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A Bayesian approach to ecosystem service trade-off analysis utilizing expert knowledge

Solveig Höfer¹ · Alex Ziemba^{1,2} · Ghada El Serafy^{1,2}

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Abstract

The concept of ecosystem services is gaining attention in the context of sustainable resource management. However, it is inherently difficult to account for tangible and intangible services in a combined model. The aim of this study is to extend the definition of ecosystem service trade-offs by using Bayesian Networks to capture the relationship between tangible and intangible ecosystem services. Tested is the potential of creating such a network based on existing literature and enhancement via expert elicitation. This study discusses the significance of expert elicitation to enhance the value of a Bayesian Network in data-restricted case studies, underlines the importance of inclusion of experts' certainty, and demonstrates how multiple sources of knowledge can be combined into one model accounting for both tangible and intangible ecosystem services. Bayesian Networks appear to be a promising tool in this context, nevertheless, this approach is still in need of further refinement in structure and applicable guidelines for expert involvement and elicitation for a more unified methodology.

Keywords Bayesian Network · Ecosystem services · Expert elicitation · Curonian Lagoon

1 Introduction

Ecosystem Services (ESs) are described as a combination of ecosystem goods and services derived from ecosystems and their subsequent utilization, which support the process and conditions necessary to perpetuate the existence of humans (human well-being) and other species. ESs thereby result in direct benefits for humans and society (Costanza et al. 1997; MA 2005). Managers and decision-makers dealing with ESs are often forced to make decisions within restricted time frames and under limited resources (Douglas and Newton 2014). To counteract the loss of biodiversity (UNEP-WCMC 2014) and safeguard the perpetuity of ESs, the need for a meaningful approach of accounting for tangible and intangible values provided by ecosystems has been identified (e.g., Douglas and Newton 2014). One concept which is gaining attention in the field of Ecosystem Service (ES) assessment and scenario development is the Bayesian Network (BN)

approach (Marcot et al. 2006; Haines-Young 2011; Landuyt et al. 2013b). Previous work of Uusitalo et al. (2015) describes the advantage for decision-makers of using models readily incorporating uncertainties in order to draw a more realistic picture. A fact on which this work is moving forward by taking advantage of Bayesian Networks (BNs) being able to propagate uncertainties through the network. Hence, this study aims to further advance in the practical application of BNs in Environmental Sciences, and particularly in ESs trade-off analysis, by performing a case study.

1.1 The study area

The Curonian Lagoon in Lithuania is utilized as a case study. It is situated at the south-eastern edge of the Baltic Sea making it a shared water body between Lithuania (North) and the Russian Federation (South). Its eastern shoreline is dominated by the Nemunas Delta and the western edge is formed by the Curonian Spit (Fig. 1). Generally, the lagoon's edges are predominantly covered by reed beds (Breber et al. 2008; Gasiūnaitė et al. 2008; Razinkovas-Baziukas et al. 2016). The Curonian Lagoon is one of the several protected areas included into the ECO-POTENTIAL project (<http://ecopotential-project.eu/2016-05-24-14-52-12/protected-areas/16-curonian-lagoon>) and is well known to tourists and locals

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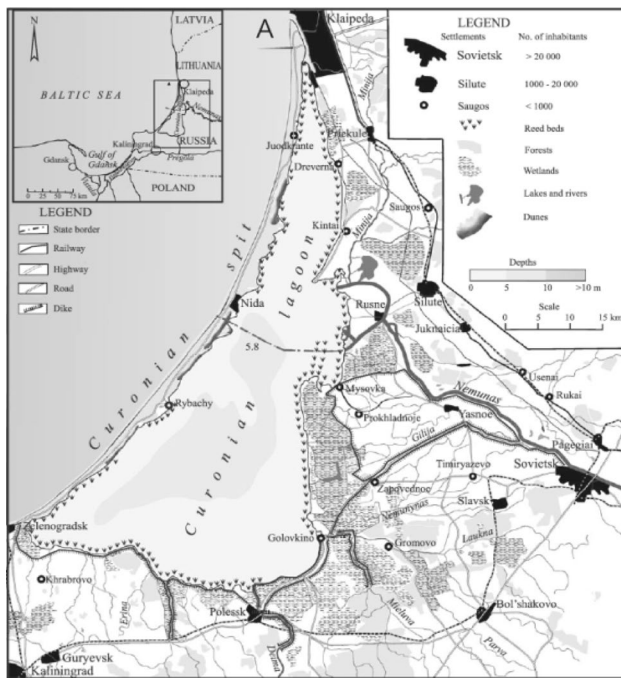


