NATURAL RESOURCES INSTITUTE FINLAND

Jukuri, open repository of the Natural Resources Institute Finland (Luke)

This is an electronic reprint of the original article.
This reprint *may differ* from the original in pagination and typographic detail.

Author(s): Laura Uusitalo, Riikka Puntila-Dodd, Janne Artell, Susanna Jernberg

Title: Modelling framework to evaluate societal effects of ecosystem management

Year: 2023

Version: Publisher's version

Copyright: The author(s) 2023

Rights: CC BY 4.0

Rights url: https://creativecommons.org/licenses/by/4.0/

Please cite the original version:

Laura Uusitalo, Riikka Puntila-Dodd, Janne Artell, Susanna Jernberg (2023). Modelling framework to evaluate societal effects of ecosystem management. Science of the Total Environment 898 165508 . doi:10.1016/j.scitotenv.2023.165508

All material supplied via *Jukuri* is protected by copyright and other intellectual property rights. Duplication or sale, in electronic or print form, of any part of the repository collections is prohibited. Making electronic or print copies of the material is permitted only for your own personal use or for educational purposes. For other purposes, this article may be used in accordance with the publisher's terms. There may be differences between this version and the publisher's version. You are advised to cite the publisher's version.

Science of the Total Environment 898 (2023) 165508

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Modelling framework to evaluate societal effects of ecosystem management

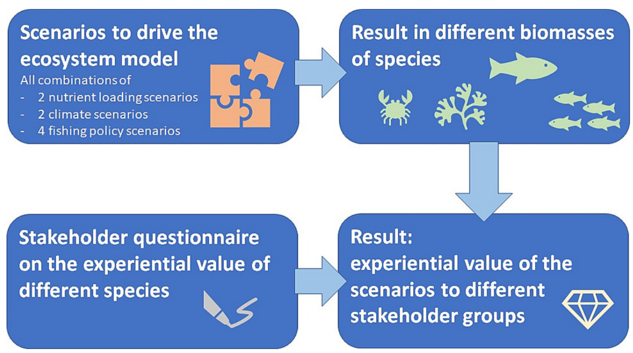
Laura Uusitalo [a,b,*], Riikka Puntila-Dodd [a], Janne Artell [b], Susanna Jernberg [a]

[a] Finnish Environment Institute SYKE, Finland
[b] Natural Resources Institute, Finland

HIGHLIGHTS

- Probabilistic model evaluates the effects of drivers on experiential values.
- Ecosystem simulation model results combined with stakeholder questionnaire.
- In the case study, the same management options were best to all stakeholders.

GRAPHICAL ABSTRACT



ARTICLE INFO

Editor: Martin Drews

Keywords:
Stakeholder
Bayesian
Baltic Sea
Archipelago Sea
Preferences
ECOPATH
ECOSIM

ABSTRACT

The ecosystem effects of different management options can be predicted through models that simulate the ecosystem functioning under different management scenarios. Optimal management strategies are searched by simulating different management (and other, such as climate) scenarios and finding the management measures that produce desirable results. The desirability of results is often defined through the attainment of policy objectives such as good environmental/ecological status. However, this often does not account for societal consequences of the environmental status even though the consequences can be different for different stakeholder groups. In this work we introduce a method to evaluate management alternatives in the light of the experiential value of stakeholder groups, using a case study in the Baltic Sea. We use an Ecopath with Ecosim model to simulate the ecosystem responses to management and climate scenarios, and the results are judged based on objectives defined based on a stakeholder questionnaire on what aspects of the ecosystem they value or detest. The ecosystem responses and the stakeholder values are combined in a Bayesian decision support model to illustrate which management options bring the highest benefits to stakeholders, and whether different stakeholder groups benefit from different management choices. In the case study, the more moderate climate scenario and strict fisheries and nutrient loading management brought the highest benefits to all stakeholders. The method can be used to evaluate and compare the effects of different management alternatives to various stakeholder groups, if their preferences are known.

1. Introduction

Ecosystem based management aims at managing the socio-ecological system holistically, taking into account physical, biological, and socio-economic aspects and seeing humans as one part of the system (Arkema et al., 2006; Berg et al., 2015; Long et al., 2015; McLeod and Leslie, 2012; Slocombe, 1993). The task is challenging, as the management measures might affect multiple different parts of the ecosystem through processes that introduce uncertainty, stochasticity and time lags. Ecosystem simulation models are good tools to evaluate the ecological consequences of different management actions (Korpinen et al., 2022), and the information

* Corresponding author.
E-mail address: laura.uusitalo@luke.fi (L. Uusitalo).

http://dx.doi.org/10.1016/j.scitotenv.2023.165508
Received 26 October 2022; Received in revised form 26 June 2023; Accepted 11 July 2023
Available online 12 July 2023
0048-9697/© 2023 Published by Elsevier B.V.

stemming from one or multiple simulation models, can be summarized in decision support models for easier, holistic analysis (Barton et al., 2012; Kaikkonen et al., 2020; Stelzenmüller et al., 2011; Uusitalo et al., 2022). Probabilistic (Bayesian) models allow the explicit treatment of uncertainties, which is highly useful, especially in future projections or if the decision makers want to ensure avoiding certain undesirable outcomes.

However, including human societies into the ecosystem requires a mapping from the predicted ecosystem states to societal benefits. Studies considering how well policy goals such as agreed ecosystem state or fisheries targets will be reached under different management options (Fulton et al., 2014; Punt et al., 2016; Uusitalo et al., 2022), can be seen as evaluating the attainment of the society level goals. However, different stakeholder groups may prefer different ecosystem states (Schroeder, 2012; Uusitalo et al., 2020), and therefore the management may benefit or harm different stakeholders differently. This is an important issue in relation to the sense of fairness, having repercussions also on denizens' willingness to commit to management measures (Haapasaari et al., 2007).

Experiential value refers to the benefits an individual derives from their experience (Mathwick et al., 2001). Experiential value has been studied largely in the context of consumer behaviour and marketing (Varshneya et al., 2017), but Schroeder (2012) notes that the value people find in their environment can also be an important aspect of their quality of life. Experiential values can be used to measure non-monetary benefits of stakeholders in relation to the potential changes in the natural environment. The effects of environmental management measures on the experiential value derived from nature can be studied through linking the changes in the ecosystem components' abundance or biomass to the stakeholders' experienced value of these components. This gives a new perspective on the well-being effects of environmental management, and can provide a valuable tool to analyse the societal effects of environmental changes and potential management options on, potentially disagreeing, stakeholder groups.

In this work, we introduce and demonstrate a modelling approach to track the effects of management and climate scenarios to the level of the experiential values of stakeholder groups. The approach uses an ecological model that is driven under different scenarios, a stakeholder experiential value questionnaire, and a Bayesian network (BN) based decision support model that draws the results together. BNs are useful for integrating knowledge and results from different sources (Barton et al., 2008; Kelly et al., 2013; Uusitalo, 2007; Uusitalo et al., 2022), which is useful for modelling cross-sector systems (Chen and Pollino, 2012) such as environmental management. The proposed approach fills in the gap in holistic assessment of socio-ecological systems by enabling the evaluation of the predicted changes in experiential values of stakeholders under different management scenarios. We argue that the presented framework is easy to understand and communicate, making it a good candidate to be used also in stakeholder consultations.

2. Materials and methods

2.1. Study area

The study was conducted in the Archipelago Sea area in the northern Baltic Sea, south-western coast of Finland. The area is characterized by a mosaic-like archipelago with more than 40,000 islands and skerries, and ecologically important areas (Virtanen et al., 2018) as well as intensive human use (Leppäkoski et al., 1999). The main pressures include nutrient loading, ship traffic, and alteration of habitats (Leppäkoski et al., 1999), as well as impacts of invasive species (Kraufvelin et al., 2018). The Archipelago Sea is important for commercial and recreational fisheries, as well as other recreational activities, and supports a variety of ecosystem services (Viirret et al., 2019).

2.2. Scenarios and management options

We developed scenarios for different trajectories of three central factors affecting the Baltic Sea ecosystem: climate change, nutrient loading, and fisheries. Two climate scenarios, Representative Concentration Pathways (RCP) (Moss et al., 2010; van Vuuren et al., 2011) 4.5 and 8.5 were chosen. RCP4.5 is an intermediate scenario, while RCP8.5 is a high-emission scenario (van Vuuren et al., 2011). These scenarios were chosen as they are considered realistic, yet contrasting, development pathways, and they are also widely evaluated in literature (Bauer et al., 2019; Giorgetta et al., 2013; He and Zhou, 2015; Luomaranta et al., 2014; Moore et al., 2013; Rusu, 2020; Tebaldi and Knutti, 2007). Two scenarios of nutrient loading were the current loading trajectory, referred to as PLC55 after HELCOM's updated fifth Baltic Sea pollution load compilation (HELCOM, 2015), and the reduced nutrient loading compliant with the Baltic Sea Action Plan (BSAP) (HELCOM, 2007).

The BALTSEM-model illustrates the dynamics of nitrate, ammonium, phosphate, three phytoplankton taxa, zooplankton, detritus and oxygen (Eilola et al., 2009; Gustafsson et al., 2012; Savchuk et al., 2012). In BALTSEM the Baltic Sea is characterized as a set of 13 horizontally homogeneous coupled basins with high vertical resolution. Climate change and biogeochemical scenarios were run with atmospheric forcing based on a downscaled global General Circulation Model (GCM), the Max Planck Institute Earth System Model-Low Resolution (MPI-ESM-LR) (Saraiva et al., 2019). In this study, the BALTSEM-model was used to simulate the primary production, temperature and salinity under the climate change and nutrient loading scenarios for years 2000–2099, and these values were used to force the EwE -model under these scenarios.

