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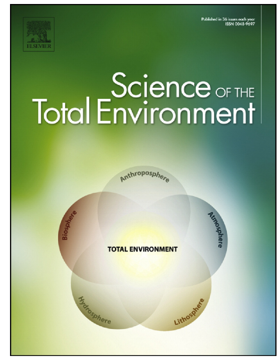

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Mirka Laurila-Pant, Samu Mäntyniemi, Riikka Venesjärvi, Annukka Lehikoinen

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Incorporating stakeholders' values into environmental decision support: A Bayesian Belief Network approach

Mirka Laurila-Pant [a,*], Samu Mäntyniemi [b], Riikka Venesjärvi [b], Annukka Lehikoinen [c]

[a] University of Helsinki, Ecosystems and Environment Research Programme, Fisheries and Environmental Management group. Viikinkaari 2, FI-00014 University of Helsinki, Finland

[b] Natural Resources Institute Finland, Latokartanonkaari 9, FI-00790 Helsinki, Finland

[c] University of Helsinki, Ecosystems and Environment Research Programme, Fisheries and Environmental Management group. Kotka Maritime Research Centre, Keskuskatu 10, 48100 Kotka, Finland

[*] Corresponding author, Tel. +358 503 185 679; E-mail: mirka.laurila-pant@helsinki.fi

Abstract

Participatory modelling increases the transparency of environmental planning and management processes and enhances the mutual understanding among different parties. We present a sequential probabilistic approach to involve stakeholders' views in the formal decision support process. A continuous Bayesian Belief Network (BBN) model is used to estimate population parameters for stakeholder groups, based on samples of individual value judgements. The approach allows quantification and visualization of the variability in views among and within stakeholder groups. Discrete BBN is populated with these parameters, to summarize and visualize the information and to link it to a larger decision analytic influence diagram (ID). As part of ID, the resulting discrete BBN element serves as a distribution-form decision criteria in probabilistic evaluation of alternative management strategies, to help find a solution that represents the optimal compromise in the presence of potentially conflicting objectives. We demonstrate our idea using example data from the field of marine spatial planning. However, this approach is applicable to many types of management cases. We suggest that by advancing the mutual understanding and concrete participation this approach can further facilitate the stakeholder involvement also during the various stages of the environmental management process.

Keywords: Participatory modelling, Stakeholder involvement, Bayesian Belief Network, Multi-Criteria Decision Analysis

1 Introduction

Human activities create pressures on ecosystems, upon which the societies rely at the same time (Allen et al., 2016). Natural resources should not be treated in isolation from the rest of the ecosystem and the social system, thus recognition of the linkages between the ecological and social spheres is needed (Östrom, 2009; Virapongse et al., 2016). Ecosystem-based management (EBM) aims for operationalizing this systemic social-ecological thinking as it requires adaptive management that takes into account the dynamics within ecosystems but also between the ecosystems and societies (Levin et al., 2009; Langhans et al., 2019).

Currently, EBM is one of the key principles in the US National Ocean Policy (NOP, 2018) as well as in European Union policies, for example, the Water Framework Directive (European commission, 2000), the Marine Strategy Framework Directive (European Commission, 2008), and the Maritime Spatial Planning Directive (European Commission, 2014).

The success of environmental management depends on the acceptance and commitment of stakeholders to the chosen policy and measures of implementation (Verweij & van Densen, 2010; Jones et al., 2011; Haapasaari et al., 2012). By increasing the transparency of the process and enhancing the mutual understanding among different parties, participatory modelling can accelerate the decision-making and increase the implementation success (Voinov & Bousquet, 2010; Voinov et al., 2016). Participatory modelling consists of variety of methods for including a broad group of stakeholders in the process of formal decision analysis (Voinov et al., 2016). Stakeholders have, for example, participated in recognizing cultural, social or recreational values associated to areas (Rees et al., 2010; Ruiz-Frau et al., 2011; Sherrouse et al., 2011; Kobryn et al., 2018) or identified areas where human uses and coastal habitats are in conflict (Tuda et al., 2014; Moore et al., 2017).

However, society consists of a multitude of parties having variety of interests towards the services and benefits ecosystems provide, thus trade-offs are unavoidable in the EBM context (Cavanagh et al., 2016; Epstein et al., 2018). Sectoral disagreements may arise, concerning sustainable management objectives, as well as the best measures for reaching those (Cavanagh et al., 2016). Multi-Criteria Decision Analysis (MCDA) is a decision analytic approach used to frame complex decision-making problems with multiple and often conflicting objectives (Adem Esmail and Geneletti, 2018; Pesce et al., 2018). When aiming for collectively fair decision-making, all the parties who have interest or are affected by the decisions should be heard (Dietz, 2003; Gopnik et al., 2012). Although not necessarily equally weighted, all the arguments should be taken seriously (Dietz, 2003). Therefore, one of the significant aspect in participatory modelling is how multiple views from individuals can be combined. In the field of MCDA, commonly used methods to combine perceptions from a diverse set of participants include e.g. summing, averaging or taking the median of the individual scores (Porthin et al., 2013; Baudry et al., 2018; Godskesen et al., 2018; Inotai et al., 2018). However, when the decision maker is concerned about perceptions of the entire stakeholder group instead of only the respondents in a sample, it becomes necessary to admit uncertainty about the mean of the entire population of stakeholders. This uncertainty depends on the prior knowledge about the stakeholder preferences, but also on sample size and variation among respondents.

Although the variability between the individual values in a group has been studied earlier in the context of MCDA (Scala et al., 2016; Yan et al., 2017), probabilistic approaches to combine perceptions and quantify the uncertainty about the group consensus from a diverse set of participants to be used in formal decision-making models are lacking. We propose a sequential Bayesian Belief Network (BBN) approach (Korb & Nicholson, 2010) to analyse and acknowledge the uncertainty about the group mean as part of the MCDA. The approach consist of two stages: (1) a continuous model for estimating the stakeholder group-specific parameters and the related uncertainties, and (2) a discrete state graphical element for more interactive and visual analysis. The latter can be connected to an influence diagram (ID) – an extension of a BBN for solving decision analytic problems under uncertainty (Nielsen & Jensen, 2009) – where it serves as a multi-criteria utility function in probabilistic evaluation of alternative management strategies, enabling the search of jointly optimal solution. The present approach allows transparent analysis of estimated variability between and within the stakeholder groups selected, as well as providing insights regarding whether listening to one group instead of another would actually change the formally optimal management strategy.

Bayesian inference has been widely utilized in population analyses and fisheries stock assessments to evaluate the uncertainty about unknown population parameters (Mäntyniemi & Romakkaniemi, 2002; Mäntyniemi et al., 2005; Michielsens et al., 2006; Mäntyniemi et al., 2015). Here we suggest to use the approach to estimate the opinions of the stakeholder populations. The estimation of uncertainty about population mean can be achieved using the Bayesian approach, whereas frequentist approaches, such as bootstrapping, only provide measures of uncertainty about potential values of point estimators of the population mean under assumed true value (e.g. standard error of the sample mean). They do not measure uncertainty about the population mean itself. Even if the population mean was known exactly, potential point estimators still have non-zero variance. The approach works even for small sample sizes, as Bayesian statistics provide probabilistic expression of uncertainty about parameters of interest for the given sample size (Hox et al., 2012, 2014; McNeish, 2016).