Fig. 1 Map of the Lithuanian and Russian segments of the Curonian Lagoon including identification of reed bed locations (Breber et al. 2008)

alike for the natural aesthetic, cultural values, and environmental richness. Previous investigations by the ECO-POTENTIAL working group have subdivided the lagoon into different habitats and identified numerous ESs provided by each habitat (El Serafy et al. 2016). This study focuses on the lagoon fringes, more specifically, on the issue of unregulated, continuous overgrowth of the fringes by extensive reed beds which is perceived to be the driving force behind the homogenization or degradation of ESs within these fringes. In short, a competition between open spaces versus reed belts.

Reed beds, both in general and specifically in relation to the Curonian Lagoon, are known to provide valuable ESs which can be divided into two categories. The first category entails ESs linked to the continuous presence of reed beds including, but not limited to habitat provision (e.g., as key breeding habitat for birds and fishes), coastal protection/stabilization, biodiversity, and scenery (Mal and Narine 2004; Breber et al. 2008; Iital et al. 2012; Fogli et al. 2014; ECO-POTENTIAL 2015; Razinkovas-Baziukas et al. 2016). The second category encompasses ESs derived from utilizing reed as raw material: for agricultural use (e.g., fodder), as industrial material (e.g., thatching material), and for energy production (Breber et al. 2008; Iital et al. 2012; Köbbing et al. 2013). The utilization of winter harvested reed as raw material for thatching and biofuel is experiencing a revival. However, the impacts of reed harvesting as a management

intervention on other ESs are largely unknown. Research investigating the impact of such management measures on reed bed morphology suggests the chance of the reed bed's morphology being altered, and threats to biodiversity, the ecosystem, and its services might arise (Iital et al. 2012; Huang et al. 2014). These results are still subject to uncertainty and require further research (Iital et al. 2012).

The Curonian Lagoon is also an area which is rich in fish stocks (Repečka 2003) and provides essential spawning, feeding, and nursery grounds for various fish species (Repečka 2003; Breber et al. 2008; Iital et al. 2012; Zolubas et al. 2014). There is very little literature published on how exactly fish utilize reed belts as spawning grounds; particularly in the case of the Curonian Lagoon. Mostly, the stated consensus is that reed beds are essential habitats for fish providing feeding, spawning, and nursery grounds (Žiliukienė and Žiliukas 2000; Žiliukas 2003; Žiliukas and Žiliukienė 2009; Iital et al. 2012; Zolubas et al. 2014). Breber et al. (2008) contradicts this opinion, stating that reed beds reduce valuable spawning, and nursery areas since dense reed beds are unsuitable habitats. A proposed solution by Breber et al. (2008) is to restore and increase areas suitable for fish to dwell and spawn and to reinstate natural hydrological and ecological processes by commercially exploiting reed belts to sell as thatching material, thereby benefiting the local communities by creating additional income. However, there is still a lack on research about the optimal density of reed beds, therefore the question remains, how winter reed harvesting influences the ability of reed beds to provide essential spawning, feeding, and nursery grounds for fish and their juveniles. The above-stated situation is deemed suitable to be utilized as case study on the concept of BN.

