Global Ecology and Biogeography, (Global Ecol. Biogeogr.) (2016)

A Journal of Macroecology
Global Ecology and Biogeography

RESEARCH PAPER

Effects of model assumptions and data quality on spatial cumulative human impact assessments

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ABSTRACT

Aim Many studies have quantified and mapped cumulative human impacts on marine ecosystems. These maps are intended to inform management and planning, but uncertainty in them has not been studied in depth. This paper aims to: (1) quantify the uncertainty in cumulative impact maps and related spatial modelling results; (2) attribute this uncertainty to specific model assumptions and problems with data quality; (3) identify and test sound approaches to such analyses.

Location We used the Baltic Sea and the Mediterranean and Black Seas as example regions. The methods and conclusions are relevant for human impact mapping anywhere.

Methods We conducted computational experiments to test the effects of nine model assumptions and data quality problems (factors) on maps of human impact and related modelling results. The factors were implemented on the basis of a literature review. We quantified aggregate uncertainty using Monte Carlo simulations, and ranked the factors by their influence on modelling results using the elementary effects method. Both methods are well established and theoretically suitable for complex models, but had to be modified for application to spatial human impact models.

Results Some, but not all, modelling results were robust. This contradicts previous studies that found only minor effects of the factors they tested. Of the nine factors tested here, eight had a considerable influence on at least one modelling result in at least one of the two study regions.

Main conclusions Model assumptions and data quality have larger aggregate effects on maps of human impact than found in previous analyses. These effects depend on the study region and the data that describe it. Future human impact mapping studies should thus include comprehensive uncertainty analyses. Computational experiments allow us to distinguish robust from less reliable modelling results and to prioritize improvements in models and data.

Keywords
Baltic Sea, Black Sea, cumulative effects, cumulative impacts, mapping, Mediterranean Sea, modelling, sensitivity analysis, uncertainty analysis.

INTRODUCTION

Marine ecosystems are affected by many anthropogenic stressors at the same time. For example, intensive fishing has led to the collapse of fish stocks and the alteration of entire food webs (Pauly *et al.*, 2002), and climate change affects species abundances and distributions, food web dynamics and ocean productivity (Hoegh-Guldberg & Bruno, 2010). However, the responses of ecosystems to many stressors, and especially their combinations, are still unknown (Claudet & Fraschetti, 2010). Understanding the relationship between stressors and the state of marine ecosystems thus remains a 'grand challenge' for marine ecologists (Borja, 2014).

Meanwhile, marine spatial planning and ecosystem-based management need information about the cumulative impacts of multiple interacting stressors (Foley *et al.*, 2010; Kelly *et al.*, 2014; Stamoulis & Delevaux, 2015). Recent environmental laws in the USA, Europe and elsewhere require spatial cumulative impact assessments (SCIAs; Prahler *et al.*, 2014; Judd *et al.*, 2015). While stressors interact in complex ways, most SCIAs have so far relied on simple impact models (Stelzenmüller *et al.*, 2013).

The most widely used spatial model for SCIAs is the additive model proposed by Halpern *et al.* (2008a). This model, and variations of it, have since been used in many studies (Halpern *et al.*, 2009, 2015; Selkoe *et al.*, 2009; Ban *et al.*, 2010; HELCOM, 2010; Korpinen *et al.*, 2012, 2013; Allan *et al.*, 2013; Andersen *et al.*, 2013; Maxwell *et al.*, 2013; Micheli *et al.*, 2013; Agbayani *et al.*, 2015; Holon *et al.*, 2015; Murray *et al.*, 2015a,b; Okey *et al.*, 2015). Some authors have proposed alternative approaches (e.g. Stelzenmüller *et al.*, 2010; Coll *et al.*, 2012; Parravicini *et al.*, 2012; Kelly *et al.*, 2014; Goodsir *et al.*, 2015; Knights *et al.*, 2015; Marcotte *et al.*, 2015). Yet Halpern *et al.*'s model is the only spatial model that has been widely used for human impact mapping around the world.

Like all models, Halpern *et al.*'s uses imperfect input data and makes many assumptions (Halpern & Fujita, 2013). For example, it assumes that the effects of multiple stressors simply add up, whereas much research in fact suggests that effects of multiple stressors are complex and that stressors can interact non-additively (Crain *et al.*, 2008; Darling & Côté, 2008; Ban *et al.*, 2014; Strain *et al.*, 2014; Cheng *et al.*, 2015). The results of SCIAs could thus be highly uncertain.

Applications of modelling results to ecosystem-based planning and management require an understanding of the uncertainty in model outputs (Agumya & Hunter, 2002; Saltelli & Funtowicz, 2014). Rigorous studies of uncertainty in SCIA results and other spatial data intended to inform policy, planning and management are thus important. Several existing SCIAs have conducted uncertainty analyses, and have generally concluded that the results of SCIAs based on Halpern *et al.*'s model are robust. However, previous analyses have only studied the effects of a few model assumptions or problems with data quality (called 'factors' in the following). This is problematic, because for modelling results with many potential sources of uncertainty, studying a few factors only reveals a fraction of the potential aggregate uncertainty. Furthermore, previous analyses used one-at-a-time (OAT) approaches. These typically start with a baseline in factor space, i.e. a set of factor values that are used as a reference. OAT approaches then systematically explore the effects of one factor at a time by changing it while keeping the other factors at their baseline values. But this can be misleading if factors interact. For example, consider two factors A and B, each ranging from 0 to 1. A has strong effects on the model output if $B \geq 0.6$, but negligible effects otherwise. In this situation, an OAT approach could find either a large or a negligible effect of A, depending on the baseline chosen for B. If B has little direct influence on model outputs and $B < 0.6$ at the baseline, the OAT analysis would furthermore falsely conclude that neither A nor B change model outputs much, although they would in fact be very different for some values of A if $B \geq 0.6$. Saltelli & Annoni (2010) thus make a strong case against the use of OAT approaches. For these two reasons, additional analyses are needed to provide a sound picture of aggregate uncertainty in SCIAs.

This paper aims to quantify and map the uncertainty in SCIA results (uncertainty analysis, UA), to attribute this uncertainty to different factors (sensitivity analysis, SA) and to demonstrate sound methods for such analyses. We investigated the effects of nine factors, some of which have not been studied before, by means of computational experiments. In contrast to previous efforts, we used global methods that assess the effects of all factors simultaneously, including their interactions: the elementary effects (EE) method (Morris, 1991; Campolongo *et al.*, 2007) for SA and Monte Carlo (MC) simulations for UA. The EE method, while also varying one factor at a time, avoids the pitfalls of standard OAT approaches by evaluating the effect of each factor at many points in factor space. In the example above, it would evaluate the effect of A for different values of B, and vice versa. Similarly, our MC simulations avoid the limitations of previous UAs by exploring the full factor space. This paper thus presents the most comprehensive analysis of uncertainty and its sources in SCIAs to date. While using regional analyses as examples, and providing regionally relevant results as supporting figures and tables, it focuses on general conclusions about uncertainty in SCIAs. It also demonstrates how to use MC simulations and the EE method with a spatial cumulative impact model, and hence complements other recent studies suggesting global UA and SA methods for spatial models (e.g. Lilburne & Tarantola, 2009; Chen *et al.*, 2010). While we focus on marine SCIAs, terrestrial and freshwater ecosystems are also subject to multiple stressors (Sanderson *et al.*, 2002; Vörösmarty *et al.*, 2010; Hecky *et al.*, 2010). Our methods and conclusions are thus relevant beyond the marine realm.