Graphical BBN is an efficient approach when modelling uncertain and complex issues associated with stakeholder involvement (Maskrey et al., 2016; Salliou et al., 2017; Xue et al., 2017) as it provides a transparent system to engage stakeholders in complex management and decision-making processes (Xue et al., 2017; Kim et al., 2018). Being well suited for integrating data of different types and forms (Holzkämper et al., 2012; Landuyt et al., 2013) and for exploring the diversity of stakeholders' representations about the system at hand (Salliou et al., 2017), graphical BBN and ID bear many characteristics advantageous for environmental modelling and knowledge integration (Uusitalo, 2007; Carriger & Barron, 2011; Hjerppe et al., 2017).

The presented approach turns conceptual value-thinking of stakeholders into a quantitative format and generalizes and pools their views group-wise, and additionally retains the information concerning the variability among the respondents. Utilizing valuation survey data, the continuous state BBN combines the perceptions of individual stakeholders belonging to a certain group and estimates the uncertainty about the group mean opinion. The estimated posterior distributions are transferred to a graphical discrete state BBN and are further connected to an ID, where they are used as decision-making criteria in probabilistic evaluation of alternative management actions. The graphical BBN enables visualization of differences between the groups, providing a solid foundation for discussion between the participants. Defining the optimal solution under divergent conditions, the ID calculates the best management options specific to different groups - or for different weightings.

The objectives of this article are: (1) to present a novel methodological framework for analysing and acknowledging the uncertainty in participatory decision analytic framework; (2) to illustrate the functioning of the methodology with a piece of stakeholder valuation survey data and to present how to estimate and visualize the uncertainty about the group means; (3) to demonstrate how these probabilistic estimates can be used as distribution-form decision criteria in MCDA model.

The presented approach is a step towards more fluent integration of the different stages of participatory modelling, including conceptual stage, quantitative state and the stage of reporting and testing (which have been called for e.g. (Voinov, 2017). We demonstrate our idea using an example data from the field of marine spatial planning (MSP). However, the proposed approach can be applied in any management case where robust decision-making processes requires integrating perceptions from a wide array of stakeholders.

2 Bayesian Belief Networks in Multi-Criteria Decision Analysis

BBN is a semi-quantitative causal model (a directed acyclic graph, DAG) consisting of a set of variables with probabilistically defined dependencies (Jensen, 2001; Korb & Nicholson, 2010). DAG represents the qualitative graphical component of the BBN, where nodes denote the variables of interests that are linked with arrows indicating the existence of probabilistic conditional dependence between two variables. Each of the variables is defined by mutually exclusive states that represent alternative choices or conditions for the specific variable. The quantitative element of a BBN consists of conditional probability distributions (CPD) assigned for the nodes having incoming links. The strengths of the dependencies between nodes are defined in CPDs in a probabilistic manner.

BBN can be used for three types of inference: a) predictive inference from causes to their likely consequences, b) diagnostic inference from consequences to their likely causes, and c) omnidirectional mixed inference (Korb & Nicholson, 2010; Carriger et al., 2016). CPDs can be defined using variety of sources such as observed or modelled data (Uusitalo et al., 2011; Rahikainen et al., 2014; Moe et al., 2016), stakeholder or expert beliefs (O'Hagan et al., 2006; Mäntyniemi et al., 2013; Barton et al., 2016; Shaw et al., 2016), literature reviews (Lecklin et al., 2011) and divergent mixtures of these (Lehikoinen et al., 2013; Xue et al., 2017).

In the Bayesian causal inference existing knowledge is revised when more information becomes available. According to the Bayes' theorem, the posterior probability of proposition A given proposition B represents what is the probability of the 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 B. The prior distribution describes how much is known about the subject before seeing the data. If there is some prior knowledge about the subject beforehand, this should be incorporated in the prior density. When there are no prior information or it is preferred to have a prior with minimal influence on our inference, an uninformative prior is selected. Then, the interpretation of observed data has more relative weight in the estimated parameters compared to the prior (Van de Schoot et al., 2014). The interpretation of data is controlled by the prior knowledge about the link between parameters (A) and data (B), which is encoded in P(B|A). The Bayes' theorem is utilized to obtain a posterior distribution by updating the prior distribution with the given data. The posterior distribution represents the conditional probability that is assigned after the relevant evidence is taken into account.

Multi-criteria decision analysis (MCDA) is an approach to better understand and analytically support decisions with multiple, potentially conflicting, criteria. These decisions are typically characterized by both complexity and uncertainties arising from a variety of sources (Kougkoulos et al., 2018; Pesce et al., 2018). Influence diagram (ID) is generalization of a BBN, capable of solving decision-making problems under uncertainty (Nielsen and Jensen, 2009), also those with multiple selection criteria. Therefore, ID have proven to be a useful in the context of MCDA (Abaei et al., 2017; Arzaghi et al., 2017; Qazi et al., 2018).

An ID includes three types of nodes: uncertain nodes, decision nodes that can be controlled (e.g. policy options, management strategies), as well as utility nodes that measure the utility (or loss) to be attained by the alternative decisions. The utility nodes express our relative preferences for all the alternative result combinations of the target attributes. Then, an ID computes the maximum expected utilities (EU) given the state of knowledge and the decisions made in the network (Eq. 2):

$$EU(d_i) = \sum_j U(h_j, d_i) P(h_j \mid X) \tag{2}$$

where d_i is the action *i* of the decision node, h_j is the state of the outcome variable, $U(h_j, d_i)$ is the utility that is gained if the h_j comes true (when the action d_i has been taken), and *X* is the observed data or evidence.

To implement a Bayesian model, the discrete and continuous state BBNs are the two main ways. Most of the models can be implemented in the both ways but there are some restrictions relating to the use of continuous variables. When the models become complex using continuous variables, the analytical calculation of the posterior distributions using Bayes' theorem is often impossible in practice. Then the distributions can be either discretized or numerical approximations of the posteriors can be used. Monte Carlo simulation is typically used to approximate the posterior distribution by randomly drawn values from the posterior distribution (Gilks et al., 1996). Therefore, the posteriors for the parameters can be estimated using Monte Carlo Markov Chain (MCMC) sampling with tools such as WinBUGS (Lunn et al., 2000), OpenBUGS (Spiegelhalter et al., 2007) and JAGS (Plummer, 2003). However, discrete BBN tools, such as Hugin software (Madsen et al., 2005), can utilize continuous variables only with certain restrictions as (1) it only allows using Gaussian (normal) distribution, (2) a continuous node cannot be parent of a discrete child node, and (3) a continuous nodes cannot be used in IDs.

