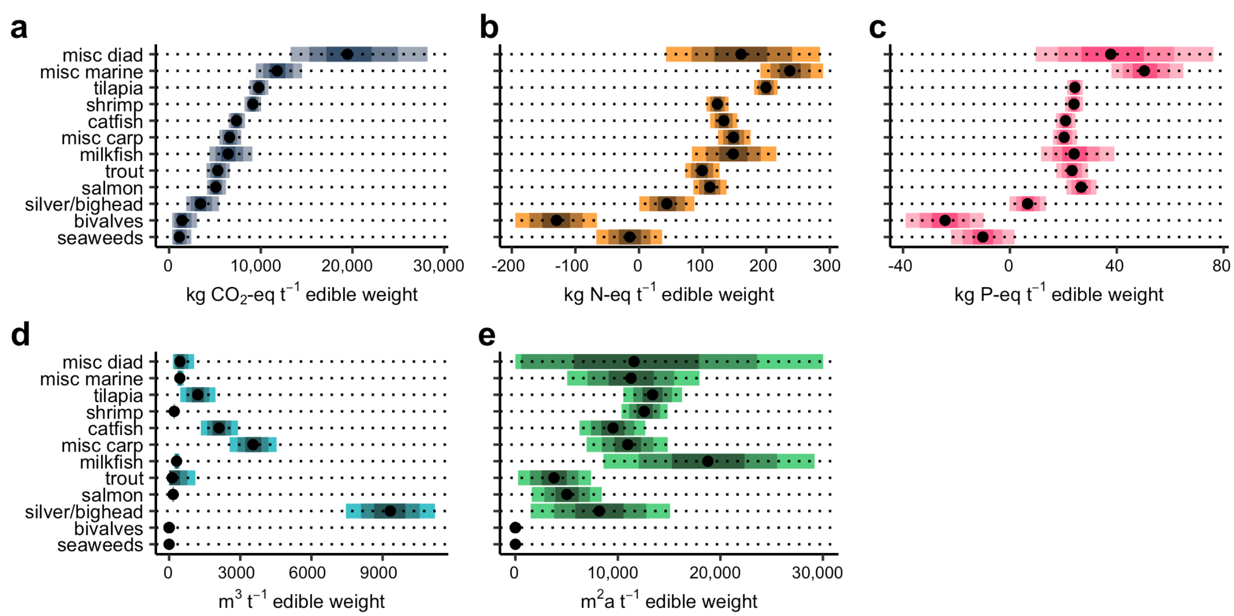

Fig S12 | Total stressor estimates using energy allocation. Posterior distributions by taxa for aquaculture include: a) GHG emissions (kg CO2-eq t^{-1}); b) N (kg N t^{-1}); c) P (kg P t^{-1}); d) Water use (m3 t^{-1}); e) Land use (m2a t^{-1}). Values represent tonnes in edible portion equivalent and use gross energy content allocation. Intervals show 95% (light), 80%, and 50% (dark) credible intervals. Dot indicates the median. Taxa groups are abbreviated as follows: silver/bighead = silver or bighead carp; misc diad = miscellaneous diadromous fishes; misc marine = miscellaneous marine fishes. No data was available for wild capture fisheries.

S4.6 Stressor estimates with weakly informative priors

Stressor estimates were largely similar whether the model was run with informative versus weakly informative priors (Fig. S10), however slight shifts were seen in the median and distributions When comparing tuna vs squid greenhouse gas emissions, tuna have higher emissions under the no priors scenario, while squid have higher emissions when priors are implemented. Wild salmon vs bivalves also switch in terms of their relative greenhouse gas emissions depending on whether priors are implemented or not. In all cases, however, the differences in the median estimate were less than 500 kg CO2-eq t^{-1}.