DATA AND METHODS

Original model

Halpern *et al.* (2008a) estimate a unitless human impact score I for each cell (x,y) of a regular grid as

$$I_{\mathrm{sum}}(x,y) = \sum_{i=1}^{n} \sum_{j=1}^{m} D_i(x,y) e_j(x,y) \mu_{i,j} \tag{1}$$

where D_i is the $\log(X+1)$-transformed and rescaled (to maximum 1) intensity of stressor i, e_j is the presence (1) or absence (0) of ecosystem component j, and $\mu_{i,j}$ is a weight representing the sensitivity of ecosystem component j to stressor i.

Table 1 Factor ranges in the Monte Carlo (MC) simulations and levels in the Morris (elementary effects) design.

Factor	Range in MC simulations	Levels in Morris design
X_0: missing stressor data	0 to 1/3 of data sets missing	0, 1/9, 2/9, 1/3 missing
X_1: sensitivity weight errors	Errors from uniform distribution $U(-k,k)$ with k ranging from 0 to 2 (original range of sensitivity weights is 0–4)	Errors up to $\pm$ 0, 0.67, 1.33, 2
X_2: point stressor linear decay	Decay distance 0–20 km	Decay distance 0, 7, 13, 20 km
X_3: nonlinear responses	Threshold response function for 0–100% of ecosystem component–stressor combinations	Threshold response function for 0, 1/3, 2/3 and all ecosystem component–stressor combinations
X_4: reduced analysis resolution	0 (original) or 1 (reduced) resolution	As MC simulation
X_5: improved stressor resolution	0 (original) or 1 (improved) resolution	As MC simulation
X_6: mean or sum of impacts	0 (sum) or 1 (mean)	As MC simulation
X_7: transformation type	0 [$\log(X+1)$], 1 (CDF) or 2 (P-transformation)	As MC simulation
X_8: MSEM	0 (additive), 1 (dominant stressor) or 2 (antagonistic)	As MC simulation

CDF, cumulative distribution function; MSEM, multiple stressor effect model.

The main output of SCIAs with Halpern *et al.*'s model is a regular grid where each cell contains an impact score. However, the input data are typically coarse, and the output maps therefore do not accurately represent local details. They are instead interpreted in terms of broad-scale patterns. We thus investigated uncertainty in the output maps as well as the following commonly reported model outputs:

- ranks of the subregions of the study area (most to least impacted, as proxy for broad-scale spatial patterns);
- ranks of stressors (highest to lowest impact in the whole study area, normalized to account for changing number of stressors);
- ranks of ecosystem components (most to least impacted).

We used existing open source software implementing Halpern *et al.*'s original model (Stock, 2016) as a foundation, and extended it by adding alternative model assumptions as well as UA and SA functions (see Appendix S1).

Input data

We reproduced two published SCIAs: for the Baltic Sea (Korpinen *et al.*, 2012) and for the Mediterranean and Black Seas (Micheli *et al.*, 2013). To achieve acceptable computation times, we changed the spatial resolution of the Mediterranean/Black Sea data from 1-km to 2-km grid cells. We defined subregions for studying the effects of the factors on broad-scale spatial patterns on the basis of existing HELCOM and FAO regions. We split large subregions into coastal (up to 12 nautical miles from the mainland or large islands) and offshore. We also split the Black Sea into four coastal and four offshore subregions of similar sizes. Table S1 summarizes the data sources and Fig. S1 shows the subregions.

Factors and model extension

Table 1 summarizes the factors included in this analysis. Figure 1 illustrates a single model evaluation. Details and equations are provided in Appendix S1.

Missing stressor data (X_0)

SCIAs typically suffer from missing stressor data. For example, Halpern *et al.* (2009) identified 53 relevant stressors for their study area, but could only obtain data for 25. Andersen *et al.* (2013) identified 47 relevant stressors and could only obtain data for 33. We investigated the effect of missing stressor data by randomly excluding up to a third of stressors.

Sensitivity weight errors (X_1)

Halpern *et al.*'s (2008a) model uses sensitivity weights ($\mu_{i,j}$ in equation (1)) to estimate the impact of stressor i on ecosystem component j. These weights are derived by expert judgement (e.g. Halpern *et al.*, 2007; Teck *et al.*, 2010), but it is unknown how well they describe ecosystem component sensitivity (Halpern & Fujita, 2013). We thus added random errors to the sensitivity weights up to plus or minus half the maximum of the original weights (equation S1 in Appendix S1).

Spreading of impacts from point stressors (X_2)

Halpern *et al.*'s (2008a) model assumes that many stressors affect only those grid cells where the human activities that cause them occur, while in fact impacts can occur tens of kilometres away (Andersen *et al.*, 2013). This underestimates impacts from stressors represented by point or line data (e.g. fish farms). Thus, some studies (Ban *et al.*, 2010; Andersen *et al.*, 2013; Batista *et al.*, 2014) assumed that stressor intensity decays linearly from sites of human activities. We investigated the effects of assuming linear decay of stressors represented by points, using 20 km as the maximum decay

