

Vulnerability of blue foods to human-induced environmental change

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Supplemental Information

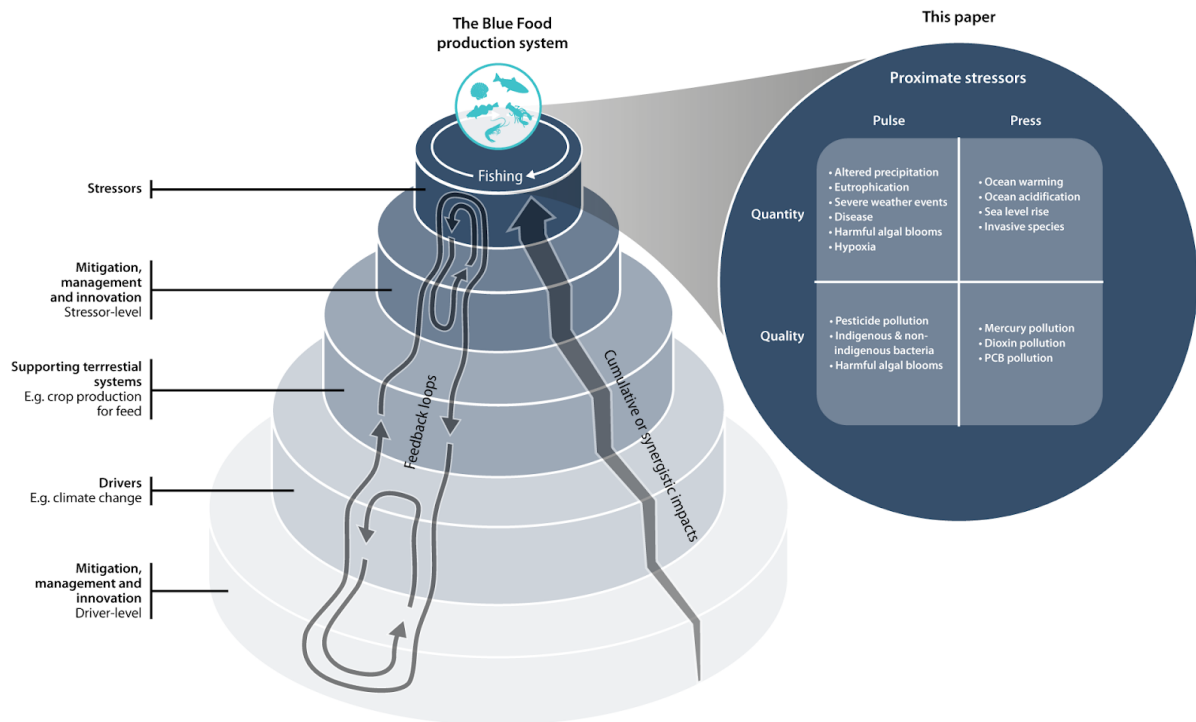


Figure S1. A conceptual framework for analysis in the broader context of the blue food production system. Layers of the cake indicate the hierarchy and scale of impacts on aquatic food production systems and human mitigation efforts, from the first level of underlying drivers (e.g., climate change), to the influence of linked terrestrial systems (e.g., nutrient inputs) and the resulting direct stressors for which vulnerability assessments are performed (e.g., eutrophication). Feedback loops indicate the potential ameliorative effect of human mitigation efforts at the driver and stressor levels. Gray arrows indicate the potential for cumulative and/or synergistic impacts on production systems as consecutive layers are considered. The fishing feedback loop indicates the unique self-impacting nature of wild capture fisheries as both a production system and a stressor, and consequently fishing is not included in our assessment. The zoomed-in matrix indicates the nature of the focal stressors as addressed in this study - including effects on both quantity and quality (food safety) and the distinction between pulse and press type of stress.

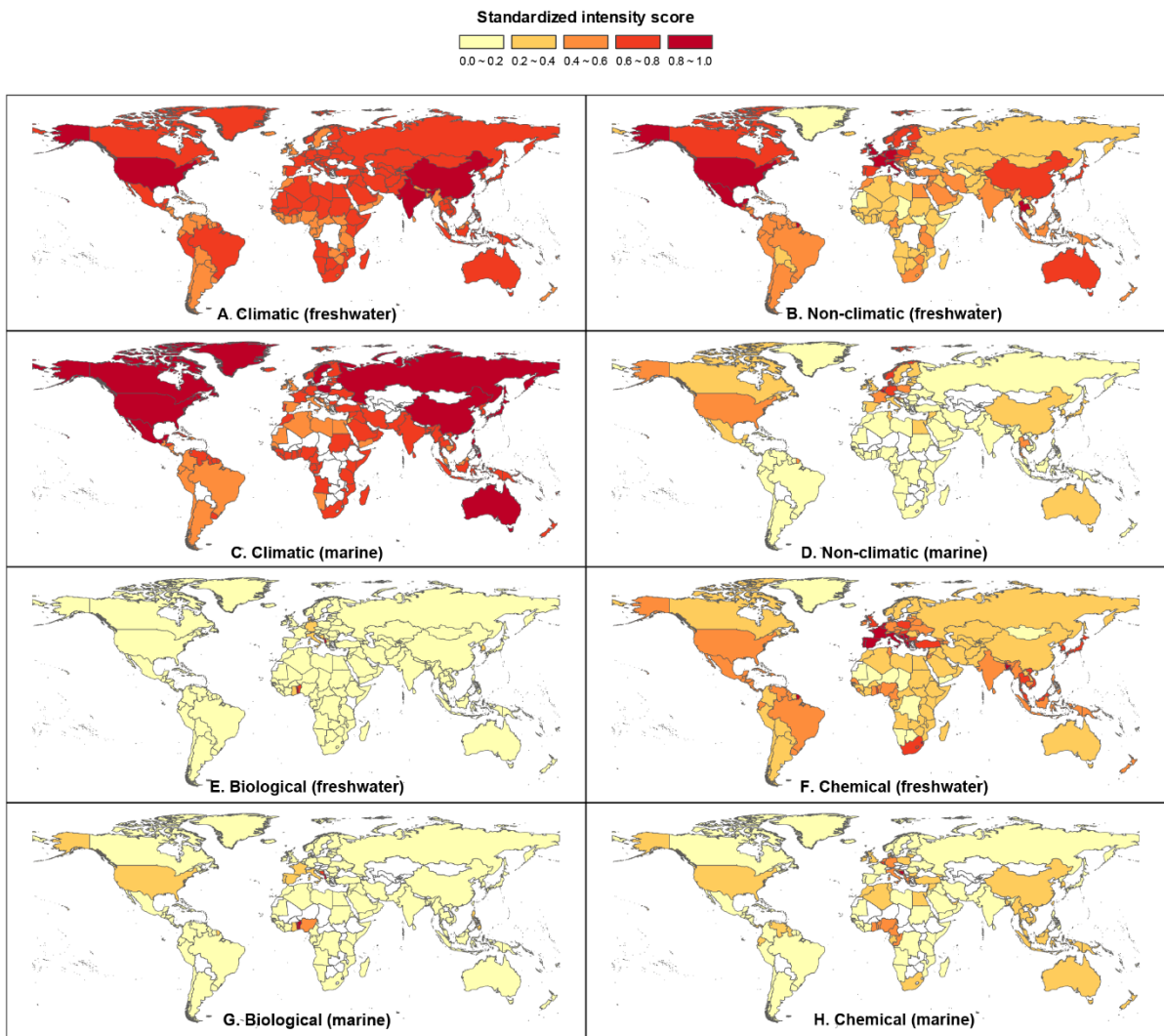


Figure S2. Intensity of environmental stresses affecting blue food production quantity (A-D) and safety (E-H). Results were standardized and presented at the national level.