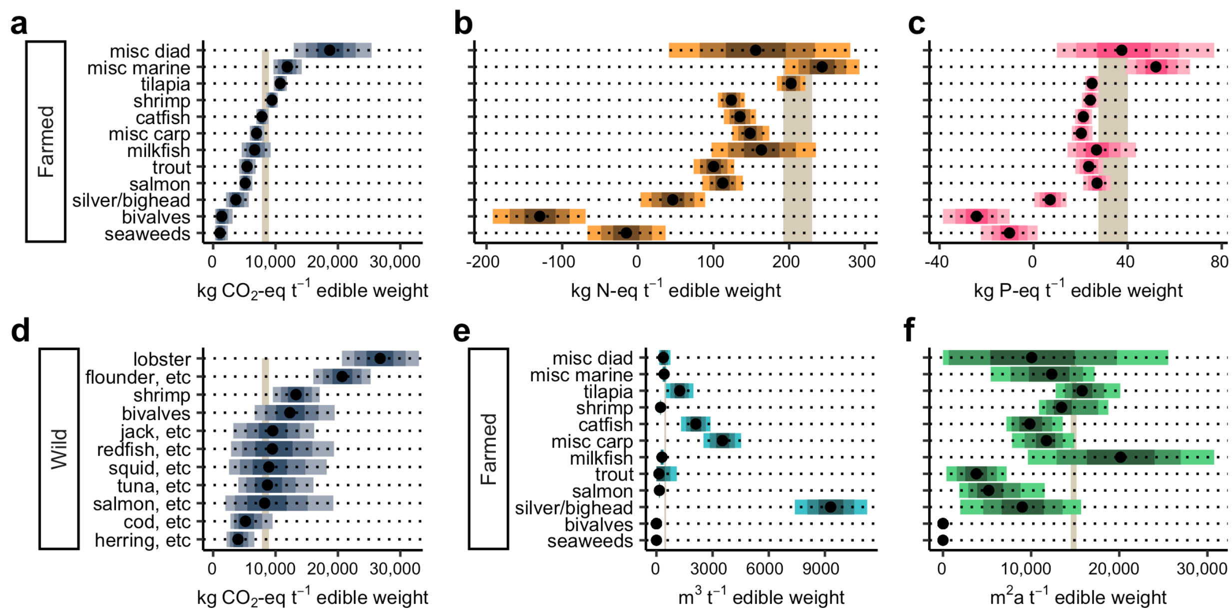

Fig S13 | Stressor estimates with weakly informative priors. Bands represent posterior distributions by taxa for a) Aquaculture GHG emissions (kg CO2-eq t^{-1}); b) Aquaculture N (kg N t^{-1}); c) P (kg P t^{-1}); d) Capture GHG emissions (kg CO2-eq t^{-1}); e) Aquaculture Water use (m3 t^{-1}); f) Aquaculture Land use (m2a t^{-1}). Values represent tonnes in edible portion equivalent and use mass allocation. Intervals show 95% (light), 80%, and 50% (dark) credible intervals. Dot indicates the median. Taxa groups are abbreviated as follows: silver/bighead = silver or bighead carp; cod, etc = cods, hakes, haddocks; flounder, etc = flounders, halibuts, soles; herring, etc = herrings, sardines, anchovies; jack, etc = jacks, mullets, sauries; misc diad = miscellaneous diadromous fishes; misc marine = miscellaneous marine fishes; redfish, etc = redfishes, basses, congers; salmon, etc = salmons, trouts, smelts; squid, etc = squid, cuttlefishes, octopuses; tuna, etc = tunas, bonitos, billfishes. Beige bands represent chicken min to max range.

Table S5 | Feed conversion ratio priors Feed conversion ratio priors applied based on expert judgement.

Group name	Ave FCR	Upper FCR	Lower FCR
Grass carp	1.8	3.2	1.2
Crucian carp	1.4		0
Common carp	1.5		0
Silver and bighead carp	0	0	0
Tilapias and other cichlids	1.6	2.1	1.2
Miscellaneous freshwater fishes	1.8	2	1.5
Salmon	1.1	1.3	1
Trouts	1.1	1.4	1
Milkfish	1.5	1.9	1.3
Freshwater crustaceans	1.7	4.5	0
Shrimps, prawns	1.3	2.2	0
Oysters	0	0	0
Mussels	0	0	0
Aquatic plants	0	0	0

S4.7 Stressor estimates for poultry

We used several sources to derive poultry's muscle fraction from live weight. In these sources we extracted the carcass weight (eviscerated weight) and the relative weights of the main prime cuts. Using muscle fractions from those prime cuts, we derived total muscle from carcass weight, and consequently from live weight (see Table S6). We only list single values although the values presented in those references varied slightly based on sex or feed regimes. Based on these estimates, we apply an edible portion from live weight value of 40% for poultry.