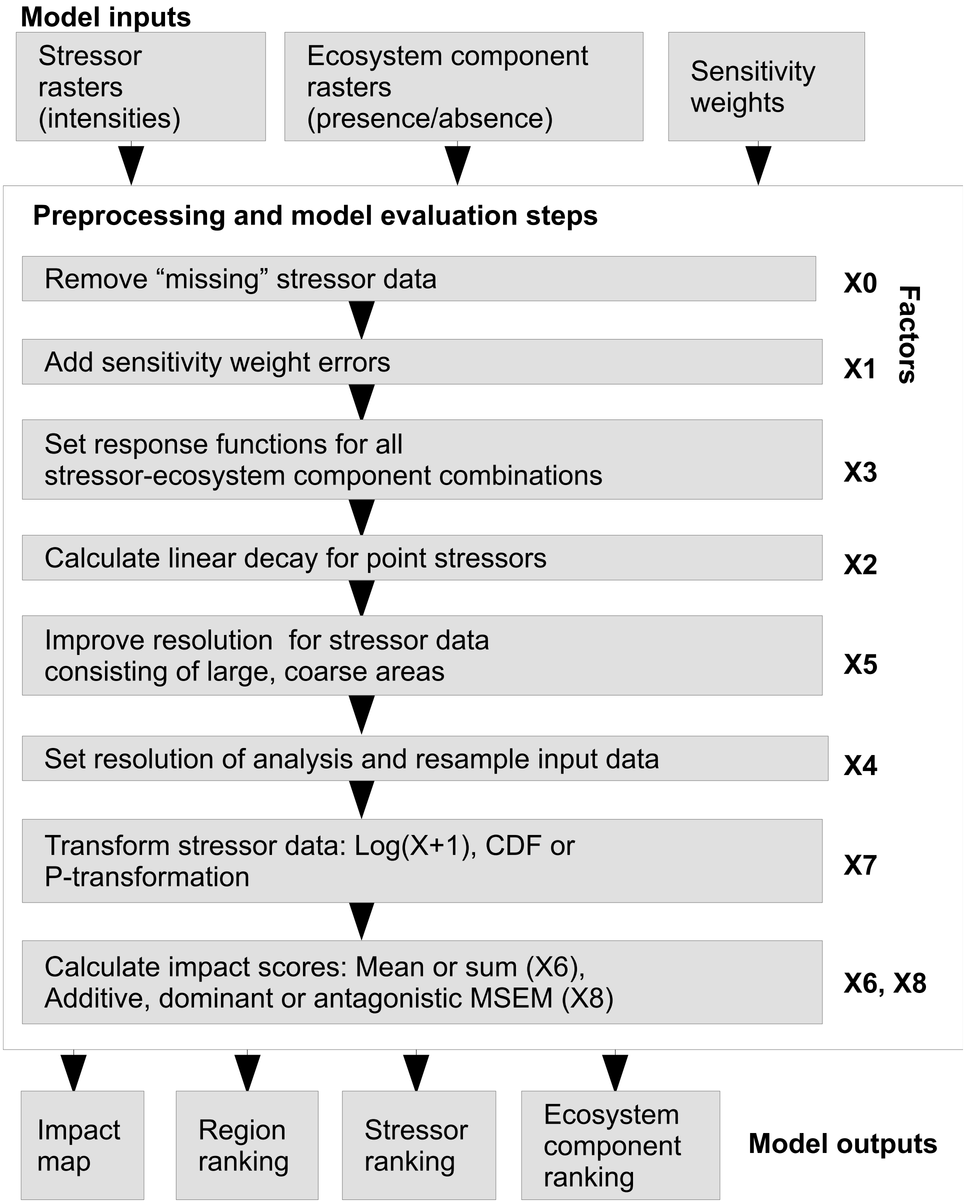

Figure 1 Overview of a single evaluation of the extended model.

distance (equation S2 in Appendix S1), which was the mean for stressors represented by point or line data in an expert survey (Andersen *et al.*, 2013).

Nonlinear responses to stressors (X_3)

Halpern *et al.*'s model assumes that the impact on individual ecosystem components increases linearly with increasing (log-transformed) stressor intensity, but the responses of ecosystems to stressors are often nonlinear (Hughes *et al.*, 2005; Large *et al.*, 2015). In our simulations, the response of each ecosystem components to each stressor could be either linear (equation S3 in Appendix S1) or nonlinear (equation S4 in Appendix S1). The nonlinear responses represented ecological thresholds and mimicked empirical relationships between marine ecosystem status and pressures from harbours and coastal urbanization (Parravicini *et al.*, 2012). Figure S2 shows some examples. Hunsicker *et al.* (2015) found that nonlinear responses to anthropogenic and natural stressors are common in pelagic ecosystems, and argue that, in the absence of better knowledge, it may be safer to assume a nonlinear response than a linear one. We thus let the proportion of nonlinear responses vary between 0% and 100%.

Reduced analysis resolution (X_4)

Most cumulative human impact maps have spatial resolutions of 1 km (e.g. Micheli *et al.*, 2013) to 5 km (Korpinen *et al.*, 2012). We investigated the effects of reducing the spatial resolution of all stressor and ecosystem data by factor of two.

Improved resolution for coarse stressor data (X_5)

The stressor data have different, sometimes coarse, spatial resolutions. For example, important data sets for the Mediterranean/Black Sea (e.g. demersal fishing with seabeddestructing gear) had a spatial resolution of one geographical degree. We created fine-resolution versions of such coarse data (Baltic Sea: fishing, atmospheric deposition, hunting; Mediterranean and Black Seas: fishing, ocean acidification, UV) by randomly redistributing stressor intensities inside the original coarse-resolution cells (Fig. S3 shows an example).

Mean or sum of impacts on present ecosystems (X_6)

Halpern *et al.* (2008a) and some later studies (e.g. Korpinen *et al.*, 2012) calculate human impact scores as sums of impacts over all ecosystem components that are present in a given cell (Eq. (1)). Other studies (e.g. Halpern *et al.*, 2009) use the mean impact across all ecosystem components present in a cell (calculated by dividing the summed impact by the number of ecosystem components present; equations S5 & S6 in Appendix S1). We investigated the effects of this decision.

Transformation type: log, CDF, P (X_7)

Halpern *et al.*'s (2008a) approach makes different measures of stressor intensity (e.g. fishing effort and pollutant concentrations) comparable by $\log(X+1)$-transforming and then rescaling so that the largest rescaled stressor intensity is 1. While transformation is necessary for summing impacts from different stressors (Halpern *et al.*, 2015) and 'a standard procedure for spatial pressure mapping' (Geldmann *et al.*, 2014), such transformation modifies numbers that may represent real differences. A purpose of the log-transformation is to reduce the effect of rare, extremely high, stressor intensities on model outputs (Micheli *et al.*, 2013). But this could also be achieved using other transformation types. A common approach to normalize variables uses their cumulative distribution functions (CDFs; Allan *et al.*, 2013). For spatial stressor data this can in practice be achieved by setting the intensity of each stressor to the percentile to which it corresponds (Vörösmarty *et al.*, 2010). The effects of extreme values could also be avoided by setting all stressor intensities higher than the 99th percentile to equal the 99th percentile (in the following called 'P-transformation'), but leaving smaller stressor intensities untransformed. We tested the effects of choosing one of these three transformation types (equation S7 in Appendix S1).

Modelling multiple stressor effects (X_8)

Halpern *et al.*'s (2008a) model assumes that the effects of multiple stressors in a cell simply add up. However, stressors can interact in complex ways (Shears & Ross, 2010; Ban *et al.*, 2014) and non-additive effects are common in nature (Crain *et al.*, 2008; Darling & Côté, 2008). We thus investigated the effects of using three different 'multiple stressor effect models' (MSEMs) suggested in the literature. First, we used an additive model (equation (1); Halpern *et al.*, 2008a), with extensions as described above (equation S8 in Appendix S1). Second, we used a 'dominant impacts' model (Halpern *et al.*, 2008b), where the impact score of a cell depended only on the stressors having the highest impact on each ecosystem component present (equation S9 in Appendix S1). Such a model could be plausible for high-impact stressors that alone can destroy habitat, such as dredging (Folt *et al.*, 1999). Third, we used an antagonistic impacts model, in which multiple stressors had diminishing effects on each ecosystem component (Stelzenmüller *et al.*, 2010). For example, in a location where three stressors have impacts >0 on ecosystem component *j*, this model weighed the impacts of the stressor with the highest impact by 1, the impacts of the stressor with the second-highest impact by 2/3, and the impacts of the stressor with the third-highest impact by 1/3 (equation S10 in Appendix S1). Because we could find no published synergistic MSEM for more than two stressors, we did not include such a model here (see Section 4.2).

Uncertainty analysis

We investigated the range of possible SCIA results under alternative model assumptions and data quality problems using Monte Carlo simulations with 3000 runs. In each simulation run, we set all quantitative factors to random values taken from a uniform distribution within their ranges, and all qualitative factors to one of their values with equal probability (Table 1). We recorded how often each grid cell was in the most and least impacted 25% and 10% of the study areas. We also recorded how often each subregion, ecosystem component and stressor was among the most and least impacted or impacting 25%. We chose 25% as the main threshold following Halpern *et al.*'s (2015) distinction of high and low impacts.

Sensitivity analysis

We ranked the factors by influence on the ranks of subregions, stressors and ecosystem components using the Elementary Effects (EE) method (Morris, 1991; Campolongo *et al.*, 2007). This method estimates the effect of each factor on the model output repeatedly, while the other factors take on different values from their entire ranges, and then averages these estimates into a measure of overall effect. It allows robust and computationally efficient ranking of factors, and is model-free (Saltelli *et al.*, 2004, 2008). Table 1 lists the factor levels.