Figure S3. Standardized predicted impact on blue food production by continent: (a) production quantity; (b) food safety. Box limits indicate lower and upper quartiles; horizontal lines are median values; whiskers indicate minimum and maximum values of 1.5 times the interquartile range; solid points on the symmetry axis of each box are outliers.

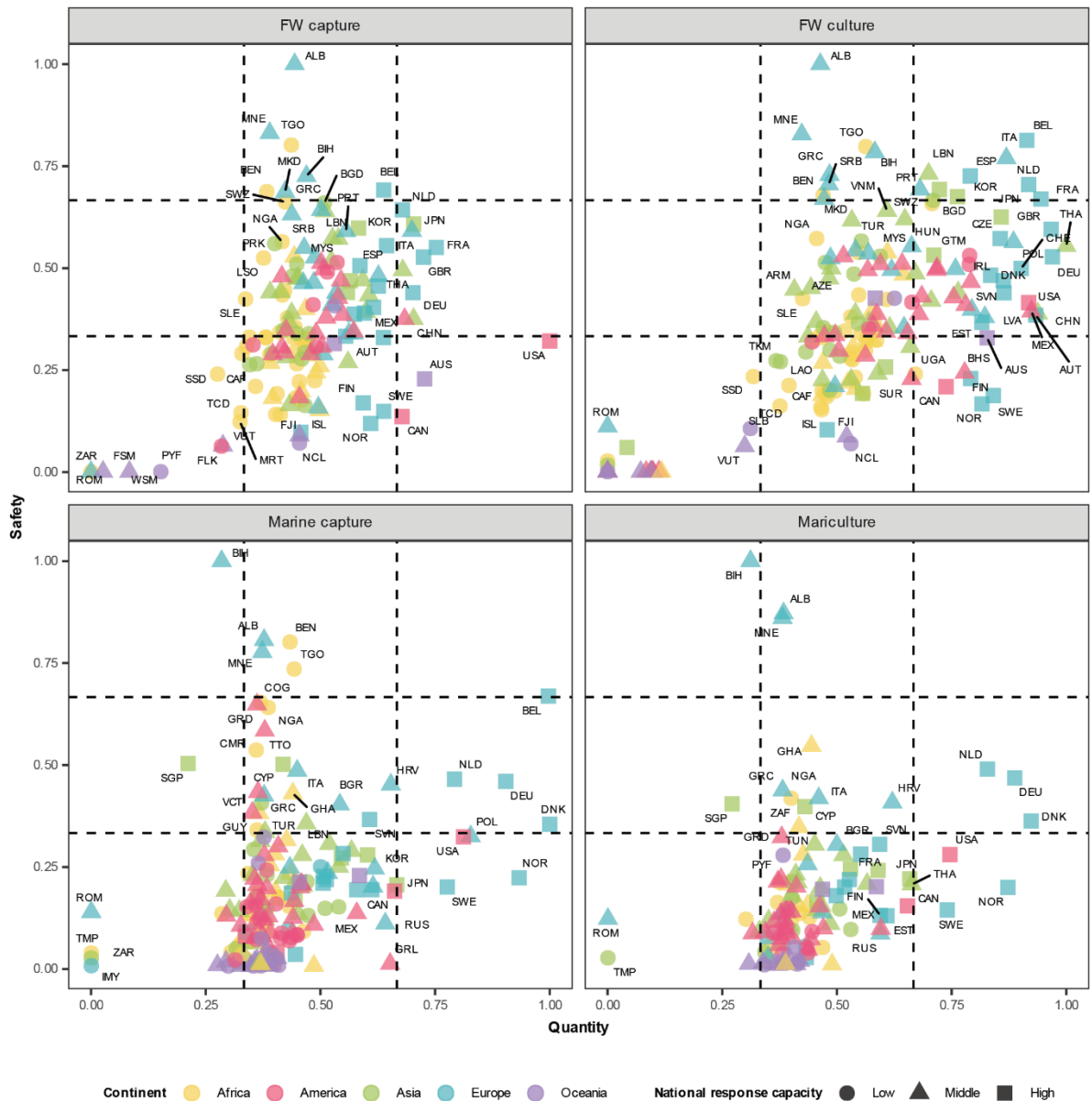


Figure S4. Standardized predicted impacts on the quantity versus food safety of blue food production by country. Country names are abbreviated according to the International Organization for Standardization (ISO) three-digit standard country code. The dashed lines indicate the one-third division lines of the maximum values of the horizontal and vertical axes. Triangles, squares, and circles indicate low, medium, and high national response capacity, respectively. The colors represent the continent in which each country is located.

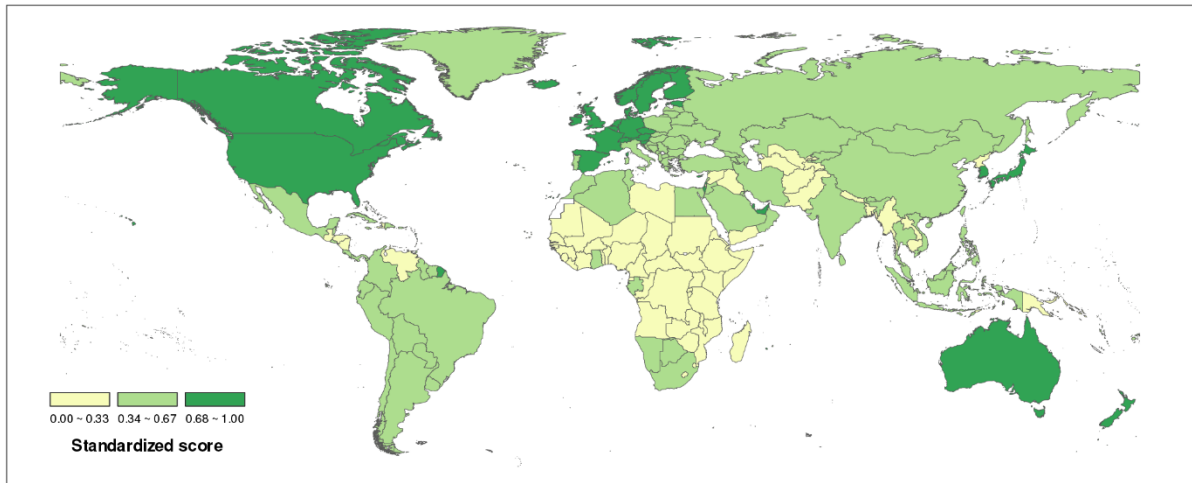


Figure S5. Standardized scoring of national response capacity based on human development, governance, and economic status. Low, medium, and high national response capacities were defined as standardized values of 0.00 to 0.33, 0.34 to 0.67, and 0.68 to 1.00, respectively.

