SUPPLEMENTARY INFORMATION FOR:

Stock & Micheli (2016). Effects of model assumptions and data quality on spatial cumulative human impact assessments. *Global Ecology and Biogeography*.

SUPPLEMENTARY METHODS

1. Implementation of factors

The quantitative factors (X_0 to X_3) ranged from 0 to 1. The qualitative factors (X_4 to X_8) took values according to Table 1 in the main text.

1.1 Missing stressor data (X_0)

We investigated the effect of missing stressor data by excluding $\left\lfloor \frac{n*X_0}{3} \right\rfloor$ randomly chosen stressors, where *n* is the number of stressors included in the original analysis. Each stressor had the same probability of exclusion.

1.2 Sensitivity weights (X_1)

We added random errors to the sensitivity weights as follows:

$$\hat{\mu}_{i,j} = \mu_{i,j} + X_1 u_{i,j} \qquad \text{(Eq. S1)}$$

where $u_{i,j}$ were random numbers drawn from a uniform distribution $U(-0.5*max(\mu_{i,j}), 0.5*max(\mu_{i,j}))$.

1.3 Spreading of impacts from point stressors (X_2)

We modeled the decay of stressor intensity from point sources (e.g. fish farms) as

$$\dot{D}_i(\hat{x},\hat{y}) = \sum_x \sum_y \max\left(0, 20000X_2 - \sqrt{(x-\hat{x})^2 + (y-\hat{y})^2}\right) * \widehat{D}_i(x,y) \qquad \text{(Eq. S2)}$$

where *(x,y)* are the coordinates of cell centroids in meters and $\widehat{D}_i(x,y)$ is the intensity of stressor *i* in original units (before transformation and rescaling). Note that this linear decay function creates values much larger than the original ones, but that all stressor intensities are rescaled to maximum 1 before equations S8, S9 or S10 are applied to calculate the impact scores. For stressors not represented by points, we set $\dot{D}_i(\hat{x},\hat{y}) = \widehat{D}_i(\hat{x},\hat{y})$.

1.4 Non-linear responses to stressors (X_3)

We assigned response functions $r_{i,j}$ to each combination of stressor and ecosystem component. Each $r_{i,j}$ could be one of the following:

$$r_{lin}(x) = x \qquad \text{(linear response; Eq. S3)}$$

$$r_a(x) = \frac{1}{1 + \exp(-50x - a)} \qquad \text{(threshold response; Eq. S4)}$$

where a ranged from 0.3 to 0.7. Fig. S2 shows examples. We randomly selected $\lfloor n * m * X_3 \rfloor$ stressor-ecosystem component combinations and assigned functions r_a with each a drawn from a uniform distribution *U(0.3,0.7)*. We assigned linear response functions r_{lin} to all other stressor-ecosystem component combinations.

1.5 Reduced analysis resolution (X_4)

We investigated the effects of reducing the spatial resolution of all stressor and ecosystem data by factor 2. We calculated the values of coarser-resolution cells as means of all contained finer-resolution cells with values >0.

1.6 Improved resolution for coarse stressor data (X_5)

We created fine-resolution versions of coarse stressor data (Baltic Sea: fishing, atmospheric deposition, hunting; Mediterranean and Black Seas: fishing, ocean acidification, UV) as follows: We first set each cell's value to a random number drawn from *U(0,1)*. We then rescaled the resulting values so that the sum of all cells in each originally same-value area remained the same. We then applied a 25km x 25km low-pass filter (Fig. S3).

1.7 Mean or sum of impacts on present ecosystems (X_6)

Depending on the value of X_6, we calculated a cell's impact index as sum or mean of the impacts on all present ecosystem components:

$$I(x, y) = t(X_6) I_{Sum}(x, y) \qquad \text{(Eq. S5)}$$

with

$$t(X_6) = \begin{cases} 1 & if\ X_6 = 0 \\ \frac{1}{\sum_{j=1}^{m} e_j(x, y)} & if\ X_6 = 1 \end{cases} \qquad \text{(Eq. S6)}$$

1.8 Transformation type: Log, CDF, P (X_7)

We implemented the three transformations for the stressor data as follows:

$$\ddot{D}_i(x,y) = \begin{cases} \log(\dot{D}_i(x,y) + 1) & if\ X_7 = 0 \\ F_i(\dot{D}_i(x,y)) & if\ X_7 = 1 \\ \min(\dot{D}_i(x,y), p_{i,99}) & if\ X_7 = 2 \end{cases} \quad \text{(Eq. S7)}$$

where F_i is the CDF of $\dot{D}_i$, estimated by setting each stressor intensity to the percentile it corresponds to, and $p_{i,99}$ is the 99-percentile of $\dot{D}_i$. In each model evaluation, the chosen transformation was applied to all stressors.