There were three complications using the EE method for our model. First, the method as originally described requires that changes in factors have a direction (i.e. the factors can increase or decrease). This was not the case for our qualitative factors with multiple levels (e.g. selecting one of three transformation functions). Second, 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* stressors. Third, our model does not have a single numerical output but produced one rank for each subregion, for each stressor and for each ecosystem component, which we then used to estimate the effects of each factor on the overall rankings. We thus adjusted the EE method as described in Appendix S1. The adjusted method produced two results for each factor: μ^*, an estimate of the overall influence of a factor on the model output (including interactions with other factors), and σ^*, an estimate of how much the influence of a factor depended on interactions and stochasticity.

The multiple model outputs and stochasticity made our results more variable than they would be for a deterministic model with a single number as output. We thus had to use a larger than usual sample size ($t = 500$). We confirmed that this sample size was sufficient by repeating the calculations twice.

RESULTS

Uncertainty analysis

Some, but not all, spatial patterns of modelled human impacts were robust. Figure 2 compares high- and low-impact areas according to the original Baltic and Mediterranean/Black Sea models with the results of the MC simulations (see also Figs S4–S6). Of the 25% of the Baltic Sea's grid cells identified as most impacted using the original model, 31% were in the same category in more than 75% of simulation runs. Of the 25% identified as least impacted using the original model, 64% were in the same category in more than 75% of simulation runs. Uncertainty was slightly greater in the Mediterranean model. Of the 25% of the Mediterranean/Black Sea grid cells identified as most impacted using the original model, 26% were in the same category in more than 75% of simulation runs. Of the 25% of those identified as least impacted using the original model, 21% were among the least impacted in more than 75% of simulation runs. Compared with the most and least impacted 25% of grid cells in the study areas, there were fewer robust results for the most and least impacted 10% (Fig. S6). This suggests that human impact maps produced with Halpern *et al.*'s model are best interpreted in broad, qualitative terms (e.g. distinguishing high, intermediate and low impact areas). Only tiny areas were among the most or least impacted in more than 75% of simulation runs but not in the original model.

UA for region, stressor and ecosystem component ranks also found both robust and unreliable results (Fig. S7, Tables S2 & S3). Note that while we reported robust proportions of original results for the most and least impacted areas, the following numbers are totals (i.e. the maximum in the absence of uncertainty would be 25%). For the Baltic Sea: 13% of regions were ranked among the most impacted 25% in more than 75% of simulation runs; 20% of regions were ranked among the least impacted 25% in more than 75% of simulation runs; 17% of stressors were ranked among the 25% with the highest impact in more than 75% of simulation runs; 15% of stressors were ranked among the 25% with the lowest impact in more than 75% of simulation runs; no ecosystem components were ranked among the most or least impacted 25% in more than 75% of simulation runs. For the Mediterranean/Black Sea: 5% of regions were ranked among the most impacted 25% in more than 75% of simulation runs; 11% of regions were ranked among the least impacted 25% in more than 75% of simulation runs; 12% of stressors were ranked among the 25% with the highest impact in more than 75% of simulation runs; 18% of stressors were ranked among the 25% with the lowest impact in more than 75% of simulation runs; 6% of ecosystem components were ranked among the most impacted 25% in more than 75% of simulation runs; 12% of ecosystem components were ranked among the least impacted 25% in more than 75% of simulation runs.

Sensitivity analysis

Which factors were most influential overall depended on the SCIA (Baltic or Mediterranean/Black Sea) and the modelling result considered. Figure 3 shows μ^* and σ^* averaged over all subregions, stressors and ecosystem components. Note that we do not report the effects of X_0 on stressor ranks (because the removal of stressors automatically changes the ranks of others), and that X_2 had no effect in the Mediterranean/Black Sea (because there were no point stressors).

All factors except X_5 (improved stressor resolution) were among the three most influential factors for at least one modelling result in one SCIA. Furthermore, while some factors had a greater influence overall on specific model outputs than did other factors, there was much variability in the influence of these factors on the ranks of particular subregions, stressors and ecosystem components (Fig. S8). An example is the spatial decay of point stressors (X_2) in the Baltic Sea. Overall, it was one of the less important factors, but was among the three most important factors affecting the rank of 10% of subregions: it changed the ranks of those subregions that contained or were close to many point stressors, but was irrelevant elsewhere. High values of σ^* compared with μ^* for some factors (e.g. X_0 for Mediterranean/Black Sea regions) suggest that the effects of these factors depended on the values of other factors and on stochastic model components.

DISCUSSION

Comparison with the findings of earlier studies

Several previous studies tested the effects of model assumptions and data quality problems on the results of spatial cumulative impact assessments (SCIAs), including errors in sensitivity weights (Halpern *et al.*, 2008a; Selkoe *et al.*, 2009; Korpinen *et al.*, 2012; Allan *et al.*, 2013), missing stressor data (Selkoe *et al.*, 2009; Allan *et al.*, 2013) and stressor data transformation (Halpern *et al.*, 2008a; Allan *et al.*, 2013). None found major effects on the results of SCIAs for any factor studied here (but see Brown *et al.*, 2014). Our results, based on a more comprehensive analysis, contradict these findings. Not all results were robust, and a considerable part of the total uncertainty was caused by factors such as stressor data transformation, missing stressor data and errors in sensitivity weights that previous studies (which assessed the

