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A Bayesian approach for assessing the boundary between desirable and undesirable environmental status – An example from a coastal fish indicator in the Baltic Sea

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A R T I C L E I N F O

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A B S T R A C T

Ecological indicator approaches typically compare the prevailing state of an ecosystem component to a reference state reflecting good environmental conditions, i.e. the desirable state. However, defining the reference state is challenging due to a wide range of uncertainties related to natural variability and measurement error in data, as well as ecological understanding. This study propose a novel probabilistic approach combining historical monitoring data and ecological understanding to estimate the uncertainty associated with the boundary value of an ecological indicator between good and poor environmental states. Bayesian inference is used to estimate the epistemic uncertainty about the true state of an indicator variable during an historical reference period. This approach replaces the traditional boundary value with probability distribution, indicating the uncertainty about the boundary between environmental states providing a transparent safety margin associated with the risk of misclassification of the indicator's state. The approach is demonstrated by applying it to a time-series of an ecological status indicator, 'Abundance of coastal key fish species', included in HELCOM's Baltic Sea regional status assessment. We suggest that acknowledgement of the uncertainty behind the final classification leads to more transparent and better-informed decision-making processes.

1. Introduction

Environmental status assessments form the basis of environmental management (Borja et al., 2011; 2013). Comparing the current state of ecosystem components to their desirable and undesirable states provides information about the need for protective or restorative measures. Many indicator-based approaches, such as applied in the EU's Water Framework Directive (WFD; European commission, 2000), the Marine Strategy Framework Directive (MSFD; European Commission, 2008) and the Baltic Sea Action Plan (BSAP; HELCOM, 2007), use data from long-term monitoring programs that are intended to assess trends and changes in marine ecosystems over time (Danovaro et al., 2016). An indicator is a data-based metric assumed to reflect the status of the ecosystem component. The current value, based on recently collected data, is compared to a reference (or boundary) value, reflecting a healthy ecosystem. Depending on the indicator, the desirable state can be represented by a single boundary value, by two boundary values where the target level is found between them, as well as by multiple boundary values of several parameters, where the good environmental status is achieved when multiple parameters meet the required conditions simultaneously (HELCOM, 2012).

Alternative approaches to determine the boundary values based on reference conditions are applied in marine management (Borja et al., 2012). Historical data (Muxika et al., 2007), analysis of indicator responses to pressures (Borja et al., 2012; Piroddi et al., 2015), or information concerning the spatial gradients of anthropogenic pressures (Zucchetta et al., 2016) can be used to define reference conditions. However, epistemic uncertainty about the actual state of the ecosystem is unavoidable regardless of the approach. This uncertainty arises from several sources, including stochasticity in ecosystem dynamics and

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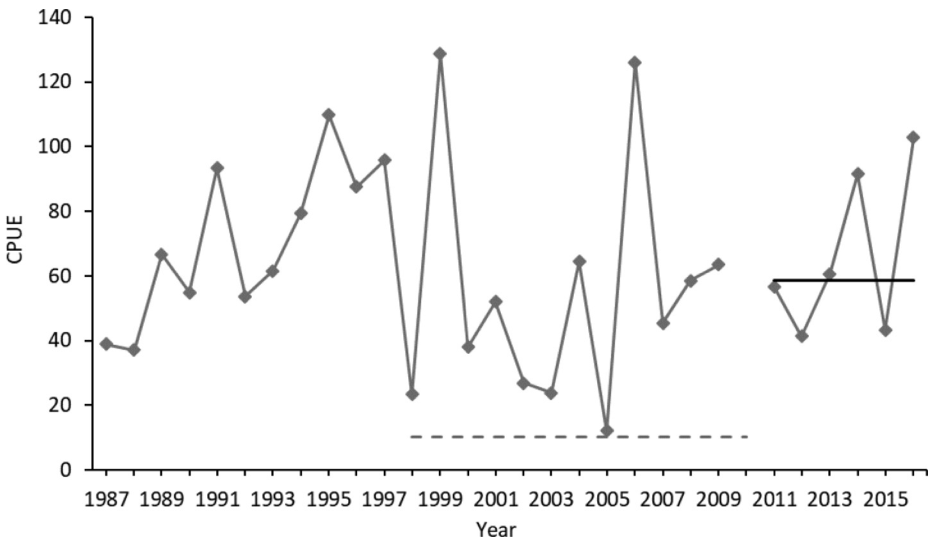

Fig. 1. Catch per unit effort (CPUE, yearly average over the sampling stations) data (grey solid line) in the Forsmark area between 1998 and 2016, based on the survey fishing data (https://www.slu.se/KUL). The GES boundary at the 5th percentile of the baseline period data (grey dashed line) and the median value of the indicator during the assessment period (black solid line).

errors in sampling (e.g. Borja et al., 2014; Carstensen & Lindegarth, 2016; Wach et al., 2019).

In this paper we propose the use of Bayesian inference to estimate the epistemic uncertainty associated with the boundary value between a desirable (Good Environmental Status "GES") and a non-desirable ("Sub-GES") states. Earlier studies have not addressed this particular uncertainty. Instead, given a fixed boundary value with no associated uncertainty, they have focused on the confidence of status assessments arising from e.g. the errors and variabilities related to sampling (Balsby et al., 2013; Carstensen & Lindegarth, 2016; Ramos-Merchante and Prenda, 2017). Being transparent about the uncertainty related to the boundary values and the data behind them is important, since the boundary value is a crucial element of the indicator-based status assessment, and its uncertainty affects the overall uncertainty of the assessment result.

Bayesian inference is commonly used in population analyses and fisheries stock assessments to evaluate the uncertainty related to population structure and abundance, or other population dynamic parameters (Mäntyniemi et al., 2005, 2015; Michielsens et al., 2006). In the indicator-based status assessment context, the approach could help quantify the epistemic uncertainty about both the boundary and current value of an indicator. This information can then be used to estimate the uncertainty related to the derived boundary values in the assessment. In the present study we use monitoring data to demonstrate how Bayesian inference can support the establishment of accurate boundary values in indicator-based ecological assessments and how the result differs from the output of the prevailing approach.

As a case example, we use an ecological indicator '*Abundance of coastal key fish species*', included in the regional status assessment of coastal fish communities in the Baltic Sea (HELCOM, 2018a). The indicator is represented by the catch per unit effort (CPUE) of European perch (*Perca fluviatilis*) in standardised fisheries independent surveys. Perch is a prevalent predatory fish species along large parts of the Baltic Sea coast (HELCOM, 2018b). In our Bayesian approach, the CPUE is not seen as a direct proxy of species abundance, but as a naturally noisy metric with observation error adding the noise. We develop a probabilistic model that, based on the prevailing ecological knowledge and available data, computes posterior distributions of population abundance indices. The model estimates relative perch abundance during a reference period, and the uncertainty of this estimate. These posterior distributions of population abundance indices are used in the status evaluation, instead of an estimator (e.g. CPUE data) that is a direct function of data including both the actual natural variation of the population and variation caused by the sampling procedure. The proposed Bayesian model filters out random observation error so that status assessment rules can be developed on the basis of natural variation only. As its output, this approach produces probability distributions for the boundary value that distinguishes "GES" from "Sub-GES" as well as the indicator's status, representing the amount of uncertainty concerning the classification result. Our analysis demonstrates how the selection of a safety margin – an inherent, but often neglected element of evidence-based management processes – affects the final assessment. The probabilistic form of the result saddles decision-makers with the burden of outlining an acceptable risk of misclassification of the indicator's state.

2. Materials and methods

2.1. Overview of the current indicator calculation and assessment protocol

The current status evaluation protocol for the indicator 'Abundance of key coastal fish species', used as the example in this article, consists of three steps (HELCOM, 2018c):

1. Defining, whether the predefined baseline (reference) period reflects GES or Sub-GES conditions. This can be done based on historical data, identification of structural changes during the baseline period or expert judgement (Östman et al., 2020).
2. Defining the GES boundary. The boundary is calculated as the value of the indicator at the 5th (Fig. 1: if the baseline is defined as GES) or 98th (if the baseline is defined as Sub-GES) percentile of the median distribution of the baseline data (HELCOM, 2018c). The distribution of medians during the baseline period is approximated by using resampling of observed CPUE values with replacement. Additionally, a smoothing parameter is applied to the resampled data of the baseline period.
3. Assessing the indicator's status during the assessment period. To reflect GES, the median value of the indicator during the assessment period must be above the GES boundary.