Furthermore, climate projections for Representative Concentration Pathways (RCP) 4.5 and 8.5 (IPCC, 2014, applied also in Saraiva et al., 2019) were combined with nutrient load scenarios according to the status quo reference (REF) conditions (Saraiva et al., 2019) and loads outlined in the Baltic Sea Action Plan (BSAP) (HELCOM, 2007). The REF condition assumes that the nutrient emissions will be controlled by current measures and will change due to climate that may impact runoff and atmospheric conditions (Saraiva et al., 2019). The BSAP scenario assumes that the nutrient loads decrease to the level of the maximum allowable load outlined by HELCOM (2007) by 2020, and will remain on that lever after that (Saraiva et al., 2019).

Fishing scenarios were kept as simple as possible since predicting dynamic fisheries management for long term simulations is always unrealistic. We tested four scenarios that were driven by forcing changes to fishing effort: effort remains the same, 50 % decline, 100 % increase and no professional gillnets. The gillnet fishery in the area has been divisive due to their non-selectiveness and large amount of bycatch that has especially impacted pikeperch populations (Heikinheimo et al., 2006; Saulamo and Thoresson, 2005). The four fishing scenarios were implemented directly in the EwE-model.

The ecological scenario data for the BN come from the ecosystem model simulations, including uncertainty assessment (Ecopath with Ecosim with Monte Carlo procedure), and the experiential values are derived from a stakeholder questionnaire asking about the experiential value of different ecosystem components for the recreation and livelihood prospects of the respondent. This information is combined to show predictions of how much experiential value the different stakeholder groups are expected to gain under different climate, nutrient loading, and fisheries management scenarios. The present model enables a direct comparison of the total experiential value of each decision option, and comparison of the experiential value for different stakeholder groups under different climate and management scenarios. As the experiential values of the different stakeholder groups are directly presented, it is easy to evaluate whether some decision options are the most beneficial to all stakeholders, or whether the decision-makers need to decide to benefit some group while harming another.

2.3. Ecopath with Ecosim ecosystem simulation model

Ecopath with Ecosim (EwE, http://www.ecopath.org) is a widely used tool for analysis of food web interactions in exploited aquatic ecosystems. In this study the EwE version 6.6 was used. EwE is built around three main components: Ecopath – a static, mass-balanced snapshot of the system; Ecosim – a time dynamic simulation module; and Ecospace – a spatial and temporal dynamic module (Christensen et al., 2008). The scenarios presented in this work are based on an Ecosim model built and calibrated for the Archipelago Sea ecosystem for years 2000–2016 (Puntila-Dodd et al., 2022; Fig. 1).

The mass balanced Ecopath-model that includes the most important components (taxa or groups of taxa) in the system, with information on their biomass, production and food consumption in the area was created for the year 2000. The Ecopath-model was then checked for model consistency in regard of biomasses, biomass ratios, vital rates and their ratios, and total production and removals following criteria by Link (2010), using a PreBal script in R (written by Barbara Bauer). At the second phase, the model was calibrated in Ecosim (Pauly et al., 2000; Walters et al., 1997) against available time series data (catches, biomass time series) from 2000 to 2016 along with abiotic forcings (salinity, temperature, primary production) and fishery effort impacting the components. The capabilities and limitations of the approach have been thoroughly described by Christensen and Walters (2004), Plagányi (2007) and Plagányi and Butterworth (2004).

The mass balanced Archipelago Sea model includes 29 components ranging from detritus and primary producers (both micro and macroalgae) to seals and birds. Two species in the model, sander and perch, both important species for coastal fishery, have two age groups: juvenile and adult (multi stanza). Fishery (and hunting) is described through seven fleets: Nets, traps, lines, trawls, recreational fishing, hunting, and others. Data for basic parameters biomass, P/B and C/B were gathered from literature and utilizing local monitoring data. Diets for groups were gathered from various reports and publications. Data for fishery (effort and catch) was obtained from the Natural Resources Institute Finland statistics.

There are three invasive species included in the model: round goby (*Neogobius melanostomus*) since 2005, Harris mud crab (*Rhithropanopeus harrisii*) since 2010 and fish-hook water flea (*Cergopagis pengoi*), which was established in late 1990s. Since invasions of *N. melanostomus* and *R. harrisii* occurred during model calibration period, they were modelled using the approach described by Langseth et al. (2012). In short, the invasive species biomass in the system was set initially low and kept low using high artificial "fishing pressure" only targetting the invasive species, which was released 2 years prior to first observations.

Forcing functions of abiotic factors were used to describe relationships between drivers and some components in the food web. Forcing functions were extracted from Baltsem-model outputs and were related to nutrients, salinity and temperature or their combinations. *Fucus vesiculosus* production was forced with the inverse of the primary production index, considered as a proxy for water transparency. Filamentous algae production was forced with the primary production index. Phytoplankton production was forced with the phytoplankton primary production index (PtoB), and cyanobacteria production with the N fixation index. Furthermore, for perch and sander, egg production was forced with summer month (June–August) average temperature (Kokkonen et al., 2019; Pekcan-Hekim et al., 2011). Furthermore, environmental response functions were used to describe the impact of summer temperature on production of perch and sander juveniles as well as spring temperature on round goby and Harris mud crab production. In addition, environmental response function was used to describe the impact of salinity on Mytilus production.

The model scenarios were run until 2099 using forcing outputs from the Baltsem-model. The resulting data was extracted using the Ecosampler module, which allows estimating the impacts of parameter uncertainty to the results with Monte Carlo process (Steenbeek et al., 2018).

2.4. Questionnaire on experiential value of ecosystem components

The questionnaire used to measure experiential values was prepared to study the preferences of stakeholder groups regarding the ecosystem features and components, and on how the respondents would see the increase or decrease in their abundance. The questionnaire targeted the population living or spending time in the Archipelago Sea area. An open invitation to respond to the questionnaire was disseminated in the Archipelago Sea area using paper advertisements with QR codes and links to the survey, and with online advertisements in local Facebook groups. Convenience sampling over a random approach was chosen as the population of Archipelago Sea users is unknown and, due to its iconic nature, attracts visitors from all over Finland. The sampling likely reached respondents who visit, the Archipelago Sea area more often, on average, and hence possibly have more interest in its ecological state. Further, the sampling mechanism reached visitors most likely during their stay, their answers thus being based on fresh memory of the Archipelago Sea ecosystem.

The questionnaire could be answered in the two local languages, Finnish and Swedish, as well as in English. In this work, we used as data the responses to questions on how the presence of the ecosystem components affect recreation or livelihood of the respondent (total of 10 different species, species groups and ecosystem features: bladderwrack, cyanobacterial blooms, water clarity, seals, great cormorants, pikeperch, herring, perch, invasive species, filamentous algae). These components represent commercially and recreationally important fish species, features that may affect

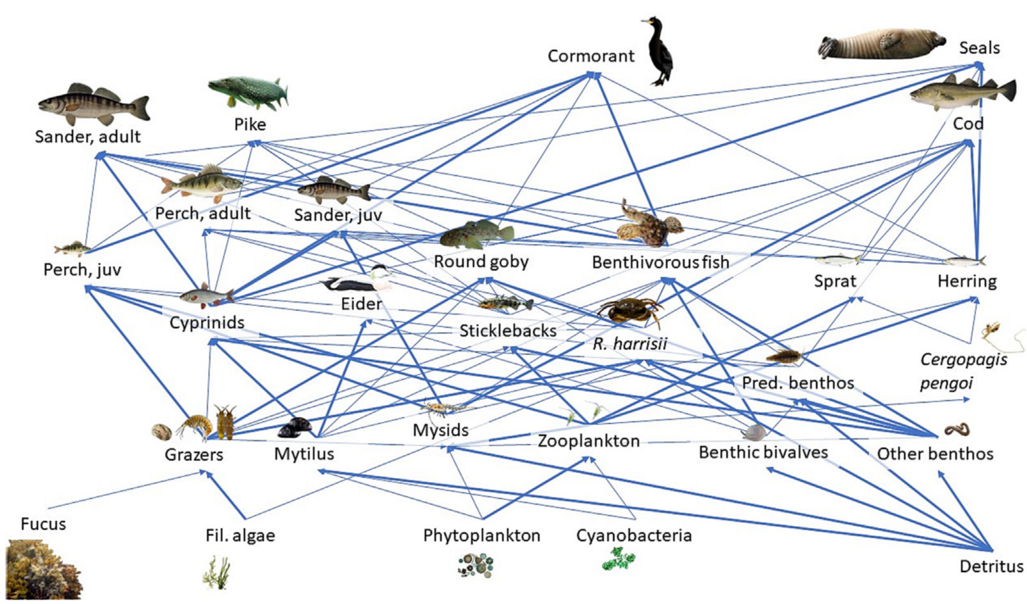


Fig. 1. The feeding relationships in the Ecopath with Ecosim model.

Table 1
The respondents divided by self-identified primary stakeholder group. The columns on the right indicate, which identifications were combined. The lowest 4 rows show the 9 respondents we were unable to group into the three main groups, and therefore left out of the analysis.