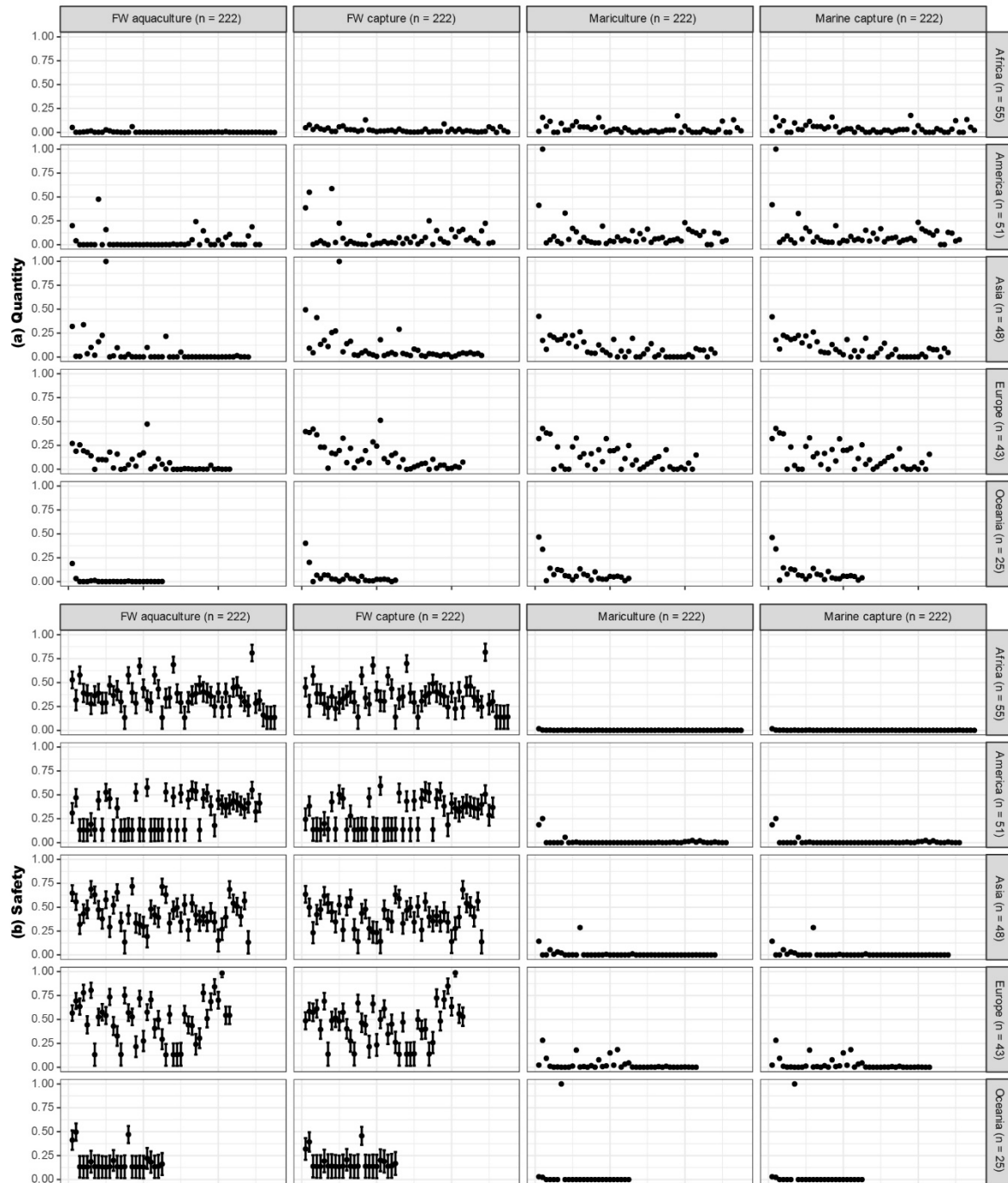


Figure S6. Uncertainty of the predicted impact on blue food production by continent: (a) production quantity; (b) food safety. The X-axis represents countries listed by country name to prevent each country from stacking on top of each other and to give the chart better readability. The Y-axis indicates the original predicted impact scores. Each solid point represents a country. Solid points are the mean values of the predicted impacts and bars are their standard deviations.

Full Details of Expert assessment protocol

In the first expert assessment, experts were asked to individually answer one main question: “What are the main blue food systems and archetypes?”. To represent the diversity of blue food systems and capture how each system will be affected by environmental stressors, we initially classified production into freshwater and marine systems, inclusive of both capture fisheries and aquaculture. Archetypes were then developed through a series of workshops with the co-author team, alongside discussions of the scope of the paper. Following such discussions, it was agreed that categorization should aim to represent dominant global production systems and, in particular, to categorize these systems by aspects that affect their vulnerability to stressors. The defining characteristics of such systems are linked broadly to the habitats or environments utilized, and the species targeted or cultured. Further discussion refined these aspects to be broadly dominated by operation-type and target environment for fisheries, and operation-type and taxa produced for aquaculture. A resulting initial long list of 28 production types was then refined for feasibility to the final 15 archetypes with the aim to best capture differences with respect to how stressors may impact production.

In the second expert assessment, all experts were firstly given the results of environmental stressors screened from the literature, and were asked two questions: “Which of the stressors are reasonable to be retained in this research?” and “What are the indicators available for each stressor?”. Each expert was then asked to write down their responses independently. All responses were collected and synthesized by the facilitator, and anonymous results were returned to all experts, thus allowing them to give the 2nd round of feedback accordingly. This step was repeated until none of the experts disagreed, thus reaching a consensus.

In the third expert assessment for vulnerability scoring, co-authors were divided into six groups based on their expertise to process and synthesize information related to archetypes, ranging from species to system level, which was obtained from the literature review. Each expert group was responsible for a different subset of archetype-stressor combinations. Each expert in the same group was asked to give an individual confidence score for each archetype-stressor assessment. Individual confidence scores were subsequently synthesized and shared with the entire co-author team to allow for feedback until a consensus was reached.