1.9 Multiple stressor effects model (X_8)

We tested the effects of assuming one of three models for the effects of multiple stressors. First, we used an additive model (Eq. 1 in the main text), with extensions according to equations S1-S7):

$$I_{Add}(x,y) = t(X_6) * \sum_{i=1}^{n}\sum_{j=1}^{m} r_{i,j}(\dddot{D}_i(x,y)) * e_j(x,y) * \hat{\mu}_{i,j} \quad \text{(Eq. S8)}$$

where $\dddot{D}_i(x,y)$ is derived from $\ddot{D}_i(x,y)$ (Eq. S7) by rescaling so that the maximum for each stressor is 1.

Second, we used a "dominant impacts" model, where the impact score of a cell depended only on the stressors having the highest impact on each present ecosystem component:

$$I_{Dom}(x,y) = t(X_6) * \sum_{j=1}^{m} \max_{i=1\ldots n}(r_{i,j}(\dddot{D}_i(x,y)) * e_j(\mathrm{x,y}) * \hat{\mu}_{i,j}) \quad \text{(Eq. S9)}$$

Third, we used an antagonistic impacts model, in which multiple stressors had diminishing effects on each ecosystem component:

$$I_{Ant}(x,y) = t(X_6) * \sum_{i=1}^{n}\sum_{j=1}^{m} \frac{s_j(x,y) - c_{i,j}(x,y) + 1}{s_j(x,y)} r_{i,j}(\dddot{D}_i(x,y)) * e_j(x,y) * \hat{\mu}_{i,j} \quad \text{(Eq. S10)}$$

where $s_j(x,y)$ is the number of stressors in cell (x,y) with $r_{i,j}(\dddot{D}_i(x,y)) * \hat{\mu}_{i,j} > 0$ and $c_{i,j}(x,y)$ is the rank of stressor i if stressors where ranked by $r_{i,j}(\dddot{D}_i(x,y)) * \hat{\mu}_{i,j}$ in descending order. For example, in a location where 3 stressors have impacts > 0 on present ecosystem component j, this model weighed the impacts of the highest-impact stressor with 1, the impacts of the second-highest-impact stressor with 2/3, and the impacts of the third-highest-impact stressor with 1/3.

2. Sensitivity analysis

We ranked the factors by influence on the ranks of sub-regions, stressors and ecosystem components using the elementary effects (EE) method (Morris 1991). This method evaluates a model following random trajectories in factor space. The factor values making up a trajectory are represented by an orientation matrix, where each row represents a tuple of values $X=(X_0,X_1,\ldots,X_l)$. The $l+1$ factors take on predetermined levels (Table 1 in the main text). Each trajectory begins at a random point, and exactly one factor changes from one row of the orientation matrix to the next. Once all factors have changed exactly once, the trajectory is completed, and the next one is evaluated. Because only one factor X_k changes between subsequent orientation matrix rows i and j, X_k*'s* effect on the model output at this point in factor space can be estimated as its elementary effect (EE):

$$EE_k(X) = \frac{Y(X_{0,i}, X_{1,i}, \ldots, X_{k,i}, \ldots, X_{l,i}) - Y(X_{0,j}, X_{1,j}, \ldots, X_{k,j}, \ldots, X_{l,j})}{\Delta_k} \qquad \text{(Eq. S11)}$$

where $Y(X)$ is the model output for factor values given by X, $X_{a,i} = X_{a,j}$ for $a \neq k$, $X_{k,i} \neq X_{k,j}$, and Δ_k is the difference between $X_{k,i}$ and $X_{k,j}$. For the quantitative factors X_0 to X_3, we set $\Delta_k = X_{k,i} - X_{k,j}$. For the qualitative factors X_4 to X_8, we set $\Delta_k = 1$.

Evaluating t trajectories produces t EEs for each factor. The mean μ_k of X_k's EEs is a measure of its overall influence on model outputs. The variance σ_k of X_k's EEs indicates how much its influence depends on other factors' values. However, μ_k can be misleading if X_k changes the model output non-monotonically. We thus used $\mu_k *$, the mean of X_k's EEs' absolute values (Campolongo et al., 2007), instead of μ_k. Furthermore, because some of our factors were qualitative with multiple levels (e.g. selecting 1 of 3 transformation functions), we could not meaningfully assign a direction to these changes. We thus used σ_k*, the variance of X_k's EEs' absolute values, instead of σ_k.

There are two further complications using the EE method for our model. First, the model has stochastic components that are not determined by the input data and factors. For example, X_0 determines *how many* stressors are excluded, but not *which* are excluded. The EE calculation however depends on one factor and nothing else changing between subsequent steps in a trajectory. We thus set the model's stochastic components before and held them constant throughout the evaluation of each trajectory. Model stochasticity did thus not confound the calculation of EEs. However, because EEs depended not only on location in factor space but also on the model's stochastic components, σ_k* became a joint measure of how much X_k's effects depended on other factors and on stochastic components.