Table S6 | Poultry edible portion calculations.

Reference	Item	Carcass weight	wing	thigh	Drum-stick	breast	back	neck	Muscle from live weight
Lukaszewics 2014	Fraction (%)	75							
	Muscle (% of carcass)			21		27			48%×75%=**36%**
Preston 1972	Fraction from carcass weight (%)	71	12	17	16	27	19	4	71%×(12%×39% +17%×75%+16% ×64%+27%×68 %+19%×43%) = **38%** 0r based on 58% whole carcass: 58%×71% = **41%**
	Muscle (%)		39	75	64	68	43		
Moran 1990	Fraction from carcass weight	67	14	19	16	30	13	7	67%×(14%×38% +19%×67%+16% ×55%+30%×75 %+13%×40%+7 %×47%) = **39%** 0r based on 58% whole carcass: 58%×67%=**39%**
	Muscle %		38	67	55	75	40	47	

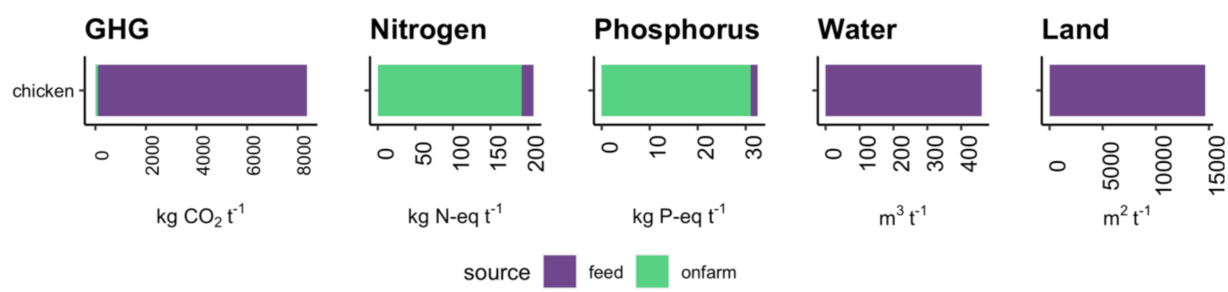

Fig S14 | On- and off-farm poultry stressor estimates. Stressor estimates represent GHG emissions (kg CO2-eq t^{-1}), Land use (m2a t^{-1}), N emissions (kg N-eq t^{-1}), P (kg P-eq t^{-1}), and Water use (m^3 t^{-1}).

Table S7 | Poultry model stressor estimates. Minimum, median, mean and maximum total stressor estimates for poultry (edible portion) for GHG emissions (kg CO_2-eq t^{-1}), Land use (m_2a t^{-1}), N emissions (kg N-eq t^{-1}), P (kg P-eq t^{-1}), and Water use (m^3 t^{-1})

	Total GHG	**Total N**	**Total P**	**Total Land**	**Total Water**
Min	7817	192.2	28.4	14485	424.5
Median	8335	204.1	30.5	14525	454.7
Mean	8365	207.3	32.5	14664	459.7
Max	8973	228.8	40.3	15119	505.0

S5 Analysis of levers

Table S8 | Intervention scenario descriptions

Name	**Description**	**Example impact magnitude or policy**
FCR lower 20th	Move all taxa observations to the 20th percentile FCR value	**Improved husbandry:** Selective breeding showed 18.4% increase in survival and additionally 21.2% increase in weight gain compared with the unselected control group (Dey et al. 2020; Argue et al. 2002).
		Feed improvements: Shift from farm-made feed to pelleted feeds reduced FCR in Pangasius from 2.25 to 1.69. (Phan et al. 2009)
		Genetic improvements: Average reduction in FCR of 13% on avg. across species (Gjedrem & Rye 2018)
Replace FMFO with deforestatio n-free soy	Replace FMFO portion of feeds with land change-free soy based on US	Replacement of fish oil with soy or with by-product would reduce the forage fish dependency ratio. A substitution of fish oil with plant oils (rapeseed, palm and camelina) in salmon feed is associated with an estimated 18% rise in CO^2-eq . Replacing fish meal with plant ingredients in shrimp feeds is associated with a 67% increase in land occupation and 63% in water consumption .
Replace FMFO with fish by-products	Replace FMFO portion of feeds with fishery by-product impact factors	The replacement of fishmeal and fish oil with fishery and aquaculture by-products, including with low-impact fishery by-products has been discussed to reduce reliance on reduction fisheries. This includes the Organic Standards for Aquaculture 2020 (https://www.soilassociation.org/media/18611/soil-association-eu-equivalent-standards-aquaculture.pdf) and other certification standards, such as ASC, Global GAP, BAP. There are also initiatives from major feed suppliers.
Replace FMFO with low impact fishery by-products	Replace FMFO portion of feeds with low-impacts fishery by-product impact factors (based on Alaska pollock by-products)	
Yield upper	Move all taxa	Opportunities to improve yield include disease management

