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

Authors: Andy Stock & Fiorenza Micheli

Andy Stock, Emmett Interdisciplinary Program in Environment & Resources, Stanford University, Stanford, CA, USA. astock@stanford.edu

Fiorenza Micheli, Hopkins Marine Station, Stanford University, Pacific Grove, CA, USA. micheli@stanford.edu

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Corresponding author: Andy Stock

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Abstract

Aim Many studies have presented quantification and maps of 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 modeling results; 2) attribute this uncertainty to specific model assumptions and data quality problems; 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 human impact maps and related modeling results. The factors were implemented based on literature review. We quantified aggregate uncertainty using Monte Carlo simulations, and ranked the factors by their influence on modeling results using the elementary effects method. Both methods are well established and theoretically suitable for complex models, but had to be modified to be applicable to spatial human impact models.

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

Main conclusions Model assumptions and data quality have larger aggregate effects on human impact maps than previous analyses found. 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 to distinguish robust from less reliable modeling results and to prioritize model and data improvements.

1. 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 alteration of whole 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, ecosystem responses to many stressors and especially their combinations are still unknown (Claudet & Fraschetti, 2010). Understanding the relationship between stressors and marine ecosystem state 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). The model and variations of it have since been used in many studies (Halpern et al., 2009; Selkoe et al., 2009; Ban et al., 2010; HELCOM 2010; Korpinen et al., 2012; Allan et al., 2013; Andersen et al., 2013; Korpinen et al., 2013; Maxwell et al., 2013; Micheli et al., 2013; Agbayani et al., 2015; Halpern 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 suggests that multiple stressor effects are complex and that stressors can interact non-additively (Crain et al., 2008; Darling & Coté, 2008; Ban et al., 2014; Strain et al., 2014; Cheng et al., 2015). SCIA results could thus be highly uncertain.

Applications of modeling results to ecosystem-based planning and management require understanding 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 SCIA results based on Halpern et al.'s model are robust. However, previous analyses studied the effects of few model assumptions or data quality problems (in the following called factors). This is problematic because for modeling results with many potential sources of uncertainty, studying few factors reveals only 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. 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 $B>=0.6$, 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 $B>=0.6$. Saltelli & Annoni (2010) thus make a strong case against using 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 each factor's effect 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 supplementary 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.

2. Data and methods

2.1 Original model

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

$$I_{Sum}(x,y) = \sum_{i=1}^{n}\sum_{j=1}^{m} D_i(x,y)\, e_j(x,y)\, \mu_{i,j} \qquad \text{(Eq. 1)}$$

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.

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 study areas' sub-regions (most to least impacted, as proxy for broad-scale spatial patterns)
- Ranks of stressors (highest to lowest impact in the whole study areas, 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 Supplementary Information).

2.2 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 1km to 2km grid cells. We defined sub-regions for studying the factors' effects on broad scale spatial patterns based on existing HELCOM and FAO regions. We split large subregions into coastal (up to 12nm 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. Fig. S1 shows the subregions.

2.3 Factors and model extension

Table 1 summarizes the factors included in this analysis. Fig. 1 illustrates a single model evaluation. Details and equations are provided in the Supplementary Methods.

2.3.1 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 obtain data for 25. Andersen et al. (2013) identified 47 relevant stressors and could obtain data for 33. We investigated the effect of missing stressor data by randomly excluding up to 1/3 of stressors.

2.5.2 Sensitivity weight errors (X_1)

Halpern et al.'s (2008a) model uses sensitivity weights ($\mu_{i,j}$ in Eq. 1) to estimate the impact of stressor i on ecosystem component j. These weights are derived by expert judgment (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 +/- half the original weights' maximum (Eq. S1).

2.5.3 Spreading of impacts from point stressors (X_2)

Halpern et al.'s (2008a) model assumes that many stressors only affect the grid cells where the human activities that cause them occur, while impacts can in fact occur tens of kilometers 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 stressor intensity to decay linearly from the sites of human activities. We investigated the effects of assuming linear decay of stressors represented by points using 20km as maximum decay distance (Eq. S2), which was the mean for stressors represented by point or line data in an expert survey (Andersen et al., 2013).

2.5.4 Non-linear responses to stressors (X_3)

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

2.5.5 Reduced analysis resolution (X_4)

Most cumulative human impact maps have spatial resolutions of 1km (e.g. Micheli et al., 2013) to 5km (Korpinen et al., 2012). We investigated the effects of reducing the spatial resolution of all stressor and ecosystem data by factor 2.

2.5.6 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 seabed-destructing 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.

2.5.7 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 present ecosystem components; Eqs. S5, S6). We investigated the effects of this decision.