2.1.1. Study area and example data

We use long-term fisheries-independent data (Fig. 1) from the Forsmark monitoring area at the southern part of the Bothnian Sea coast of Sweden (Fig. 2). Perch were caught using a passive fishing gear, the multi-mesh coastal survey net, in eight sampling stations within the area (HELCOM, 2015). The data consists of the number of perch individuals ≥ 14 cm as the smaller sizes are not representatively sampled by the gear (Olsson et al., 2012). The data covers the years 1987 – 2016, excluding 2010. The same methodology and the number of stations has been used throughout the time-series but the data has two formats that

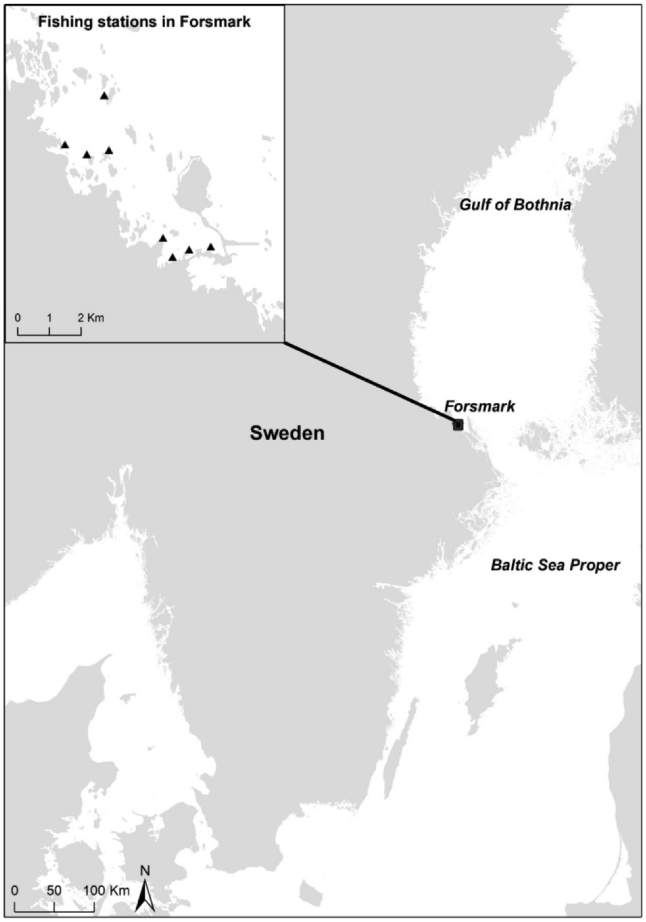

Fig. 2. Map of the Forsmark monitoring area in the southern part of the Bothnian Sea on the Swedish coast. Triangles denote the eight sampling stations.

are used in the developed model (see section 2.2) differently. The data between 1987 and 2006 consist of the number of perch caught per sampling station per year (the individual number of perch per night is not listed), whereas the data between 2007 and 2016 includes also the number of perch per night. The presented status assessment is based on a baseline period of 12 years (from 1998 to 2009) and an assessment period of six years (from 2011 to 2016) (Fig. 1). The quantity currently used for the status assessment of the 'Abundance of key coastal fish species' indicator is catch per unit effort (CPUE) calculated as the average number of perch ($\geq$14 cm) caught per station per fishing night.

2.2. Bayesian Belief Networks

The developed approach applies Bayesian statistics to compute probability distributions of the perch indicator for the given amount of survey data. In Bayesian inference, the existing knowledge (i.e. a prior probability) is revised after more information (i.e. data) becomes available, leading to an updated state of knowledge (i.e. posterior probability).

Bayesian Belief Networks (BBNs) consist of directed acyclic graphs (DAG) describing dependencies between the variables in a probabilistic form (Jensen, 2009; Korb & Nicholson, 2010). DAG defines the dependencies between the variables, and the variable values are denoted as probability distributions. If the variable's value depends, i.e. is conditional, on other variables, it has a conditional probability distribution (CPD). These probability distributions can be continuous or discrete. There is a variety of ways and sources to define CPDs: a) observed or modelled data (Rahikainen et al., 2014; Uusitalo et al., 2015; Moe et al., 2016), b) stakeholder or expert beliefs (Shaw et al., 2016; Salliou et al., 2017), c) literature reviews (Forio et al., 2015), and d) mixtures of these (Lehikoinen et al., 2013; Xue et al., 2017).

According to the Bayes' theorem, the posterior probability of proposition A being true given that the state of proposition B is known (Eq. (1)):

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{1}$$

where $P(A)$ and $P(A|B)$ are the prior and posterior distributions, respectively, and the term $P(B|A)$ denotes the probability density of data B given the parameters A. The term $P(B) = \int P(B|A)P(A)dA$ is the marginal (predictive) probability of proposition B. The prior distribution defines the amount of information about the subject before seeing the data. If there are no prior information about the subject or a prior is preferred to have minimal influence on our inference, an uninformative prior is selected. Then, the data has relatively more effect on the posterior compared to the prior information (Van de Schoot et al., 2014).

2.3. Estimating the uncertainty concerning the reference state

We develop a model to estimate the epistemic uncertainty about both the reference and the current states of the perch indicator. The probabilistic model accounts for the stochastic variation and the spatial and temporal observation errors of the CPUE to infer the underlying relative perch abundance.

The fish survey data aims at detecting changes in the targeted stock over time. However, the abundance is not independent between years. An autoregressive model is a typical method to analyse the change between years in time-series data for relative abundance and dynamics by using values from previous time steps as an input to a regression equation to predict the value at the next time step (Berryman and Turchin, 2001). In our study, the autoregressive model with log-normal distributions is used to describe the assumption that the yearly population index depends on the previous year's population index:

$$log(N_{t+1}) \sim \mathrm{N}[log(\mu_t) - 0.5\sigma_t^2, \sigma_t^2] \tag{2}$$

$$\mu_t = (1 - \phi)I + \Phi N_t \tag{3}$$

$$\sigma_t^2 = log\left[\left(\frac{(1 - \Phi^2)\nu^2}{\mu_t}\right)^2 + 1\right] \tag{4}$$

where N_{t+1} is the population index of the next year, μ_t is the expected population mean at year t, ϕ defines the amount of autocorrelation in the time-series, $\sigma_t^2$is the residual variance of the autoregressive process on the log-scale, I is the mean log-population index over the time-series, i.e. assuming that the population index fluctuates around the given mean, and ν is the marginal standard deviation, i.e. the standard deviation of the population index over the time-series. Table 1 shows all the prior distributions used in the model.

Count data, which is common in ecological monitoring, is prone to overdispersion. When it comes to the process of collecting fish monitoring data, overdispersion can be caused by schooling behaviour, sampling error and environmental variability (Lemos and Gomes, 2004; Linløkken and Haugen, 2006; Lindén and Mäntyniemi, 2011; Pagel et al., 2014; Zipkin et al., 2014). Overdispersion means that the variance in the data is higher than is predicted by a reference statistical model (Ver Hoef and Boveng, 2007). Perch might show aggregative behaviour and schooling (Thorpe, 1977), the size of the school depending on the foraging strategies, habitat complexity and the size of the individuals (Eklöv, 1997). As a result of schooling behaviour the fish are not caught independently from each other. A passive monitoring gear might hence rather catch or miss entire schools, which leads to overdispersion of observed counts compared to dispersion expected under independent behaviour.

Negative binomial distribution is often used when count data is

Table 1
Model parameters and their prior distributions. *Beta* = beta-distribution; *N* = normal distribution; *Unif* = uniform distribution.

	Abbreviations	Explanation	Prior distribution
An autoregressive model	ϕ	The autocorrelation parameter	$\Phi \sim Beta(2, 2)$
	I	The mean log-population index over the time-series	$log(I) \sim N\begin{bmatrix} log(60), \\ log(2) \end{bmatrix}$
	ν	The marginal standard deviation	$\nu \sim Unif(0, 200)$
Overdispersion	ω	The mean size of schools	$\omega \sim N(5, 100),\ truncated[1.01, \infty]$
The spatial variation between the stations	μ_S	The average station effect	$\mu_S \sim N(0, \sigma_S^2)$
	σ_S^2	Variance of station effects between stations	$\sigma_S^2 \sim Unif(0, 2)$
	σ_T^2	The variance over years within each station	$\sigma_T^2 \sim Unif(0, 2)$
Night effect	γ_{night_n}	Effect of the fishing night on expected catch	$\gamma_{night_1}=0 \gamma_{night_2} \sim N(0, 1) \gamma_{night_3} \sim N(0, 1)$

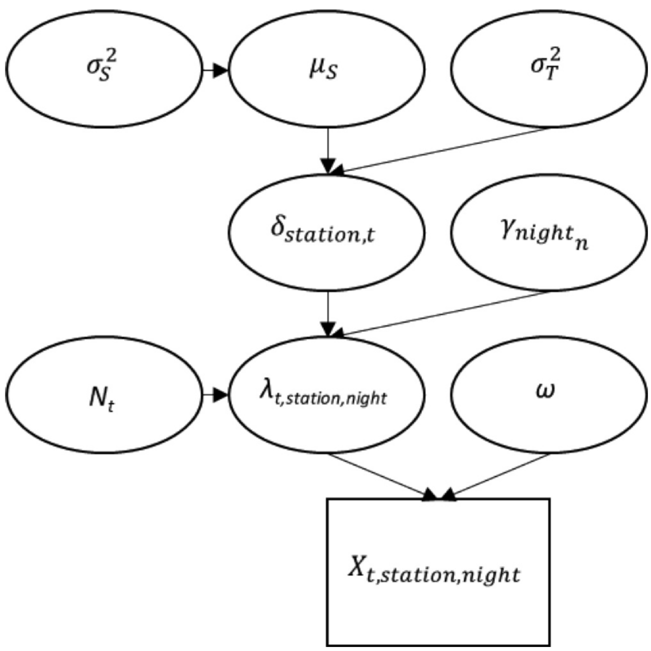

Fig. 3. Structure of the Bayesian Belief Network describing conditional relationships between data (rectangle) and parameters (ovals) at different levels. $X_{t,station,night}$ (the observed counts at year t), $\lambda_{t,station,night}$ (the expected number of individuals caught per station and night in a year t), N_t (the population index at a year t), ω (the size of the school), γ_{night_n} (the effect of fishing night), $\delta_{station,t}$ (the spatial variation between the stations), μ_S (the average station related effect), σ_T^2 (the variance over years within each station), $\sigma_S^2$the (variance of station effects between stations).

assumed to show clustering of counts (Lindén and Mäntyniemi, 2011; Ver Hoef and Boveng, 2007), applied also here to describe the process of catching perch at each sampling night (Fig. 3; see e.g. Lindén and Mäntyniemi, 2011):

$$X_{t,station,night} \sim NB\left(\frac{\lambda_{t,station,night}}{\omega - 1}, \frac{1}{\omega}\right) \tag{5}$$

where $X_{t,station,night}$ denotes observed counts within a station and fishing nights in year t, $\lambda_{t,station,night}$ denotes expected number of individuals caught within the station and fishing nights in year t, and ω denotes the mean size of schools.