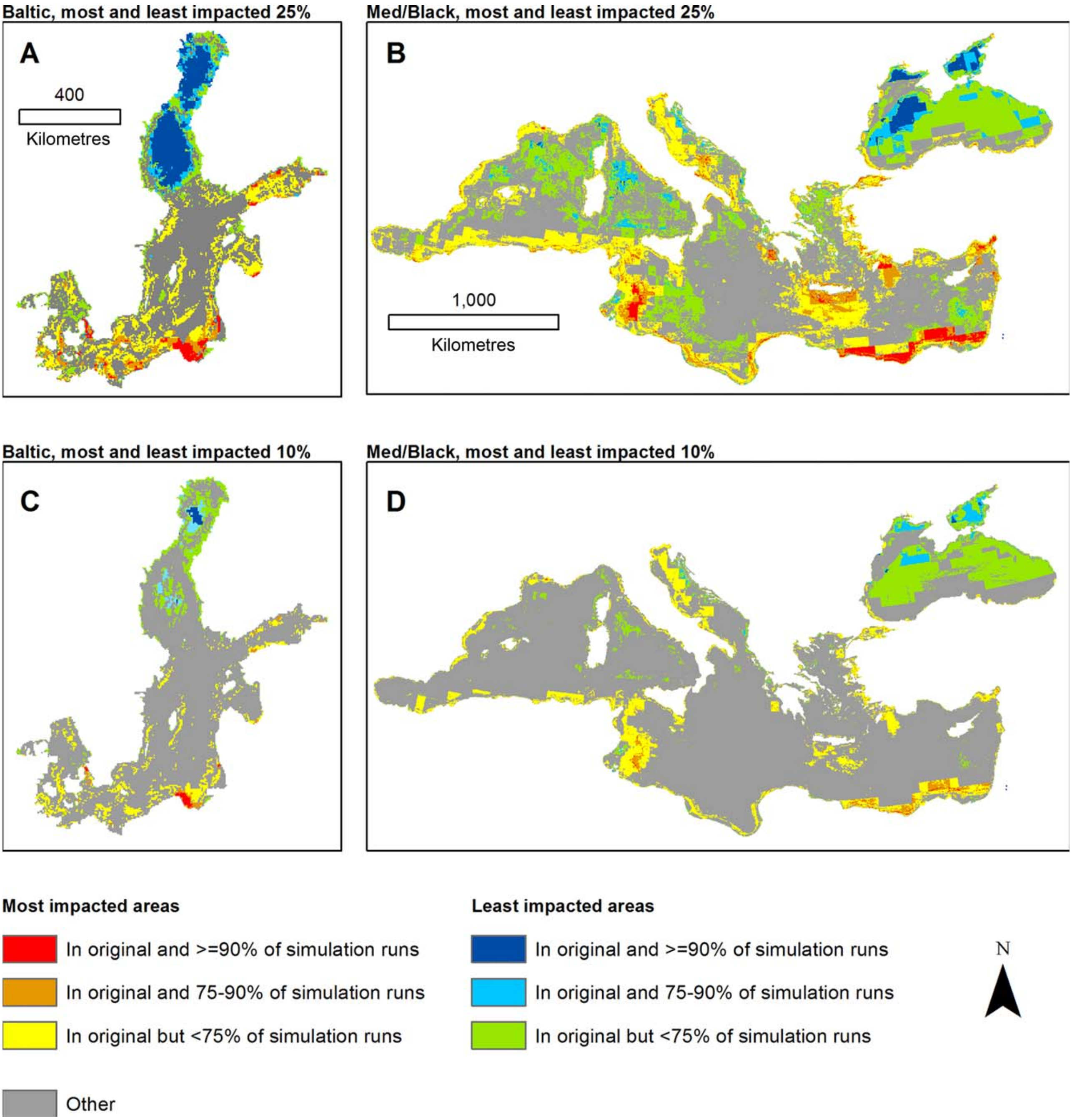

Figure 2 Spatial distribution of high and low human impacts (defined as the 25% (a, b) or 10% (c, d) of the study areas with the highest or lowest impact scores) in the cumulative human impact maps reproduced with the original model and in the Monte Carlo simulations. Red and dark blue areas and to a lesser extent orange and light blue areas are robust results (a colour version of the figure is available online).

effects of fewer factors and each one in isolation) found to have little influence.

Limitations of study design

We could obtain most but not all of the original input data from Korpinen *et al.* (2012) and Micheli *et al.* (2013). We also extracted sensitivity weights from other documents (Halpern *et al.*, 2007; HELCOM, 2010), and it was not always clear which spatial data sets corresponded to which sensitivity weights. Furthermore, we did not know about Korpinen et al.'s and Micheli et al.'s data processing (e.g. how raw vector data were transformed to a regular grid) in sufficient detail to reproduce the analyses exactly. We could therefore not exactly reproduce the results of the original assessments. Lastly, we reproduced Micheli *et al.*'s SCIA at a coarser spatial resolution (2 km

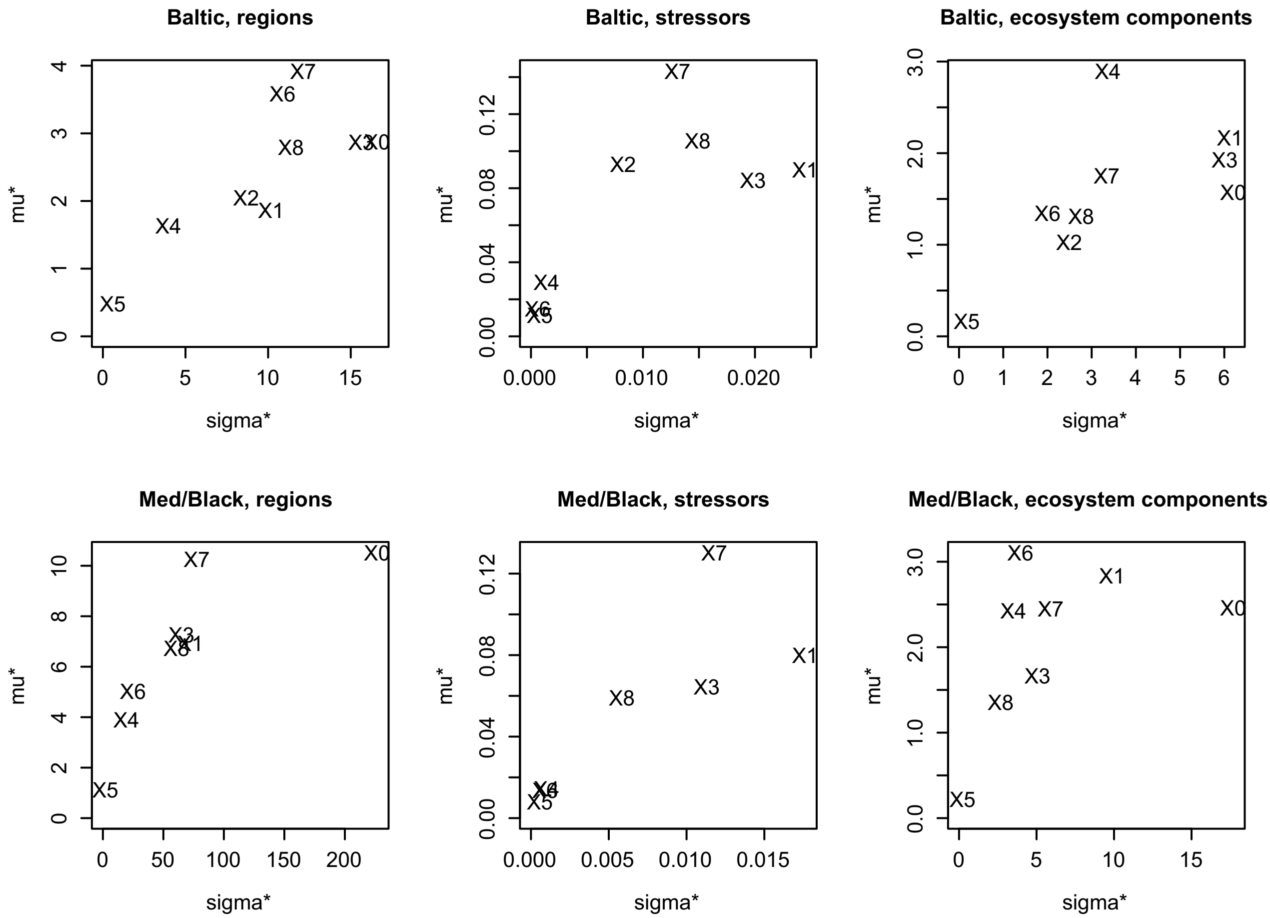

Figure 3 Plots of μ^* (denoted as mu* in the figure; an estimate of the overall influence of a factor on the model output, including interactions with other factors) and σ^* (denoted as sigma* in the figure; an estimate of how much the influence of a factor depended on interactions and stochasticity). See Table 1 for a list of factors, and note the different scales of the *x* and *y* axes.

instead of 1 km) to achieve acceptable computation times for thousands of model evaluations. This imperfect reproduction is unlikely to have affected our findings, for three reasons. First, our analyses were conducted on realistic data. The reproduced maps were very similar to the original maps (correlation coefficients *c.* 0.9; Fig. S9) and the tested factors changed the maps much more than the imperfect reproduction. Second, this paper focuses on general insights about uncertainty in SCIAs, and our conclusions are supported by the results for both example regions. It is unlikely that small within-region differences between the original SCIAs and reproduction could affect findings that are consistent across both example regions. Third, the differences between our findings and those of the previous studies are much better explained by our use of global UA and SA methods than by the imperfect reproduction.