Stakeholder groups included in the analysis			
Final group	n	Original groups included	n
Locals	58	Local inhabitant	56
		Professional fishers	1
		Other: Farmer	1
Recreational users and professionals	50	Recreational user	38
		Tourism professional	11
		Other: Hotel owner	1
Cabin and sailing	42	Cabin dweller	32
		Other: Sailors	10
Stakeholder groups left out of the analysis due to small n:			
		Original groups	***n***
		Policy maker	*6*
		Environmental NGO	*1*
		Professional NGO	*1*
		Researcher	*1*

All the R scripts used to manipulate and visualise the data can be found at https://github.com/luusitalo/Archipelago-Sea-article-scripts-2022.

recreational activities in the area and otherwise easily visible and recognizable species. The responses were recorded on a 5-point Likert scale, where the options were "Promotes a lot", "Promotes somewhat", "Neither promotes nor harms", "Harms somewhat", "Harms a lot", "Cannot say". The respondents were also asked to identify their primary stakeholder group. The options were local inhabitant, professional fisher, tourism professionals, regulator/politician, scientist, environmental educator, NGO (environmental), industrial interest group (specify), cabin dwellers, recreational users, boat owner/sailor, birdwatcher, other (specify). Finally, some basic demographic questions were asked. There were 159 responses to the questionnaire.

2.5. Data wrangling

The species biomass time series resulting from the EwE model Ecosampler runs were discretized into 10 classes of equal frequency using *discretizeDF* function from R package *arules* (version 1.7.1, https://cran.r-project.org/package=arules). The cyanobacteria biomass variable was discretized into 8 classes due to the extreme skewness of the distribution which led to *discretizeDF* function not finding 10 different bins. A new variable Total_phytoplankton_BM was created by summing up cyanobacteria and other phytoplankton biomass before discretization. This new variable was discretized like the others. Cyanobacteria are included in total phytoplankton as well as the specific cyanobacteria variable. This is because the total phytoplankton biomass acts as a proxy for water clarity, a variable in the questionnaire, and cyanobacteria naturally contribute to the decrease of water clarity as well as being a variable of interest on its own.

The Likert scale results of the experiential value from the questionnaire were turned into numerical scores by mapping the values on a scale (-2, -1, 0, 1, 2), benefits having positive values and harm negative values. "Cannot say" responses were discarded. They constituted 0.6–11 % of the responses on recreational value and 10–18 % of responses on livelihood value.

The distribution of respondents between primary stakeholder groups was very uneven (Table 1), with highest numbers of respondents in the groups "Local inhabitant" (56 respondents), "Cabin dwellers" (32), and "Recreational users" (38). The other groups were "Tourism professional" (11), "Policy maker" (6), "Environmental NGO", "Professional NGO", "Professional fisher", and "Researcher" (1 each), and "Other" (12). Some of the respondents who had selected "Other" had clarified their role in a free text field. Final stakeholder groups used in this analysis were formed by combining some of these classes: a professional fisher and a farmer (Other) were grouped with the locals to form the final group "Locals", professional tourism operators and hotel owners (Other) were grouped with recreational users to form the final group "Recreational users and professionals", and sailors (Other) were combined with cabin owners to form the final group "Cabin and sailing". These three groups ended up having 58, 50, and 42 respondents, respectively (Table 1). These groups' questionnaire responses are included in the BN models as their experiential values. The average experiential value of each ecosystem component in relation to recreation and livelihood was computed for each group.

2.6. Decision support model

The final decision support model was created in two steps. The first one was to build a simple Bayesian network that links the management scenario combinations to the projected species biomasses from the EwE-model (Fig. 2, left side). The model structure does not repeat the causal structures of the EwE-model, but simply encodes the combinations of the scenarios (for different decades) and the projected biomasses of the different species/ecosystem components for each scenario combination and decade. This can be considered a simple model emulator. The model parameters were learnt from the EwE Ecosampler output data using the EM algorithm (Dempster et al., 1977; Lauritzen, 1995). The model was implemented in Hugin software (Madsen et al., 2005), version 8.8.

Recreational and livelihood experiential values of the ecosystem components for each stakeholder group were encoded as utility variables (Fig. 2, right side). The mean experiential value computed from the

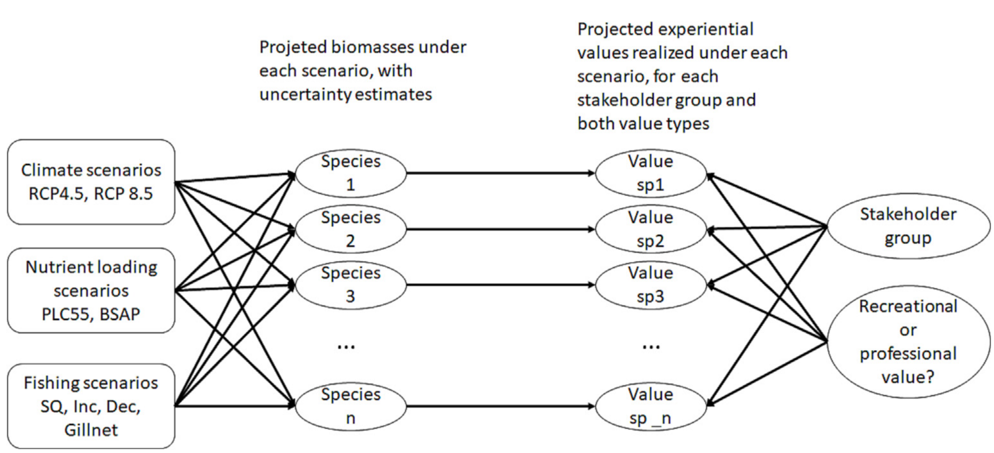


Fig. 2. Conceptual structure of the influence diagram. The predicted biomass distributions of the species (based on Monte Carlo runs on the EwE-model) under each combination of these scenario variables (on the left) are summarized in the "Species" nodes. The experienced values are encoded as utility variables ("Value" nodes) for each stakeholder group and both value types (recreation or profession related values).

Local n=58	Cabin and sailing n=42	Recreational users and professionals n=50	
1.40	1.44	1.58	Water clarity
1.04	1.37	1.17	Perch
0.96	1.00	0.90	Sander
0.91	1.00	0.85	Fucus
0.62	0.66	0.52	Herring
0.04	0.46	1.10	Seals
-0.35	-0.59	-0.52	NIS
-0.75	-1.08	-0.89	Filamentous algae
-1.26	-1.10	-1.06	Cormorants
-1.66	-1.78	-1.86	Cyanobacteria

Fig. 3. The experiential value for recreation of each ecosystem component within stakeholder groups local, cabin and sailing, and recreational users and professionals. Each cell shows the value on a scale from −2 to +2, and the colour corresponds to this value: Dark blue for high positive values, lighter blue for lower positive values, and yellow-orange-red for lower to higher negative values.

questionnaire responses (for each group and value type) was assigned to the highest biomass class, and the value was scaled towards zero so that the second-highest class value was 0.9 times the mean value, and the lowest was 0.1 times the mean value. (The same logic was applied to cyanobacteria-related experiential value, with 8 bins.)

To take into account the value of water clarity, a variable that is not present in the EwE-model, it was modelled as the reverse of total phytoplankton biomass, i.e. the lowest biomass was linked with the highest value of water clarity, and vice versa.

3. Results

3.1. Experiential values of the ecosystem components

The experiential values of the different ecosystem components were much higher for recreation than for livelihood for all three considered stakeholder groups (Figs. 3-4). Water clarity, traditionally captured fish species and the bladderwrack algae *Fucus* had positive value for all groups both recreationally and professionally, while cyanobacteria, cormorants, filamentous algae, and non-indigenous species had negative value. Seals were clearly positive for recreational users and tourism professionals (Fig. 3), while they had a slightly negative experiential value in respect to locals' livelihoods (Fig. 4).

3.2. Predicted utilities under different management and climate scenarios

Below, we use the term "utility" to refer to the sum of all ecosystem-component-wise experiential values. If the ecosystem components that have a positive experiential value, such as perch, are abundant, and those

Local n=58	Cabin and sailing n=42	Recreational users and professionals n=50	
0.50	0.27	0.43	Water clarity
0.48	0.28	0.32	Perch
0.42	0.21	0.29	Sander
0.37	0.23	0.20	Fucus
0.31	0.11	0.26	Herring
-0.12	0.08	0.07	Seals
-0.20	-0.08	-0.08	NIS
-0.33	-0.28	-0.29	Filamentous algae
-0.56	-0.29	-0.28	Cormorants
-0.63	-0.63	-0.68	Cyanobacteria

Fig. 4. The experiential value for livelihoods of each ecosystem component within stakeholder groups local, cabin and sailing, and recreational users and professionals. Each cell shows the value on a scale from −2 to +2, and the colour corresponds to this value: Dark blue for high positive values, lighter blue for lower positive values, and yellow-orange-red for lower to higher negative values. The colour scheme is the same as in the above picture.

components that have a negative experiential value, such as cyanobacteria, are scarce, the utility is high, and vice versa. This approach lets us summarise the predicted experiential benefits arising under different management and climate scenarios.

The utilities show clear patterns, as shown for the years 2050–2059 (Fig. 5), for example. As expected, the livelihood-related utilities have smaller absolute values than the recreational utilities, reflecting their smaller experiential values. There is a clear difference between predicted utilities under RCP4.5 and RCP8.5 climate scenarios: the utilities under RCP4.5 (top half of the chart) are much higher than those under RCP8.5 (bottom half of the chart). This means that under RCP4.5, the positive values of water clarity, fish, and seals overweigh the negative values of NIS, algae, cormorant and cyanobacteria, while under RCP8.5 the situation is largely reversed. The utilities under the BSAP nutrient loading scenario tend to be higher than those under PLC55, but the effect is smaller than that of the climate scenario.