The second complication is that our model had not a single output, but produced one rank (and thus one μ_k* and σ_k* for each X_k) for each sub-region, for each stressor and for each ecosystem component. We estimated the overall effects of the factors by calculating the means of μ_k* and σ_k* for all sub-regions, stressors and ecosystem components.

SUPPLEMENTARY FIGURES

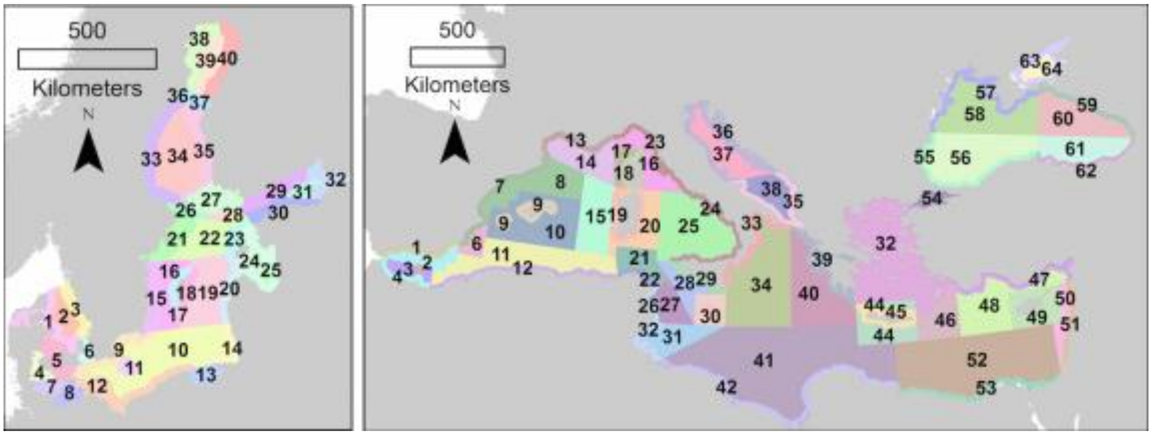

Figure S1. Subregions used to analyze the effects of model assumptions and data quality on broad-scale spatial patterns of human impacts.

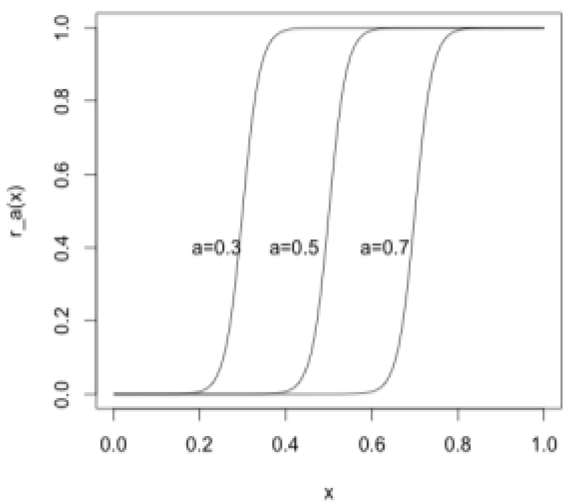

Figure S2. Example non-linear response functions r_a for different values of a.

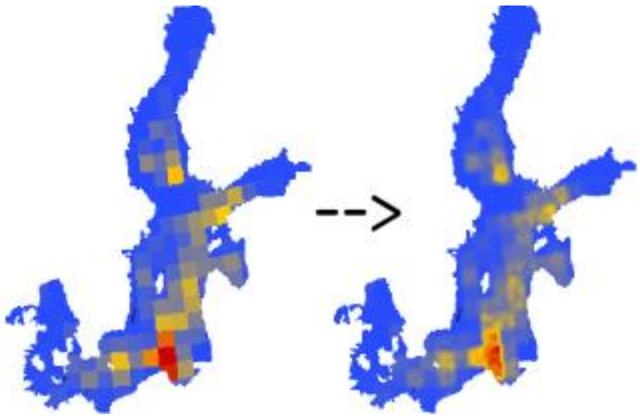

Figure S3. Example of a randomly generated fine-resolution version of a coarse-resolution data set based on locally rescaled noise.