3 Methods

The general principle of the sequential BBN approach is presented in the section 3.1. In the section 3.2 we introduce the example data, which is used in the following sections to provide a practical demonstration on the construction and use of the proposed methodological approach. We wish to highlight that the intention of this method paper is not to analyse the example data or the case study behind it, but the data is here used for the demonstrative purposes only.

3.1 General principle of the approach

First, random samples (subsets) of the identified stakeholder populations are picked (Fig.1; $v_{1,A}$, $v_{2,A}$, $v_{3,A}$, $v_{4,A}$ and $v_{5,A}$) and their ratings for different attributes elicited. Bayesian inference is applied to numerically approximate the posterior distributions for the population mean (Fig. 1: posterior distributions for the means, μ_A, μ_B, μ_C, μ_D) and standard deviation of each stakeholder group (Fig. 1; *Continuous state Bayesian Belief Network*). These posterior distributions for the population means are then used to populate a discrete state BBN (Fig. 1: *Discrete state Bayesian Belief Network*). The created BBN can be integrated to an influence diagram (ID) as presented in figure 1. The decisions considered by the ID can be any actions increasing or decreasing the human pressure to different attributes of ecosystems (or further on, the societal attributes dependent on the ecosystem). The attributes of interest are the assessment endpoints of the decision analysis (i.e. the target variables of the management problem), and the stakeholders are asked to provide their opinion on the importance of them.

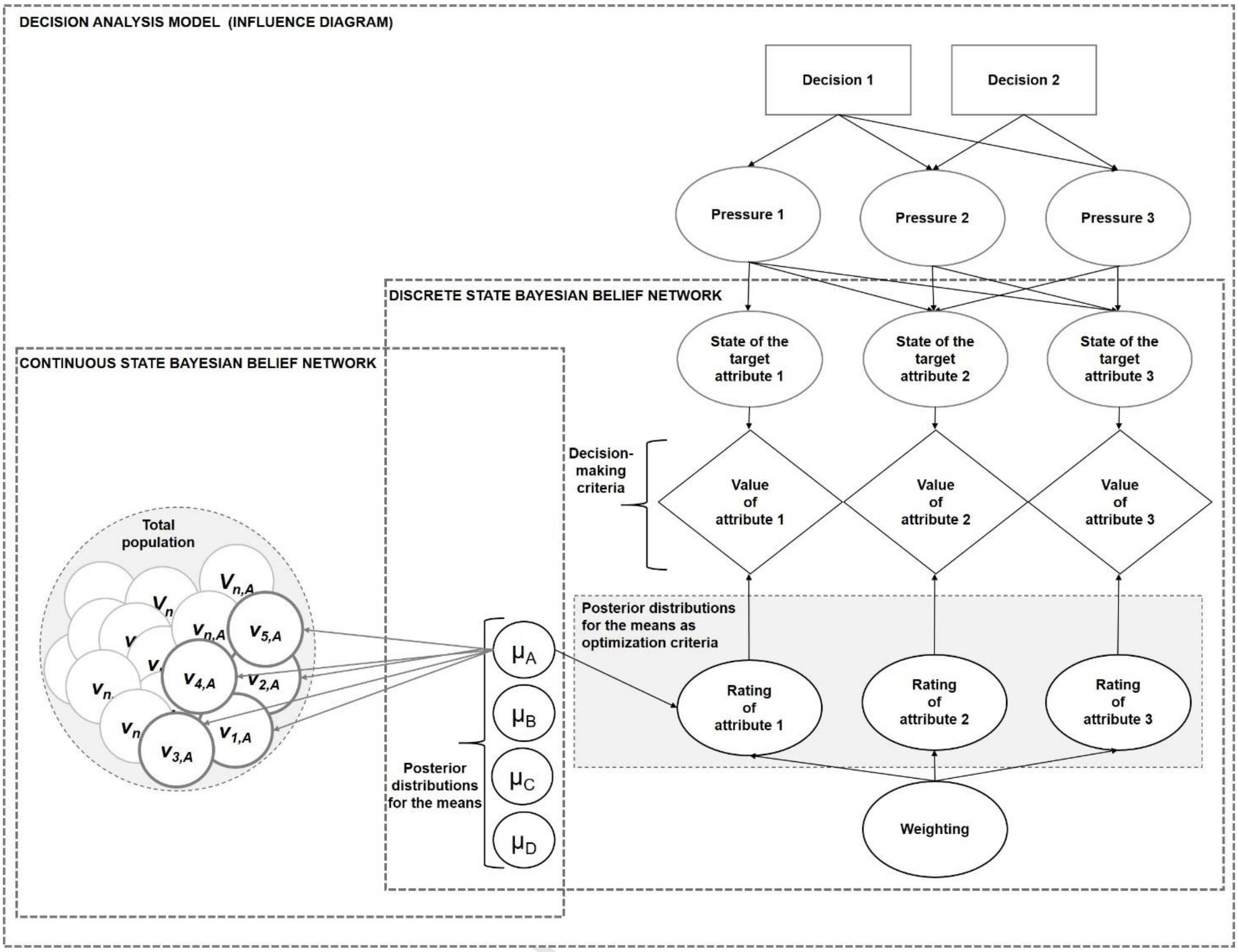

Figure 1. Illustration of the sequential BBN framework. *Total population* indicates all individuals belonging to a certain group of stakeholders (A, B, C, D). *S*ubset of the stakeholders (nodes with bolded edges) indicates the elicited random sample of the total population (e.g. a subset of stakeholder group A; $v_{1,A}$, $v_{2,A}$, $v_{3,A}$, $v_{4,A}$ and $v_{5,A}$). Posterior distributions of population means (μ_A, μ_B, μ_C, μ_D) for the parameters represent the estimates for the different stakeholder groups. In the BBN, the estimated posterior distributions are used to generate the CPDs of the nodes "*Rating of attribute 1, 2, 3*". The distributions of the stakeholder groups are pooled or used separately, given the weighting rules represented by the node "*Weighting*". The diamond-shaped nodes represent the utility functions used in the IDs for decision analysis to evaluate the ranking of alternative decisions. The utility function should produce relative scores for the different combinations of the status of the target attributes and the value the stakeholders give to those attributes. These scores make the decision optimization criteria of the ID.