2.5.8 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 each stressor intensity to the percentile it corresponds to (Vörösmarty et al., 2010). The effects of extreme values could also be avoided by setting all stressor intensities higher than the 99-percentile to equal the 99-percentile (in the following: P-transformation), but leaving smaller stressor intensities untransformed. We tested the effects of choosing one of these three transformation types (Eq. S7).

2.5.9 Multiple stressor effects model (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 et al., 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 (Eq. 1; Halpern et al., 2008a), with extensions as described above (Eq. S8). 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 present ecosystem component (Eq. S9). Such a model could be plausible for high impact stressors that alone can destroy habitat, like 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 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 (Eq. S10). Because we found no published synergistic MSEM for more than two stressors, we did not include such a model here (see Section 4.2).

2.6 Uncertainty analysis

We investigated the range of possible SCIA results under alternative model assumptions and data quality problems using Monte Carlo simulations with 3,000 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 in the 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 main threshold following Halpern et al.'s (2015) distinction of high and low impacts.

2.7 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; Campolongo et al., 2007). This method estimates each factor's effect 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 1 of 3 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* are excluded. Third, our model does not have a single numerical output, but produced one rank for each sub-region, for each stressor and for each ecosystem component, which we then used to estimate each factor's effects on the overall rankings. We thus adjusted the EE method as described in the Supplementary Methods. The adjusted method produced two results for each factor: $\mu *$, an estimate of a factor's overall influence on the model output (including interactions with other factors), and $\sigma*$, an estimate of how much a factor's influence 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 ($t=500$) sample size. We confirmed that this sample size was sufficient by repeating the calculations twice.

3. Results

3.1 Uncertainty analysis

Some, but not all spatial patterns of modeled human impacts were robust. Fig. 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 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 the identified as least impacted using the original model, 21% were among the least impacted in more than 75% of simulation runs. Compared to the most and least impacted 25% of 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% were ranked among the least impacted 25% in more than 75% of simulation runs. 17% of stressors were ranked among the highest-impact 25% in more than 75% of simulation runs. 15% were ranked among the lowest-impact 25% 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 Seas, 5% of regions were ranked among the most impacted 25% in more than 75% of simulation runs. 11% were ranked among the least impacted 25% in more than 75% of simulation runs. 12% of stressors were ranked among the highest-impact 25% in more than 75% of simulation runs. 18% were ranked among the lowest-impact 25% 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% were ranked among the least impacted 25% in more than 75% of simulation runs.

3.2 Sensitivity analysis

Which factors were most influential overall depended on the SCIA (Baltic or Mediterranean/Black Seas) and which modeling result was considered. Fig. 3 shows $\mu*$ and $\sigma*$ averaged over all sub-regions, stressors and ecosystem components. Note that we do not report

X_0*'s* effects on stressor ranks (because removing stressors automatically changes the ranks of others), and that X_2 had no effect in the Mediterranean/Black Seas (because there were no point stressors).

All factors except X_5 (improved stressor resolution) were among the three most influential for at least one modeling result in one SCIA. Furthermore, while some factors overall influenced specific model outputs more than others, there was much variability in the factors' influence on particular sub-region, stressor and ecosystem component ranks (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 for the rank of 10% of sub-regions: It changed the ranks of those sub-regions that contained or were close to many point stressors, but was irrelevant elsewhere. High values of σ^* compared to $\mu *$ for some factors (e.g. X_0 for Mediterranean/Black Sea regions) suggest that these factors' effects depended on other factors' values and on stochastic model components.

4. Discussion

4.1 Comparison to earlier studies' findings

Several previous studies tested the effects of model assumptions and data quality problems on spatial cumulative impact assessment (SCIA) results, 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 SCIA results 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 like stressor data transformation, missing stressor data and errors in sensitivity weights that previous studies assessing the effects of fewer factors and one-by-one in isolation found to have little influence.

4.2 Limitations of study design

We could obtain most but not all 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, neither paper describes 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 original assessments' results. Lastly, we reproduced Micheli et al.'s SCIA at a coarser spatial resolution (2km instead of 1km) to achieve acceptable computation times for 1000s 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 ~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 and previous studies' findings are much better explained by our use of global uncertainty analysis (UA) and sensitivity analysis (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 included. Using too small ranges for quantitative factors and omitting reasonable alternative model assumptions could result in underestimating uncertainty. Using too large factor ranges or including unjustified alternative model assumptions, in contrast, could result in overestimating 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 in part caused 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 SCIA results were less robust than previous studies found, and that the factors' effects depended on the study area and result considered), are not affected. The example also illustrates that it is important to understand 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.