Based on the literature screening results, vulnerability levels were qualitatively defined by co-authors as: (1) High: System performance or safety severely impacted; (2) Medium: System performance or safety moderately impacted, or a moderate subsection of the system was impacted; (3) Low: Low impact on performance at the system level, or a minor subsection of system was impacted; (4) None: No impact. Then vulnerability of a high-level blue food production system to a specific stressor

was determined as the mode value of archetype vulnerability levels in that system (Table S2). The final results were placed in a pre-coded Excel template and shared with all experts. Feedback was incorporated and shared again with the entire team. This step was repeated until a consensus was reached.

Meanwhile, co-authors also discussed and quantified the uncertainty of each vulnerability score for each archetype-stressor assessment in order to communicate the level of our “confidence” in the validity of the result (Gardali et al., 2012; Case & Lawler, 2016). Confidence scores were defined as: (1) Sufficient: A sufficient amount of evidence existed for this assessment to be made, such as a relevant review. Impacts were communicated in the primary policy narratives, and the papers were largely up to date (<10 years); (2) Partial: A robust level of evidence existed, but with gaps in knowledge or some difficulty in aligning evidence directly with the archetype categorization. The papers were relatively up to date (<20 years); (3) Poor: Largely theoretical evidence or poor empirical research that may only loosely align with the archetype categorization, and few recent papers. (4) None - No evidence was found. Each expert group was responsible for a different subset of archetype-stressor combinations.

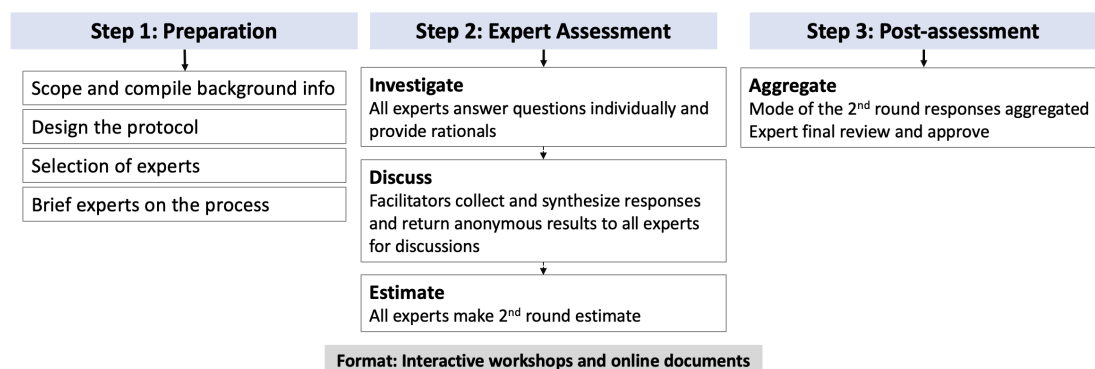


Figure S7. Flow diagram for the expert assessment protocol (Adapted from Hanea et al., 2016 and Hemming et al., 2018).

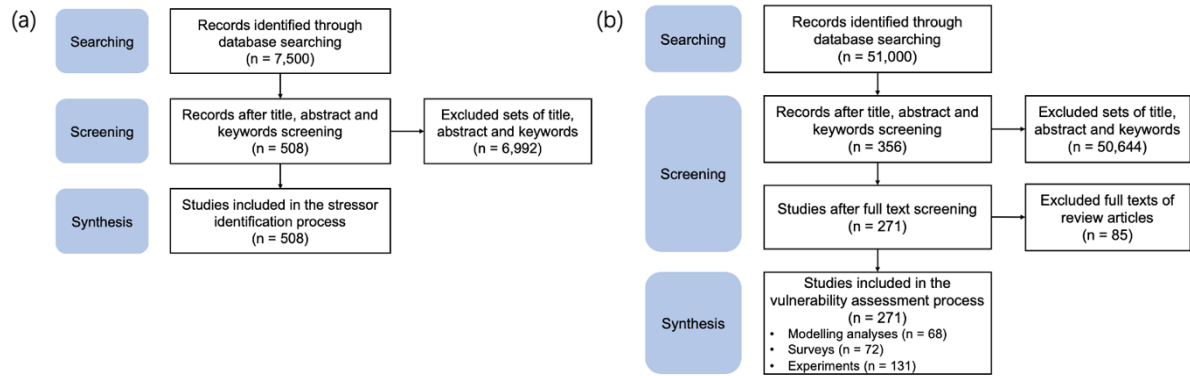


Figure S8. Flow diagrams for the literature review process: (a) stressor identification; (b) vulnerability scoring.

Sample case studies: methods and results

We assessed the expected consequence of anthropogenic pressures on the quantity of food in two related ways: vulnerability to exposure and predicted impacts. Both were measured as a combination of the vulnerability of each aquatic food group to a stressor, the production amount of that food group, and the stressor intensity to which it is exposed. To assess vulnerability, we calculated the production-weighted average level of vulnerability to each stressor to which the food group was exposed in each half-degree cell. Stressors were rescaled to the maximum global value, such that each cell had a value from 0.0 to 1.0 for each stressor. We then created vulnerability-weighted stressor scores for each stressor-food group combination, where these rescaled stressor intensity values were multiplied by the categorical vulnerability score of the stressor (1.0 for high vulnerability, 0.67 for medium, 0.34 for low, 0 for none). Finally, using gridded production data, we calculated a production (tonnes) weighted-average of the vulnerability-weighted stressor scores. Thus, this measure provides an estimate of the likely proportional change in the quantity of food based on the amount of food produced, its vulnerability to a stressor, and the intensity of the stressor. Using this approach, a production system's maximum weighted average for each stressor will not exceed its vulnerability score. For example, a production system's weighted average of pressure exposure for a stressor of which it has a medium vulnerability score will not exceed 0.67.

We also measured and mapped the predicted impact, or expected change in production, by multiplying the production of each food group in each cell by an expected impact measure, essentially an inverse vulnerability-weighted stressor score. In this case, inverse vulnerability scores (i.e., 0 for high vulnerability, 0.33 for medium, 0.67 for low, and 1.0 for none) were multiplied by the rescaled stressor scores to create the expected impact measure that is used to modify production values. Thus, this measure provides an estimate of the likely absolute amount of food produced as a result of the stressor.

Using our measure of exposure vulnerability, we produced maps of how much of each aquatic food archetype is likely impacted by each stressor for which spatially-explicit data exists, as well as global summaries of the production-weighted average expected vulnerability to stressors (sample figures listed in Fig. S7). In both cases, the results accounted for the vulnerability of the archetype to the stressor, the amount of production of the archetype, and the spatial overlap of the stressor with the locations of food production. With impact maps, we found this overlap spatially. Higher impacts occurred in two types of locations: those with at least low vulnerability, high production, and high stressor intensity, or those with high vulnerability, at least some production, and some stressor intensity. With global weighted averages of expected vulnerability, spatial overlap plays a key role in driving results. For example, benthic systems have higher average stressor exposure to sea surface temperature (SST) and ocean

acidification (OA) than eutrophication due to high landings at extreme latitudes where SST and OA values are higher.