1.2 The Bayesian Network

A BN is a statistical model functioning on the basis of causal dependencies between considered system elements. To predict these causal dependencies, BNs make use of two structural model components: (1) a directed acyclic graph (Bayesian diagram), which depicts the current knowledge of causal inter- and independence of all elements included in the model (qualitative) (Aguilera et al. 2011; Haines-Young 2011; Kjærulff and Madsen 2013; Landuyt et al. 2013); (2) the conditional probability tables (quantitative), quantifying the strength of the links depicted in the Bayesian diagram. The strength of those defined causal relations is expressed as probabilistic dependencies. For a more comprehensive explanation also see e.g., Bromley (2005); Aguilera et al. (2011); Chen and Pollino (2012); Kjærulff and Madsen (2013); Landuyt et al. (2013). BNs represent a means of investigating the likelihood of various future states given past and present experience (Kuhnert et al. 2010). This method's attributes make it popular in various fields, i.e., medical

diagnoses, classification problems, and environmental management (Landuyt et al. 2013; Ban et al. 2014). It has been applied in projects such as habitat suitability models, risk assessments, management evaluation, and decision support. Previous work by Aguilera et al. (2011) further provides a list of reviewed papers that have tackled various problems utilizing BNs. Lately, its potential to be used in ES modeling has been acknowledged, though published research on the matter is scarce (Landuyt et al. 2013; Ban et al. 2014). BNs may be used when quantitative data are readily available, as well as in cases with incomplete or unavailable data; they are particularly beneficial in the latter situations, as they are able to be developed on expert's system knowledge, a benefit also discussed by Aguilera et al. (2011), Schmitt and Brugere (2013), and Uusitalo et al. (2015).

Advantages of including expert knowledge in constructing BNs to overcome data limitations, to strengthen and/or adjust networks based on empirical data, to fine-tune conceptualization of causal relationships, and to break down the complexity of the system easing the ascription of probabilities are widely discussed in the literature (e.g., Uusitalo 2007; Landuyt et al. 2013; Ban et al. 2015). Landuyt et al. (2013) furthermore describe that integrating expert knowledge during the individual steps of constructing a BN improves the process flexibility, allowing for integrating causal relations that might otherwise not be supported by the available data. However, this must be done with care. Previous research on utilizing expert elicitation has identified difficulties during data elicitation. Most ecological researchers are accustomed to work with real data and/or use classical statistical analysis. As the concept of BN is only starting to advance in this area of research, reservation and even distrust towards the approach of BN has been reported as a potential issue for slow adoption. Experiences described in the literature (Uusitalo 2007; Landuyt et al. 2013; Ban et al. 2014, 2015) state that experts may perceive it as rather difficult to assign prior probabilities. All these factors may cause the expert providing biased prior probabilities. Even if the expert is familiar with the concept of BN, O'Hagan (2019) found that they are still prone to have difficulties and inadvertently incorporate biases in their estimates. Therefore, a thorough introduction to the topic and methodology must be provided, counteracting any distrust towards the methodology based on a lack of knowledge and to minimize biases (Uusitalo 2007; Landuyt et al. 2013; Frank et al. 2014; Ban et al. 2014, 2015; O'Hagan 2019).

BNs have been utilized for trade-off analysis to inform policy- and decision-makers on possible consequences of their policy strategies. The BN, thereby, aimed to function as a decision support system, mediating multiple trade-offs in complex socio-economic and natural systems interactions (Schmitt and Brugere 2013; Frank et al. 2014). Schmitt and Brugere (2013) build their BN in cooperation with experts

via interviews, to define the models' purpose, and three workshops, on the network structure, parameterization, and discussion of the final output. This study resulted in a BN able to visualize trade-offs between different types of ESs. The work of Frank et al. (2014) builds on the fact that BNs can handle uncertainty and non-linear relationships covering both ecological and economical qualitative and quantitative data. Experts were involved to populate the conditional probability tables of chance nodes, lacking data. With the help of the experts they managed to develop a BN able to mediate trade-offs, while simultaneously acknowledging the effect of stakeholder's diverse interest on the magnitude of uncertainty for different scenarios.