4.3 Implications for SCIAs and future directions

Some SCIAs refer to UA and SA results reported in others, 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 Seas.

Each SCIA should thus include its own UA and SA, using global methods that can account for factor interactions and considering the factors that are expected to be most relevant for the specific study area and the modeling 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. Using existing software can reduce the required work. Our source code is available online. 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 are 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 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 modeling have been recently developed. They are promising because they empirically identify ecosystem responses 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.

4.4 Conclusions

We found that studying uncertainty and its sources in spatial cumulative human impact assessments is important, and 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 modeling 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 spatial cumulative impact assessments should include global, comprehensive uncertainty and sensitivity analyses. The methods demonstrated in this paper can serve as a minimum standard.

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Supplementary material

1. Supplementary methods, Figs. S1-S9 and Tables S1-S3
2. Source code: https://github.com/anstoc/ImpactMapper---UA

Biosketch

Andy Stock is a PhD candidate at Stanford University. He studies the methods and concepts around human impact mapping. Fiorenza Micheli is the David and Lucile Packard Professor of marine science at Stanford University, where she teaches and conducts research in marine ecology and conservation.

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TABLES

Table 1. Factor ranges in the 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 +/- 0, 0.67, 1.33, 2
X_2: Point stressor lin. decay	Decay distance 0 to 20km	Decay distance 0km, 7km, 13km, 20km
X_3: Non-linear responses	Threshold response function for 0% to 100% of ecosystem component-stressor combinations	Threshold response function for 0, 1/3, 2/3, all ecosystem component-stressor combinations
X_4: Reduced analysis res.	0: original or 1: reduced resolution	same
X_5: Improved stressor res.	0: original or 1: improved resolution	same
X_6: Mean or sum of impacts	0: Sum or 1: Mean	same
X_7: Transformation type	0: Log(X+1) or 1: CDF or 2: P-transformation	same
X_8: MSEM	0: Additive or 1: Dominant stressor or 2: Antagonistic	same

FIGURE LEGENDS

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

Fig. 2. Spatial distribution of high and low human impacts (defined as the 25%: A, B or 10%: C, D of the study areas with 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.

Fig. 3. Plots of $\mu *$ (an estimate of a factor's overall influence on the model output, including interactions with other factors) and σ* (an estimate of how much a factor's influence depended on interactions and stochasticity). See Table 1 for a list of factors, and note different scales of the x and y axes.

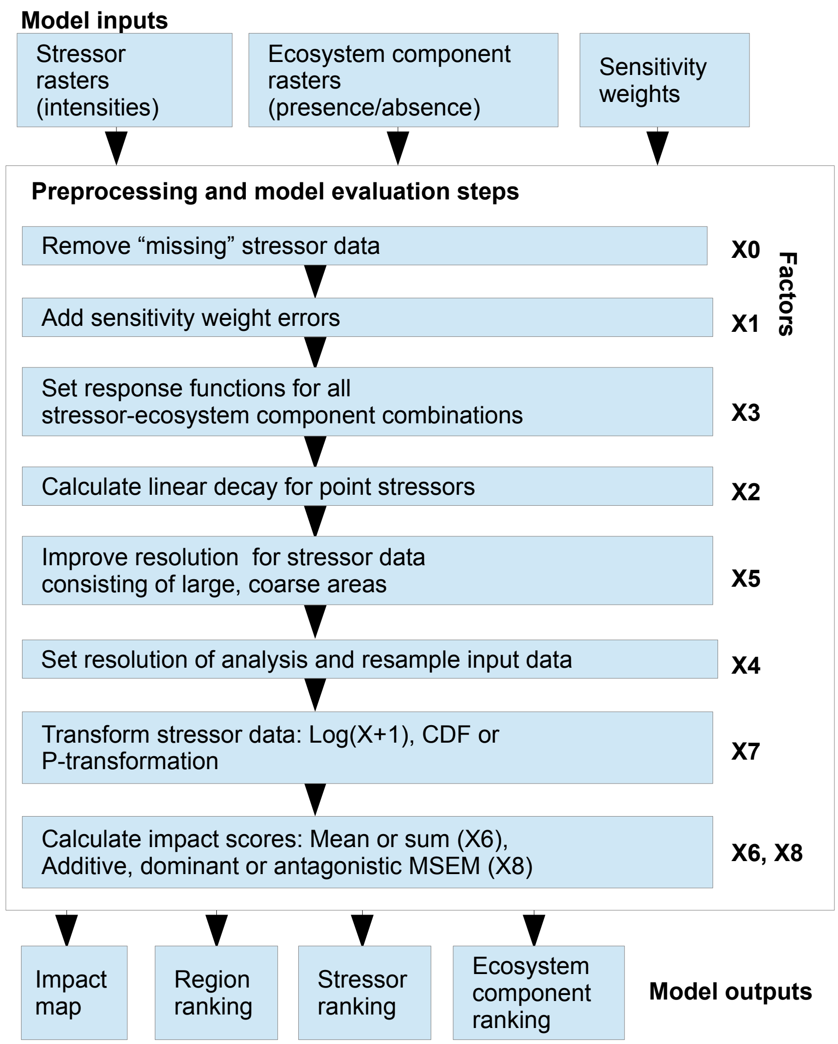
Model inputs
Stressor rasters (intensities)
Ecosystem component rasters (presence/absence)
Sensitivity weights
Preprocessing and model evaluation steps
Remove “missing” stressor data
X0
Factors
Add sensitivity weight errors
X1
Set response functions for all stressor-ecosystem component combinations
X3
Calculate linear decay for point stressors
X2
Improve resolution for stressor data consisting of large, coarse areas
X5
Set resolution of analysis and resample input data
X4
Transform stressor data: Log(X+1), CDF or P-transformation
X7
Calculate impact scores: Mean or sum (X6), Additive, dominant or antagonistic MSEM (X8)
X6, X8
Impact map
Region ranking
Stressor ranking
Ecosystem component ranking
Model outputs