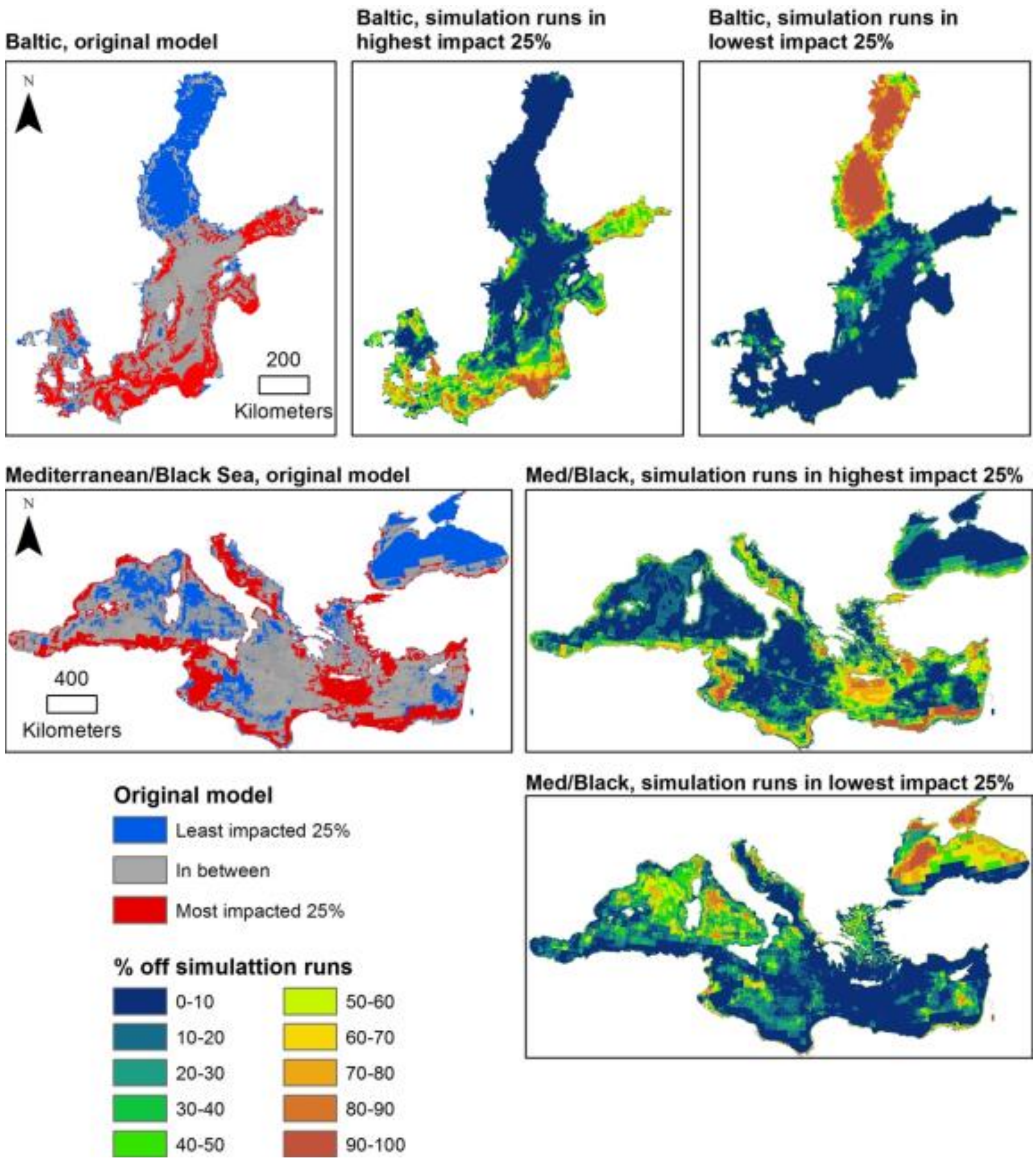

Figure S4. Spatial distribution of high and low human impacts (defined as the 25% of the study areas with highest and lowest modelled impact scores) in maps reproduced with the original model and in the Monte Carlo simulations.