Variability of the total catch of the fish survey arise from several factors. Expected catch ($\lambda_{t,station,night}$) is assumed to depend on a latent population index (N_t) as well as on station ($\delta_{station,t}$) - and night effects (γ_{night_n}) through a log-linear model:

$$\log(\lambda_{t,station,night}) = N_t + \delta_{station,t} + \gamma_{night_n} \tag{6}$$

Hierarchical model structure for the spatial variation between the stations is defined as

$$\mu_S \sim N(0, \sigma_S^2) \tag{7}$$

where μ_S isspatial effect of each station and σ_S^2 describes variation between stations. Temporal variation within each station is modelled using similar structure:

$$\delta_{station,t} \sim N(\mu_S, \sigma_T^2) \tag{8}$$

where $\delta_{station,t}$ defines annual effect (difference in catch of the fish survey) within each station and σ_T^2 represents variance over years at each station. In our example, the stations are distributed around the monitoring area (Forsmark) and therefore each of the stations are treated as independent. However, these are replicated samples of the same (Forsmark) population.

Parameter γ_{night_n}describes the effect that can be used to account for any systematic variation in catch of the fish survey between the consecutive fishing days (three nights in a row). As the fishing is done in consecutive days, the parameter γ_{night_n}can be used to detect if the amount of caught fish is systematically highest or lowest during a certain night.

The hierarchical model structure is presented in Fig. 3. The posterior distributions of model parameters were approximated using Markov Chain Monte Carlo (MCMC) sampling with the JAGS -software version 4.3.0 (Plummer 2003). We ran the MCMC simulations for 2 000 000 iterations in three chains using thinning of 1000 and dropped the first 1 000 000 iterations as a burn-in block, thus leaving 1000 samples in the analysis. Convergence was assessed by visual inspection of the chains. The model code for estimating the variance in population index inferred in scientific survey data is provided as part of the SI.

2.4. Estimating the uncertainty related to the boundary value

We apply the computed posterior distributions of population indices for estimating the uncertainty related to the boundary value. The key idea here is to follow the logic of the BSAP and MSFD assessments (HELCOM, 2018a; 2018c) with the twist that instead of using pooled CPUE observations in the evaluation, we use the computed posterior distributions of population indices (Table 2). The posterior distributions of population indices (N_t) represent the relative variation of population abundance, since the observation process variance has been filtered out by the hierarchical model. We provide the model code for the probabilistic status evaluation in the SI.

Fig. 4 shows the main steps of the proposed probabilistic status evaluation approach. Comparison between the calculated GES boundary, $Y_{B,q}$, and the median value of the assessment period, Y_A , is done within each MCMC simulation at a time (Fig. 4A) and not at the end of all the MCMC simulations to avoid the correlation between the baseline (reference) period and the assessment period to influence on the result. Fig. 4B illustrates how probability distribution P(GES boundary) for the GES boundary (of 50th percentile) is produced by computing the distribution (Fig. 4A) repeatedly by X MCMC simulations. Probability distribution for the GES boundary shows the level of

Table 2
Steps of the proposed probabilistic status evaluation approach and the specific model settings used in this example.

	Proposed approach	Model settings for the perch example
Step 1	Define whether the predefined baseline period reflects GES or Sub-GES conditions. In data-poor cases, this may be based on expert elicitation.	The baseline period is selected from the years 1998 to 2010 and according to HELCOM (2018c) it is defined to reflect good status.
Step 2	Determine the boundary value(s) defining the target state (GES). This is calculated at the qth percentile of resampled population indices (N_t) used to define the baseline period, Y_B to produce the GES boundary at$Y_{B,q}$. The selected qth percentile depends on whether the baseline period reflects GES or Sub-GES conditions.	In the first demonstration, the 5th percentile of resampled distribution of medians Y_B is used as the baseline period, and assessed to reflect GES conditions (HELCOM, 2018C). This GES boundary is represented as$Y_{B,0.05}$. In the second demonstration, the approach is also presented for the 50th percentile of resampled distribution of medians, Y_B for comparison to illustrate the significance of the percentile choice. This GES boundary is represented as $Y_{B,0.5}$.
Step 3	Each MCMC simulation is a random draw from the posterior distributions of population indices and represents a hypothesis about the relative variation of the populations. For each MCMC simulation at a time, the population indices from the baseline period, Y_B are used. From each of theseY_B, the random samples are picked by using the resampling with replacement. The number of samples should equal the number of years used to determine the assessment period (e.g. 6 years). After each computed random sample, the median value is calculated. Resampling is repeated multiple times (preferably $n > 1000$) to create the resampled distribution of medians, Y_B. Then from this Y_B, the GES boundary, $Y_{B,q}$, is calculated.	As the assessment period is selected from the years 2011 to 2016, the number of samples is six. The resampling with replacement is repeated 1000 times for each of the MCMC simulations.
Step 4	Compare the calculated GES boundary, $Y_{B,q}$, to the median value of the assessment period, Y_A , to evaluate whether Y_A is above or below the GES boundary (Fig. 4A). Each of the repeated status evaluation produces either 1 or 0, depending whether the $Y_{B,q} < Y_A$(reflecting GES) or $Y_{B,q} > Y_A$(reflecting Sub-GES), respectively. *Note*: The steps 2 to 4 mostly correspond the currently used status evaluation for the indicator 'Abundance of key coastal fish species' (HELCOM, 2018c). The only difference is that instead of using the raw CPUE data, the proposed probabilistic status evaluation use the population indices taken from the posterior distributions by MCMC method.	
Step 5	The steps 2 to 4 are repeated for each of the MCMC simulations (e.g. 1000). After repeating this for all the MCMC simulations, the probability distribution for the GES boundary (Fig. 4B) is produced and the consequent probabilistic status evaluation (Fig. 4C)created. The probability of reaching GES is estimated by comparing the number of MCMC simulations, where GES was reached to total number of MCMC simulations.	The steps are repeated for the total 1000 MCMC simulations.

knowledge concerning the reference conditions. Final step of the approach is to estimate the probability distribution P(GES) indicating the uncertainty associated with the final classification result (Fig. 4C). Fig. 4C presents also how the safety margin operates behind the manager's final judgement, setting the required level of certainty to judge the status as GES. For instance, when the GES boundary at 50th is used with the safety margin set to 0.75 (Fig. 4C), the probability of the status being GES is below the limit, which means that the system should not be evaluated to reach GES.

3. Results

3.1. Uncertainty about the reference state

Fig. 5 shows the estimated relative variation in the population abundance (i.e. the posterior distributions for the population index) of perch in the Forsmark area between 1987 and 2016, based on the survey fishing data. Medians of the posterior distributions follow a similar pattern to the raw CPUE data (Fig. 5). The medians exhibit a slightly lower interannual variation compared to the raw CPUE data because the observation error has been filtered out. Fig. 5 also reveals evident year-to-year variation in the population indices (N_t).

Fig. 6 shows the observation error related to the spatial variation between the stations. The station effect of each sampling stations in the Forsmark monitoring area varies slightly between years. Fig. 7 a shows the observation error related to the night effect showing the systematic variation in catch of the fish survey between the consecutive fishing days. The estimated size of the perch school is shown in the Fig. 7 b.

3.2. Uncertainty related to the boundary value

As each resampling ($n = 1000$) is calculated using a random MCMC draw from the posterior distributions of the population indices, the population indices of both the baseline and assessment periods vary between MCMC simulations (Fig. 8 and 9a-c).

Fig. 9 illustrates the probability distribution of the GES boundary computed from the MCMC simulations. Each MCMC simulation produces a different GES boundary, $Y_{B,q}$ (Fig. 9), which then yields a posterior probability distribution for the GES boundaries at $Y_{B,0.05}$ (Fig. 10a) and at $Y_{B,0.5}$ (Fig. 10b) when all MCMC simulations are combined.

The probabilistic status evaluation result in the probability that the evaluation period median is within the defined GES boundaries, i.e. the proportion of MCMC simulations in which the median value of the assessment period reached the GES boundary computed based on the baseline period of the same simulation. Thus, the overall probabilistic status evaluation in the Forsmark monitoring area indicates that when the GES boundary is set at $Y_{B,0.05}$, the probability to reach GES, i.e. P (GES), is 1, suggesting that GES is reached in all simulations (Fig. 11a). Whereas when the GES boundary is set at $Y_{B,0.5}$,the P(GES) is 0.96, thus 4% of the MCMC simulations indicating that GES is not reached (Fig. 11b). Fig. 9c and f illustrate one MCMC simulation where the median of the assessment period, Y_A is below the calculated $Y_{B,0.5}$.