Fig. 5 presents the predicted utilities of the combinations of climate and management scenarios. The influence diagram also allows the computation of predicted utilities of each scenario or management alternative assuming that we do not know which decision will be taken in the other policies or which climate scenario will be realised. We can, for example, compute the predicted utility of each of the fisheries management options assuming that any of the nutrient loading and climate scenario combinations can take place equally likely (Fig. 6). Similarly, we can compute the utilities of the climate scenarios and nutrient management options (Fig. 6). The same pattern emerges as from the scenario combinations (Fig. 5): the highest utilities are related to the RCP4.5 climate scenario, while RCP8.5 scenario gives negative or only slightly positive utilities for all stakeholder groups (Fig. 6a) BSAP nutrient loading scenario gives higher expected utilities than the PLC55 scenario for all stakeholder groups (Fig. 6b). Similarly, the Dec fishing scenario gives the highest utilities for all stakeholder groups, followed by Gil, SQ, and Inc., in this order (Fig. 6c).

Since the fisheries and nutrient loading scenarios are manageable on a more local level than the climate, it may be useful to examine the expected utilities of different manageable variables under both climate scenarios (Figs. 7-8). While the utilities of all fisheries management options are positive under RCP4.5 and mostly negative under RCP8.5, the preference order of the fisheries management options is the same both for recreational and livelihood utilities of all stakeholder groups under both climate scenarios: Dec brings the highest utilities, followed by Gil, SQ, and Inc. (Fig. 7).

Similarly, BSAP nutrient loading policy brings higher utilities than PLC55 for all stakeholder groups under both climate scenarios, both for recreational and livelihood prospects (Fig. 7).

4. Discussion

This work demonstrates a method to numerically integrate and analyse the long path from scenarios and management alternatives to the realised utilities (benefits and harms) that different groups may perceive. This approach can be used in a variety of studies where it is important to estimate how potential human activities will feed back to human well-being through their ecosystem effects. The system is fully transparent, and the possible differences in the feedback effects can be pinpointed to differences in preferences, the ecosystem responses, or both. The approach also allows the evaluation of whether the effects will benefit or harm all stakeholder groups in equal manner, or if the benefits or harms will be felt by one group more than the others. This will allow decision-making to consider the societal effects of ecosystem use and environmental management in a transparent way.

The results show clearly that in the Archipelago Sea area, the strict management measures, leading to RCP4.5 climate instead of stronger climate change of the RCP8.5 scenario, the lower nutrient loadings of the BSAP scenario, and the decrease in fishing effort, brought the highest benefits to all stakeholder groups in this study, compared to other scenarios that were examined (Figs. 5-8). This was largely due to the rather similar experiential values across the stakeholder groups (Figs. 3-4), despite previously

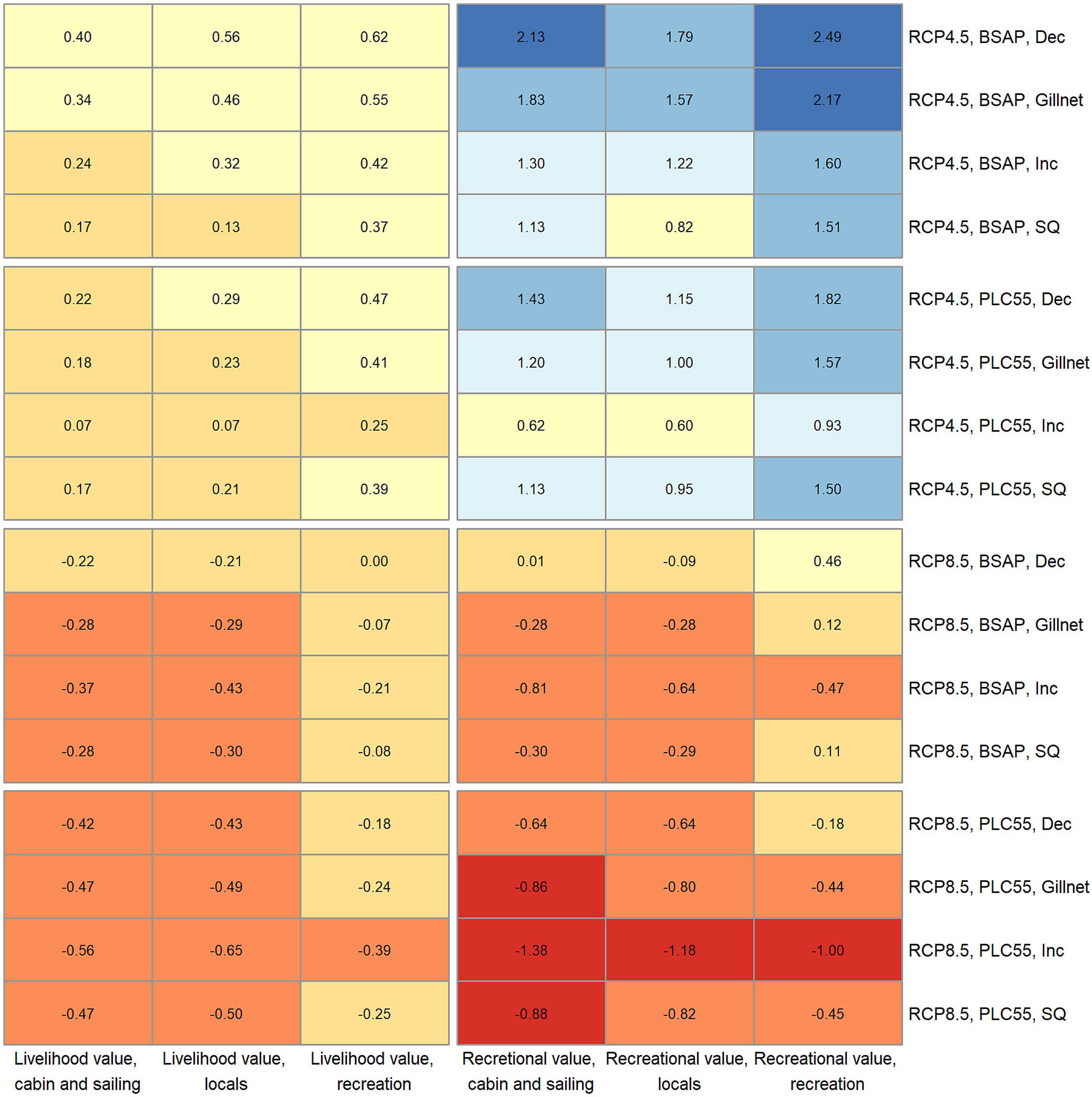


Fig. 5. Predicted overall utilities for each climate, nutrient loading, and fisheries management scenario and for the recreational and livelihood aspects of each stakeholder group for the decade 2050–2059. Each cell shows the value on a scale from −2 to +2, and the colour corresponds to this value: Dark blue for high positive values, lighter blue for lower positive values, and yellow-orange-red for lower to higher negative values.

reported conflicts among the stakeholder groups. The study clearly highlights, however, major differences in the predicted experiential values under different management scenarios. This is a novel contribution and allows the explicit and semi-quantitative consideration of experiential values in management decision making along economic and judicial considerations.

The stakeholder groups that were analysed in this study arose from the data; the questionnaire had some proposed stakeholder groups, but users were also allowed to choose and specify an "Other" group. These groups are to some extent overlapping, but the self-identified primary group was used as the grouping factor. There is no established stakeholder typology in the area. Often, professional fishers are seen as one stakeholder group, but they are relatively few, and we were not able to have enough respondents in this questionnaire to represent them as their own group. Likewise, the views of local and national decision makers would be interesting to analyse, but the current sample size did not allow that. The data could also be analysed in relation to other factors such as by age, gender, or education level, allowing the evaluation of different types of demographic fairness of political decisions.

The study area of the demonstration case, the Archipelago Sea, is an excellent candidate for demonstrating the approach. It is culturally very important, making it of interest to a variety of stakeholders (leading to a good number of responses to the stakeholder questionnaire), and has also been studied extensively, allowing for the building of the complex EwE-model. While the current application had a fine temporal resolution (one year in the EwE-model, grouped to 10-year intervals in the decision model), the whole Archipelago Sea area was treated as one spatial unit. This was partly due to the restrictions of the available EwE-model, which