3.2 Example: a valuation study for MSP in the eastern Baltic Sea

The present sequential BBN approach was originally developed and tested as part of a MSP project at the easternmost arm of the Baltic Sea, the Gulf of Finland. We do not analyse the case as such, but use it to provide a concrete example on the idea of the approach. The area is moderately to severely altered by multiple human activities such as fisheries, dredging, agriculture, coastal construction and maritime transportation (Korpinen et al., 2012; HELCOM, 2018). Anthropogenic pressure to the sensitive brackish water ecosystem, caused by the above mentions activities, include physical damage to the seabed, human-induced disturbance, interference with hydrological processes, contamination by hazardous substances, nutrient and organic enrichment, and the introduction of non-indigenous invasive species. The Gulf of Finland has diverse set of ecosystems and habitats providing important breeding and nursery grounds, shelter and food sources for the variety of populations and biotic communities (Helle et al., 2016) that respond to these pressures in different ways. Therefore, allocating human activities in the area unavoidably lead to some trade-offs. Considering the perceptions of stakeholders could help the managers with these difficult trade-offs and guide them to make informed and more defendable management decisions.

As the demonstrative example, we use data from interviews, where local representatives of different stakeholder groups were asked to provide their personal values for three ecosystem-based key objectives for MSP: keystone species, fish nursery areas and important bird areas (Table 1). As the healthy and productive marine ecosystem provides vast amount of ecosystem services to local communities, for example in terms of recreational fishery, livelihood, aesthetic, food and education, stakeholders for the interviews were selected to cover diverse set of representatives. Our example data is built on the responses from four stakeholders groups: general public, scientific community, educational organizations, and decision makers. General public (n = 19) was represented by people who do not directly belong to any other above-mentioned groups but represent the members of the local people who get livelihood or recreational benefits from the sea area. Scientific community (n = 5) consisted of the representative researchers who are involved in marine related research. They are domain experts in the fields of the Baltic Sea ecology and provide data, reports, and expert knowledge for the planners and decision makers concerning the marine ecosystems of the Baltic Sea. Educational community (n = 4) was represented by the environmental educators. This group consisted of class teachers and educational planners. Decision makers (n = 6) consisted of local and regional authorities and municipal planners who are responsible for the planning and decision-making processes.

3.3 Value elicitation process

The applicable alternatives for the elicitation technique to use with the presented approach are manifold, including e.g. divergent surveys (e.g. Sun & Müller, 2013), interviews (e.g. Haapasaari et al., 2012), questionnaires (e.g. Cárcamo et al., 2014), online surveys (e.g. Aubert & Lienert, 2019) or mobile applications (e.g. Fraternali et al., 2012; Imottesjo & Kain, 2018). Our example data was collected in pursuance of individual face-to-face interviews and include responses to a question, how important it is for the respondent to safeguard the following ecosystem elements: a) the occurrence of keystone species (i.e. where variety of keystone species are observed, it may point to a biodiversity hotspot area), b) the occurrence of fish nursery areas, and c) the occurrence of important bird areas (for additional information on these target attributes, see Tables 1 and S1).

Table 1. Definitions of the ecosystem-based key objectives rated by the stakeholders in the example data.

The ecosystem-based key objectives	Definition of the ecosystem-based key objectives
Keystone species	Keystone species are important for the local ecosystem as many other species rely the existence of them. They maintain the ecological equilibrium of the environment and therefore losing one of these species may possibly degrade the equilibrium.
Fish nursery areas	Safeguarding the fish nursery grounds is one of the main priority for the survival and reproduction capacity of the fish species. Human activities may reduce the productivity of the fish nursery grounds.
Important bird areas	Important bird areas are significant nesting and gathering sites at the eastern Gulf of Finland. These areas are known to have high biodiversity. Every year different birds migrate to nest in these islets and rocks and to feed in the surrounding areas. Birds are

	sensitive during the nesting therefore human activities at the site or nearby may have a significant impact on the survival.

In preference or value elicitation, the key point is to use some rating scale (McDowell, 2006), where a set of categories are designed to provide relative information about quantitative or qualitative features of subjects (Johnson & Desvousges, 1997; Soo Wee and Quazi, 2005). To use the data for the present approach, qualitative rating scale (e.g. Likert scale (Likert, 1932) including statements like *agree* - *disagree*) should, however, be converted into a relative quantitative format to be used for parameter estimation. When it comes to our example data, the interviewees were requested to indicate their personal rating towards the given ecosystem-based key objectives on a rating scale from 0 (low importance) to 100 (high importance).

3.4 Continuous BBN: estimating population parameters based on the sample

Using the values elicited from the sample of individuals from the stakeholder groups, the continuous BBN model estimates the mean rating (population mean; μ_j) for the whole population (the stakeholder group in question) and the variation between individuals within the population (standard deviation, σ_j). Bayesian approach allows us to estimate the uncertainty about these parameters (μ_j and σ_j) that arise from (a) the sample size used for the estimation, and (b) the variability in the views within the group, together with (c) the prior distribution provided.

To construct the continuous BBN model, the analyst has to define a) the model structure i.e. the dependencies between the parameters of interest (mean values and measures of variation), b) the types of the probability distributions (e.g. normal, beta etc.) and c) the prior distributions to formulate the level of knowledge about the parameters and their dependencies, prior to adding the new data (e.g. Kruschke, 2014). Our example code is provided as part of the SI. The structure of the code (also the priors as in this case they are uninformative) is the same for all the three key objectives rated by the respondents and only the data used varies per objective and stakeholder group.

The model specification begins by assuming the opinion (rating) $v_{i,j}$ by each individual *i* within stakeholder group *j* follow a given type of probability distribution, which is here selected to be normal distribution (N), (Eq. 3):

$$v_{i,j} \sim N(\mu_j, \sigma_j) \quad (3)$$

where μ_j represents the population mean value of the stakeholder group (as we do not expect biased sampling) and σ_j represents the variation within each group. The selected scaling method influences the choice of the distribution. For instance, when the value elicitation is done using interval or ratio scale as in our example case, the selected distribution should be a continuous probability distribution (e.g. normal distribution). In the case of nominal or ordinal scale, a discrete probability distribution (e.g. multinomial distribution) should be selected.

When it comes to our example data, as we did not have any earlier information about how the stakeholders in this study area might rate the objectives in focus, an uninformative prior for both μ_j and σ_j (the possible rates for both varying between 0 and 100) is given by formulating uniform distributions $\mu_j \sim Unif(0, 100)$ and $\sigma_j \sim Unif(0, 100)$. Anyhow, if earlier studies had reported applicable findings, this information could be formulated in the priors. The continuous BBN model updates the prior distribution with the new data by applying the Bayes' theorem (Eq. 1). The resulting posterior distributions represent what is currently known about the opinion of the whole stakeholder group. If the analysis is repeated in the future, these posteriors can be used as prior information in the new model (Rahikainen et al., 2014). In the case of continuous parameters, as in our example, the analytical calculation of the posterior distributions is often impossible in practice: Monte Carlo simulation is typically used to approximate values randomly drawn from the posterior distribution (Gilks et al., 1996). Therefore, we estimated the posteriors for the parameters using Markov chain Monte Carlo sampling with the OpenBUGS version 3.2.2 (Spiegelhalter et al., 2007). We ran the models for all the groups for 500 000 iterations in three chains using thinning of 10 and dropped first 200 000 iterations as burn-in, thus leaving 900 000 samples in the analysis.