4. Discussion

We have presented a novel probabilistic approach to quantify the uncertainty associated with the boundary value between good (GES) and poor environmental (Sub-GES) state of an ecological indicator. Bayesian inference was applied to estimate epistemic uncertainty

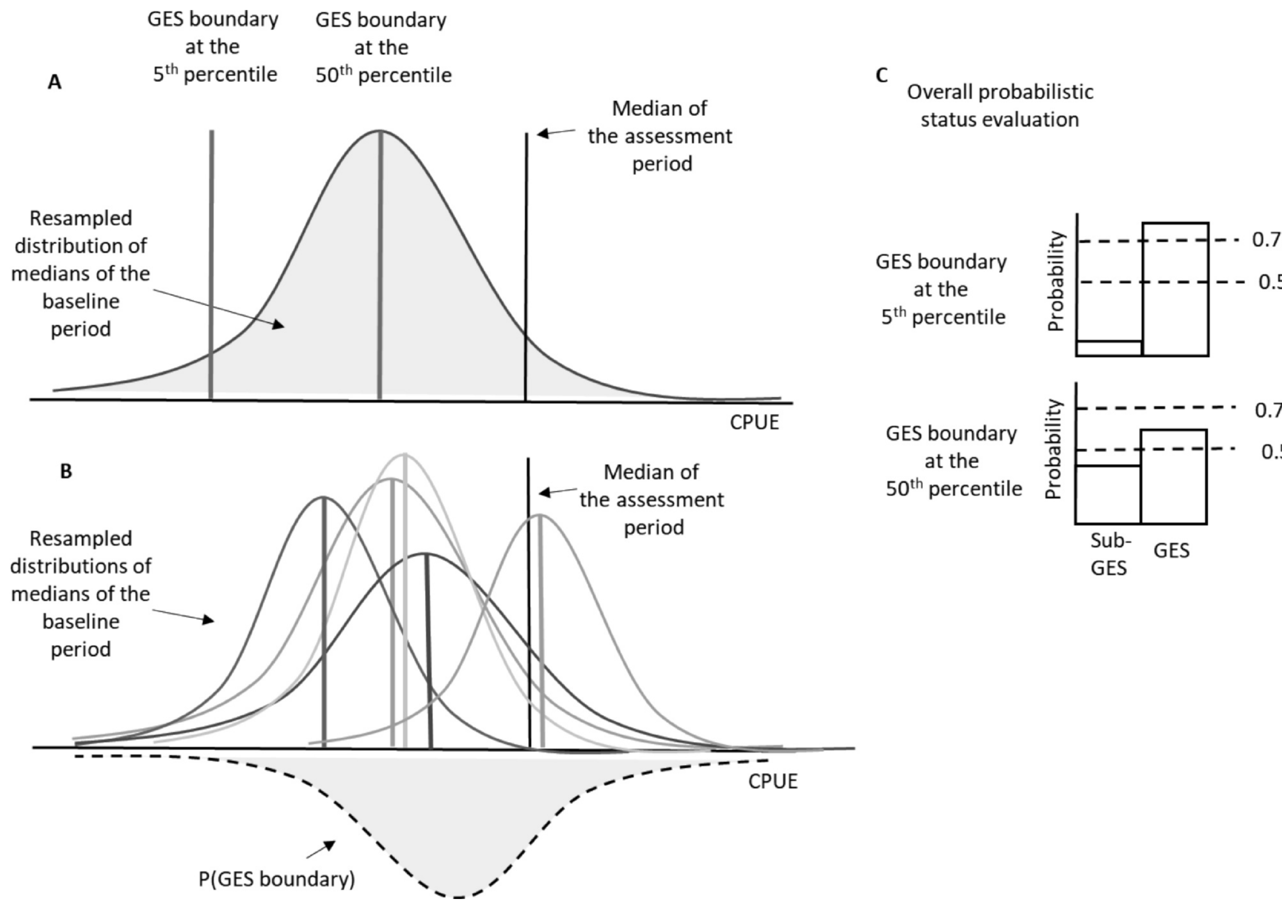

Fig. 4. Illustration of the main steps of the probabilistic status evaluation (for demonstrative purposes only, not based on any data from the study). (A) depicts the GES boundaries at 5th and 50th to be compared with the *median of the assessment period* to inform whether the GES is achieved or not. (B) illustrates the probability distribution *P(GES boundary)* for the GES boundary (of 50th percentile). (C) demonstrates the resulting probability distribution P(GES) quantifying the uncertainty associated with the final classification result and how the safety margin operates behind the manager's final judgement.

arising from sampling variation, concerning the reference conditions of a coastal fish species abundance. Explicit consideration of uncertainty affects our confidence in the indicator's target state, determined by the GES – Sub-GES -boundary value resulting in a probabilistic classification (i.e. status assessment result). In this chapter, we discuss the results of the presented case study, the general applicability of the approach, as well as its potential implications to environmental management.

4.1. Case study

The results of our case study support the notion that good environmental status (GES) of the perch abundance indicator is attained

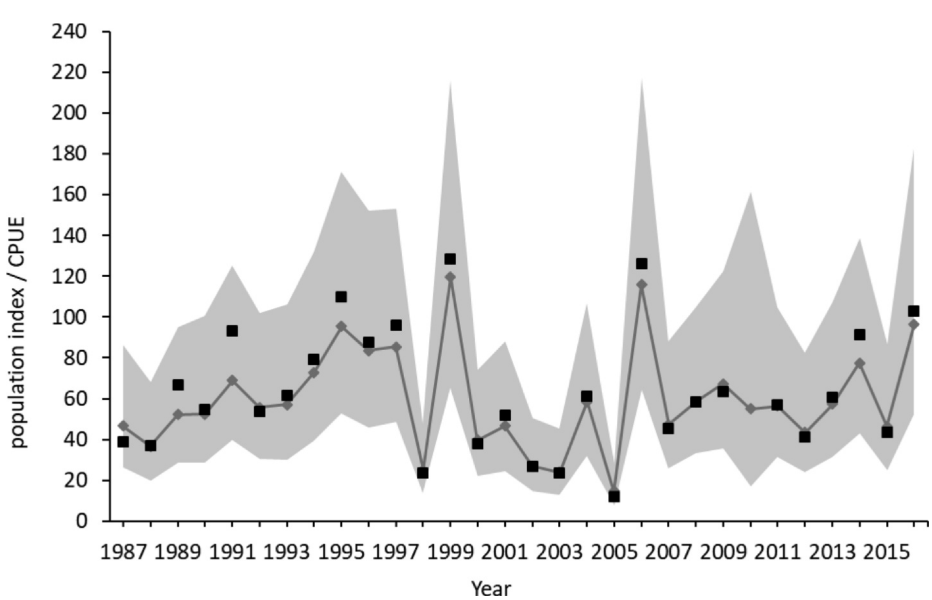

Fig. 5. Estimated relative time-series of medians of the posterior distributions (grey line with the grey dots) with 95% posterior credible interval (shaded area) of the population index compared to the raw catch per unit effort (CPUE, yearly average) data (black squares) in the Forsmark area between 1987 and 2016 (https://www.slu.se/KUL).

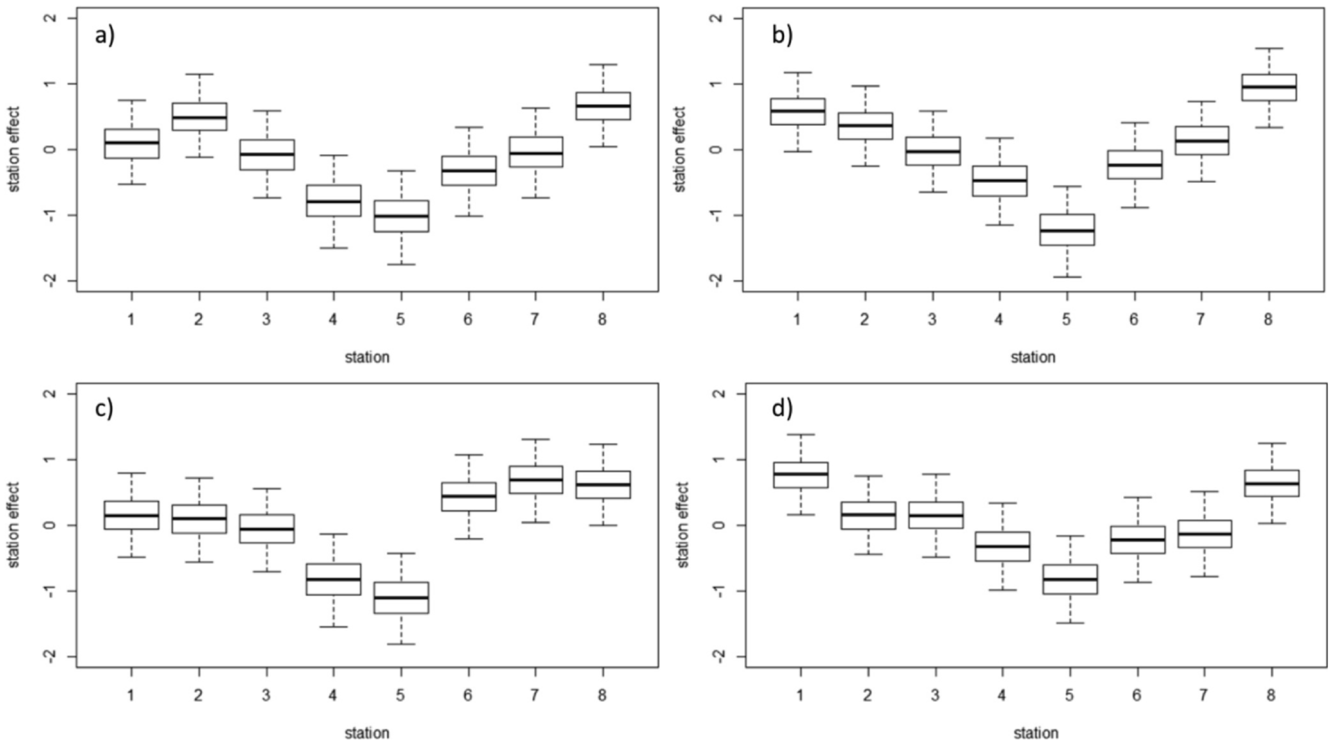

Fig. 6. Illustration of the spatial variation between the stations in year 1 (a), 10 (b), 25 (c), and 30 (d).