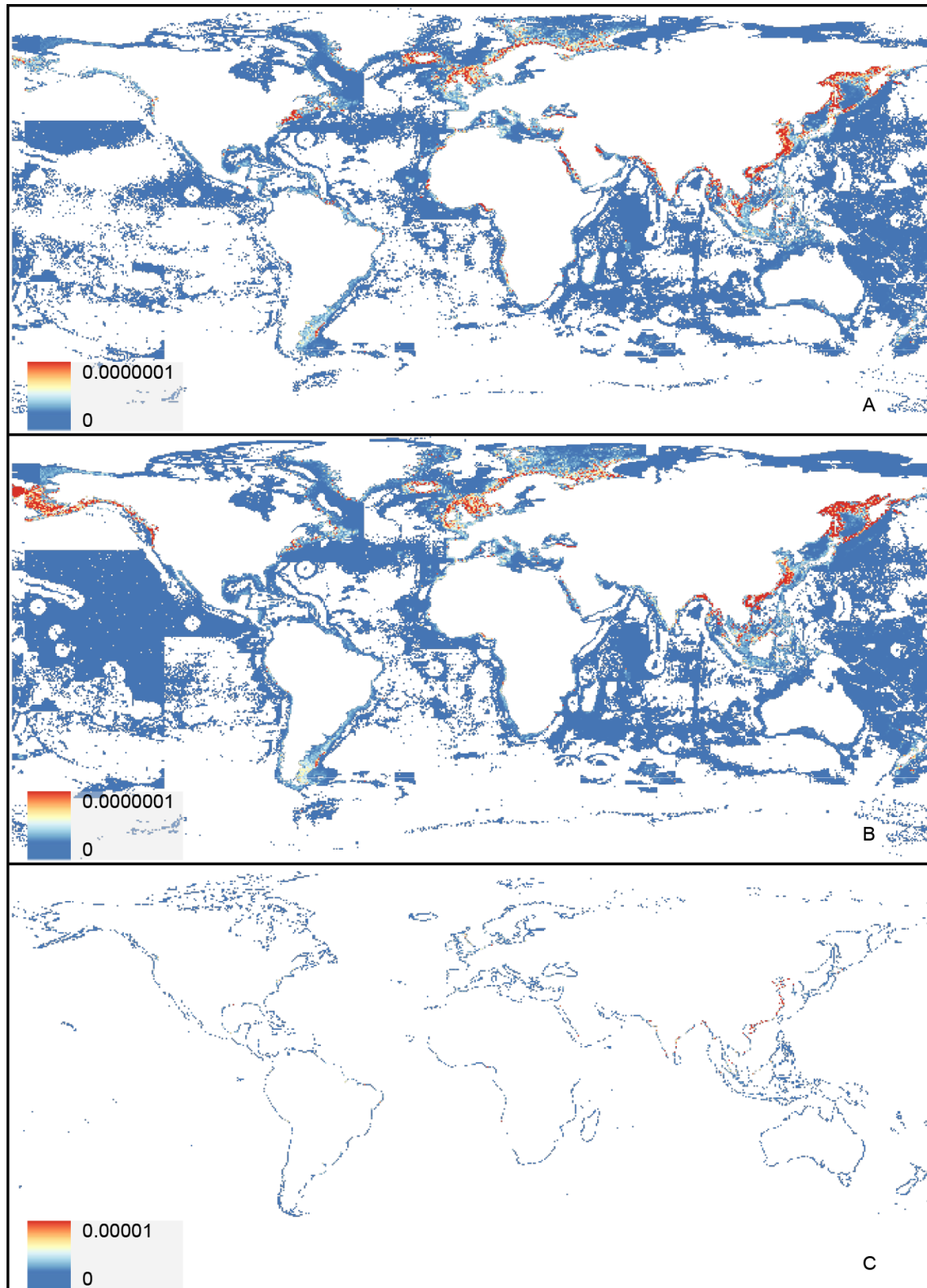


Figure S9. Exposure vulnerability of production quantity of benthic fisheries to (A) sea surface temperature, (B) acidification and (C) eutrophication.

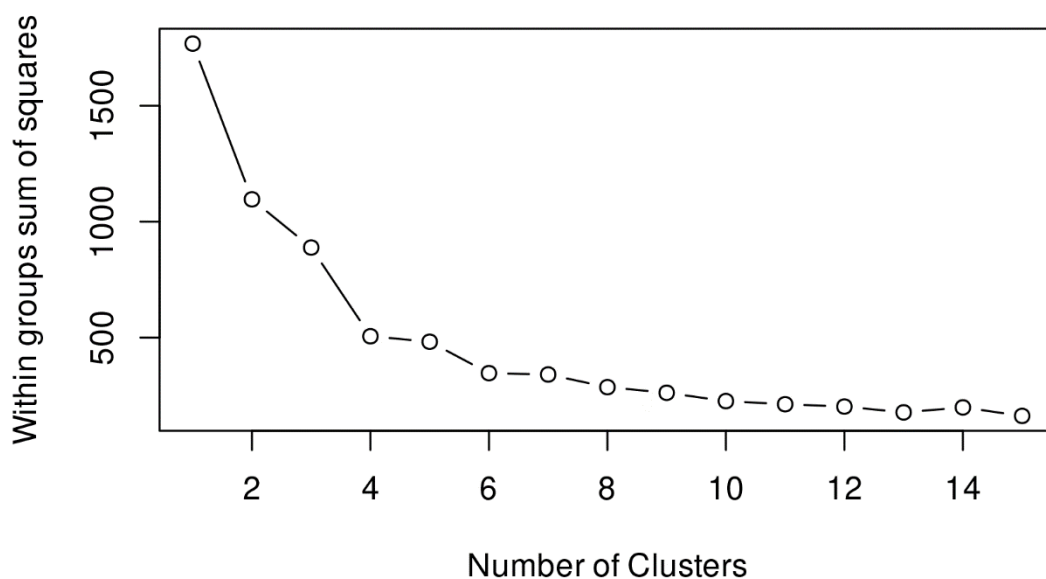


Figure S10. Scree plot of within-cluster sum of squares (WSS) for k varying from 2 to 15 clusters.