20th	observations to the 20th percentile yield value	policies[55] as well as improved farm management[56].
13% more catch with 56% of the effort	Best management resulting in 13% more catch and 56% of the effort	A suite of fishery management best practices could increase catch, while decreasing the effort (and therefore the emissions per tonne)[57]
Min GHG gear-type	Switch gear to min. GHG per species	There is substantial variability in greenhouse gas emissions associated with different gears. This scenario represents an optimization of gear type by species.
Changes to constants		
Deforestation-free soy & crops	Source crops and soy from non-rainforest depleting sources	Land use change for soy and other crops is a major source of greenhouse gas emissions for feeds. Eco-certification of crops and traceability programs that aim to eliminate soy and other crops associated with deforestation would reduce the emissions associated with these crops. Notably, this could reduce emissions associated with a farmed fish product, but may not reduce total emissions given the integrated nature of the soy and feed-crop markets and the demand for these products in other sectors.
Zero emission electricity	Assume zero emissions associated with on-farm energy use	Decarbonising the global energy system, including that used by fisheries and aquaculture, is a prerequisite for reaching the Paris Agreement of limiting global warming to 2°C (and aiming for 1.5°C; Willett et al. 2019). This would entail on-farm energy use would be associated with zero emissions.

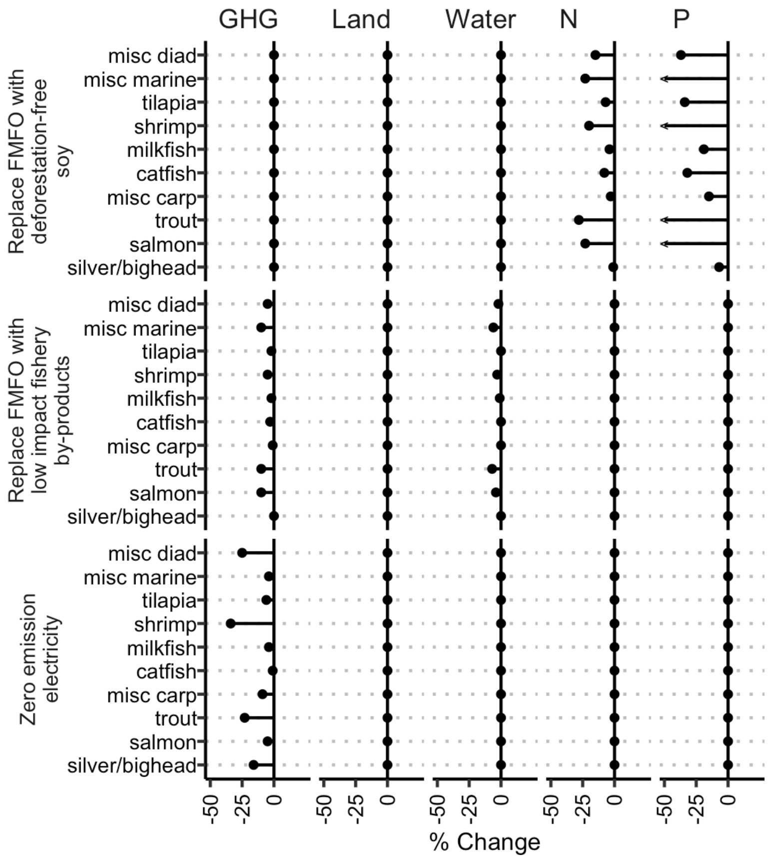

Fig S15 | Additional aquaculture scenario results. Change (%) in stressor values three additional scenarios (using mass allocation; defined in Table S5) relative to the current estimate.