in the Forsmark area, with a minor risk of misclassification. However, this result relies on the predefined assumption of the baseline period representing a GES, which is uncertain in itself. This uncertainty is out of the scope of this study, but should still be acknowledged. In this study, the estimated posterior probability distributions of population indices denote the relative variation of population abundance, as the observation process variance has been filtered out by the Bayesian hierarchical model structure. We assumed spatial and temporal variation within and between the fishing stations in the Forsmark area. In the hierarchical model structure, the stations were treated as independent of each other, but still able to exchange information. For instance, considering the spatial effect of each station, we may detect whether the location of a certain fishing station has higher or lower catches on average, and thus acknowledge the spatial variation as a source of uncertainty. The suggested Bayesian hierarchical model structure becomes useful here as our model allows to build dependence between the interrelated parameters on multiple levels (Gelman et al., 2013; Pagel et al., 2014). If the available data is discontinuous or has random missing values, the hierarchical model structure allows the information to flow between parameters, updating information poor parameters (Punt et al., 2011).

In general, models for discrete count data often estimate abundance by assuming random spatial distribution of the individuals as well as random catch processes (Trenkel and Skaug, 2005). The Poisson process is commonly used to model stochastic variation around the model expectation (Ver Hoef and Boveng, 2007). For a Poisson distribution, the variance is equal to the mean, which rarely is the case in ecological count data (Lindén and Mäntyniemi, 2011). In case of fish species, an aggregated distribution is more typical due to schooling behaviour, environmental stochasticity, habitat complexity, and sampling variability (Richards, 2008; Lindén and Mäntyniemi, 2011; Dorazio et al., 2013). Negative binomial distribution was therefore used in our model to account the observation error related to overdispersion in the estimated population indices. As stated earlier in this paper, the type of overdispersion in ecological data can arise from multiple factors, and the presented modelling approach is adaptable to include different types of mean–variance relationships described by the negative binomial distribution (as presented in Lindén and Mäntyniemi, 2011).

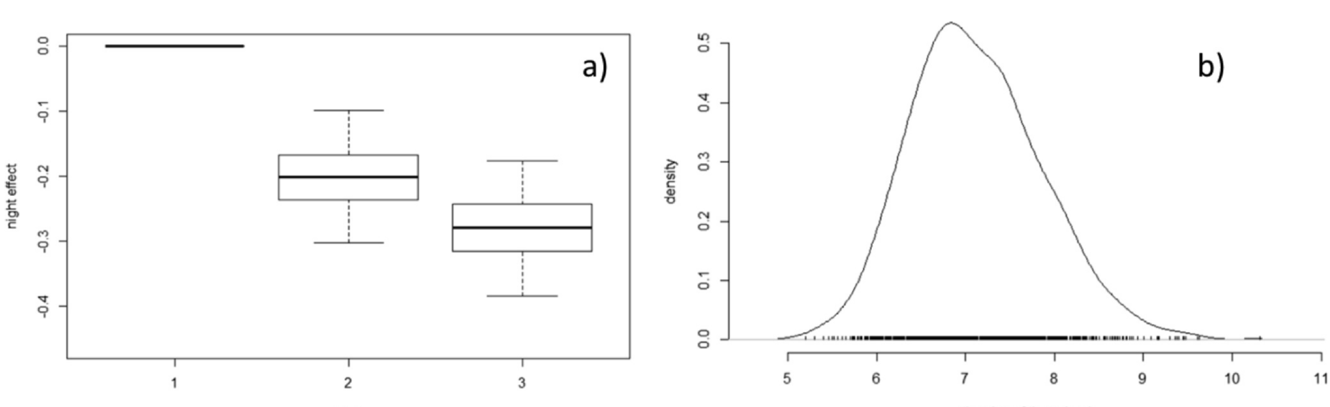

Fig. 7. Model outputs for night effect (a) and the size of the school (b).

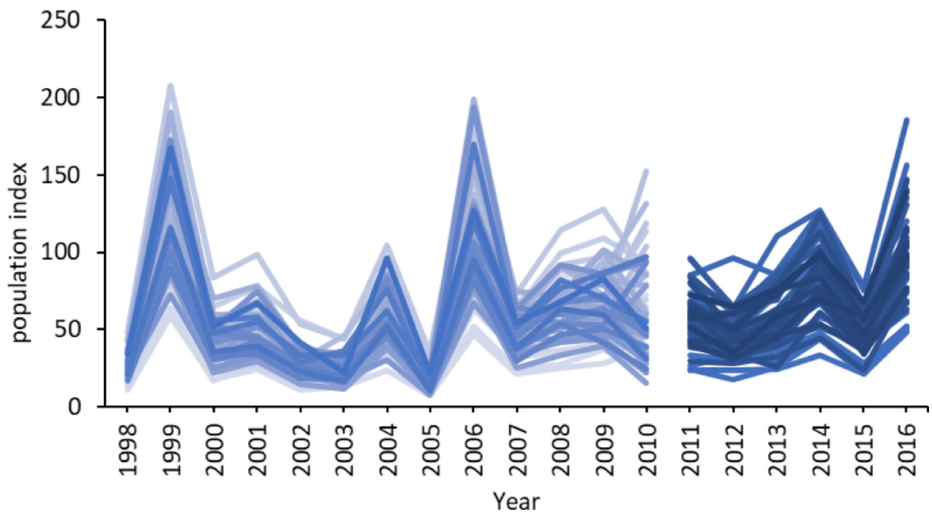

Fig. 8. For the clarity of illustration, only the first 50 MCMC simulations out of total 1000 MCMC simulations for both the baseline (light blue lines) and assessment (dark blue lines) periods is shown here.

After considering the different sources of uncertainty, our model does not level out the substantial variation of the catch data between some years. Although the natural population is known to fluctuate over time, it is unlikely that the true variation of the perch population would show variance of this magnitude between years, such as the population index doubling or being halved from one year to the next, especially as the data includes only adult individuals (> 14 cm) that likely have lower natural mortality rate than younger individuals. The year-to-year fluctuations could be caused by the fish migrating between areas or the varied fishing survey conditions (e.g. water temperature at fishing is an obvious factor that can affect the catchability of fish in passive gears). Perch is known to be local and rarely move > 5 km (Saulamo & Neuman, 2002), thus the latter explanation may be more plausible in our case. One way to handle substantial variation in the indicator values in time series data could be to use a breakpoint analysis (Probst and Stelzenmüller, 2015; Östman et al., 2020). In the current model, the autocorrelation parameter of the autoregressive model controls how much the population is allowed to fluctuate between the years. In future studies, it is possible to provide more realistic range for the changes in the annual population abundance indices by providing more informative prior for the autocorrelation parameter, for instance by using information from simulation-based population dynamics model or other studies with same or similar species.

4.2. General applicability of the approach for divergent types of ecological indicators

As temporal and spatial uncertainty of indicator-based status assessments such as the WFD, BSAP and MSFD vary across spatial assessment units, in the accuracy of the assessment units is unequal (Borja & Elliott, 2013; Carstensen, 2014; Fleming-Lehtinen et al., 2015). The uneven distributions of monitoring sites across European Seas (Patrício et al., 2016) may lead to a lack of proper data for the assessments in certain areas, causing difficulties to use the agreed indicators and to compare the assessment results of the above-mentioned assessment protocols. Additionally, confidence of a status evaluation can be lower in those locations where available data series are short. Bayesian approach gives valid uncertainty estimates for the parameters of interest given the available data (Hox et al., 2012, McNeish, 2016). As the focus is in analysing the level of prevailing knowledge, the inference is coherent regardless of the amount of data or missing values in it. This makes the approach applicable also in areas where systematic monitoring and time-series data are relatively short or discontinuous.

Many of current status assessment protocols rely heavily on statistical thinking, and it is suggested that for this reason the class boundaries may not correspond to biologically meaningful changes in ecosystems (Birk et al., 2012). The presented approach can add the prevailing ecological understanding to the assessment process via the hierarchical model structure, such as the acknowledgement of schooling behaviour explaining part of the variance in the perch monitoring data in our case study. The general approach of assessing spatial and temporal sources of uncertainty as we suggest is applicable for all kinds of indicators that describe the abundance, distribution or trend of species, inferred from survey-based count data. It could be possible to make similar models for commercial fishery data as well, but the model should be modified to take into account the fishers' tendency to concentrate at the best fishing locations.