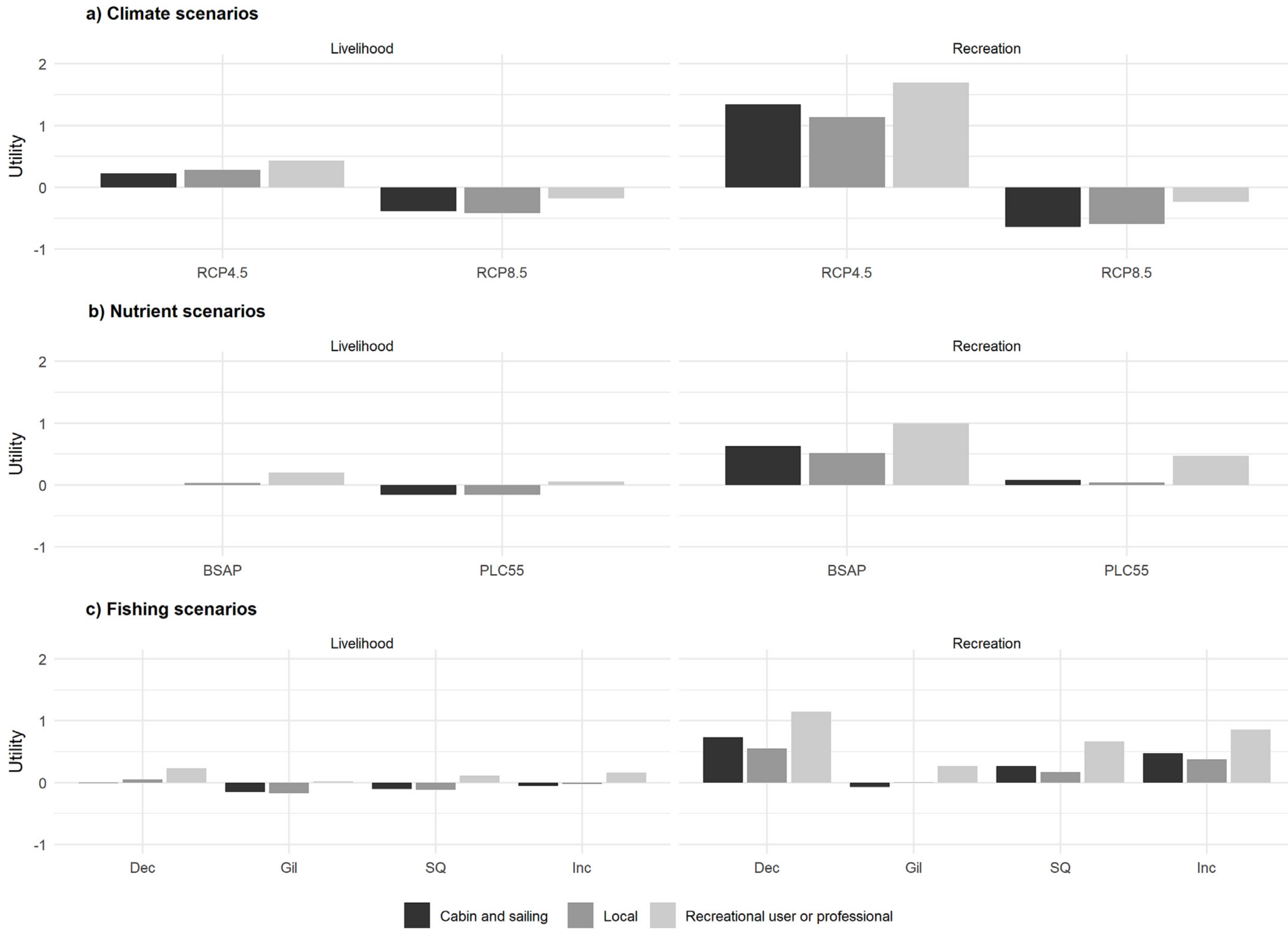


Fig. 6. The expected total utilities of different climate and management scenarios, assuming that there is no information about the other scenario variables.

simulates the area as one unit (a spatially explicit model is being built at the moment), but additionally, because gathering the stakeholder preference data with more spatial resolution was logistically challenging. However, in principle there are no restrictions to making a both temporally and spatially explicit model by using a spatially explicit ecosystem model and collecting the stakeholder preference data accordingly. It could also be possible to extend the current model to cover, for example, the whole Finnish coastline, or the whole Baltic Sea.

The developed decision support model is largely modular so that parts of it can be updated without having to revise or re-calibrate the whole model. New ecosystem components could be added based on other models, the experiential values could be updated, new stakeholder groups could be added, and entirely new utility types could be added into the comparison, such as economic considerations or reaching the environmental policy goals (Uusitalo et al., 2022). This means that the approach can be employed in a truly iterative, interactive way together with stakeholders and decision-makers.

Bayesian methods are especially useful in their ability to handle uncertainties explicitly. This is a valuable feature in evaluating the potential outcomes of environmental management, as the decision makers and the public may be interested not only in the most likely or expected outcome, but also in the possible risks of extremely high or low values. In the presented approach, the uncertainty estimates originate from the Monte Carlo protocol of the EwE-model, giving a plausible range and distribution of the outcomes under each scenario (Steenbeek et al., 2018). This uncertainty is fully incorporated into the decision support model, as the conditional probability tables are populated using the EwE Monte Carlo outputs. This uncertainty is also reflected in the resulting expected values, as the probability distribution of the biomass is taken fully into account when computing the resulting value; each possible outcome is multiplied by its stakeholder-based utility value, and these are weighted based on their probability to reach the final expected value. This means that if there is a possibility of very low perch populations in a certain scenario, for example, this will lower the expected value compared to a scenario where the distribution is otherwise similar, but the very low values do not have any probability. Therefore, the Bayesian uncertainty approach is fully utilized in this decision support model. The representativeness of the used uncertainty estimates relies on the EwE-model, which has been parameterized using all the available data as well as scientific literature and ecological knowledge. While the decision support model structure is simple and not causal, it incorporates all the causal interactions modelled in the EwE-model.

A recent review by Kaikkonen et al. (2020) of Bayesian networks in environmental risk assessment found only a limited role of stakeholders in model construction and quantification, but some literature exists. For example, Borsuk et al. (2001, 2004) created a eutrophication model that included variables that are important for the stakeholders, such as cyanobacteria blooms and shellfish kills. Chan et al. (2010) used stakeholder knowledge to formulate the model structure for their model for integrated water resources modelling in the Solomon Islands, that included variables important to the stakeholders such as “water for human survival”. Carmona et al. (2013) created a Bayesian network model in a participatory process together with stakeholders, with the resulting model including impacts of scenarios on farm income and environment. Xue et al. (2017) also created a model through a participatory process involving stakeholders, but in this instance it was for integrated water resources management. None of

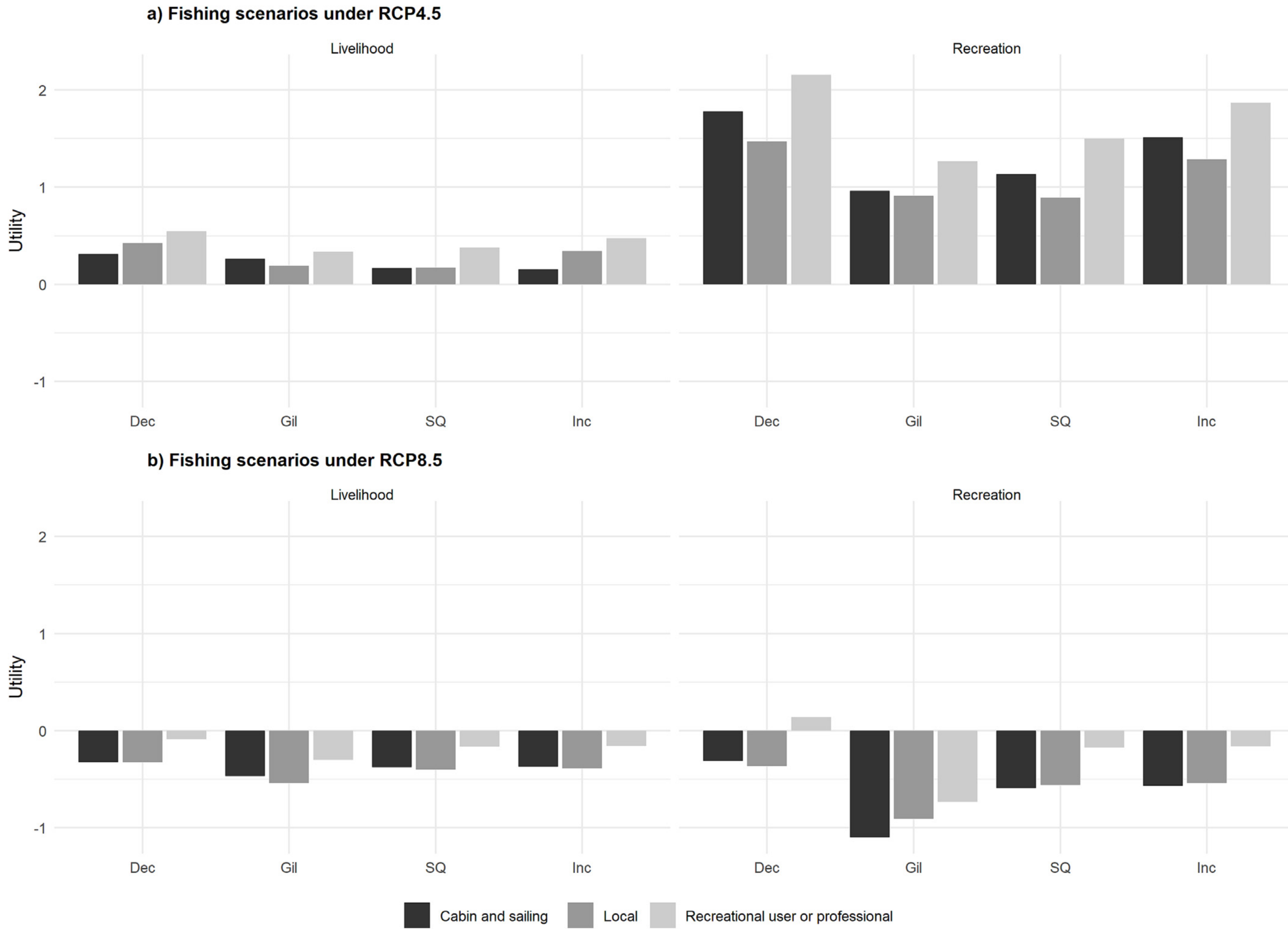


Fig. 7. Expected utility of the different fisheries management scenarios for the three stakeholder groups under the two climate scenarios.

these models explicitly included stakeholder values, however, but ended at the changes in the variables important to the stakeholders. In contrast, Barton et al. (2020) developed a model for environmental flows and physical habitat restoration measures in a hydropower regulated river, and included utility functions related to ecosystem outcomes, as well as their weighing.