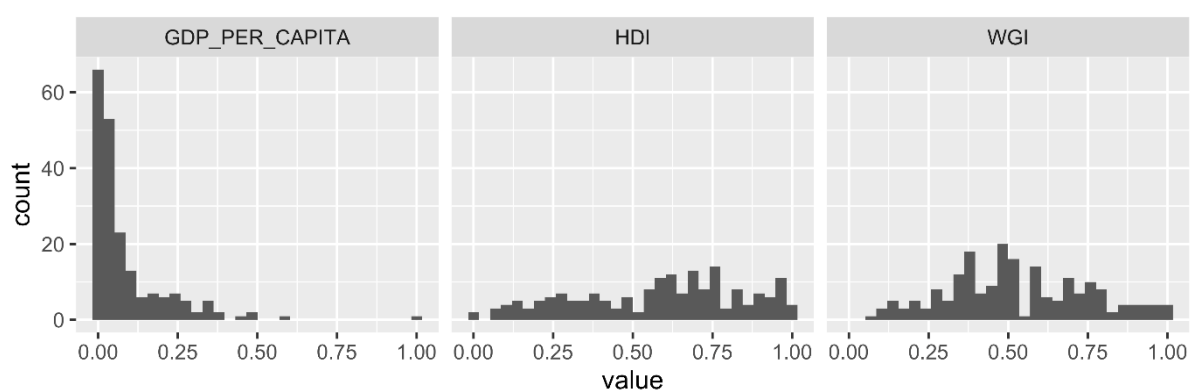


Figure S11. Histograms of the distribution of national response capacity indicators.

Table S1. Data description and sources for environmental stressors and corresponding indicators in this study

Stressors	Indicators used	Year	Original resolution	Data source	Links
Warming	Air temperature	1990-2020	5°×5°	CRU, University of East Anglia	https://crudata.uea.ac.uk
	Sea surface temperature	1990-2020	5°×5°	CRU, University of East Anglia	https://crudata.uea.ac.uk
Acidification	pH	1770-2000	1°×1°	NCEI, NOAA	https://www.ncei.noaa.gov/access/metadata/landing-page/bin/iso?id=gov.noaa.nodc:0206289
Altered precipitation	Altered precipitation	1990-2020	2.5°×2.5°	PSL, NOAA	https://psl.noaa.gov/data/gridded/data.gpcp.html
Sea level rise	Sea level rise	1993-2020	0.25°×0.25°	Aviso+	https://www.aviso.altimetry.fr/en/data/products/ocean-indicators-products/mean-sea-level/data-acces.html#c12195
Severe weather events	Typhoon	Up to 2021	Pathways	Tropical cyclone best track data	https://climatedataguide.ucar.edu/climate-data/ibtracs-tropical-cyclone-best-track-data
	Flood/Drought	1900-2021	Occurrences	EM-DAT	https://public.emdat.be/data
Parasites	Lice	Up to 2021	Occurrences	GBIF	https://www.gbif.org
	Leech	Up to 2021	Occurrences	GBIF	https://www.gbif.org
	Protozoa	Up to 2021	Occurrences	GBIF	https://www.gbif.org
Diseases	Outbreaks	2005-2021	National	World Organization for Animal Health	https://wahis.oie.int/#/dashboards/qd-dashboard
Invasion	Invasive species	Up to 2021	National	Global Invasive Species Database	http://www.iucngisd.org/gisd
Hypoxia	Observed Hypoxia	Up to 2010	National	Eutrophication & Hypoxia Map Data Set	https://www.wri.org/data/eutrophication-hypoxia-map-data-set
Eutrophication	Observed Eutrophication	Up to 2010	National	Eutrophication & Hypoxia Map Data Set	https://www.wri.org/data/eutrophication-hypoxia-map-data-set
	Nitrate	2002-2017	National	Our World in Data	https://ourworldindata.org
	Phosphorus	2002-2017	National	Our World in Data	https://ourworldindata.org
Mercury	Methylmercury	1995-2018	National	Liu et al. (2021)	https://doi.org/10.1038/s41561-021-00793-2
POPs	PCBs	Up to 2021	National	International Pellet Watch database	http://www.pelletwatch.org
	HCHs	Up to 2021	National	International Pellet Watch database	http://www.pelletwatch.org

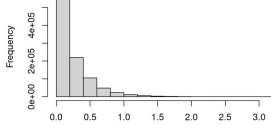
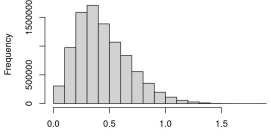
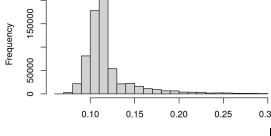
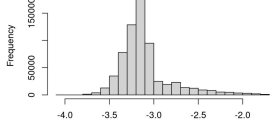
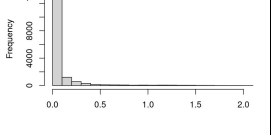
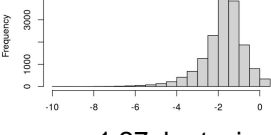
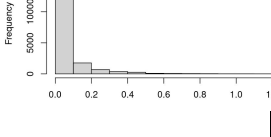
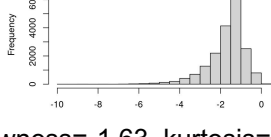
	DDT	Up to 2021	National	International Pellet Watch database	http://www.pelletwatch.org
Pesticide	Pesticide	2015	5 arcmin	Tang et al. (2021)	https://doi.org/10.1038/s41561-021-00712-5
Antibiotics	Antibiotics usage	2010 2000-2015	National National	OurWorld in Data Klein et al. (2021)	https://ourworldindata.org https://doi.org/10.1016/S1473-3099(20)30332-7
HAB toxins	HAB occurrences	Up to 2021	National	Harmful Algae Event Database	http://haedat.iode.org/browseGrids.php
Bacteria	Listeria	Up to 2021	Occurrences	GBIF	https://www.gbif.org
	Salmonella	Up to 2021	Occurrences	GBIF	https://www.gbif.org
	Vibrio	Up to 2021	Occurrences	GBIF	https://www.gbif.org
	Yersinia	Up to 2021	Occurrences	GBIF	https://www.gbif.org