As the output we get posterior distribution parameters for the stakeholder group-specific mean rating μ_j (means and variances in Table 2) and the variation within each group σ_j (Figure S2) per each key objective. When it comes to this example data, all the stakeholder groups seem to have quite similar opinion of these three objectives, thinking keystone species are the most important to keep safe (means in Table 2). In contrast, the fish nursery grounds are estimated to be slightly less important by most of the groups (public, scientific community and educational organizations). The educational organizations are estimated to give the lowest mean ratings in general, while the public and scientific community are likely to give the highest. The uncertainty about the mean rating (variances in Table 2) is generally highest for the educational organizations and lowest for the common public. The latter was most strongly represented in the data, having clearly higher sample size (n 19) than the other groups (n 4-6).

Table 2. Posterior statistics of the population mean (*means* and *variances*) for the rating of the ecosystem-based key objectives estimated, calculated using the example data. The results are presented stakeholder group-wise (weightings 2-5 in Table 4) and as averaged over the groups (weighting 1 in Table 4).

	Keystone species		**Fish nursery areas**		**Important bird area**	
	mean	variance	mean	variance	mean	variance
Average (1)	91.16	40.03	84.57	83.63	87.81	48.96
Decision makers (2)	91.89	27.04	87.49	66.96	85.05	71.13
Scientific community (3)	93.43	29.96	89.95	47.79	93.41	30.21
Educational organization (4)	86.78	94.69	72.41	210.54	83.33	85.19
Public (5)	92.5	8.40	88.42	9.22	89.46	9.32

The estimate on the within-group variation, i.e. how much the values vary between individuals inside each group, can be caught by studying the resulting posterior distributions of the group-specific standard deviations (σ_j). This is demonstrated with the example data in figure S2.

3.5 Discrete state BBN to summarize, visualize and connect with decision analysis model

To summarize the results in a visually attractive and easy-to-analyse format that also allows using them as part of a decision analysis (see Fig. 1), a discrete state BBN element (Fig. 2) is constructed. For this, we have used a graphical BBN tool Hugin (Researcher 8.6; Madsen et al., 2005). Probability tables of the BBN can be populated in Hugin either by providing the type and parameters of a distribution, or reading in data simulated from the distributions (especially if the distribution type is not supported by the graphical software) by using the expectation maximization (EM; Dempster et al., 1977; Lauritzen, 1995) learning wizard. In our example model, the former option was applied (using normal distribution truncated for 0 – 100).

The variables of our example case and their alternative discrete states are defined in details in Table 3 and 4. The random variables *State of keystone species* / *fish nursery areas* / *important bird areas* are the target variables (the assessment endpoints valued by the stakeholders) that link our stakeholder valuation element to the MSP impact assessment model to make it a full decision analytic ID. In the ID, the valuation element provides the mutual weighting among the decision-making criteria of the multi-objective management problem. In figure 2, the valuation element is presented separately, the target variables being independent (without any incoming links). Figures 1, 3 and S1 show the element as connected to a decision impact assessment model (simplified presentation), where the statuses of the assessment endpoint variables are dependent on the management strategies. In our example the states of the target variables are specified in a nominal scale as *Good, Moderate,* and *Poor* (Table 3). However, the states can be defined in multiple ways, using any nominal, ordinal or ratio scales relevant to the management question.

Table 3. The variables and their mutually exclusive states included in the discrete state Bayesian Belief Network.

Type	**Name**	**States**
Decision	Management strategy	Strategy 1, Strategy 2
Random	State of keystone species	Good, Moderate, Poor
	State of fish nursery areas	Good, Moderate, Poor

	State of important bird areas	Good, Moderate, Poor
	Rating of keystone species	0-20, 20-40, 40-45, 45-50, 50-55, 55-60, 60-65, 65-70, 70-75, 75-80, 80-85, 85-90, 90-95, 95-100
	Rating of fish nursery areas	0-20, 20-40, 40-45, 45-50, 50-55, 55-60, 60-65, 65-70, 70-75, 75-80, 80-85, 85-90, 90-95, 95-100
	Rating of important bird areas	0-20, 20-40, 40-45, 45-50, 50-55, 55-60, 60-65, 65-70, 70-75, 75-80, 80-85, 85-90, 90-95, 95-100
	Weighting	1, 2, 3, 4, 5
Utility	Value of keystone species	0… 100
	Value of fish nursery areas	0...100
	Value of important bird areas	0… 100

Table 4. Weightings presented. Values represent the percentiles for each of the stakeholder groups in a specific weighting. Weighting 1 gives equal weight for the groups and thus produces equally weighted joint distributions over their views.

Weighting	**Decision makers**	**Scientific community**	**Educational organizations**	**Public**
1	25	25	25	25
2	100	0	0	0
3	0	100	0	0
4	0	0	100	0
5	0	0	0	100

The estimated posteriors for the population mean values towards the target variables (the ecosystem-based key objectives) are in our example model represented by the variables *Rating of keystone species* / *fish nursery areas* / *important bird areas* (Fig. 2). Variable *Weighting* is used to define the mutual weighting of the different stakeholder groups in the analysis. In general, variable *Weighting* is used to analyse stakeholder groups either separately of each other or by pooling their opinions with varying weights. This allows sensitivity testing of the decision optimization results of the ID against, e.g., the between-group variability.

In other words, adjustments in the node *Weighting* provide a practical and transparent way to study whether the ranking order of the alternative management strategies included in the decision analysis model change depending on whose opinion is selected or given the highest weight. In our example, five alternative weighting options are included, allowing the analysis to be run based either on group-wise opinions (weighting 2-5 in Table 4) or as an equally-weighted average opinion (weighting 1 in Table 4).

The utility variables (the diamond-shaped nodes in Fig. 1), in our example model named as *Value of keystone species / fish nursery areas / important bird areas* (Fig. 2, 3 and Fig. S1), include the information about the level of stakeholder satisfaction based on the status of the valued ecosystem-based key objectives. These nodes specify the utility functions (U) of the ID. Computationally, the resulting expected utility value is a probability-weighted sum over the values assigned for the alternative state combinations of the parent nodes with incoming links to the utility node (Eq. 2). In our example case, each utility node is a product of the corresponding pair of *State…* and *Rating…* variables (that is U_n = $state_n$ * $rate_n$, where *n* is the number of attribute in Fig. 1). To calculate the expected utility, the qualitative states of the target (*State…*) variables are assigned relative multipliers 1 (good), 0.5 (moderate) and 0 (poor).