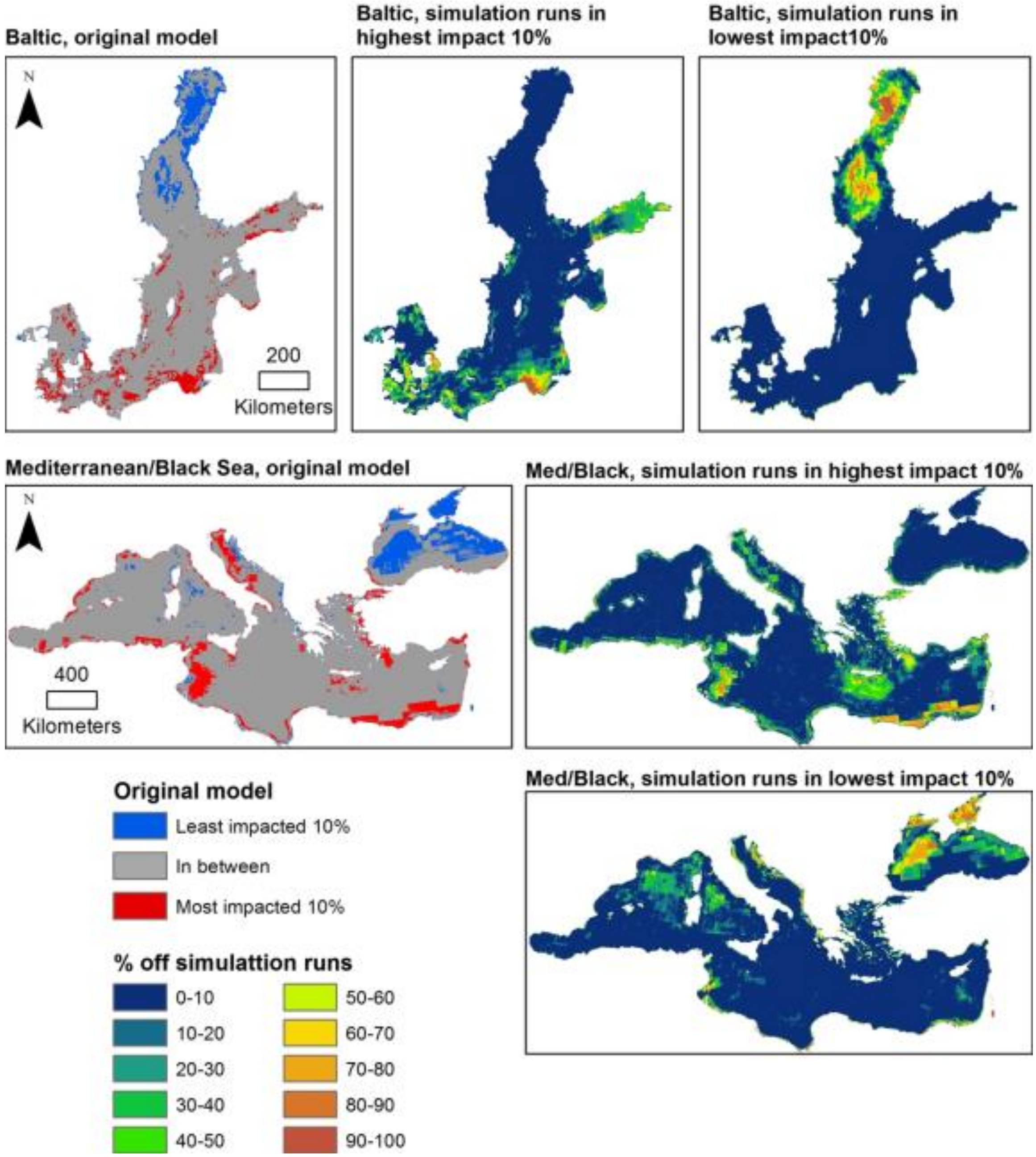

Figure S5. Spatial distribution of high and low human impacts (defined as the 10% of the study areas with highest and lowest modelled impact scores) in maps reproduced with the original model and in the Monte Carlo simulations.