Applying this approach to other types of ecological indicators could be beneficial too, as the systemic understanding about ecological processes giving rise to the data is often good. For instance, sea ice thickness is known to affect the breeding success of Baltic grey seal (*Halichoerus grypus*) (Jüssi et al., 2008) whereas salinity is known to be one of the main environmental factors influencing the macroalgal (*Fucus vesiculosus*) growth and survival (Barboza et al., 2019; Rothäusler et al., 2019). Using the prevailing ecological understanding in the data analysis makes the interpretation of data more informative, potentially improving the quality of the status assessments. However, applying this approach to different types of indicators and units of measurement (e.g. whether using areal density, spatial coverage or biomass estimates as the measures of abundance) requires modifying the hierarchical modelling structure and the type of distributions used for each parameter. The process could be generalised for the similar types of indicators and measures, though.

4.3. Management under uncertainty

As demonstrated, it is not straightforward to define the target state and set the corresponding boundary value for an ecological indicator. Acknowledgement of the uncertainty behind the classification result might lead to more transparent and better-informed decision-making processes. However, the probabilistic approach requires the decision-makers to make an explicit statement about the acceptable level of risk for the potential misclassification – in other words, them being transparent about their risk attitude (Fig. 4C). The risk attitude is a crucial – but often hidden - factor in the decision-making process, affecting the decision-maker's definition of the need for management actions (Pratt, 1964; Burgman, 2005; Keith, 2009; Burgman et al., 2018).

In practice, with the probabilistic outcome, one have to make a

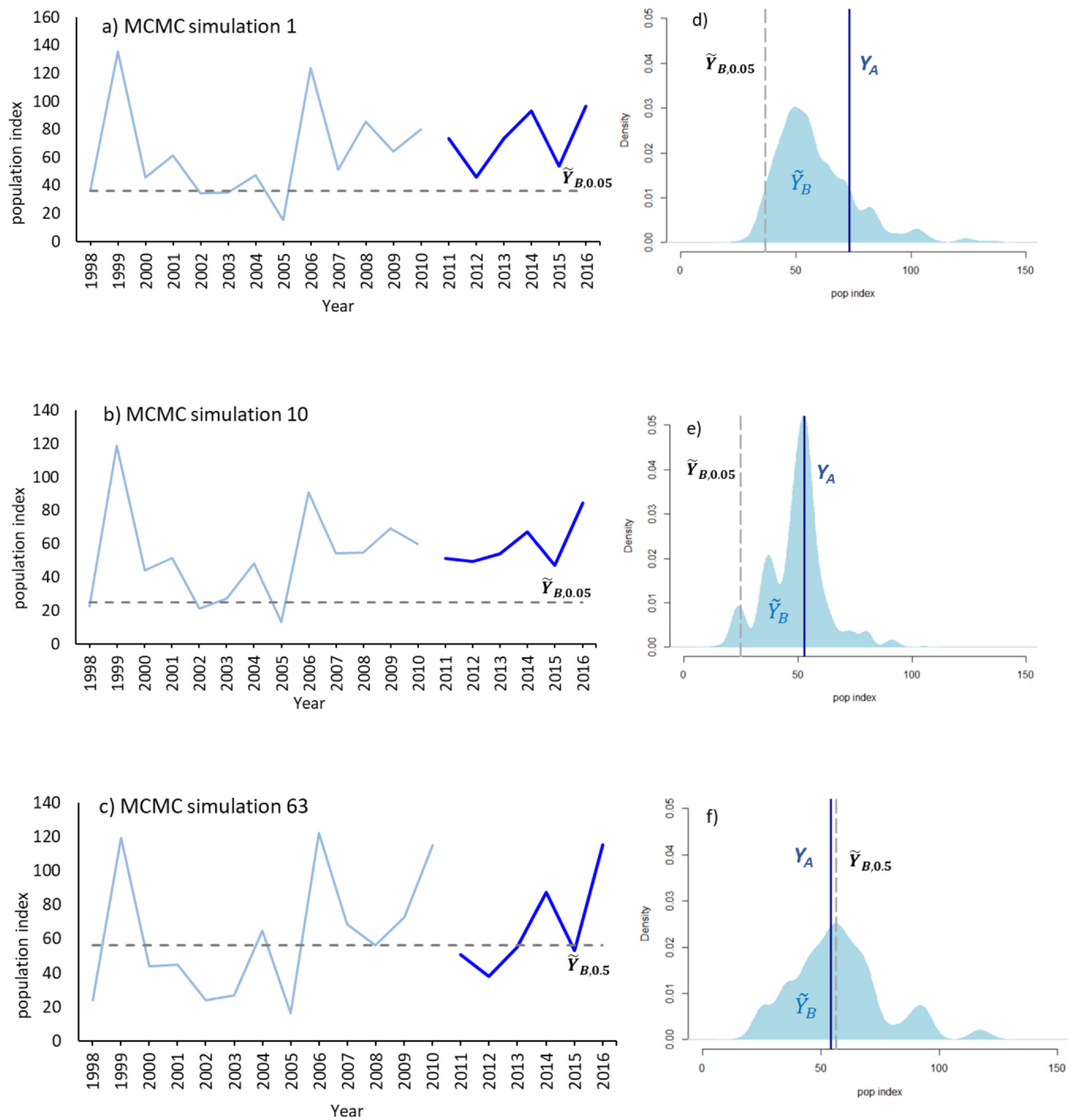

Fig. 9. Illustration of the GES boundary evaluation for a selected suite of MCMC simulations. The posterior distributions of the population indices during the baseline period Y_B (light blue) and the assessment period (dark blue) for three MCMC simulations (a-c). The median of the assessment period, Y_A, compared to the calculated $Y_{B,0.05}$ (*d,e*) and $Y_{B,0.5}$ (*f*) from the resampled distributions of medians, Y_B.

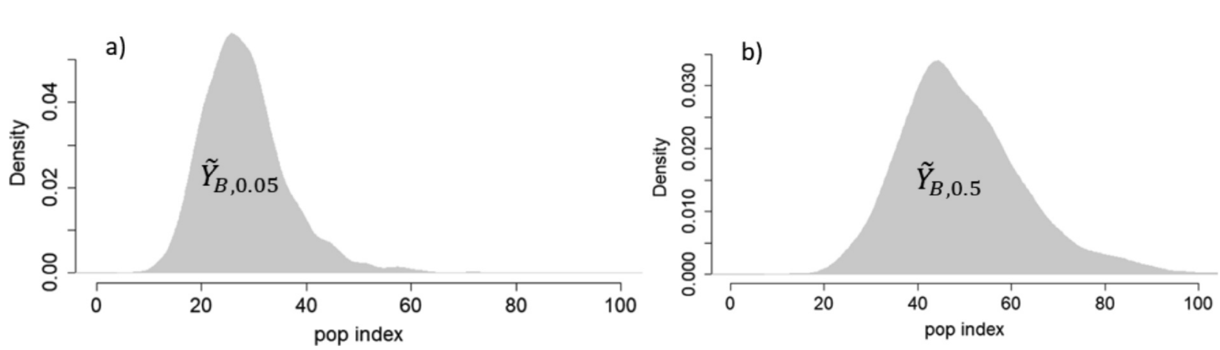

Fig. 10. The probability distribution for the GES boundary (a) at the 5th percentile, $Y_{B,0.05}$ and (b) at the 50th percentile, $Y_{B,0.5}$ after all MCMC simulations.

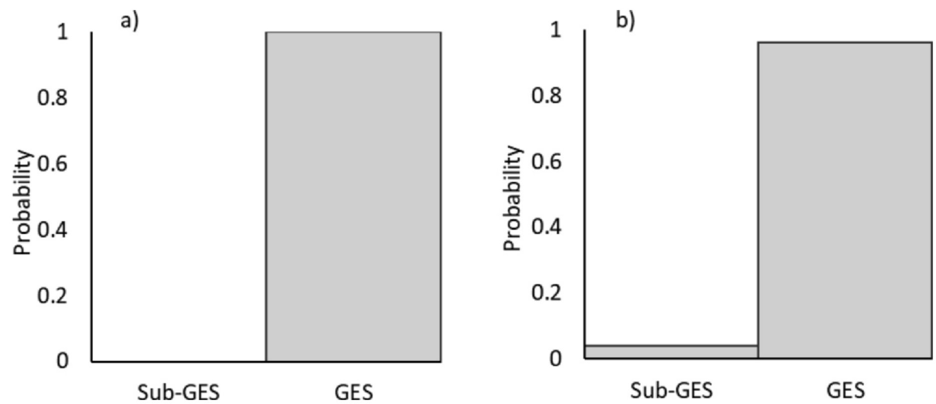

Fig. 11. The probabilistic status evaluation for after all the MCMC simulations when GES boundary is set (a) at $Y_{B,0.05}$ and (b) at $Y_{B,0.5}$.

decision on the acceptable safety margin for the risk of misclassification of the indicator's status (and further on – after integration of the probabilistic status classification results for several indicators from the same area - a spatial assessment unit). For example, if the safety margin is set to 0.75, GES should be achieved with the minimum probability of 0.75, as demonstrated in Fig. 4C. In the presented case study analysis of Forsmark, the probability of the perch indicator representing GES was 0.96 (Fig. 11b), thus with the safety margin of 0.75 good status is achieved. Similar probabilistic safety margins have been adopted e.g. in the management of the Baltic salmon (*Salmo salar*) stocks (Kuikka et al., 2014; ICES, 2019).