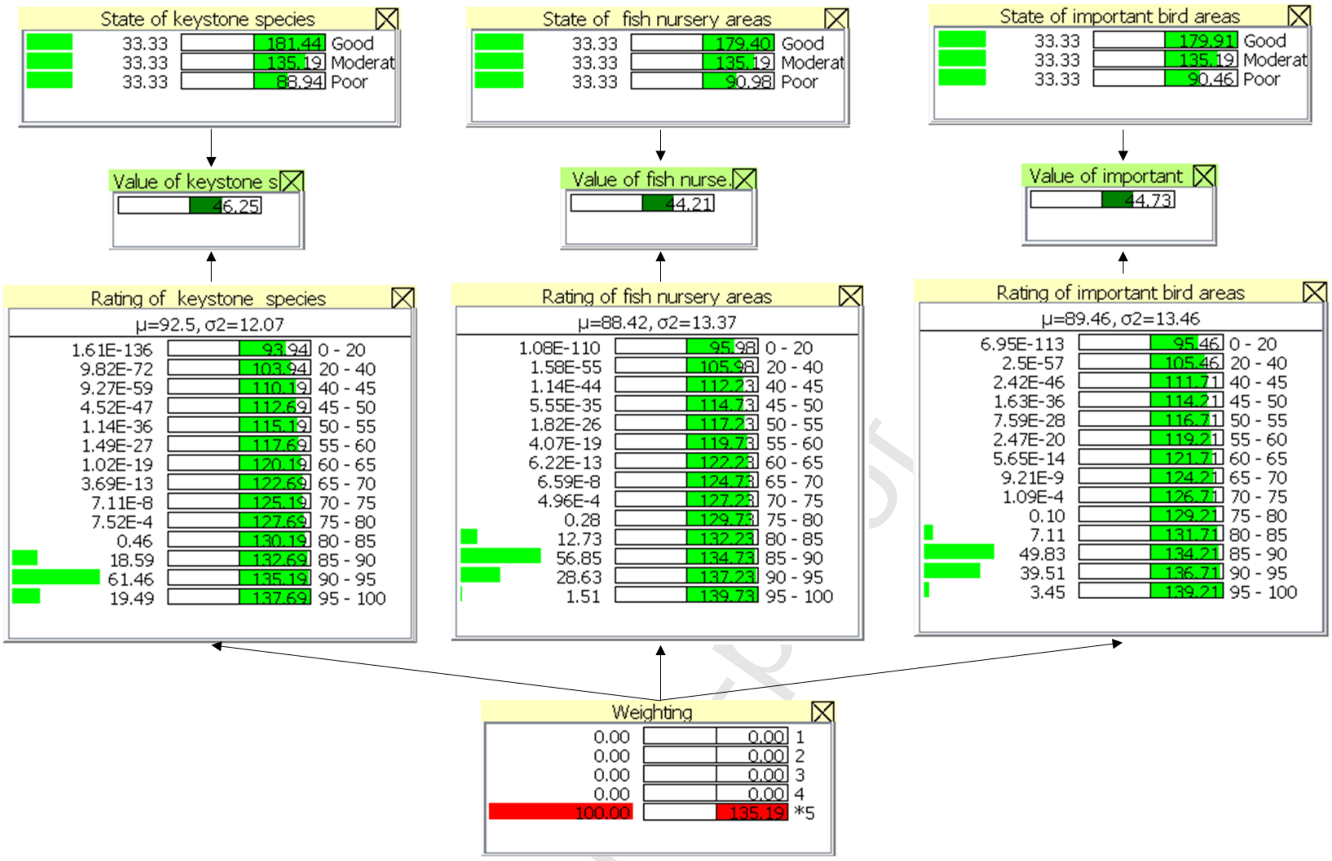

Figure 2. The discrete state BBN valuation element constructed for the example case. The realization probabilities (summing up to 100%) of the alternative states of the random variables are shown on the left side of the monitor windows. State of the variable *Weighting* (here weighting 5; common public only – see table 4), has to be selected prior to analysing the results (the selection made is shown in red with P100%). Monitor windows for the *Rating…*-variables show the estimated posterior distributions reflecting the opinion of the selected stakeholder population. Probability distributions of the *State…* -variables are uninformative (uniform) as no input information is here coming from an impact assessment model. The resulting criteria-specific expected utilities are shown in the utility (*Value…*) nodes. The values shown within the bars of the random nodes tell the total expected utility (summed over all three criteria) if the state in question is locked ("observed") next. Theoretical maximum total utility of this model is 3*100 = 300.

4 The valuation element as part of an Influence Diagram for MCDA

To demonstrate the functioning of the discrete state BBN element (Fig. 2) as part of a MCDA model, we extend the BBN element to an influence diagram by adding a decision node, shown in Fig. 3 and Fig. S1. This node is not based on any true case, but is created for the demonstration only and contains two alternative decision options, named as "Strategy 1" and "Strategy 2". Table 5 shows how we have formulated the conditional probability distributions of the target variables, given each fictive strategy.

Table 5. Conditional probability distributions of the target variables, given our demonstrative fictive management strategies as we have formulated them. Each distribution (the columns) summing up to 1 (i.e. P = 100%), stating one of the alternative states (Good / Moderate / Poor) come true.

	State of keystone species		**State of fish nursery areas**		**State of important bird areas**	
	Strategy 1	**Strategy 2**	**Strategy 1**	**Strategy 2**	**Strategy 1**	**Strategy 2**
Good	0.6	0	0.3	0.5	0	0.75
Moderate	0.4	0.4	0.6	0.1	0.2	0.25
Poor	0	0.6	0.1	0.4	0.8	0

The ID allows decision optimization (Fig. 3), as well as the comparison of the resulting expected utilities produced by certain decision or combination of decisions (Fig. S1), from the perspectives of divergent stakeholder populations. In Figure 3, the values within the bars of the decision node (*Management strategy*) show the total expected utilities resulting from each decision option, when only the opinion of group representing *Educational organizations* is acknowledged. From this perspective, Strategy 2 produces the higher utility (EU 119.11 for Strategy 1 vs. 128.50 for Strategy 2) and would be the optimal solution in this fictive case.