Fig. 1

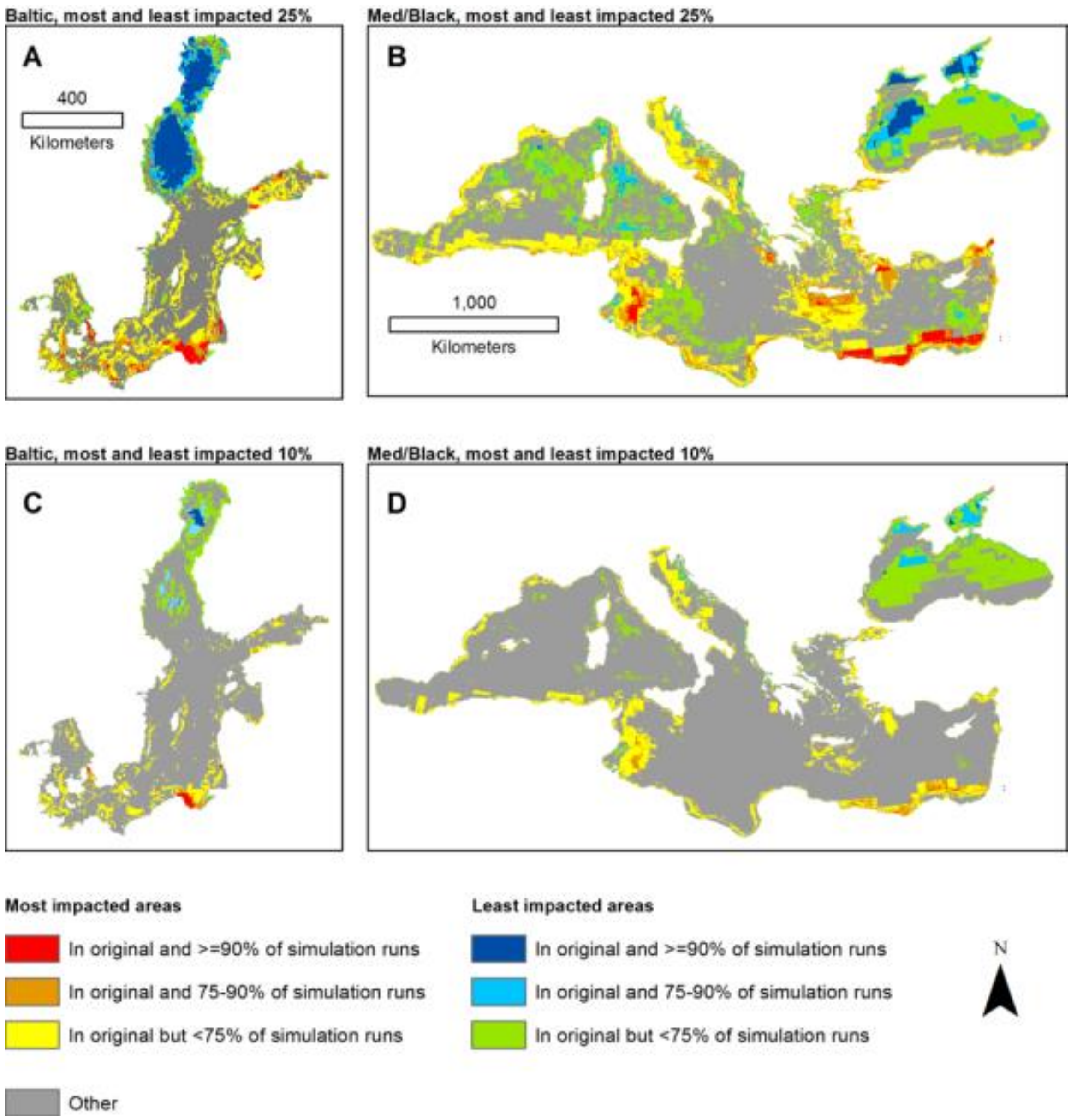
Baltic, most and least impacted 25%
A
400
Kilometers
Med/Black, most and least impacted 25%
B
1,000
Kilometers
Baltic, most and least impacted 10%
C
Med/Black, most and least impacted 10%
D
Most impacted areas
In original and >=90% of simulation runs
In original and 75-90% of simulation runs
In original but <75% of simulation runs
Least impacted areas
In original and >=90% of simulation runs
In original and 75-90% of simulation runs
In original but <75% of simulation runs
N
Other