The current approach was to build the ecological model (EwE) based on scientific literature and ecological knowledge on the species interactions and parameterize it using monitoring data and literature. This was seen as a solid approach, since there is a lot of ecological knowledge and research on the species interactions, and while there are controversial discussions on the environmental management of the area, the stakeholders don't hold dissenting views of the ecosystem functioning as such (Uusitalo et al., 2020). Stakeholder values were brought into the current model through the questionnaire. Laurila-Pant et al. (2019) presented a conceptual case that was largely similar to the present approach: the ecosystem interactions were not the subject of stakeholder elicitation, but stakeholder's valuation of the ecosystem state was included based on interviews. Unlike the current approach, in which the questionnaire-derived values were used as is, their approach treated the interviewed stakeholders as a statistical sample of a population and made statistical inference about the likely opinion of the population.

In this case study, we made several technical decisions that affect the results, and which must be considered when building similar influence diagrams. The first decision was how to discretize the data coming from the EwE-models. We chose to discretize the data so that each of the 10 bins had (approximately) equal number of observations. This means that the bin size, i.e. the difference between the upper and lower boundary of the bin, varies. As the distributions were largely lognormally shaped, the bin size was larger particularly at the higher biomasses. Equal frequency discretization makes the model relatively robust, as none of the classes are dominated with only few observations. An alternative solution could have been to use equal interval discretization, i.e. making the difference between the upper and lower limit of each bin equal. This approach is possibly easier to communicate to stakeholders. However, if the distributions have very long tails, i.e. have relatively few very large values, the bin sizes have to be large in order to have enough observations in each bin, effectively restricting the number of bins.

A second technical decision having repercussions on the results is related to the encoding of the experiential values. The values were originally given on a Likert scale and encoded into numerical values $[-2, -1, 0, 1, 2]$. This encoding carries two assumptions: that the perceived distance between "Promotes a lot" and "Promotes somewhat" is the same as from "Promotes somewhat" to "Neither promotes nor harms" (and similarly with the negative values), and that the positive and negative values are equally large. These assumptions have not been validated in this study. Therefore, the numerical results obtained in this study are indicative and not strictly quantitative.

The third technical solution affecting the results is how the experiential values are linked to the biomasses. As the bins are larger in the low and especially in the high end of the biomass scale, and the experiential value of each ecosystem component is scaled so that the highest biomass bin gets the highest value and the value decreases evenly for each bin (see the Materials and Methods section), this means that for the experiential value to increase, larger absolute biomass increases are needed in the high end of the scale. The discretization and uneven size of bins causes the marginal

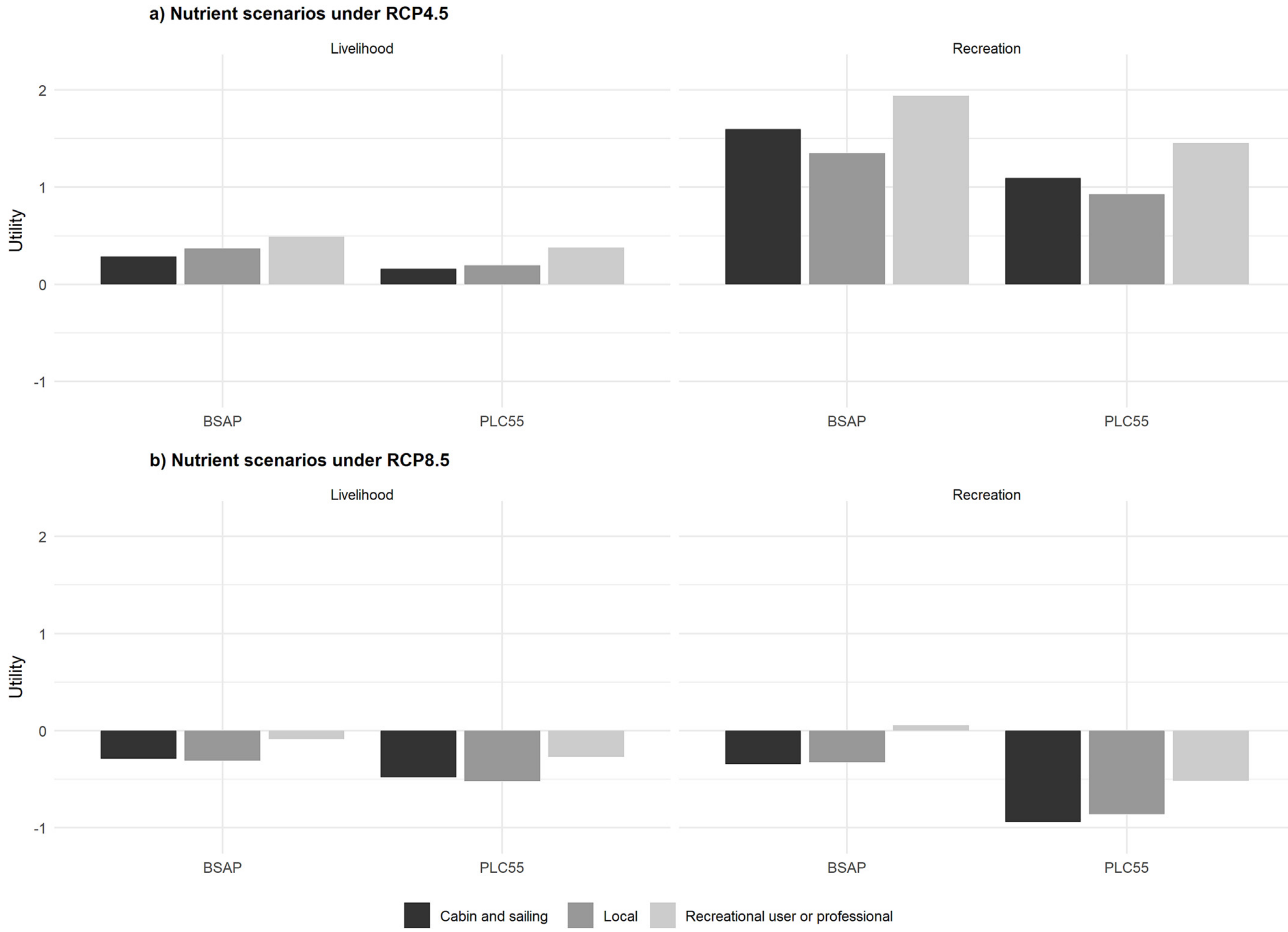


Fig. 8. Expected utility of the different nutrient loading scenarios for the three stakeholder groups under the two climate scenarios.

utility of a unit change in biomass to decrease at the extremes. While this feature is an artefact of the chosen binning, it would behaviorally suggest loss aversion at higher biomasses, and slower recovery of utility at the smaller biomasses. Similarly, if the experiential value is negative, as is the case for example with non-invasive species, the experienced harm increases more slowly than the biomass. It must be remembered that the experiential value of each ecosystem component at the highest biomass is that detailed in Fig. 2, meaning that the contributions of the different components to the total utility varies.

Our assumption that the positive and negative values are of equal value probably underestimates the loss of experiential value related to environmental deterioration. As losses typically inflict higher losses to benefits than equal-sized improvements (see e.g. Georgantzís and Navarro-Martínez (2010) for more information on the gap between willingness to accept and willingness to pay) our results under(over)estimate the relative effects of declined (increased) experiential values, all other things being constant. The questionnaire respondents were asked to rate how much the presence of the ecosystem components affects their recreation or profession. This information was then assumed to apply also to the increases and decreases of the biomass following the logic explained above. A more rigorous approach would be to ask the respondents explicitly, how much they would value a certain increase or decrease of biomasses from the current state. This would give a more explicit understanding of the experiential value the respondents would expect to have. However, this kind of a questionnaire would also be much more difficult to respond to, potentially reducing the number of respondents and yielding responses that are inconsistent with the actual beliefs of the respondent. If this approach were successful, it would, however, enable the model to include, for example, a very high negative value for population collapse, indicating that the stakeholders would consider this an extremely undesirable event regardless of how much they would enjoy the population increase.

The experiential value from water clarity was difficult to include into the influence diagram, as the EwE-model doesn't include water clarity as a variable. Total phytoplankton biomass was used as a proxy for water clarity so that the highest experiential value water clarity was allocated to the lowest total phytoplankton biomass, and the lowest value to the highest biomass. A more rigorous alternative would be to derive the water clarity, e.g. Secchidepth predictions, from a biogeochemical model that predicts the water clarity directly.

The Ecosampler approach in the EwE-model results in a range of simulation results describing possible pathways the system can take under a realistic range of parameter values. This approach accounts for parameter uncertainty and thence avoids overconfidence about the results (Uusitalo et al., 2022). The probabilistic decision support model includes all of this information, and the expected utilities are computed based on the range of possible outcomes under each scenario. Therefore, if there is, for example, a risk of population collapse, this is reflected in the expected utilities. The EwE-model used to produce the predictions of ecosystem responses to management measures assumes that once a policy (e.g. to follow the BSAP nutrient loading) is selected, the same policy is applied throughout the simulation.

Despite the limitations of the presented model's capacity in predicting the future, it can be used to assess differences between scenarios and has potential for improvements. In this work we show that regardless of perceived conflicts of interests among stakeholder groups, the most value is achieved when good ecological status is reached.

CRediT authorship contribution statement

Laura Uusitalo: Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Riikka Puntila-Dodd:** Conceptualization, Data curation, Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing. **Janne Artell:** Conceptualization, Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing. **Susanna Jernberg:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Writing – original draft, Writing – review & editing.