The objective of this study is to investigate the suitability of BNs in quantifying the ramifications of ES management and/or how their utilization affects interventions within the ecosystem, utilizing the Curonian Lagoon in Lithuania as a case study, by answering the following questions: (i) How can trade-offs between ESs, associated with the lagoon fringe reed beds of the Curonian Lagoon be depicted most realistically by using a Bayesian Network? (ii) What are the advantages and constraints associated with using a BN developed based solely on available literature in contrast to a network developed in cooperation with experts? To do so, a selection of exemplar ESs identified during this process is used to generate the final nodes in the BN. This is resultant of an extensive literature review and is subsequently validated and modified with a panel of experts, building on suggestions by previous work (e.g., Aguilera et al. 2011), and lastly quantified using the developed BN. The final output is an alpha-level BN model, not intended to readily reflect a real-world situation but to structure knowledge and provide a base for further development.

2 Methodology

The methodology used for this research can be subdivided into three stages, Knowledge Acquisition, Design Phase, and Site Application. Each stage is comprised of several sub-elements which can be considered stepping stones (Fig. 2). During the Knowledge Acquisition, a general overview of the case study area is gained. This is achieved via extensive literature review which is organized in a Driver-Pressure-State-Impact-Response (DPSIR) (Atkins et al. 2011; Newton et al. 2014; Lupp et al. 2015) styled structure of the collected knowledge. Creating a DPSIR model implies thorough research on a variety of issues associated with the study area and aids the identification of key elements and their subsequent relation within. Resulting in a generic overview of some key issues affecting the provision of ES's in the Curonian Lagoon, it allows the user to visually structure the acquired knowledge which is beneficial in the later process

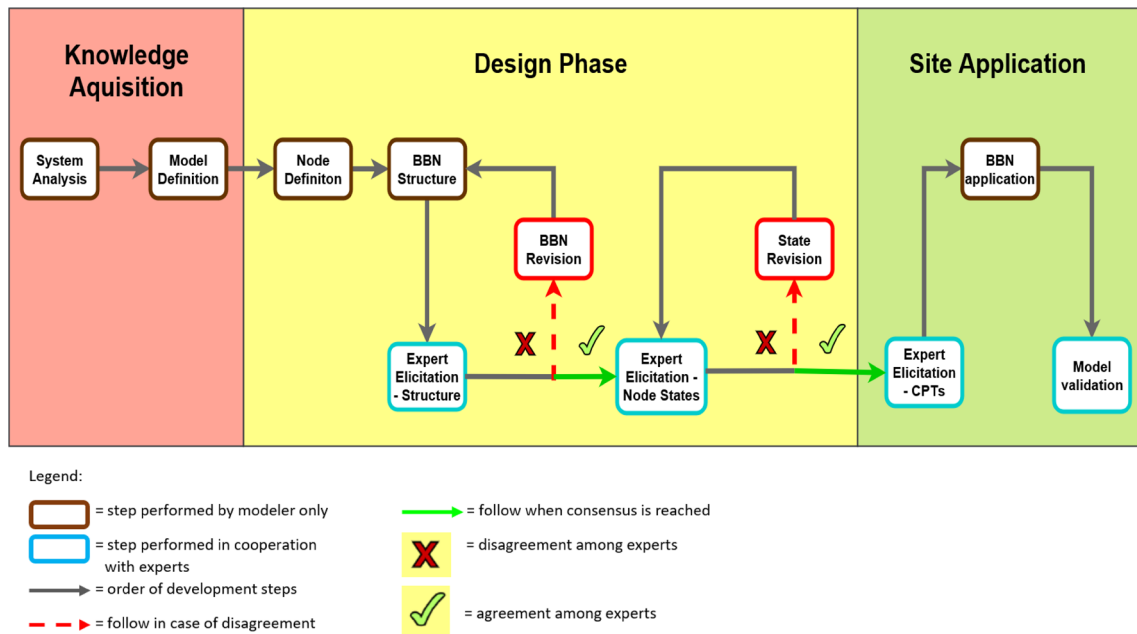


Fig. 2 Step-wise Methodology flowchart for developing, enhancing, populating, and validating a Bayesian Belief Network (BBN) constructed through combined literature and expert development