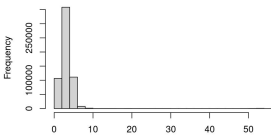
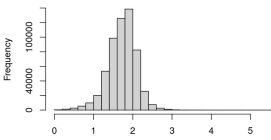
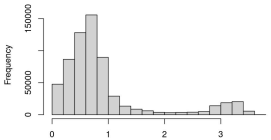
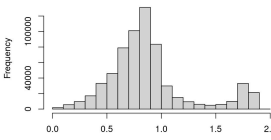
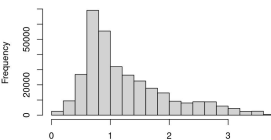
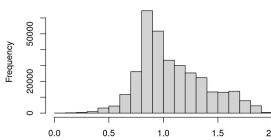
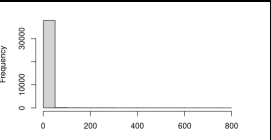
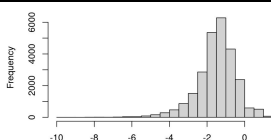
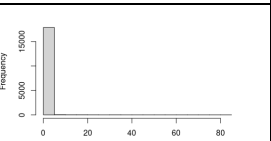
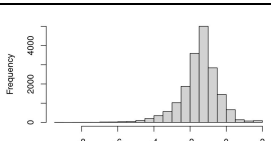
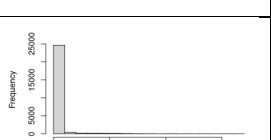
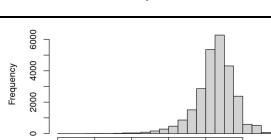
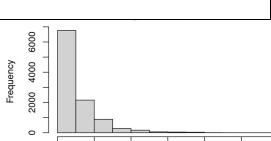
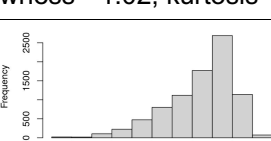
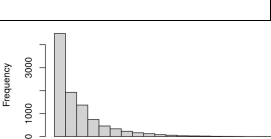
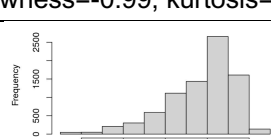
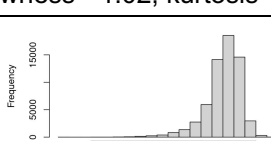
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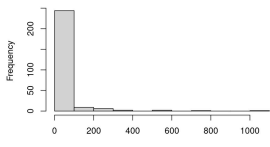
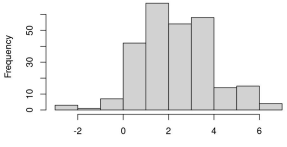
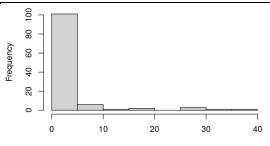
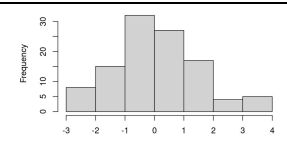
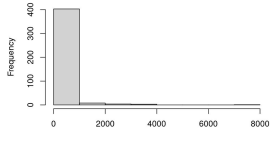
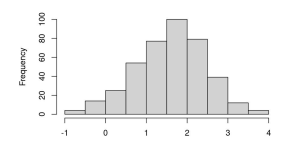
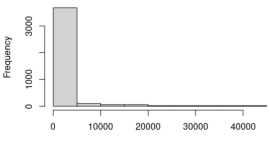
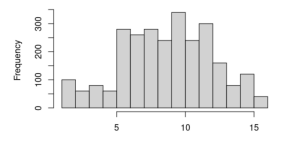
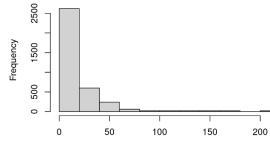
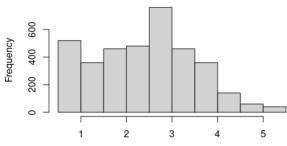
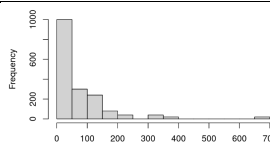
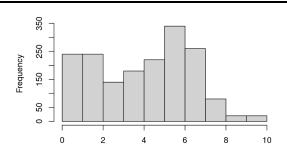
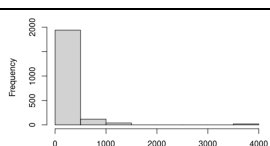
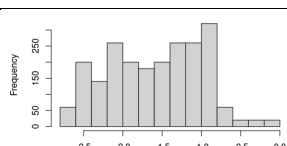
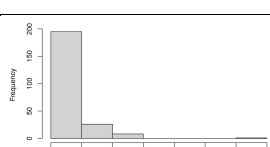
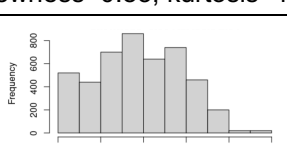
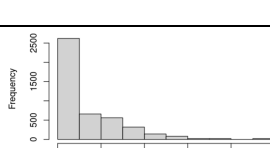
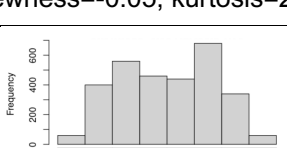
Distributions of raw data were checked for normality. Skewed indicators were transformed (e.g., logarithmic or square root transformations) to support subsequent analysis which requires mean and variance to be meaningful summaries of the data. Table S2 listed the type of transformation used and histograms of variables before and after transformation. In addition, the skewness and kurtosis coefficients of the transformed results were checked and they all fell in the acceptable ranges (skewness coefficients in the range of ± 2 and kurtosis coefficients in the range of ± 7 ; Byrne 2010, Hair et al. 2010, Kline 2016). It was concluded that the shape of these histogram graphs after transformation was not severely non-normal.

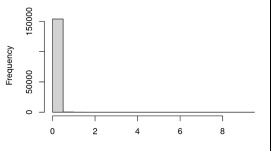
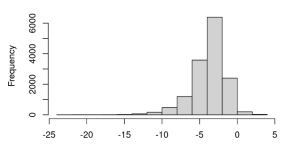
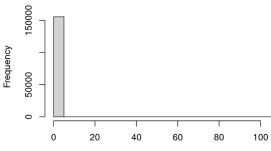
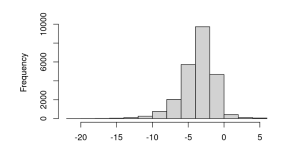
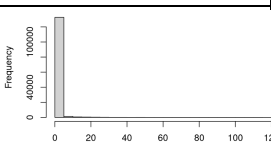
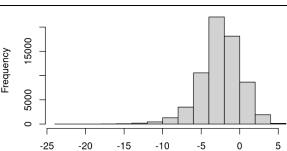
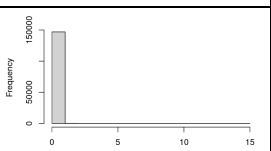
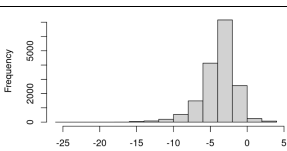
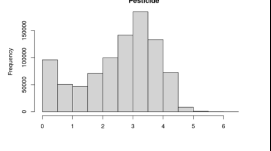
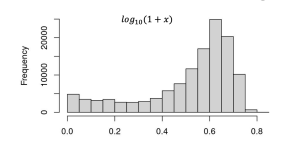
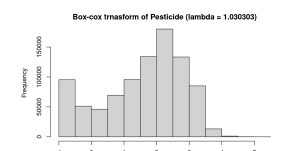
We considered the outliers in this study to represent natural variations, so they were left for further analysis. To make the variables measured at different scales and units comparable in subsequent spatial analysis, we used the min-max range to rescale all values to a unit interval between 0 and 1. That's to say, the Min-Max normalization method (Equation: $x' = (x - \min) / (\max - \min)$, where x' is the rescaled value, x is the original value, $\max$ is the maximum value of x , and $\min$ is the minimum value of x) was applied to rescale the values of each feature to a dimensionless range between 0.0 and 1.0.