Data availability

All the R scripts used to manipulate and visualise the data can be found at https://github.com/luusitalo/Archipelago-Sea-article-scripts-2022. The EwE simulation data are not shared due to their size.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work was carried out within the BONUS BLUEWEBS project, which has received funding from BONUS (Art 185), funded jointly by the EU and the Academy of Finland, and FutureMARES project which receives funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 869300. Susanna Jernberg was partly funded by the Maj and Tor Nessling foundation (Grant No. 201700022). We thank Bärbel Müller-Karulis for allowing us to use environmental driver scenarios from the Baltsem model to drive the EwE model. We would also like to thank the anonymous reviewers for their comments that helped improve the paper.

References

Arkema, K.K., Abramson, S.C., Dewsbury, B.M., 2006. Marine ecosystem-based management: from characterization to implementation. Front. Ecol. Environ. 4, 525–532.

Barton, D.N., Saloranta, T., Moe, S.J., Eggestad, H.O., Kuikka, S., 2008. Bayesian belief networks as a meta-modelling tool in integrated river basin management - pros and cons in evaluating nutrient abatement decisions under uncertainty in a Norwegian river basin. Ecol. Econ. 66, 91–104. https://doi.org/10.1016/j.ecolecon.2008.02.012.

Barton, D.N., Kuikka, S., Varis, O., Uusitalo, L., Henriksen, H.J., Borsuk, M., de la Hera, A., Farmani, R., Johnson, S., Linnell, J.D., 2012. Bayesian networks in environmental and resource management. Integr. Environ. Assess. Manag. 8, 418–429. https://doi.org/10.1002/ieam.1327.

Barton, D.N., Sundt, H., Bustos, A.A., Fjeldstad, H.-P., Hedger, R., Forseth, T., Köhler, Berit, Aas, Ø., Alfredsen, K., Madsen, A.L., 2020. Multi-criteria decision analysis in Bayesian networks - diagnosing ecosystem service trade-offs in a hydropower regulated river. Environ. Model. Softw. 124, 104604. https://doi.org/10.1016/j.envsoft.2019.104604.

Bauer, B., Gustafsson, B.G., Hyytiäinen, K., Meier, H.E.M., Müller-Karulis, B., Saraiva, S., Tomczak, M.T., 2019. Food web and fisheries in the future Baltic Sea. Ambio 48, 1337–1349. https://doi.org/10.1007/s13280-019-01229-3.

Berg, T., Furhaupter, K., Teixeira, H., Uusitalo, L., Zampoukas, N., 2015. The marine strategy framework directive and the ecosystem-based approach - pitfalls and solutions. Mar. Pollut. Bull. 96, 18–28. https://doi.org/10.1016/j.marpolbul.2015.04.050.

Borsuk, M., Clemen, R., Maguire, L., Reckhow, K., 2001. Stakeholder values and scientific modeling in the Neuse River watershed. Group Decis. Negot. 10, 355–373. https://doi.org/10.1023/A:1011231801266.

Borsuk, M.E., Stow, C.A., Reckhow, K.H., 2004. A Bayesian network of eutrophication models for synthesis, prediction, and uncertainty analysis. Ecol. Model. 173, 219–239. https://doi.org/10.1016/j.ecolmodel.2003.08.020.

Carmona, G., Varela-Ortega, C., Bromley, J., 2013. Participatory modelling to support decision making in water management under uncertainty: two comparative case studies in the Guadiana river basin, Spain. J. Environ. Manag. 128, 400–412. https://doi.org/10.1016/j.jenvman.2013.05.019.

Chan, T., Ross, H., Hoverman, S., Powell, B., 2010. Participatory development of a Bayesian network model for catchment-based water resource management. Water Resour. Res. 46. https://doi.org/10.1029/2009WR008848.

Chen, S.H., Pollino, C.A., 2012. Good practice in Bayesian network modelling. Environ. Model. Softw. 37, 134–145. https://doi.org/10.1016/j.envsoft.2012.03.012.

Christensen, V., Walters, C.J., 2004. Ecopath with Ecosim: methods, capabilities and limitations. Ecol. Model. 172, 109–139.

Christensen, V., Walters, C.J., Pauly, D., 2008. Ecopath with Ecosim version 6 user guide. Lenfest Ocean Futures Project, p. 235.

Dempster, A.P., Laird, N.M., Rubin, D.B., 1977. Maximum likelihood from incomplete data via the EM algorithm. J. R. Stat. Soc. Ser. B Methodol. 39, 1–38.

Eilola, K., Meier, H.E.M., Almroth, E., 2009. On the dynamics of oxygen, phosphorus and cyanobacteria in the Baltic Sea; a model study. J. Mar. Syst. 75, 163–184. https://doi.org/10.1016/j.jmarsys.2008.08.009.

Fulton, E.A., Smith, A.D., Smith, D.C., Johnson, P., 2014. An integrated approach is needed for ecosystem based fisheries management: insights from ecosystem-level management strategy evaluation. PLoS One 9, e84242. https://doi.org/10.1371/journal.pone.0084242.

Georgantzís, N., Navarro-Martínez, D., 2010. Understanding the WTA–WTP gap: attitudes, feelings, uncertainty and personality. J. Econ. Psychol. 31, 895–907. https://doi.org/10.1016/j.joep.2010.07.004.

Giorgetta, M.A., Jungclaus, J., Reick, C.H., Legutke, S., Bader, J., Böttinger, M., Brovkin, V., Crueger, T., Esch, M., Fieg, K., Glushak, K., Gayler, V., Haak, H., Hollweg, H.-D., Ilyina, T., Kinne, S., Kornblueh, L., Matei, D., Mauritsen, T., Mikolajewicz, U., Mueller, W., Notz, D., Pithan, F., Raddatz, T., Rast, S., Redler, R., Roeckner, E., Schmidt, H., Schnur, R., Segschneider, J., Six, K.D., Stockhause, M., Timmreck, C., Wegner, J., Widmann, H., Wieners, K.-H., Claussen, M., Marotzke, J., Stevens, B., 2013. Climate and carbon cycle changes from 1850 to 2100 in MPI-ESM simulations for the coupled model Intercomparison project phase 5. J. Adv. Model. Earth Syst. 5, 572–597. https://doi.org/10.1002/jame.20038.

Gustafsson, B.G., Schenk, F., Blenckner, T., Eilola, K., Meier, H.E.M., Müller-Karulis, B., Neumann, T., Ruoho-Airola, T., Savchuk, O.P., Zorita, E., 2012. Reconstructing the development of Baltic Sea eutrophication 1850–2006. AMBIO 41, 534–548. https://doi.org/10.1007/s13280-012-0318-x.

Haapasaari, P., Michielsens, C.G.J., Karjalainen, T.P., Reinikainen, K., Kuikka, S., 2007. Management measures and fishers' commitment to sustainable exploitation: a case study of Atlantic salmon fisheries in the Baltic Sea. ICES J. Mar. Sci. 64 (4), 825–833.

He, C., Zhou, T., 2015. Responses of the Western North Pacific Subtropical high to global warming under RCP4.5 and RCP8.5 scenarios projected by 33 CMIP5 models: the dominance of tropical Indian ocean–tropical Western Pacific SST gradient. J. Clim. 28, 365–380. https://doi.org/10.1175/JCLI-D-13-00494.1.

Heikinheimo, O., Setälä, J., Saarni, K., Raitaniemi, J., 2006. Impacts of mesh-size regulation of gillnets on the pikeperch fisheries in the Archipelago Sea, Finland. Fish. Res. 77, 192–199. https://doi.org/10.1016/j.fishres.2005.11.005.

HELCOM, 2007. HELCOM Baltic Sea Action Plan, HELCOM Ministerial Meeting. Krakow, Poland, 15 November 2007.

HELCOM, 2015. Updated Fifth Baltic Sea Pollution Load Compilation (PLC-5.5).

IPCC, 2014. Climate change 2014: impacts, adaptation, and vulnerability. Part A: global and sectoral aspects. Contribution of Working Group II to the fifth assessment report of the Intergovernmental Panel on Climate Change. Clim. Chang.

Kaikkonen, L., Parviainen, T., Rahikainen, M., Uusitalo, L., Lehikoinen, A., 2020. Bayesian networks in environmental risk assessment: a review. Integr. Environ. Assess. Manag. https://doi.org/10.1002/ieam.4332.

Kelly, R.A., Jakeman, A.J., Barreteau, O., Borsuk, M.E., ElSawah, S., Hamilton, S.H., Henriksen, H.J., Kuikka, S., Maier, H.R., Rizzoli, A.E., Delden, H., Voinov, A.A., 2013. Selecting among five common modelling approaches for integrated environmental assessment and management. Environ. Model. Softw. 47, 159–181. https://doi.org/10.1016/j.envsoft.2013.05.005.

Kokkonen, E., Mitikka, S., Huuskonen, H., Olin, M., Ruuhijärvi, J., Vainikka, A., 2019. Structural equation models suggest that bottom-up processes override top-down processes in boreal pikeperch (Sander lucioperca) lakes. Freshw. Biol. 64, 1054–1063. https://doi.org/10.1111/fwb.13285.

Korpinen, S., Uusitalo, L., Nordström, M.C., Dierking, J., Tomczak, M.T., Haldin, J., Opitz, S., Bonsdorff, E., Neuenfeldt, S., 2022. Food web assessments in the Baltic Sea: models bridging the gap between indicators and policy needs. Ambio. https://doi.org/10.1007/s13280-021-01692-x.

Kraufvelin, P., Pekcan-Hekim, Z., Bergström, U., Florin, A.B., Lehikoinen, A., Mattila, J., Arula, T., Briekmane, L., Brown, E.J., Celmer, Z., Dainys, J., 2018. Essential coastal habitats for fish in the Baltic Sea. *Estuarine*. Coastal Shelf Sci. 204, 14–30.