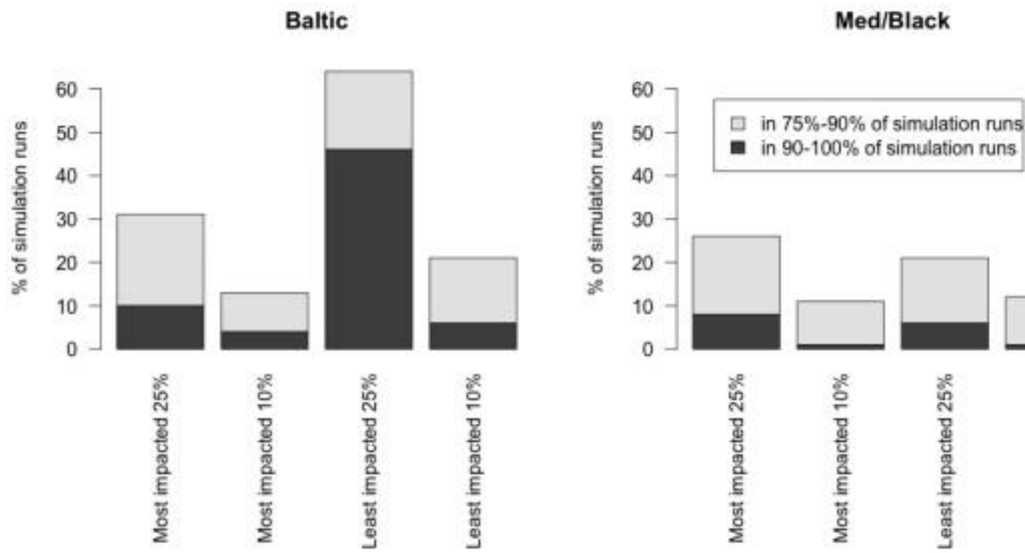

Figure S6. Percent of the most and least impacted 25% and 10% of the two study areas that were in the same impact category in at least 75% and 90% (black sub-bars) of simulation runs. For example, almost 1/3 of the most impacted 25% of the Baltic Sea according to the original model (yellow, orange and red areas in Fig. 2A in the main text) were within the most impacted 25% in more than 75% of simulation runs (orange and red areas in Fig. 2A). The remaining 2/3 of the originally identified areas (yellow areas in Fig. 2A) should not be considered robust.

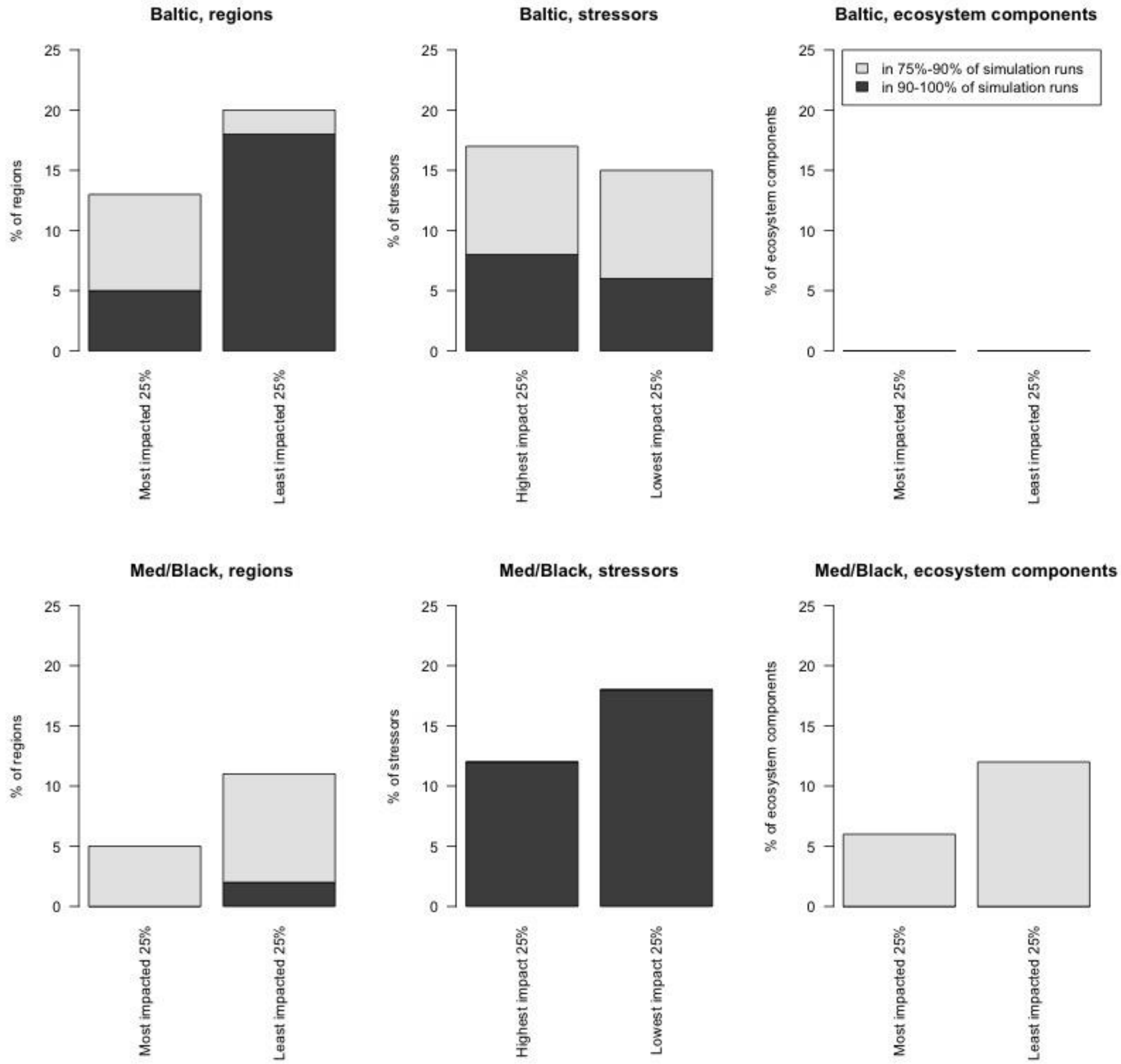

Figure S7. Percent of regions, stressors and ecosystem components that were among the most and least impacted (or, in the case of stressors, impacting) 25% in at least 75% and 90% (black bars) of simulation runs. For example, about 17% of stressors in the Baltic Sea SCIA were in the top-ranked 25% by impact in >=75% of simulation runs. Note that in contrast to Figure S6, which reports robust proportions of original results, this figure presents the total proportions of regions, stressors and ecosystem components in each class. Thus, the theoretical maximum (in the absence of uncertainty) is 25%. There were no ecosystem components in the Baltic Sea assessment that were among the most or least impacted in >=75% of simulation runs.