Notably, another type of safety margin is defined in the beginning of the status evaluation process, namely when the analysts make the statement to use either 5th or 98th percentile of the baseline period, depending on whether the baseline period is thought to represent the GES or the Sub-GES, respectively. Applying higher percentiles would mean higher boundary levels and thus impact the final classification. Often, the pristine state of the ecosystem is unknown, may not even be desirable. The extent and time range of the data used to establish the boundary value is also typically limited, and case-specific amount of uncertainty is thus inevitably associated with the status classification. One option to tackle this in the probabilistic approach is that instead of presenting the baseline status as known, the analysts would give an estimate about the amount of uncertainty related to it. Following this, the corresponding percentiles (5th and 98th) could be weighted accordingly in the computation process. This way the uncertainty related to the baseline status would be reflected in the final probabilistic status classification result.

To conclude, it is important to pay attention to how we communicate uncertainty in environmental management processes. Transparent probabilistic representation of divergent assessment outputs may even lead to easier decision-making processes with fewer conflicts between decision-makers and stakeholders (Ramos et al., 2013; Laurila-Pant et al., 2019). Showing the uncertainty related to the assessment results can also make decision-makers select actions that are less risky, in turn impacting their risk attitudes (Ramos et al., 2013). Importantly, the lack of certainty should not be taken as an argument for inaction, but instead as a call for more information (De Santo, 2010). Even though the remediation would be costly, neglecting it due to uncertain result can become much more expensive (Nygård et al. 2016). More active societal discussion on the acceptable risk for this kind of unwanted consequences is needed.

5. Conclusion

This study presents an approach to quantify the uncertainty related to the boundary value between desirable (GES) and non-desirable (Sub-GES) states of ecological indicators and consequently to the uncertainty associated with the status classification. The uncertainty related to the boundary value definition has not been addressed in earlier studies. Instead of a fixed boundary value with no associated uncertainty, we use Bayesian inference to estimate the epistemic uncertainty regarding the hidden state of an indicator during the reference period, arising from environmental and sampling variation. Defective treatment of uncertainty may lead to erroneous status classification and further on to inadequate management measures or non-optimal prioritisation of actions and investments. The proposed approach uses ecological knowledge and available data to quantify the level of knowledge concerning the reference conditions and to produce posterior probability distribution for the boundary value. The final probabilistic status classification requires decision-makers to make a statement about the acceptable safety margin for the risk of misclassification of the indicator's status. We suggest the acknowledgement and transparent presentation of the uncertainty behind status classification results lead to better-informed decision-making processes.

CRediT authorship contribution statement

Mirka Laurila-Pant: Conceptualization, Writing - review & editing, Methodology, Writing - original draft, Formal analysis. **Samu Mäntyniemi:** Methodology, Writing - original draft, Formal analysis, Writing - review & editing. **Örjan Östman:** Writing - original draft, Data curation, Writing - review & editing. **Jens Olsson:** Writing - original draft, Data curation, Writing - review & editing. **Laura Uusitalo:** Conceptualization, Writing - original draft, Writing - review & editing. **Annukka Lehikoinen:** Conceptualization, Writing - original draft, Supervision, Writing - review & editing.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2020.106975.

References

Balsby, T.J., Carstensen, J., Krause-Jensen, D., 2013. Sources of uncertainty in estimation of eelgrass depth limits. Hydrobiologia 704 (1), 311–323.

Barboza, F.R., Kotta, J., Weinberger, F., Jormalainen, V., Kraufvelin, P., Molis, M., Schagerström, E., 2019. Geographic variation in fitness-related traits of the bladderwrack Fucus vesiculosus along the Baltic Sea-North Sea salinity gradient. Ecol. Evol. 9 (16), 9225–9238.

Berryman, A., Turchin, P., 2001. Identifying the density-dependent structure underlying ecological time series. Oikos 92 (2), 265–270.

Birk, S., Bonne, W., Borja, A., Brucet, S., Courrat, A., Poikane, S., Hering, D., 2012. Three hundred ways to assess Europe's surface waters: an almost complete overview of biological methods to implement the Water Framework Directive. Ecol. Ind. 18, 31–41.

Borja, Á., Galparsoro, I., Irigoien, X., Iriondo, A., Menchaca, I., Muxika, I., Santurtún, M., 2011. Implementation of the European Marine Strategy Framework Directive: a methodological approach for the assessment of environmental status, from the Basque Country (Bay of Biscay). Mar. Pollut. Bull. 62 (5), 889–904.

Borja, Á., Dauer, D.M., Grémare, A., 2012. The importance of setting targets and reference conditions in assessing marine ecosystem quality. Ecol. Ind. 12 (1), 1–7.

Borja, A., & Elliott, M. (2013). Marine monitoring during an economic crisis: the cure is worse than the disease.

Borja, A., Elliott, M., Andersen, J.H., Cardoso, A.C., Carstensen, J., Ferreira, J.G., Uusitalo, L., 2013. Good environmental status of marine ecosystems: what is it and how do we know when we have attained it? Mar. Pollut. Bull. 76 (1–2), 16–27.

Borja, A., Prins, T.C., Simboura, N., Andersen, J.H., Berg, T., Marques, J.C., Uusitalo, L., 2014. Tales from a thousand and one ways to integrate marine ecosystem components when assessing the environmental status. Front. Mar. Sci. 1, 72.

Burgman, M., 2005. Risks and decisions for conservation and environmental management (Ecology, biodiversity and conservation). Cambridge University Press.

Burgman, M., Tennant, M., Voulvoulis, N., Makuch, K., Madani, K., 2018. Facilitating the transition to sustainable green chemistry. Curr. Opin. Green Sustainable Chem. 13, 130–136.

Carstensen, J., 2014. Need for monitoring and maintaining sustainable marine ecosystem services. Front. Mar. Sci. 1, 33.

Carstensen, J., Lindegarth, M., 2016. Confidence in ecological indicators: a framework for quantifying uncertainty components from monitoring data. Ecol. Ind. 67, 306–317.

Danovaro, R., Carugati, L., Berzano, M., Cahill, A.E., Carvalho, S., Chenuil, A., Dzhembekova, N., 2016. Implementing and innovating marine monitoring approaches for assessing marine environmental status. Front. Mar. Sci. 3, 213.

De Santo, E.M., 2010. 'Whose science?' Precaution and power-play in European marine environmental decision-making. Marine Policy 34 (3), 414–420.

Dorazio, R.M., Martin, J., Edwards, H.H., 2013. Estimating abundance while accounting for rarity, correlated behavior, and other sources of variation in counts. Ecology 94 (7), 1472–1478.

Eklöv, 1997. Effects of habitat complexity and prey abundance on the spatial and temporal distributions of perch (Perca fluviatilis) and pike (Esox lucius). Can. J. Fish. Aquat. Sci. https://doi.org/10.1139/f97-059.

European commission, 2000. Directive 2000/60/EC of the European Parliament and of the Council of 23 October 2000 Establishing a Framework for Community Action in the Field of Water Policy (2000), p. 2000.

European Commission, 2008. Directive 2008/56/EC of the European Parliament and of the Council establishing a framework for community action in the field of marine environmental policy (Marine Strategy Framework Directive). Off. J. Eur. Union L164, 19–40.

Fleming-Lehtinen, V., Andersen, J.H., Carstensen, J., Łysiak-Pastuszak, E., Murray, C., Pyhälä, M., Laamanen, M., 2015. Recent developments in assessment methodology reveal that the Baltic Sea eutrophication problem is expanding. Ecol. Ind. 48, 380–388.

Forio, M.A.E., Landuyt, D., Bennetsen, E., Lock, K., Nguyen, T.H.T., Ambarita, M.N.D., Goethals, P.L., 2015. Bayesian belief network models to analyse and predict ecological water quality in rivers. Ecol. Model. 312, 222–238.

Gelman, A., Carlin, J.B., Stern, H.S., Dunson, D.B., Vehtari, A., Rubin, D.B., 2013. Bayesian data analysis. Chapman and Hall/CRC.

HELCOM, 2007. The Baltic Sea Action Plan. In: HELCOM Ministerial Meeting Krakow, Poland, 15 November 2007, p. 101.

HELCOM, 2012. Development of a set of core indicators: Interim report of the HELCOM CORESET project. PART A. Description of the selection process. Balt. Sea Environ. Proc, No, pp. 129A.

HELCOM, 2015. Guidelines for Coastal Fish Monitoring Sampling Methods of HELCOM.

HELCOM (2018a): State of the Baltic Sea – Second HELCOM holistic assessment 2011-2016. Baltic Sea Environment Proceedings 155.

HELCOM, 2018. Status of coastal fish communities in the Baltic Sea during 2011–2016 – the third thematic assessment. Baltic Sea Environment Proceedings N° 161.

HELCOM, 2018c. Abundance of coastal fish key species. HELCOM core indicator report.

Hox, J.J., van de Schoot, R., Matthijsse, S., 2012. How few countries will do? Comparative survey analysis from a Bayesian perspective. Survey Research Methods (Vol. 6 (2), 87–93.