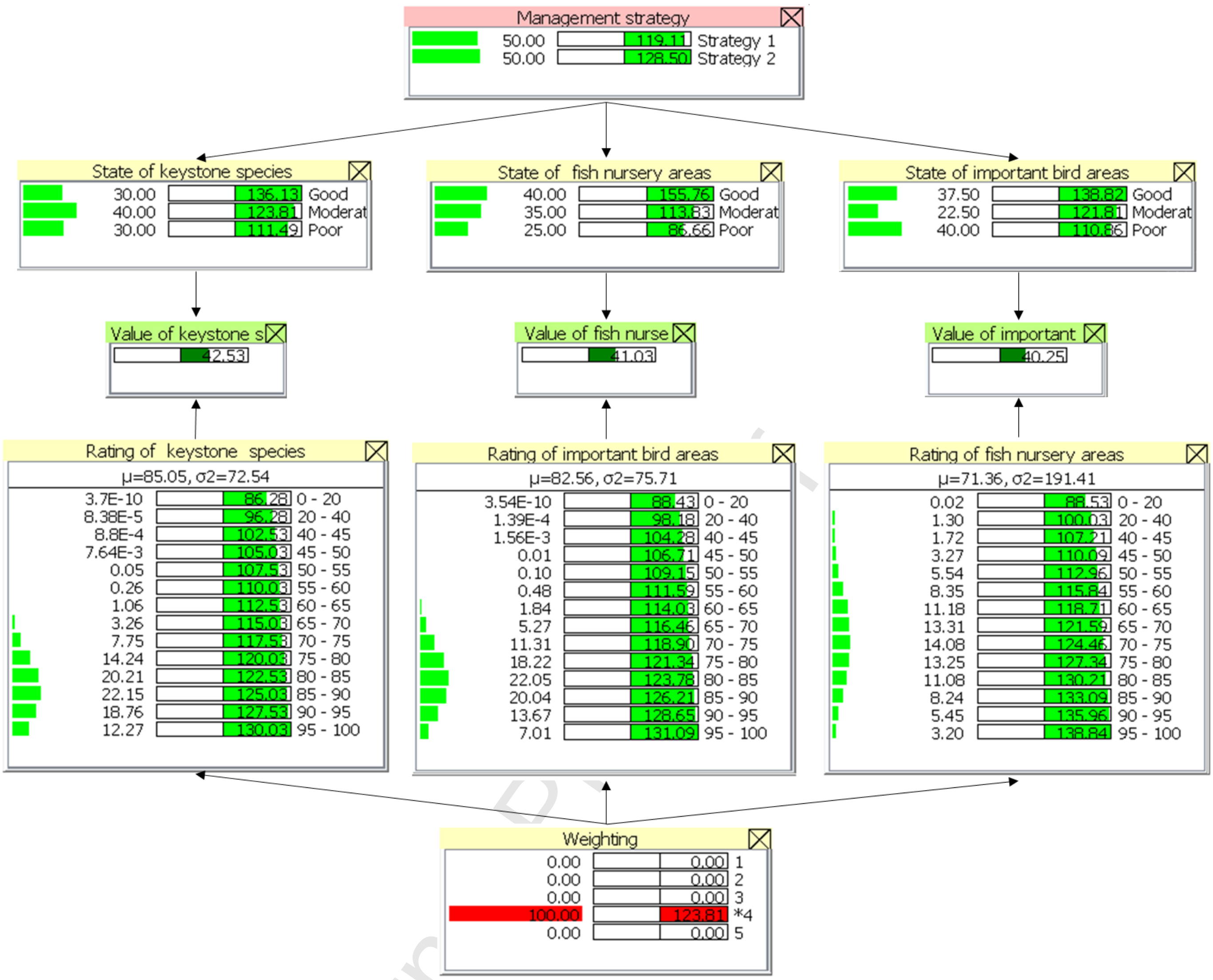

Figure 3. A decision optimization with the hypothetical ID when only the opinion of group representing *Educational organizations* is acknowledged.

Table 6 presents the expected utilities this ID produces for the constructed management strategies given different weightings (i.e. "whose opinion is heard"). The maximal utility this set-up in theory could produce is 300. That result, however, would occur only in a case, where the status of all the target variables is "Good" with the P = 1 (100%), and where all the stakeholders (the whole population acknowledged) give the maximal value for every target without any uncertainty. In addition, as the Hugin -software uses the median value of an interval-based class for the calculations, the theoretical maximum of the present ID would actually be

3*97.5 = 292.50, because 97.5 is the median value of the highest rating interval (95-100). A link to the ID model file (.oobn) is provided in the support materials.

Table 6. The calculated expected utilities for different management strategies given the different weightings. NB: The maximal utility this model (in theory) could result in is 292.50 (see the text).

Weighting	Strategy 1	Strategy 2
1	130.95	140.26
2	133.20	139.51
3	136.25	147.91
4	119.11	128.50
5	136.00	145.40

5 Discussion

We have presented a sequential Bayesian Belief Network (BBN) approach as a potential method to operationalize stakeholder involvement in formal decision support. Based on data elicited from a random sample of individuals categorized under selected stakeholder groups of interest, the suggested method provides probabilistic estimates on how the groups value divergent decision-making criteria. Quantifying uncertainty related to the estimated parameters, the Bayesian approach provides information about the quality of the population (i.e. group) level estimate in the light of the available data. By acknowledging the parameter uncertainty even with larger sample sizes, the fact that the true (exact) value of the whole stakeholder population cannot be obtained, is recognized.

In the suggested framework, a discrete state graphical BBN is used to summarize the results in a visually attractive and easy-to-analyse format, where it can also be linked to a BBN-based impact assessment model to form a full influence diagram (ID) for probabilistic decision analysis. For instance, marine spatial planners typically have to make decisions on how to distribute and locate human activities that cause divergent pressures on different environmental attributes (Pınarbaşı et al., 2019). One option could be to centralize the activities and consequently cause higher pressure in one location but keep the other areas untouched. Another option could be to distribute the activities, in which case the pressure per area is lower but allocated to a larger area. Here, the information concerning the distribution of the stakeholders' preferences combined with the potential impacts of the alternative decisions in different locations can help the managers to create comprehensive environmental management plans when multiple interests overlap (Ruiz-Frau et al., 2011). The graphical tool can also help the stakeholder groups themselves to learn about each other's thinking (Lopes et al., 2013). Improved mutual understanding is known to facilitate co-operation and consensus-finding, advancing stakeholders' commitment to the eventual decisions made (Brown et al., 2001; Lopes et al., 2013).

However, whenever the aim is to assist decision-making by modelling, one of the key issue is to ensure that the information provided by the model output is communicated and interpreted unambiguously by both the analyst and the decision-maker (Cartwright et al., 2016). The visual and interactive presentation of the discrete state BBNs, provided by the graphical software, such as Hugin, is found to be easy to communicate also for non-modellers. These platforms enable co-production of the models and social learning among the participants (Henriksen et al., 2007; Smith et al., 2018). A graphical BBN provides plenty of analytical opportunities for its user, but this comes with a great responsibility. To avoid misinterpretation of the output, the user should attentively keep track of all the settings made in the model, to be conscious of the scenario the model at the particular moment represents. Also important is to understand the inverse (from effects to causes) updating the knowledge in a BBN, as this characteristic sometimes generates results that at first sight may look confusing (Lehikoinen, 2014). In addition, acknowledging that the use of source code-based software (such as OpenBUGS and WinBUGS), needed for the continuous estimation of the group opinions, require programming skills, it is not realistic to assume decision-makers would conduct the presented analysis independently. A facilitated process, where the knowledge end-user work together with an analyst, in needed.