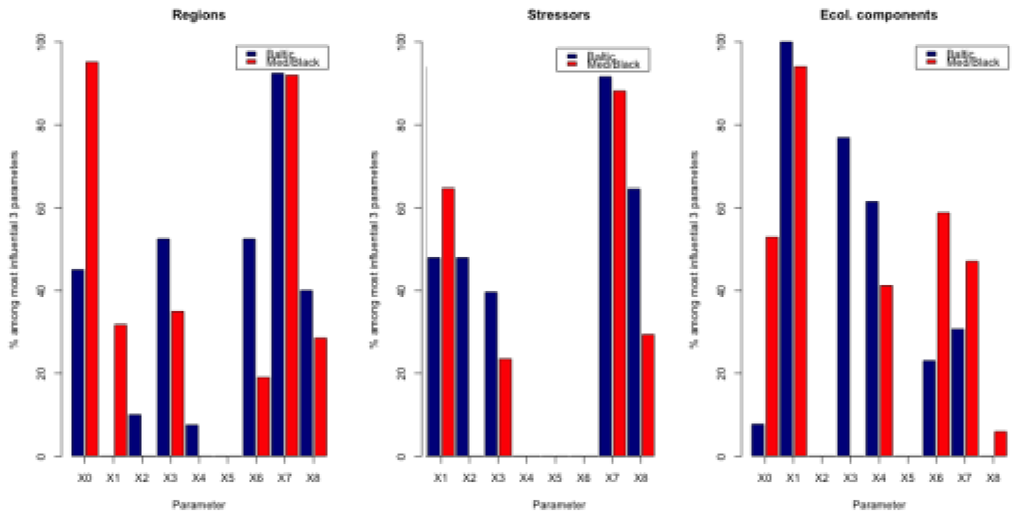

Figure S8. Percentage of sub-regions, stressors and ecosystem components for which $X_0 \ldots X_8$ were among the 3 most influential factors according to $\mu*$.