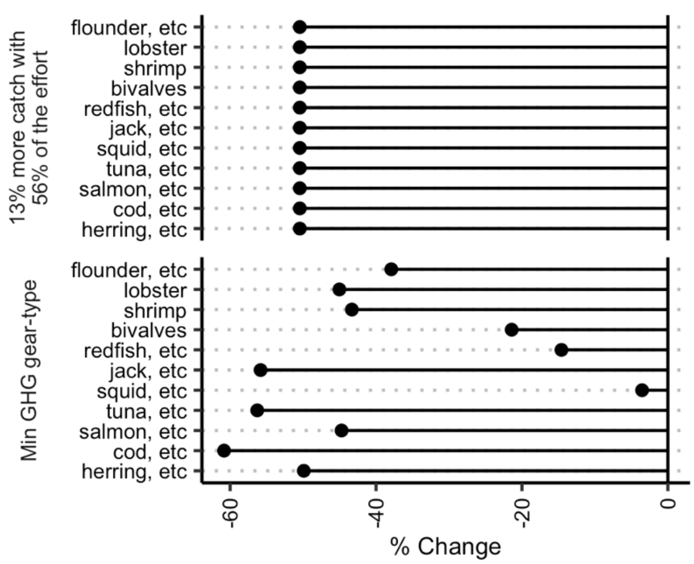

Fig S16 | Capture fishery scenario results. Change (%) in GHG emissions under a scenario with catching 13% more fish with 56% of the effort, as in[57] and a scenario where all species catch is with the gear type with the lowest GHGs.