where the BN diagram has to be developed. Afterwards, the DPSIR is used to develop a conceptual model, further narrowing down on the key elements to be considered in the BN, and building the foundation for the BN diagram (Marcot et al. 2006; Chen and Pollino 2012). This allows for the clear definition of the model’s purpose, scale, essential elements needed for creating a meaningful BN (Jakeman et al. 2006; Marcot et al. 2006; Uusitalo 2007; Chen and Pollino 2012), and paves the way for subsequent stages.

The Design Phase represents the active creation of the BN. Used is the program GeNIe Academic 2.1 (<http://www.bayesfusion.com/>) (BayesFusion, LLC, 2016). This stage is further subdivided into two parts, consisting of steps performed only by the modeler, and steps used to work in cooperation with the panel of experts. Guidelines, on how to define nodes and ascribe links, discussed in the literature, are followed with the most important ones listed below (Bromley 2005; Marcot et al. 2006; Pollino and Henderson 2010; Aguilera et al. 2011; Haines-Young 2011; Chen and Pollino 2012; Landuyt et al. 2013; Ban et al. 2014):

- Each node should have three parents at maximum, preferably less
- The number of states assigned to each node should be kept to a minimum (five or fewer)
- No feedback loops (cyclic loops) may be included in the BN diagram
- If possible, all nodes should be either quantifiable, observable, manageable, or testable

- The depth of the model represented by number of sequential layers and intermediate nodes should be kept to a minimum (four or fewer)
- As far as feasible, the model should be symmetric
- To reduce the number of parent nodes, the so-called divorcing of the nodes can be performed

The basic components of a BN model are represented in Fig. 3. In a BN, system elements are called *nodes*. Nodes are categorized in an ancestral manner with (i) *parent nodes*; a node solely depicting a cause within the network and no

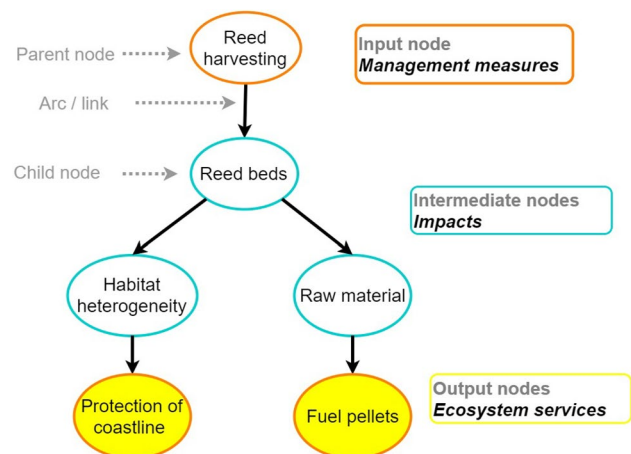


Fig. 3 Example BN

other nodes feed into a parent node; (ii) *child nodes*; representing the effects of their parent nodes (causes). The causal relationship between a parent and its child node is indicated via an *arc* (also referred to as *link*). Besides the ancestral categorization, all nodes are cataloged compliant with their role within the BN. A node can either be (a) an *input node*; (b) an *intermediate node*; (c) an *output node* (Bromley 2005; Chen and Pollino 2012; Kjærulff and Madsen 2013; Landuyt et al. 2013; Ban et al. 2014.)

The BN then functions based on the underlying conditional probability tables holding prior probabilities. Prior probabilities are probability distributions indicating what is known about a node in the context of a given scenario, and used to generate posterior probabilities, indicating the probability of the node being in any of its assigned states. These priors can be derived from various sources like experts, literature, or a variety of other data sources (Kuhnert et al. 2010). The network's ability to incorporate a variety of information types (qualitative, categorical and/or quantitative) from differing sources gives BNs an advantage over complex quantitative models, allowing for modeling systems subjected to high uncertainty and/or lack of data (Marcot et al. 2006; Uusitalo 2007; Aguilera et al. 2011; Chen and Pollino 2012; Landuyt et al. 2013; Ban et al. 2014; Hamilton et al. 2015). Those uncertainties are propagated through the model and can be analyzed based on the computed posterior probabilities. Due to data scarcity, using experts as a data source is deemed appropriate.