The main limitation of this study is the omission of some potentially relevant factors and the identification of ranges and levels for the factors that we did include. Using ranges for quantitative factors that are too small and omitting reasonable alternative model assumptions could result in an underestimation of uncertainty. Using factor ranges that are too large or including unjustified alternative model assumptions, in contrast, could result in an overestimation of uncertainty. We thus limited our analyses to factors for which there was literature suggesting ranges or alternative model structures. For example, we implemented three MSEMs: dominant, additive and antagonistic. We implemented these MSEMs based on published literature (Folt *et al.*, 1999; Halpern *et al.*, 2008a; Stelzenmüller *et al.*, 2010). However, while there is concern about synergistic effects of multiple stressors (Crain *et al.*, 2008), we could not find any studies suggesting a synergistic effects model that could be implemented for this study. There are other model assumptions and limitations that we did not address (Halpern & Fujita, 2013). For example, we did not test the effects of errors in the spatial distributions of ecosystem components and stressors, and of ignoring the timing of seasonal phenomena like spawning. We also ignored sources of uncertainty that were specific to a particular study region or data set. For example, Micheli *et al.* (2013) did not have ocean warming data for the Black Sea, which contributes to the consistently low impacts in parts of this area. But Black Sea surface temperatures are among the most rapidly increasing in the world (Belkin *et al.*, 2009). The consistently low impacts in the Black Sea are thus caused in part by a data gap. As this example illustrates, the omission of potentially important factors means that we have missed some uncertainty in the two example SCIAs. However, our general results (that the SCIA results were less robust than previous studies found, and that the effects of the factors depended on the study area and result considered), are not affected. The example also illustrates that it is important to understand the limitations of individual data sets and model assumptions for each specific study area. Our general UA and SA methods and results can complement and support, but not replace, such region-specific understanding.

Implications for SCIAs and future directions

Some SCIAs refer to UA and SA results reported in other assessments, arguing that some factors of concern have already been shown to have little influence on model outputs. However, our results suggest that such generalizations are a priori unjustified because factors can have different effects in different SCIAs and on different model outputs. For example, missing stressor data (X_0) was more important in the Mediterranean/Black Sea than in the Baltic Sea. This is because the Baltic Sea assessment includes 47 stressors, many having similar spatial patterns. The Mediterranean/Black Sea assessment, in contrast, includes 17 stressors with diverse spatial patterns. Thus, when a stressor was excluded from the Baltic Sea assessment, others with similar spatial patterns often remained. Missing stressor data had therefore less influence in the Baltic than the Mediterranean/Black Sea.

Each SCIA should thus include its own UA and SA, using global methods that can account for interactions between factors and considering the factors that are expected to be most relevant for the specific study area and the modelling results of interest. This is feasible because UA and SA as demonstrated here require additional work but no additional data. They are thus a cost-effective way to improve SCIAs and identify the most robust results. The use of existing software can reduce the work required. Our source code is available online (https://github.com/anstoc/ImpactMapper—UA). Using it as foundation for UA and SA has the advantage that it is ready to work with Halpern *et al.*'s model and the factors tested here. Disadvantages are that some code will still have to be adjusted to fit a specific SCIA, and that only the factors and methods described in this paper have been implemented so far. If different UA or SA methods are needed, general toolsets like SAFE (Pianosi *et al.*, 2015) may be a better foundation. They provide a better choice of methods, but additional work would be required to make them work with a spatial human impact model.

This paper focused on Halpern *et al.*'s model because it is the most widely used, but other promising approaches to cumulative human impact modelling have been recently developed. They are promising because they empirically identify the responses of ecosystems to stressors from data (Parravicini *et al.*, 2012; Large *et al.*, 2015; Teichert *et al.*, 2016) or are based on key ecological concepts like food webs (Fulton *et al.*, 2011; Griffith *et al.*, 2012; Giakoumi *et al.*, 2015). No matter what models future SCIAs use, UA and SA can distinguish robust from less reliable results and point out the most important model and data improvements.

CONCLUSIONS

We found that the study of uncertainty and its sources in spatial cumulative human impact assessments is important, and we suggest methods and practices for this purpose:

1. Some but not all tested impact assessment results were robust. It is thus important to distinguish robust from unreliable results.

2. Eight of nine tested factors were influential for at least one modelling result in one of the two study areas, and their aggregate effects were considerable. It is thus important to investigate the effects of many factors.

3. There were interactions between factors. Uncertainty and sensitivity analysis methods for spatial cumulative impact assessments must thus be global, i.e. explore the whole factor space.

4. The influence of the factors on assessment results depended on which model output was considered. It also depended on characteristics of the study areas and the data that describe them. Finding that one result is robust with respect to a given factor should thus not be generalized to other results or other study areas.

5. Future SCIAs should include global, comprehensive uncertainty and sensitivity analyses. The methods demonstrated in this paper can serve as a minimum standard.

ACKNOWLEDGEMENTS

A.S. was supported by a Goldman Fellowship from the Woods Institute for the Environment. Thanks to David Lobell for advice on research design, methods and presentation of results, and to Samuli Korpinen and Joni Kaitaranta for providing Baltic Sea data.

REFERENCES

Agbayani, S., Picco, C.M. & Alidina, H.M. (2015) Cumulative impact of bottom fisheries on benthic habitats: a quantitative spatial assessment in British Columbia, Canada. *Ocean and Coastal Management*, **116**, 423–434.

Agumya, A. & Hunter, G.J. (2002) Responding to the consequences of uncertainty in geographical data. *International Journal of Geographical Information Science*, **16**, 405–417.

Allan, J.D., McIntyre, P.B., Smith, S.D. *et al.* (2013) Joint analysis of stressors and ecosystem services to enhance restoration effectiveness. *Proceedings of the National Academy of Sciences USA*, **110**, 372–377.

Andersen, J.H., Stock, A., Heinänen, S., Mannerla, M. & Vinther, M, (2013) *Human uses, pressures and impacts in the eastern North Sea*. Aarhus University, DCE-Danish Centre for Environment and Energy.

Ban, N.C., Alidina, H.M. & Ardron, J.A. (2010) Cumulative impact mapping: advances, relevance and limitations to marine management and conservation, using Canada's Pacific waters as a case study. *Marine Policy*, **34**, 876–886.

Ban, S.S., Graham, N.A. & Connolly, S.R. (2014) Evidence for multiple stressor interactions and effects on coral reefs. *Global Change Biology*, **20**, 681–697.

Batista, M.I., Henriques, S., Pais, M.P. & Cabral, H.N. (2014) Assessment of cumulative human pressures on a coastal area: integrating information for MPA planning and management. *Ocean and Coastal Management*, **102**, 248–257.

Belkin, I.M. (2009) Rapid warming of large marine ecosystems. *Progress in Oceanography*, **81**, 207–213.

Borja, A. (2014) Grand challenges in marine ecosystems ecology. *Frontiers in Marine Science*, **1**, 1.

Brown, C.J., Saunders, M.I., Possingham, H.P. & Richardson, A.J. (2014) Interactions between global and local stressors of ecosystems determine management effectiveness in cumulative impact mapping. *Diversity and Distributions*, **20**, 538–546.

Campolongo, F., Cariboni, J. & Saltelli, A. (2007) An effective screening design for sensitivity analysis of large models. *Environmental Modelling and Software*, **22**, 1509–1518.

Chen, Y., Yu, J. & Khan, S. (2010) Spatial sensitivity analysis of multi-criteria weights in GIS-based land suitability evaluation. *Environmental Modelling and Software*, **25**, 1582–1591.