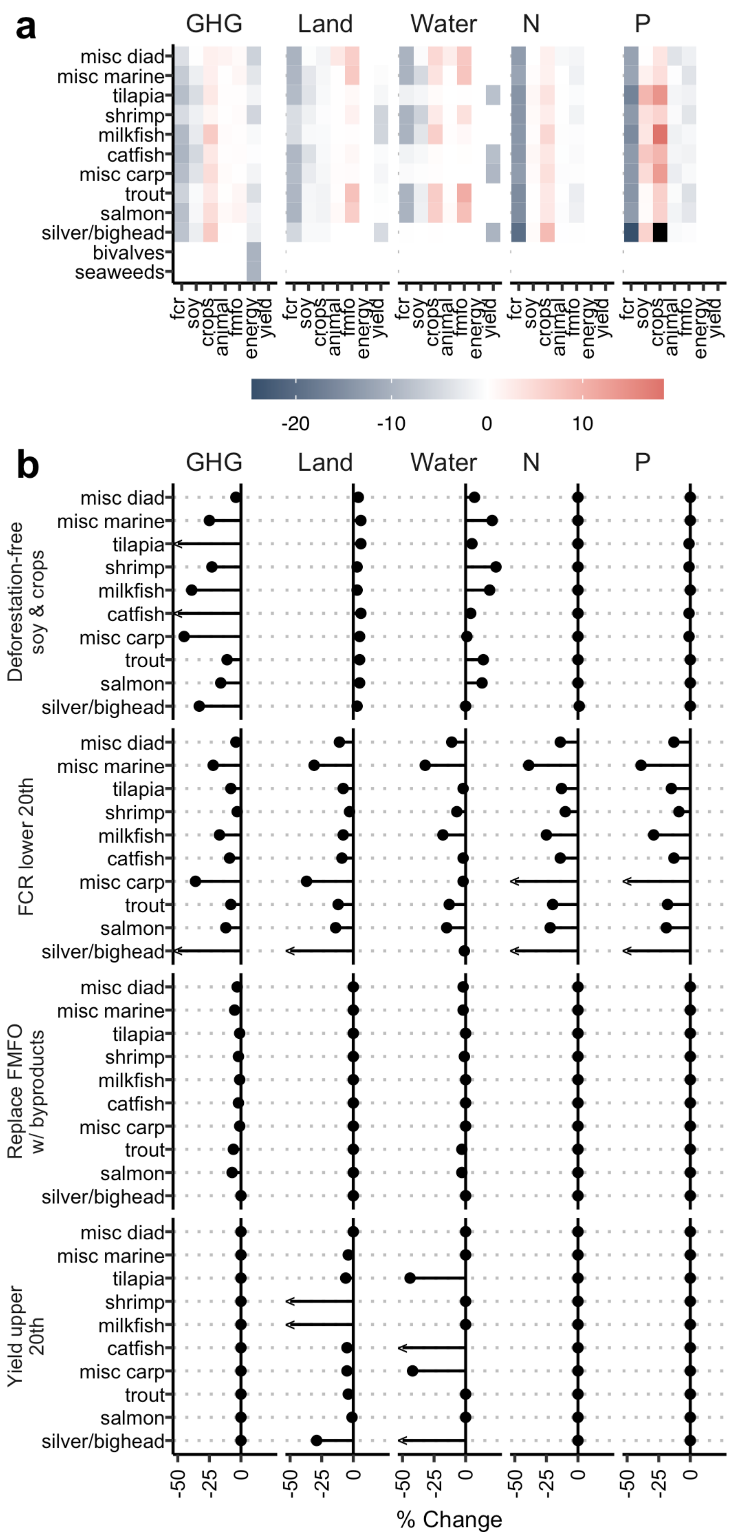

Fig S17 | Lever and scenario analysis from Fig 4 using economic allocation. a) Change (%) in each stressor associate with a 10% reduction in the parameter value (black cell indicates stressor change >20%); b) Change (%) in each stressor under four scenarios (defined in Table S5). Arrows indicate changes greater than 100%.

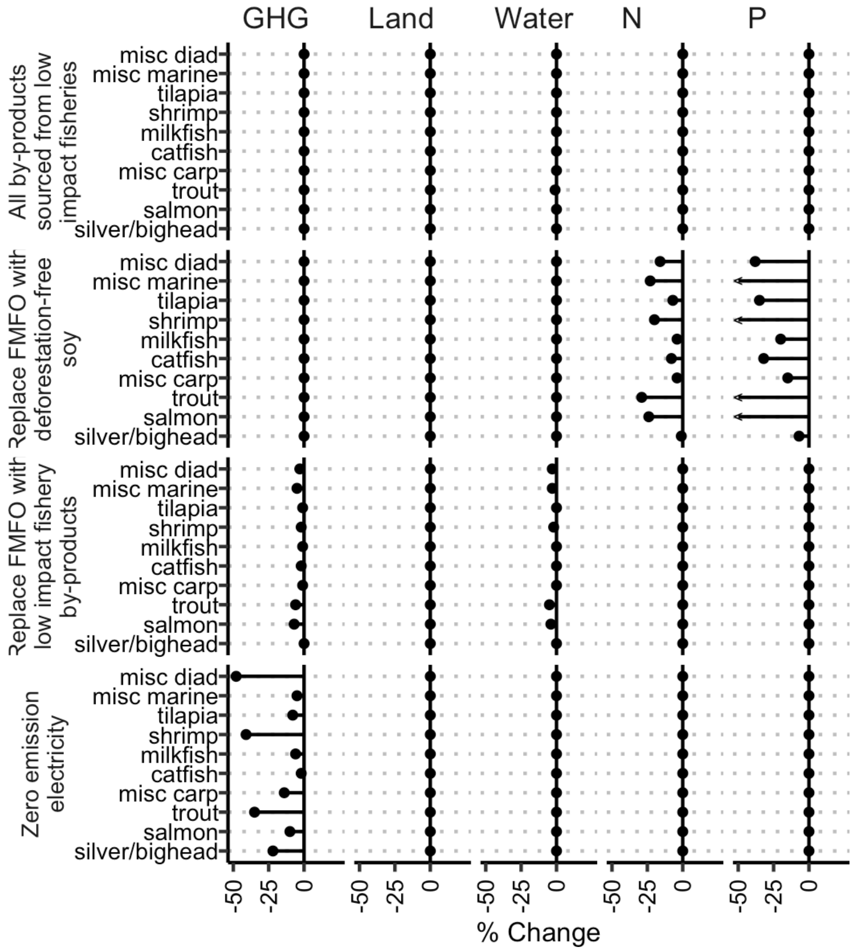

Fig S18 | Additional aquaculture scenario results using economic allocation. Change (%) in stressor values in additional scenarios (using economic allocation; defined in Table S5) relative to the current estimate.

Tables S9-S11 are included as Supplementary Table csv files.

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