ICES (2019). Baltic Salmon and Trout Assessment Working Group (WGBAST). ICES Scientific Reports. 1:23. 312 pp. http://doi.org/10.17895/ices.pub.4979.

Jensen, F.V., 2009. Bayesian networks. Wiley Interdiscip. Rev. Comput. Stat. 1 (3), 307–315.

Jüssi, M., Härkönen, T., Helle, E., Jüssi, I., 2008. Decreasing ice coverage will reduce the breeding success of Baltic grey seal (Halichoerus grypus) females. AMBIO: A Journal of the Human. Environment 37 (2), 80–85.

Keith, D.A., 2009. The interpretation, assessment and conservation of ecological communities. Ecol. Manage. Restor. 10, S3–S15.

Korb, K.B., Nicholson, A.E., 2010. Bayesian artificial intelligence. CRC Press.

Kuikka, S., Vanhatalo, J., Pulkkinen, H., Mäntyniemi, S., Corander, J., 2014. Experiences in Bayesian inference in Baltic salmon management. Statistical Science 29 (1), 42–49.

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.

Lehikoinen, A., Luoma, E., Mäntyniemi, S., Kuikka, S., 2013. Optimizing the recovery efficiency of Finnish oil combating vessels in the Gulf of Finland using Bayesian networks. Environ. Sci. Technol. 47 (4), 1792–1799.

Lemos, R.T., Gomes, J.F., 2004. Do local environmental factors induce daily and yearly variability in bluefin tuna (Thunnus thynnus) trap catches? Ecol. Model. 177 (1–2), 143–156.

Lindén, A., Mäntyniemi, S., 2011. Using the negative binomial distribution to model overdispersion in ecological count data. Ecology 92 (7), 1414–1421.

Linløkken, A., Haugen, T.O., 2006. Density and temperature dependence of gill net catch per unit effort for perch, Perca fluviatilis, and roach. Rutilus rutilus. Fisheries Management and Ecology 13 (4), 261–269.

Mäntyniemi, S., Romakkaniemi, A., Arjas, E., 2005. Bayesian removal estimation of a population size under unequal catchability. Can. J. Fish. Aquat. Sci. 62 (2), 291–300.

Mäntyniemi, S.H., Whitlock, R.E., Perälä, T.A., Blomstedt, P.A., Vanhatalo, J.P., Rincón, M.M., Kuikka, O.S., 2015. General state-space population dynamics model for Bayesian stock assessment. ICES J. Mar. Sci. 72 (8), 2209–2222.

McNeish, D., 2016. On using Bayesian methods to address small sample problems. Structural Equation Modeling: A Multidisciplinary Journal 23 (5), 750–773.

Michielsens, C.G., McAllister, M.K., Kuikka, S., Pakarinen, T., Karlsson, L., Romakkaniemi, A., Mäntyniemi, S., 2006. A Bayesian state space mark recapture model to estimate exploitation rates in mixed-stock fisheries. Can. J. Fish. Aquat. Sci. 63 (2), 321–334.

Moe, S.J., Haande, S., Couture, R.M., 2016. Climate change, cyanobacteria blooms and ecological status of lakes: a Bayesian network approach. Ecol. Model. 337, 330–347.

Muxika, I., Borja, A., Bald, J., 2007. Using historical data, expert judgement and multivariate analysis in assessing reference conditions and benthic ecological status, according to the European Water Framework Directive. Mar. Pollut. Bull. 55 (1–6), 16–29.

Nygård, H., Oinonen, S., Hällfors, H.A., Lehtiniemi, M., Rantajärvi, E., Uusitalo, L., 2016. Price vs. value of marine monitoring. Frontiers in Marine. Science 3, 205.

Olsson, J., Bergström, L., Gårdmark, A., 2012. Abiotic drivers of coastal fish community change during four decades in the Baltic Sea. ICES J. Mar. Sci. 69 (6), 961–970.

Östman, Ö., Bergström, L., Leonardsson, K., Gårdmark, A., Casini, M., Sjöblom, Y., Olsson, J., 2020. Analyses of structural changes in ecological time series (ASCETS). Ecol. Ind. 116, 106469.

Pagel, J., Anderson, B.J., O'Hara, R.B., Cramer, W., Fox, R., Jeltsch, F., Schurr, F.M., 2014. Quantifying range-wide variation in population trends from local abundance surveys and widespread opportunistic occurrence records. Methods Ecol. Evol. 5 (8), 751–760.

Patrício, J., Little, S., Mazik, K., Papadopoulou, K.N., Smith, C.J., Teixeira, H., Kaboglu, G., 2016. European marine biodiversity monitoring networks: strengths, weaknesses, opportunities and threats. Front. Mar. Sci. 3, 161.

Piroddi, C., Teixeira, H., Lynam, C.P., Smith, C., Alvarez, M.C., Mazik, K., Chust, G., 2015. Using ecological models to assess ecosystem status in support of the European Marine Strategy Framework Directive. Ecol. Ind. 58, 175–191.

Plummer, M. (2003). JAGS: A program for analysis of Bayesian graphical models using Gibbs sampling. In Proceedings of the 3rd international workshop on distributed statistical computing (Vol. 124, No. 125, p. 10).

Punt, A.E., Smith, D.C., Smith, A.D., 2011. Among-stock comparisons for improving stock assessments of data-poor stocks: the "Robin Hood" approach. ICES J. Mar. Sci. 68 (5), 972–981.

Pratt, J.W., 1964. Risk aversion in the small and in the large. Econometrice 32, 122–136.

Probst, W.N., Stelzenmüller, V., 2015. A benchmarking and assessment framework to operationalise ecological indicator based on time series analysis. Ecol. Ind. 55, 94–106.

Rahikainen, M., Helle, I., Haapasaari, P., Oinonen, S., Kuikka, S., Vanhatalo, J., Hoviniemi, K.M., 2014. Toward integrative management advice of water quality, oil spills, and fishery in the Gulf of Finland: a Bayesian approach. Ambio 43 (1), 115–123.

Ramos, M.H., Van Andel, S.J., Pappenberger, F., 2013. Do probabilistic forecasts lead to better decisions? Hydrol. Earth Syst. Sci. 17 (6), 2219–2232.

Ramos-Merchante, A., Prenda, J., 2017. Macroinvertebrate taxa richness uncertainty and kick sampling in the establishment of Mediterranean rivers ecological status. Ecol. Ind. 72, 1–12.

Richards, S.A., 2008. Dealing with overdispersed count data in applied ecology. J. Appl. Ecol. 45 (1), 218–227.

Rothäusler, E., Uebermuth, C., Haavisto, F., Jormalainen, V., 2019. Living on the edge: Gamete release and subsequent fertilisation in Fucus vesiculosus (Phaeophyceae) are weakened by climate change–forced hyposaline conditions. Phycologia 58 (2), 111–114.

Salliou, N., Barnaud, C., Vialatte, A., Monteil, C., 2017. A participatory Bayesian Belief Network approach to explore ambiguity among stakeholders about socio-ecological

systems. Environ. Modell. Software 96, 199–209.
Saulamo, K., Neuman, E., 2002. Local management of Baltic fish stocks–significance of migrations. Fiskeriverket informerar 9, 1–18.
Shaw, E., Kumar, V., Lange, E., Lerner, D.N., 2016. Exploring the utility of Bayesian Networks for modelling cultural ecosystem services: a canoeing case study. Sci. Total Environ. 540, 71–78.
Thorpe, J. (1977). Synopsis of biological data on the perch, Perca fluviatilis Linnaeus, 1785 and Perca flavescens Mitchill, 1814. FAO Fisheries Synopses (FAO). no. 113.
Trenkel, V.M., Skaug, H.J., 2005. Disentangling the effects of capture efficiency and population abundance on catch data using random effects models. ICES J. Mar. Sci. 62 (8), 1543–1555.
Uusitalo, L., Lehikoinen, A., Helle, I., Myrberg, K., 2015. An overview of methods to evaluate uncertainty of deterministic models in decision support. Environ. Modell. Software 63, 24–31.
Van de Schoot, R., Kaplan, D., Denissen, J., Asendorpf, J.B., Neyer, F.J., van Aken, M.A., 2014. A gentle introduction to Bayesian analysis: Applications to developmental research. Child Dev. 85 (3), 842–860.
Ver Hoef, J.M., Boveng, P.L., 2007. Quasi-Poisson vs. negative binomial regression: how should we model overdispersed count data? Ecology 88 (11), 2766–2772.
Wach, M., Guéguen, J., Chauvin, C., Delmas, F., Dagens, N., Feret, T., Tison-Rosebery, J., 2019. Probability of misclassifying river ecological status: A large-scale approach to assign uncertainty in macrophyte and diatom-based biomonitoring. Ecol. Ind. 101, 285–295.
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.
Zipkin, E.F., Leirness, J.B., Kinlan, B.P., O'Connell, A.F., Silverman, E.D., 2014. Fitting statistical distributions to sea duck count data: Implications for survey design and abundance estimation. Statistical Methodology 17, 67–81.
Zucchetta, M., Venier, C., Taji, M.A., Mangin, A., Pastres, R., 2016. Modelling the spatial distribution of the seagrass Posidonia oceanica along the North African coast: Implications for the assessment of Good Environmental Status. Ecol. Ind. 61, 1011–1023.