Cheng, B.S., Bible, J.M., Chang, A.L., Ferner, M.C., Wasson, K., Zabin, C.J., Latta, M., Deck, A., Todgham, A.E. & Grosholz, E.D. (2015) Testing local and global stressor impacts on a coastal foundation species using an ecologically realistic framework. *Global Change Biology*, **21**, 2488–2499.

Claudet, J. & Fraschetti, S. (2010) Human-driven impacts on marine habitats: a regional meta-analysis in the Mediterranean Sea. *Biological Conservation*, **143**, 2195–2206.

Coll, M., Piroddi, C., Albouy, C., Ben Rais Lasram, F., Cheung, W.W., Christensen, V. & Palomares, M.L. (2012) The Mediterranean Sea under siege: spatial overlap between marine biodiversity, cumulative threats and marine reserves. *Global Ecology and Biogeography*, **21**, 465–480.

Crain, C.M., Kroeker, K. & Halpern, B.S. (2008) Interactive and cumulative effects of multiple human stressors in marine systems. *Ecology Letters*, **11**, 1304–1315.

Darling, E.S. & Côté, I.M. (2008) Quantifying the evidence for ecological synergies. *Ecology Letters*, **11**, 1278–1286.

Foley, M.M., Halpern, B.S., Micheli, F., Armsby, M.H., Caldwell, M.R., Crain, C.M. & Carr, M.H. (2010) Guiding ecological principles for marine spatial planning. *Marine Policy*, **34**, 955–966.

Folt, C.L., Chen, C.Y., Moore, M.V. & Burnaford, J. (1999) Synergism and antagonism among multiple stressors. *Limnology and Oceanography*, **44**, 864–877.

Fulton, E.A., Link, J.S., Kaplan, I.C., Savina-Rolland, M., Johnson, P., Ainsworth, C., Horne, P., Gorton, R., Gamble, R.J., Smith, A.D.M. & Smith, D.C. (2011) Lessons in modelling and management of marine ecosystems: the Atlantis experience. *Fish and Fisheries*, **12**, 171–188.

Geldmann, J., Joppa, L.N. & Burgess, N.D. (2014) Mapping change in human pressure globally on land and within protected areas. *Conservation Biology*, **28**, 1604–1616.

Giakoumi, S., Halpern, B.S., Michel, L.N., Gobert, S., Sini, M., Boudouresque, C.F., Gambi, M.C., Katsanevakis, S., Lejeune, P., Montefalcone, M., Pergent, G., Pergent-Martini, C., Sanchez-Jerez, P., Velimirov, B., Vizzini, S., Abadie, A., Coll, M., Guidetti, P., Micheli, F. & Possingham, H.P. (2015) Towards a framework for assessment and management of cumulative human impacts on marine food webs. *Conservation Biology*, **29**, 1228–1234.

Goodsir, F., Bloomfield, H.J., Judd, A.D., Kral, F., Robinson, L.A. & Knights, A.M. (2015) A spatially resolved pressure-based approach to evaluate combined effects of human activities and management in marine ecosystems. *ICES Journal of Marine Science*, **72**, 2245–2256.

Griffith, G.P., Fulton, E.A., Gorton, R. & Richardson, A.J. (2012) Predicting interactions among fishing, ocean warming, and ocean acidification in a marine system with whole-ecosystem models. *Conservation Biology*, **26**, 1145–1152.

Halpern, B.S. & Fujita, R. (2013) Assumptions, challenges, and future directions in cumulative impact analysis. *Ecosphere*, **4**, 1–11.

Halpern, B.S., Selkoe, K.A., Micheli, F. & Kappel, C.V. (2007) Evaluating and ranking the vulnerability of global marine ecosystems to anthropogenic threats. *Conservation Biology*, **21**, 1301–1315.

Halpern, B.S., Walbridge, S., Selkoe, K.A., Kappel, C.V., Micheli, F., D'Agrosa, C., Bruno, J.F., Casey, K.S., Ebert, C., Fox, H.E., Fujita, R., Heinemann, D., Lenihan, H.S., Madin, E.M., Perry, M.T., Selig, E.R., Spalding, M., Steneck, R. & Watson, R. (2008a) A global map of human impact on marine ecosystems. *Science*, **319**, 948–952.

Halpern, B.S., McLeod, K.L., Rosenberg, A.A. & Crowder, L.B. (2008b) Managing for cumulative impacts in ecosystem-based management through ocean zoning. *Ocean and Coastal Management*, **51**, 203–211.

Halpern, B.S., Kappel, C.V., Selkoe, K.A., Micheli, F., Ebert, C.M., Kontgis, C., Crain, C.M., Martone, R.G., Shearer, C. & Teck, S.J. (2009) Mapping cumulative human impacts to California Current marine ecosystems. *Conservation Letters*, **2**, 138–148.

Halpern, B.S., Frazier, M., Potapenko, J., Casey, K.S., Koenig, K., Longo, C., Lowndes, J.S., Rockwood, R.C., Selig, E.R., Selkoe, K.A. & Walbridge, S. (2015) Spatial and temporal changes in cumulative human impacts on the world's ocean. *Nature Communications*, **6**, 7615.

Hecky, R.E., Mugidde, R., Ramlal, P.S., Talbot, M.R. & Kling, G.W. (2010) Multiple stressors cause rapid ecosystem change in Lake Victoria. *Freshwater Biology*, **55**, 19–42.

HELCOM (2010) Towards a tool for quantifying anthropogenic pressures and potential impacts on the Baltic Sea marine environment: a background document on the method, data and testing of the Baltic Sea Pressure and Impact Indices. *Baltic Sea Environment Proceedings No. 125*. Helsinki Commission, Helsinki.

Hoegh-Guldberg, O. & Bruno, J.F. (2010) The impact of climate change on the world's marine ecosystems. *Science*, **328**, 1523–1528.

Holon, F., Mouquet, N., Boissery, P., Bouchoucha, M., Delaruelle, G., Tribot, A.S. & Deter, J. (2015) Fine-scale cartography of human impacts along French Mediterranean coasts: a relevant map for the management of marine ecosystems. *PloS ONE*, **10**,

Hughes, T.P., Bellwood, D.R., Folke, C., Steneck, R.S. & Wilson, J. (2005) New paradigms for supporting the resilience of marine ecosystems. *Trends in Ecology and Evolution*, **20**, 380–386.

Hunsicker, M.E., Kappel, C.V., Selkoe, K.A., Halpern, B.S., Scarborough, C., Mease, L. & Amrhein, A. (2015) Characterizing driver–response relationships in marine pelagic ecosystems for improved ocean management. *Ecological Applications*,

Judd, A.D., Backhaus, T. & Goodsir, F. (2015) An effective set of principles for practical implementation of marine cumulative effects assessment. *Environmental Science and Policy*, **54**, 254–262.

Kelly, C., Gray, L., Shucksmith, R.J. & Tweddle, J.F. (2014) Investigating options on how to address cumulative impacts in marine spatial planning. *Ocean and Coastal Management*, **102**, 139–148.

Knights, A.M., Piet, G.J., Jongbloed, R.H. *et al.* (2015) An exposure-effect approach for evaluating ecosystem-wide risks from human activities. *ICES Journal of Marine Science*, **72**, 1105–1115.

Korpinen, S., Meski, L., Andersen, J.H. & Laamanen, M. (2012) Human pressures and their potential impact on the Baltic Sea ecosystem. *Ecological Indicators*, **15**, 105–114.