When it comes to the example data used in this paper for demonstrative purposes, we want to raise some points and ideas. First, instead of asking stakeholders to value actual ecosystem elements, such as fish nursery areas or keystone species, it might be reasonable to ask them value ecosystem services to which they have more direct (recreational, commercial, emotional) relationship (García-Nieto et al., 2015; Heck et al., 2018; Ruiz-Frau et al., 2019). In our data the stakeholders were not asked to trade-off one attribute for another either, which may in many cases be reasonable. This could be implemented e.g. by distributing a given number of points among the valued attributes in focus, or by some other means ranking the attributes against each other. The stakeholders could even be asked to define the management objectives by themselves. It is also notable that some of the members in one stakeholder group could belong to another included category as well. To solve the uncertainty related to the classification, the use of fuzzy set theory could be considered (e.g. Bozzeda et al., 2016; Christias and Mocanu, 2019).

We want to highlight that in the local-scale environmental management and planning context the suggested approach is not intended to provide a platform for direct "democratic voting" on which environmental attributes should be spared and which sacrificed. The ultimate purpose is to improve the understanding of both decision-makers and stakeholders on the unavoidable trade-offs and uncertainties related to the decisions that cannot be avoided. We believe the approach can create joint understanding and support communication among actors, facilitating them to reach true (and not only formal) consensus. On the other hand, in the context of large scale political outlining, the approach could be used – e.g. in connection with a large scale national or international surveys - to estimate the environmental values in the human population and based on the estimates to evaluate the collectively acceptable wider political strategies.

Importantly, an ID does not remove the fact that environmental decision-making problems are typically "wicked" (Rittel & Webber, 1973) by nature. Since wicked problems do not have any clear optimal solution, it is the process of structuring and solving them that is more important than the result. When solving these problems, the managers have to consider both the social and ecological aspects, acknowledging their interlinkages and, to some extent, making compromises between them (Castelletti et al., 2010; Gao & Hailu, 2012). A dispute over whether the management should prioritize biodiversity protection over regional employment situation is familiar to decision makers and policy scholars (Minteer & Miller, 2011). Importantly, these two might not always diminish each other. When the management action tends to improve the ecological status (e.g. fish nursery areas), it may enhance the local employment situation (e.g. recreational fishing industry) as well. Therefore, the socio-cultural and ecological nor the economic aspects cannot be separated but should instead be integrated into the same decision analytic framework (Laurila-Pant et al., 2015).

Participatory processes have been claimed to be time-consuming and costly (Voinov et al., 2016). With a web-based value elicitation process, the suggested sequential BBN approach could be a solution by allowing broad public involvement with relatively low costs. However, it is not always feasible to collect large samples. Bayesian estimation, with the informative priors, have found to be superior with small samples compared for example with the maximum likelihood estimation (e.g. Hox et al., 2014). As the stakeholder involvement is nowadays a requirement rather than an option in environmental management and planning, the question has been raised whether the costs and benefits of it can be quantitatively measured (Voinov et al., 2016). One option would be to create an ID following the idea presented and run a value of information (VOI) analysis (Mäntyniemi et al., 2009) to estimate the relative value of the participation process compared to the benefit it provides to the output. The VOI analysis reveals e.g. the threshold where it is not anymore beneficial to use more resources for additional value elicitation as the improved stakeholder population estimates would not change the ranking order of the analysed decisions.

This article have presented a methodological approach that can be applied to a variety of environmental management cases, to support stakeholder involvement, as well as transparent and informed decision-making. Covering statements on how the assessment endpoints are valued in environmental management, decision analysis can advance evidence-based decision-making (von Winterfeldt, 2013). An ID identifies the course of action that maximizes the expected utility or otherwise meets the management objectives as they are formulated in the model (Carriger & Barron, 2011). It provides a systemic approach for transparent formulation and formal assessment of a policy-making problem. Transparency in framing of the decision-making problem, as well as the evaluation criteria and logic is suggested to reduce confusion and conflict, and support better collaboration between scientists and policy makers (Cummings et al., 2018). We propose that by bringing the stakeholder involvement into a more concrete level, our approach has the potential to add stakeholders to this list of actors.

6 Conclusion

This study suggests a probabilistic approach to incorporate stakeholders' values into formal decision analysis to support decision-making. Conflicts and trade-offs in decision-making process cannot be avoided as different stakeholder groups have varied preferences and interests towards the services and benefits ecosystems provide (Wang et al., 2015). We report on methodology that could help in identifying and understanding formally optimal environmental decisions, from among the wide range of priorities and values. As management decisions should not be based on just the participants of the sample, but rather the entire stakeholder group, our probabilistic approach allows combining values from a diverse set of participants and then quantifying the uncertainty about the group mean value. Additionally, the graphical tool provides a transparent way to explore the differences between the parties and (when used as part of decision analysis) whether those differences actually lead to differing decision recommendations.

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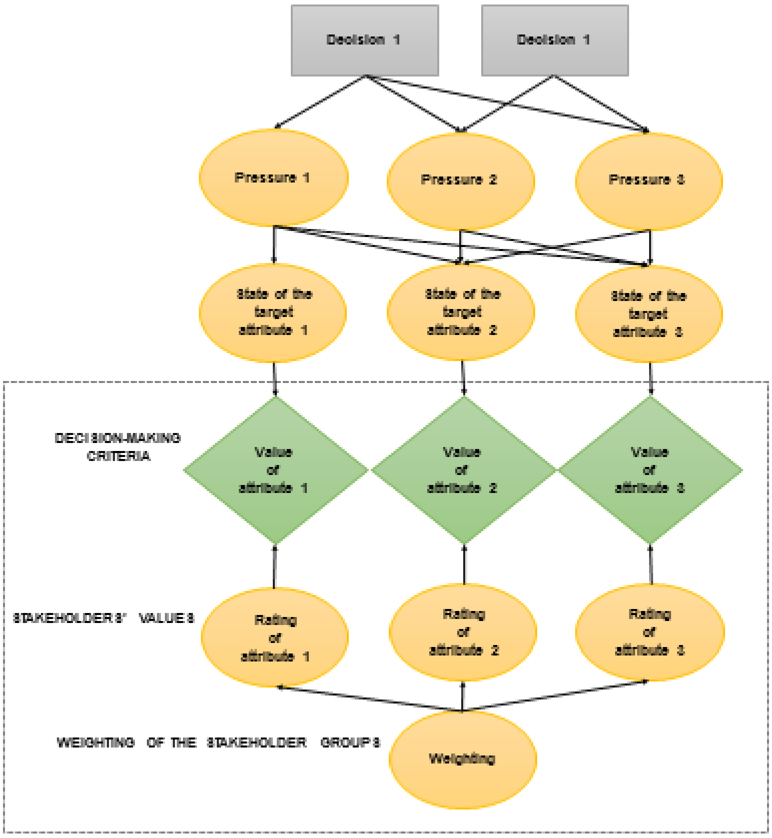
Graphical abstract



Highlights

- A Bayesian approach for involving stakeholders into the decision-making process.
- Society consists of a multitude of parties all having variety of interests.
- Our approach quantifies the uncertainty about the group consensus.
- The graphical tool enables visualization of differences between the groups.
- Offers a foundation for discussion and managing conflicting situations.