The subsequent expert elicitation is twofolded. First, for the Design phase, the expert elicitation focuses on introducing the panel of experts to the concept of BN and their role within the study, defining nodes, their states, and the BN diagram (Bromley 2005; Uusitalo 2007; Landuyt et al. 2013). This elicitation process has two possible outcomes. Either all experts readily agree on the proposed BN diagram, and states, allowing to directly proceed towards the Site Application; or the experts suggest changes, requiring a review of the proposed BN diagram. If the latter case occurs, all changes made must be subjected to the experts again until a final consensus is reached. In this particular study, this first elicitation round is done via a virtual roundtable meeting. The panel involved consists of four experts, all affiliated with the University of Klaipeda, which have extensive knowledge and working experience within the Curonian Lagoon, and are working within the ECOPOTENTIAL working group. During this meeting the experts are introduced to the concept of BNs, followed by a presentation of the BN generated through literature revision, i.e., the nodes, links, and rationales. The expert panel then provides additional information and suggests changes to the structure and rationales during a discussion round. The comments and changes are noted and utilized to update the BN diagram. The updated version is then sent to all experts for final confirmation.

The second part of the expert elicitation and last stage is the Site Application, in which the BN diagram is transformed into a fully functional BN model by populating the conditional probability tables (Pollino and Henderson 2010). Again, there is no widely accepted method to elicit prior conditional probabilities from experts (Kuhnert et al. 2010). An expert survey is compiled aiming to create a balanced mix of data precision while simultaneously trying to avoid expert fatigue. The most influential examples for the survey are Renooij and Witteman (1999), Speirs-Bridge et al. (2010), Kuhnert et al. (2010), Ban et al. (2014, 2015), and Hamilton et al. (2015). Combined are aspects described as beneficial by the before-mentioned studies. For the survey, all links between the nodes are translated into a short scenario, resulting in one scenario per possible combination of the input nodes state. Each scenario is aided by a scale providing a written description to percentage intervals. In this study, the questionnaire is sent via mail to the experts, together with an extensive explanation and example cases. All experts are encouraged to ask questions. Any points for clarification were immediately addressed and shared with all experts. Additional meta-data of the experts are collected to ensure full documentation and transparency of the sources used (Chen and Pollino 2012). This is important to account for potential biases (motivational or cognitive), and research duplication (Pollino and Henderson 2010; Douglas and Newton 2014). All surveyed prior probabilities are used to parameterize the conditional probability tables. Prior probabilities further function as a measure of uncertainty (e.g., Chen and Pollino 2012).

Uncertainty in this context is defined as “a lack of knowledge about the accuracy of a measure of a system and is an inherent property of the limitations of observing or understanding a system” (Chen and Pollino 2012). In other words, the chances that a variable takes certain values are represented in the form of probability distributions. Posterior probability distributions are computed for each node based on the prior probabilities hold by the conditional probability tables. The wider these probabilities are distributed over the states the larger is the uncertainty associated with them (Uusitalo 2007). Updating of the BN network via evidence usually reduces initial uncertainty, reflected by the posterior probabilities growing narrower (Bromley 2005; Uusitalo 2007). Measures of uncertainty allocated to expert-elicited prior probabilities, in this study, are recorded using the 95% Bayesian Credible Interval (BCI) (Kuhnert et al. 2010; Hamilton et al. 2015). The 95% BCI is a means of measuring the certainty assigned to an elicited prior probability. It refers to the highest and lowest possible prior probability for a given scenario of which the expert is 95% certain of the true value lying in between these limits. The larger the 95% BCI, the lower the certainty an expert has into the provided best guess

estimate. Uusitalo et al. (2015) provide a great definition of uncertainty and further elaborate on the various types, and approaches to account for uncertainty in decision support models. Eliciting for the 95% BCI entails that the expert is asked to assign three possible values for each prior probability (3-point elicitation) (1) the best guess, value referring to the value being most likely true in the opinion of the expert; (2) the 5% BCI limit (the lowest likely estimate for the given scenario the expert is 95% sure of); (3) the 95% BCI (the upper most likely estimate the expert assign with a 95% certainty). A more detailed explanation of how these values are elicited is provided later on in Sect. 3.3.