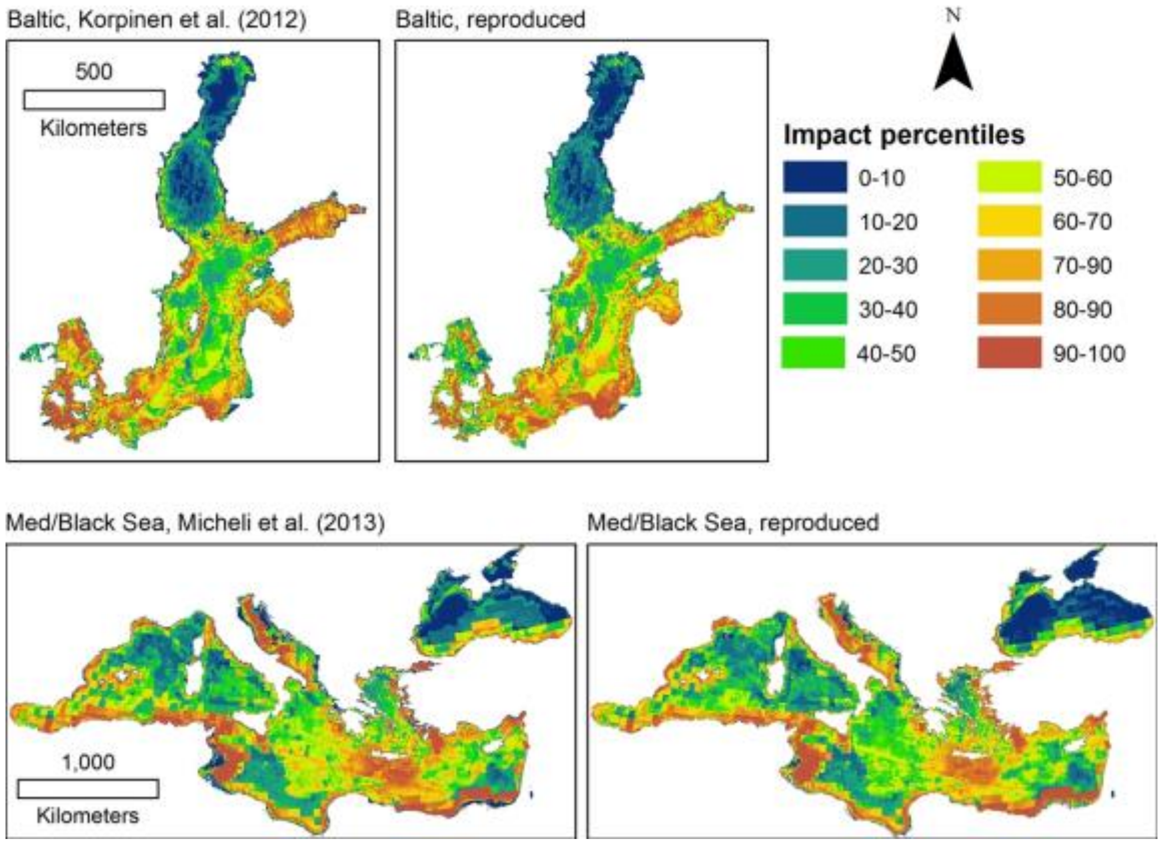

Figure S9. Korpinen et al.'s (2012) and Micheli et al.'s (2013) human impact maps and their reproduction for this study.

SUPPLEMENTARY TABLES

Table S1. Data sources for reproduction of the Baltic Sea and Mediterranean/Black Sea SCIAs.

Assessment	Data type	Source
Baltic Sea (Korpinen et al., 2012)	Stressors, ecosystems	S. Korpinen (personal communication, 2015), HELCOM (J. Kaitaranta, personal communication, 2015; Data and Map Service: www.helcom.fi, 2015).
	Sensitivity weights	HELCOM (2010)
	Sub-regions	HELCOM COMBINE sub-basins (Data and Map Service: www.helcom.fi); shorelines for coastal-offshore distinction: GSHHG.
Mediterranean and Black Sea (Micheli et al., 2013)	Stressors, ecosystems	NCEAS (https://www.nceas.ucsb.edu/globalmarine/mediterranean, 2015)
	Sensitivity weights	Halpern et al. (2007)
	Sub-regions	FAO-GFCM Geographical sub-areas http://www.fao.org/gfcm/data/map-geographical-subareas/en/; shorelines for coastal-offshore distinction: GSHHG.

Table S2. Subregions, stressors and ecosystem components that were among the most impacted (or, in the case of stressors, most impacting) 25% in at least 75% of simulation runs (% of runs reported in parentheses). Note that the Baltic Sea assessment included many more (47) stressors than the Mediterranean/Black Sea assessment (17), which explains why for the Baltic Sea there were many more stressors consistently among the highest-impact 25%.

	Baltic Sea	**Mediterranean/Black Sea**
Regions	12 (97%), 13 (97%), 6 (85%), 11 (84%), 14 (76%)	45 (82%), 54 (79%), 27 (76%)
Stressors	Commercial fishing – surface and mid-water (99%) Waterborne nutrient (nitrogen) input (96%) Waterborne nutrient (phosphorous) input (95%) Atmospheric nutrient (nitrogen) deposition (93%) Organic matter deposition from river runoff (85%) Atmospheric deposition of Pb (81%) Atmospheric deposition of Hg (80%) Atmospheric deposition of Cd (77%)	Sea surface temperature anomalies (99%) Ocean acidification (90%)
Ecosystem components	None (most frequent: Cod, 64%)	Hard shelf (85%)

Table S3. Subregions, stressors and ecosystem components that were among the least impacted (or, in the case of stressors, least impacting) 25% in at least 75% of simulation runs (% of runs reported in parentheses). Note that the Baltic Sea assessment included many more (47) stressors than the Mediterranean/Black Sea assessment (17), which explains why for the Baltic Sea there were many more stressors consistently among the lowest-impact 25%.

	Baltic Sea	**Mediterranean/Black Sea**
Regions	38 (100%), 39 (99%), 36 (99%), 37 (98%), 34 (97%), 33 (93%), 40 (91%), 35 (89%)	64 (97%), 63 (89%), 59 (87%), 60 (84%), 58 (79%), 25 (78%), 20 (77%)
Stressors	Noise from operational windfarms (99%) Noise from oil platforms (99%) Introduction of microbial pathogens by aquaculture (91%) Sealing by bridges (89%) Smothering by construction of cables and pipelines (86%) Synthetic compounds from polluting ship accidents (82%) Noise from construction of cables and pipelines (79%)	Accidents (99%) Flares (99%) Artisanal fishing (98%)
Ecosystem components	None (most frequent: Non-photic water, 64%)	Deep waters (78%) Beach (75%)

REFERENCES

See main text.