Korpinen, S., Meidinger, M. & Laamanen, M. (2013) Cumulative impacts on seabed habitats: an indicator for assessments of good environmental status. *Marine Pollution Bulletin*, **74**, 311–319.

Large, S.I., Fay, G., Friedland, K.D. & Link, J.S. (2015) Quantifying patterns of change in marine ecosystem response to multiple pressures. *PLoS ONE*, **10**, e0119922.

Lilburne, L. & Tarantola, S. (2009) Sensitivity analysis of spatial models. *International Journal of Geographical Information Science*, **23**, 151–168.

Marcotte, D., Hung, S.K. & Caquard, S. (2015) Mapping cumulative impacts on Hong Kong's pink dolphin population. *Ocean and Coastal Management*, **109**, 51–63.

Maxwell, S.M., Hazen, E.L., Bograd, S.J. *et al.* (2013) Cumulative human impacts on marine predators. *Nature Communications*, **4**,

Micheli, F., Halpern, B.S., Walbridge, S., Ciriaco, S., Ferretti, F., Fraschetti, S., Lewison, R., Nykjaer, L. & Rosenberg, A.A. (2013) Cumulative human impacts on Mediterranean and Black Sea marine ecosystems: assessing current pressures and opportunities. *PLoS ONE*, **8**, e79889.

Morris, M.D. (1991) Factorial sampling plans for preliminary computational experiments. *Technometrics*, **33**, 161–174.

Murray, C.C., Agbayani, S., Alidina, H.M. & Ban, N.C. (2015a) Advancing marine cumulative effects mapping: an update in Canada's Pacific waters. *Marine Policy*, **58**, 71–77.

Murray, C.C., Agbayani, S. & Ban, N.C. (2015b) Cumulative effects of planned industrial development and climate change on marine ecosystems. *Global Ecology and Conservation*, **4**, 110–116.

Okey, T.A., Alidina, H.M. & Agbayani, S. (2015) Mapping ecological vulnerability to recent climate change in Canada's Pacific marine ecosystems. *Ocean & Coastal Management*, **106**, 35–48.

Parravicini, V., Rovere, A., Vassallo, P., Micheli, F., Montefalcone, M., Morri, C., Paolia, C., Albertellia, G., Fabiano, M. & Bianchi, C.N. (2012) Understanding relationships between conflicting human uses and coastal ecosystems status: a geospatial modeling approach. *Ecological Indicators*, **19**, 253–263.

Pauly, D., Christensen, V., Guénette, S., Pitcher, T.J., Sumaila, U.R., Walters, C.J., Watson, R. & Zeller, D. (2002) Towards sustainability in world fisheries. *Nature*, **418**, 689–695.

Pianosi, F., Sarrazin, F. & Wagener, T. (2015) A Matlab toolbox for global sensitivity analysis. *Environmental Modelling and Software*, **70**, 80–85.

Prahler, E.E., Reiter, S.M., Bennett, M. & Erickson, A.L. (2014) It all adds up: enhancing ocean health by improving cumulative impacts analyses in environmental review documents. *Stanford Environmental Law Journal*, **33**, 351.

Saltelli, A. & Annoni, P. (2010) How to avoid a perfunctory sensitivity analysis. *Environmental Modelling and Software*, **25**, 1508–1517.

Saltelli, A. & Funtowicz, S. (2014) When all models are wrong. *Issues in Science and Technology*, **30**(2).

Saltelli, A., Tarantola, S., Campolongo, F. & Ratto, M, (2004) *Sensitivity analysis in practice: a guide to assessing scientific models*. Wiley, Chichester.

Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M. Tarantola, S, (2008) *Global sensitivity analysis: the primer*. Wiley, Chichester.

Sanderson, E.W., Jaiteh, M., Levy, M.A., Redford, K.H., Wannebo, A.V. & Woolmer, G. (2002) The human footprint and the last of the wild. *BioScience*, **52**, 891–904.

Selkoe, K.A., Halpern, B.S., Ebert, C.M., Franklin, E.C., Selig, E.R., Casey, K.S., Bruno, J. & Toonen, R.J. (2009) A map of human impacts to a 'pristine' coral reef ecosystem, the Papahānaumokuākea Marine National Monument. *Coral Reefs*, **28**, 635–650.

Shears, N.T. & Ross, P.M. (2010) Toxic cascades: multiple anthropogenic stressors have complex and unanticipated interactive effects on temperate reefs. *Ecology Letters*, **13**, 1149–1159.

Stamoulis, K.A. & Delevaux, J.M. (2015) Data requirements and tools to operationalize marine spatial planning in the United States. *Ocean and Coastal Management*, **116**, 214–223.

Stelzenmüller, V., Lee, J., South, A. & Rogers, S.I. (2010) Quantifying cumulative impacts of human pressures on the marine environment: a geospatial modelling framework. *Marine Ecology Progress Series*, **398**, 19–32.

Stelzenmüller, V., Lee, J., South, A., Foden, J. & Rogers, S.I. (2013) Practical tools to support marine spatial planning: a review and some prototype tools. *Marine Policy*, **38**, 214–227.

Stock, A. (2016) Open source software for mapping human impacts on marine ecosystems with an additive model. *Journal of Open Research Software*, **4**, e21.

Strain, E., Thomson, R.J., Micheli, F., Mancuso, F.P. & Airoldi, L. (2014) Identifying the interacting roles of stressors in driving the global loss of canopy-forming to mat-forming algae in marine ecosystems. *Global Change Biology*, **20**, 3300–3312.

Teck, S.J., Halpern, B.S., Kappel, C.V., Micheli, F., Selkoe, K.A., Crain, C.M., Martone, R., Shearer, C., Arvai, J., Fischhoff, B., Murray, G., Neslo, R. & Cooke, R. (2010) Using expert judgment to estimate marine ecosystem vulnerability in the California Current. *Ecological Applications*, **20**, 1402–1416.

Teichert, N., Borja, A., Chust, G., Uriarte, A. & Lepage, M. (2016) Restoring fish ecological quality in estuaries: implication of interactive and cumulative effects among anthropogenic stressors. *Science of the Total Environment*, **542**, 383–393.

Vörösmarty, C.J., McIntyre, P.B., Gessner, M.O., Dudgeon, D., Prusevich, A., Green, P., Glidden, S., Bunn, S.E., Sullivan, C.A., Liermann, C.R., Davies, P.M. & Davies, P.M. (2010) Global threats to human water security and river biodiversity. *Nature*, **467**, 555–561.

SUPPORTING INFORMATION

Additional Supporting Information may be found in the online version of this article at the publisher's web-site.

Appendix S1 Supplementary methods.
Figure S1 Subregions used to analyse the effects of model assumptions and data quality on broad-scale spatial patterns of human impacts.
Figure S2 Example nonlinear 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 study areas with the 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 study areas with highest and lowest modelled impact scores) in maps reproduced with the original model and in the Monte Carlo simulations.
Figure S6 Percentage 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% of simulation runs.
Figure S7 Percentage of regions, stressors and ecosystem components that were among the most and least impacted (or, in the case of stressors, most and least impacting) 25% in at least 75% and 90% of simulation runs.
Figure S8 Percentage of subregions, stressors and ecosystem components for which $X_0 \ldots X_8$ were among the three most influential factors according to μ^*.
Figure S9 Korpinen *et al.*'s (2012) and Micheli *et al.*'s (2013) human impact maps and their reproduction for this study.
Table S1 Data sources for reproduction of the Baltic Sea and Mediterranean/Black Sea SCIAs.
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.
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.

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Editor: Richard Field