Langseth, B.J., Rogers, M., Zhang, H., 2012. Modeling species invasions in Ecopath with Ecosim: an evaluation using Laurentian Great Lakes models. Ecol. Model. 247, 251–261. https://doi.org/10.1016/j.ecolmodel.2012.08.015.

Laurila-Pant, M., Mäntyniemi, S., Venesjärvi, R., Lehikoinen, A., 2019. Incorporating stakeholders' values into environmental decision support: a Bayesian belief network approach. Sci. Total Environ. 697, 134026. https://doi.org/10.1016/j.scitotenv.2019.134026.

Lauritzen, S.L., 1995. The EM algorithm for graphical association models with missing data. Comput. Stat. Data Anal. 19, 191–201.

Leppäkoski, E., Helminen, H., Hänninen, J., Tallqvist, M., 1999. Aquatic biodiversity under anthropogenic stress: an insight from the Archipelago Sea (SW Finland). Biodivers. Conserv. 8, 55–70.

Link, J.S., 2010. Adding rigor to ecological network models by evaluating a set of pre-balance diagnostics: a plea for PREBAL. Ecol. Modelling 221 (12), 1580–1591.

Long, R.D., Charles, A., Stephenson, R.L., 2015. Key principles of marine ecosystem-based management. Mar. Policy 57, 53–60. https://doi.org/10.1016/j.marpol.2015.01.013.

Luomaranta, A., Ruosteenoja, K., Jylhä, K., Gregow, H., Haapala, J., Laaksonen, A., 2014. Multimodel estimates of the changes in the Baltic Sea ice cover during the present century. Tellus Dyn. Meteorol. Oceanogr. 66, 22617. https://doi.org/10.3402/tellusa.v66.22617.

Madsen, A.L., Jensen, F., Kjærulff, U.B., Lang, M., 2005. The hugin tool for probabilistic graphical models. Int. J. Artif. Intell. Tools 14, 507–543. https://doi.org/10.1142/S0218213005002235.

Mathwick, C., Malhotra, N., Rigdon, E., 2001. Experiential value: conceptualization, measurement and application in the catalog and internet shopping environment☆11☆this article is based upon the first author's doctoral dissertation completed while at Georgia Institute of Technology. J. Retail. 77, 39–56. https://doi.org/10.1016/S0022-4359(00)00045-2.

McLeod, K., Leslie, H., 2012. Ecosystem-based Management for the Oceans. Island Press.

Moore, J.K., Lindsay, K., Doney, S.C., Long, M.C., Misumi, K., 2013. Marine ecosystem dynamics and biogeochemical cycling in the community earth system model [CESM1(BGC)]: comparison of the 1990s with the 2090s under the RCP4.5 and RCP8.5 scenarios. J. Clim. 26, 9291–9312. https://doi.org/10.1175/JCLI-D-12-00566.1.

Moss, R.H., Edmonds, J.A., Hibbard, K.A., Manning, M.R., Rose, S.K., van Vuuren, D.P., Carter, T.R., Emori, S., Kainuma, M., Kram, T., Meehl, G.A., Mitchell, J.F.B., Nakicenovic, N., Riahi, K., Smith, S.J., Stouffer, R.J., Thomson, A.M., Weyant, J.P., Wilbanks, T.J., 2010. The next generation of scenarios for climate change research and assessment. Nature 463, 747–756. https://doi.org/10.1038/nature08823.

Pauly, D., Christensen, V., Walters, C., 2000. Ecopath, Ecosim, and Ecospace as tools for evaluating ecosystem impact of fisheries. ICES J. Mar. Sci. 57, 697–706. https://doi.org/10.1006/jmsc.2000.0726.

Pekcan-Hekim, Z., Urho, L., Auvinen, H., Heikinheimo, O., Lappalainen, J., Raitaniemi, J., Soderkultalahti, P., 2011. Climate warming and pikeperch year-class catches in the Baltic Sea. Ambio 40, 447–456. https://doi.org/10.1007/s13280-011-0143-7.

Plagányi, É.E., 2007. Models for an Ecosystem Approach to Fisheries. United Nations Food & Agriculture Org.

Plagányi, É.E., Butterworth, D.S., 2004. A critical look at the potential of ECOPATH with ECOSIM to assist in practical fisheries management. Afr. J. Mar. Sci. 26, 261–287.

Punt, A.E., Butterworth, D.S., de Moor, C.L., De Oliveira, J.A.A., Haddon, M., 2016. Management strategy evaluation: best practices. Fish Fish. 17, 303–334. https://doi.org/10.1111/faf.12104.

Puntila-Dodd, R., Peltonen, H., Heikinheimo, O., Riitakorpi, J., Müller-Karulis, B., Niiranen, S., Tomczak, M., Uusitalo, L., 2022. Combined effects of eutrophication, fishery and species introductions in a temperate coastal ecosystem: Modelling changes in the Archipelago Sea food web 2000-2017. Poster presentation at ECSA 59 Conference 5.-8.9.2022, Donostia – San Sebastian.

Rusu, E., 2020. An evaluation of the wind energy dynamics in the Baltic Sea, past and future projections. Renew. Energy 160, 350–362. https://doi.org/10.1016/j.renene.2020.06.152.

Saraiva, S., Markus Meier, H.E., Andersson, H., Höglund, A., Dieterich, C., Gröger, M., Hordoir, R., Eilola, K., 2019. Baltic Sea ecosystem response to various nutrient load scenarios in present and future climates. Clim. Dyn. 52, 3369–3387. https://doi.org/10.1007/s00382-018-4330-0.

Saulamo, K., Thoresson, G., 2005. Management of Pikeperch migrating over management areas in a Baltic archipelago area. AMBIO J. Hum. Environ. 34, 120–124. https://doi.org/10.1579/0044-7447-34.2.120.

Savchuk, O.P., Gustafsson, B.G., Müller-Karulis, B., 2012. BALTSEM - A Marine Model for Decision Support Within the Baltic Sea Region. Technical report no. 7.

Schroeder, H.W., 2012. Giving voice to the experiential value of natural environments. Humanist. Psychol. 40, 136–152. https://doi.org/10.1080/08873267.2011.642488.

Slocombe, D.S., 1993. Implementing ecosystem-based management. BioScience 43, 612–622. https://doi.org/10.2307/1312148.

Steenbeek, J., Corrales, X., Platts, M., Coll, M., 2018. Ecosampler: a new approach to assessing parameter uncertainty in Ecopath with Ecosim. SoftwareX 7, 198–204. https://doi.org/10.1016/j.softx.2018.06.004.

Stelzenmüller, V., Schulze, T., Fock, H.O., Berkenhagen, J., 2011. Integrated modelling tools to support risk-based decision-making in marine spatial management. Mar. Ecol. Prog. Ser. 441, 197–212. https://doi.org/10.3354/meps09354.

Tebaldi, C., Knutti, R., 2007. The use of the multi-model ensemble in probabilistic climate projections. Philos. Trans. R. Soc. Math. Phys. Eng. Sci. 365, 2053–2075. https://doi.org/10.1098/rsta.2007.2076.

Uusitalo, L., 2007. Advantages and challenges of Bayesian networks in environmental modelling. Ecol. Model. 203, 312–318. https://doi.org/10.1016/j.ecolmodel.2006.11.033.

Uusitalo, L., Jernberg, S., Korn, P., Puntila-Dodd, R., Skyttä, A., Vikström, S., 2020. Fuzzy cognitive mapping of Baltic Archipelago Sea food webs reveals no cliqued views of the system structure between stakeholder groups. Socio-Environ. Syst. Model. 2, 16343. https://doi.org/10.18174/sesmo.2020a16343.

Uusitalo, L., Blenckner, T., Puntila-Dodd, R., Skyttä, A., Jernberg, S., Voss, R., Müller-Karulis, B., Tomczak, M.T., Möllmann, C., Peltonen, H., 2022. Integrating diverse model results into decision support for good environmental status and blue growth. Sci. Total Environ. 806, 150450. https://doi.org/10.1016/j.scitotenv.2021.150450.

van Vuuren, D.P., Edmonds, J., Kainuma, M., Riahi, K., Thomson, A., Hibbard, K., Hurtt, G.C., Kram, T., Krey, V., Lamarque, J.-F., Masui, T., Meinshausen, M., Nakicenovic, N., Smith, S.J., Rose, S.K., 2011. The representative concentration pathways: an overview. Clim. Chang. 109, 5. https://doi.org/10.1007/s10584-011-0148-z.

Varshneya, G., Das, G., Khare, A., 2017. Experiential value: a review and future research directions. Mark. Intell. Plan. 35, 339–357. https://doi.org/10.1108/MIP-05-2016-0075.

Viirret, E., Raatikainen, K.J., Fagerholm, N., Käyhkö, N., Vihervaara, P., 2019. Ecosystem services at the archipelago sea biosphere reserve in Finland: a visitor perspective. Sustainability 11 (2), 421.

Virtanen, E.A., Viitasalo, M., Lappalainen, J., Moilanen, A., 2018. Evaluation, gap analysis, and potential expansion of the Finnish marine protected area network. Front. Mar. Sci. 5, 402.

Walters, C., Christensen, V., Pauly, D., 1997. Structuring dynamic models of exploited ecosystems from trophic mass-balance assessments. Rev. Fish Biol. Fish. 7, 139–172. https://doi.org/10.1023/A:1018479526149.

Xue, J., Gui, D., Lei, J., Zeng, F., Mao, D., Zhang, Z., 2017. Model development of a participatory Bayesian network for coupling ecosystem services into integrated water resources management. J. Hydrol. 554, 50–65. https://doi.org/10.1016/j.jhydrol.2017.08.045.