Fig. 2

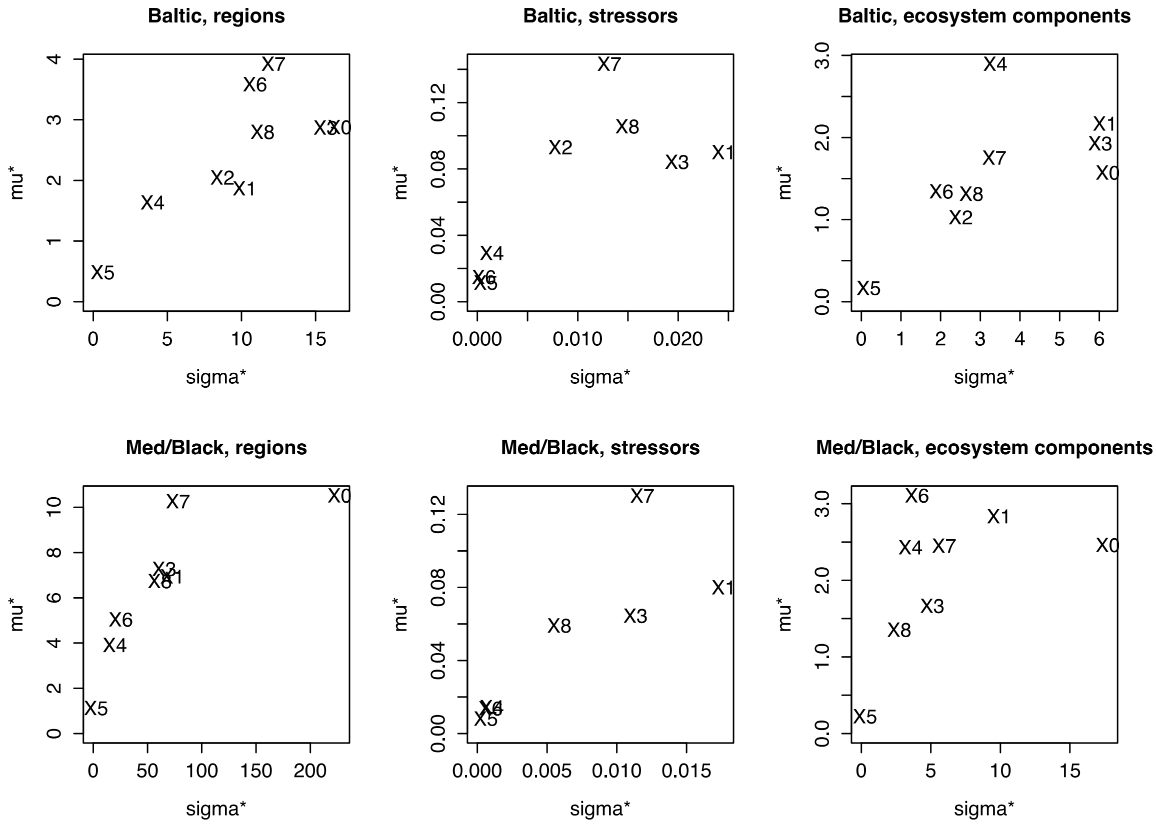
Baltic, regions
Baltic, stressors
Baltic, ecosystem components
Med/Black, regions
Med/Black, stressors
Med/Black, ecosystem components
mu*
sigma*
X0
X1
X2
X3
X4
X5
X6
X7
X8

Fig. 3