Table S2. Transformations used and evidence of their effects

Variables	Transformation method used	Histograms (Original)	Histograms (After transformed)
Altered precipitation	$\sqrt{x}$		 skewness=0.79, kurtosis=3.53
Acidification	$\log_2(x)$		 skewness=1.69, kurtosis=6.53
Hypoxia	$\log_{10}(x)$		 skewness=-1.27, kurtosis=6.17
Eutrophication	$\log_{10}(x)$		 skewness=-1.63, kurtosis=6.55

Sea level rise	$\sqrt{x}$		 skewness=-0.22, kurtosis=5.42
Warming (SST anomalies)	$\sqrt{x}$		 skewness=1.15, kurtosis=4.04
Warming (Air temperature anomalies)	$\sqrt{x}$		 skewness=0.57, kurtosis=2.83
Parasites (Leech)	$\log_{10}(x)$		 skewness=-0.39, kurtosis=5.46
Parasites (Lice)	$\log_{10}(x)$		 skewness=-0.9, kurtosis=5.25
Parasites (Protoza)	$\log_{10}(x)$		 skewness=-1.02, kurtosis=5.12
Nitrate	$\log_{10}(x)$		 skewness=-0.99, kurtosis=3.63
Phosphorus	$\log_{10}(x)$		 skewness=-1.02, kurtosis=3.76
Mercury	$\ln(x)$		 skewness=-1.52, kurtosis=6.15

DDT	$\ln(x)$		 skewness=0.21, kurtosis=3.36
HCHs	$\ln(x)$		 skewness=0.34, kurtosis=2.83
PCBs	$\log_{10}(x)$		 skewness=-0.21, kurtosis=3.00
Severe weather events (Typhoon)	$\log_2(1+x)$		 skewness=-0.17, kurtosis=2.43
Severe weather events (Flood)	$\ln(1+x)$		 skewness=0.12, kurtosis=2.39
Disease	Box-cox		 skewness=-0.02, kurtosis=1.95
HABs	Box-cox		 skewness=0.83, kurtosis=1.84
Invasion	$\ln(1+x)$		 skewness=-0.05, kurtosis=2.34
Antibiotics	$\ln(x)$		 skewness=-0.03, kurtosis=1.93

Bacteria (Listeria)	$\ln(x)$		 skewness=-1.36, kurtosis=6.17
Bacteria (Salmonella)	$\ln(x)$		 skewness=-0.94, kurtosis=5.13
Bacteria (Vibrio)	$\ln(x)$		 skewness=-0.62, kurtosis=4.72
Bacteria (Yersinia)	$\ln(x)$		 skewness=-1.21, kurtosis=5.85
Pesticide	No transform <i>Note:</i> Sqrt, log ₁₀ (x), log ₁₀ (1+x), power, and box-cox transformations were checked and the best result was obtained from box-cox (skewness: -0.54, kurtosis 2.3), which was similar to the original distribution (skewness: -0.56, kurtosis 2.3), so it was decided not to transform.		
			Just for showcasing:  

Note: SST- Sea surface temperature, HABs- Harmful algal blooms, DDT- dichloro-diphenyl-trichloroethane, HCHs-hexachlorocyclohexanes, PCBs-polychlorinated biphenyls.

Table S3. Vulnerability of main blue food production systems to environmental stresses

Stressors	Vulnerability			
	FW capture	FW culture	Marine capture	Mariculture
Diseases	Low	High	Low	Medium
Parasites	Low	High	Low	Medium
Invasion	High	None	Low	Low
Eutrophication	Low	Low	Medium	Low
Hypoxia	None	None	Medium	High
Altered precipitation	Medium	Medium	None	None
Warming	Low	Low	Medium	Low
Acidification	None	None	High	Low
Sea level rise	None	None	None	Low
Severe weather events	Low	Medium	Low	Medium
Mercury	Low	Low	Medium	Low
POPs	Low	Low	Low	Medium
Antibiotics	None	Low	Low	Low
Pesticide	Medium	Low	Low	Low
HAB toxins	None	None	Low	Low
Bacteria	Low	Low	Low	Low

Table S4. Means and standard deviations (in parentheses) of standardized impact scores for each country cluster.

System-category	Cluster			
	High impact	Medium high impact	Medium low impact	Low impact
FW capture quantity	0.57 (0.13)	0.48 (0.08)	0.44 (0.07)	0.06 (0.08)
FW capture safety	0.57 (0.14)	0.30 (0.13)	0.35 (0.14)	0.01 (0.02)
FW culture quantity	0.72 (0.18)	0.60 (0.13)	0.53 (0.14)	0.05 (0.09)
FW culture safety	0.64 (0.13)	0.34 (0.12)	0.37 (0.14)	0.01 (0.02)
Marine capture quantity	0.55 (0.18)	0.43 (0.1)	0 (0)	0.36 (0.11)
Marine capture safety	0.41 (0.23)	0.13 (0.06)	0 (0)	0.06 (0.08)
Mariculture quantity	0.55 (0.19)	0.42 (0.11)	0 (0)	0.35 (0.11)
Mariculture safety	0.45 (0.2)	0.18 (0.1)	0 (0)	0.09 (0.13)

Table S5. Data description of indicators of national response capacity

Indicators	Year	Data source	Links
Human Development Index	2010-2019	UNDP	http://hdr.undp.org/en/data
World Governance Index	2011-2020	World Bank	https://info.worldbank.org/governance/wgi
GDP per capita	2011-2020	World Bank	https://databank.worldbank.org

Table S6. Outliers detected in the analysis of the relationship between predicted impacts and national response capacity

Category	System	Country	R_student	Unadjusted <i>P</i> values	Bonferroni <i>P</i> values
Production quantity	FW capture	ROM	-5.526134	0.000000	0.000022
		FSM	-4.490976	0.000014	0.002146
		WSM	-4.237425	0.000039	0.005997
		USA	3.898543	0.000146	0.022177
	FW culture	SGP	-3.354328	0.000979	0.171280
	Marine capture	BEL	3.931008	0.000121	0.022057
		DNK	3.775424	0.000217	0.039670
		ROM	-3.720439	0.000266	0.048608
	Mariculture	ROM	-4.275433	0.000038	0.004762
Food safety	FW capture	ALB	3.724969	0.000277	0.042040
	FW culture	ALB	3.168516	0.001814	0.317380
	Marine capture	BIH	4.830491	0.000003	0.000531
	Mariculture	BIH	5.894529	0.000000	0.000004
		MNE	4.745041	0.000006	0.000715
		ALB	4.575383	0.000012	0.001439

Note: The *car* package in R was used to report the unadjusted and Bonferroni adjusted *P* values (two-sided, significance threshold at 0.05) to test whether an observation was a mean-shift outlier based on the studentized residuals (R_student) in a generalized linear model.

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