The issue of uncertainty is further addressed by testing different versions of the model. Each BN model is populated using varying combination of the input nodes' elicited prior probabilities (best guess estimate; different combinations according to the upper (95% bound) and lower (5% bound) of the 95% BCI, as done by Hamilton et al. (2015). Reason for using the 5% and 95% BCI bound is that they represent a "reasonable range" (Uusitalo et al. 2015) of the available parameters. Comparison of the results of the BNs parameterized with the upper and lower 95% BCI allows to test for the level of certainty assigned to the estimates provided. The bigger the difference the larger the uncertainty (Hamilton et al. 2015). Additionally, models are populated by merging the surveyed prior probabilities of all four experts into a combined BN. This is done via, i.e., applying a weighting factor based on the 95% BCIs. The 95% BCI in this case, denotes the range of probabilities between which the expert is 95% confident the correct probability occurs. Meaning the larger the assigned 95% BCI, the smaller the assigned weight. Averaged was a percentage, the point estimate (Best Guess) of each expert. See Appendix 1 for the formula used. The performance of the BN in context of the elicited priors is tested via a sensitivity analysis. There are different approaches available. In this study, it is looked at how the model outputs respond to changes in the input nodes. Changes in the model input are achieved by using different combinations of the input node's elicited prior probabilities by utilizing the best guess, 5% BCI, and 95% BCI provided by each experts, these experiments are elaborated upon in Table 2 within Sect. 3.3. All results are then compared against each other, investigating if the produced posterior probabilities of the output nodes change markedly in regard to their input, following one approach described in the previous work of Uusitalo et al. (2015). Initial model validation is done by investigating different scenarios for their outcome in relation to the model's initial purpose and propagated uncertainties (Uusitalo 2007; Ban et al. 2014, 2015; Hamilton et al. 2015). Lastly, the BN outputs are translated into example narratives. All computed results

are then used to evaluate the chance of trade-offs between the example ESs induced by winter reed harvesting.

3 Results desk study

3.1 The literature-based BN

During the first part of this twofold study, a literature-based BN is constructed. Literature providing information on the directional correlation between reed beds, fish dynamics, and effects of reed harvesting on any of these two is used and structured in a DPSIR model. Then, a clear definition of the model's purpose is decided upon. The model's purpose can be described as the intent to depict potential trade-offs, arising from winter reed harvesting as anthropogenic ES management measure, between

- (1) Reed beds providing essential spawning and nursery habitats for fish;
- (2) Reed harvest providing raw material to be utilized as thatching material; and
- (3) Fish migration corridors loss caused by reed bed overgrowth.

The spatial scale is set to include all lagoon fringes and reed beds of the Lithuanian part of the Curonian Lagoon, excluding the Nemunas river delta. For the temporal scale, it is decided to envision a 3-year time span, believed to be adequate to capture the initial impacts of trade-offs arising from winter reed harvesting. Quantification of the likelihood of trade-offs between ESs is deemed important to stress the implications such a management intervention could have on the ecosystem. Due to restricted data and knowledge availability, this first proposal of a literature-based BN is limited to the qualitative component. All the results found during this desk study and developed literature-based BN diagram (Appendix 2) serve as a foundation for the second part, the expert elicitation process.

3.2 Expert elicitation

During the second part of the research, the previously proposed literature-based BN diagram is further improved and enhanced to become a fully functional BN model. This was done in close cooperation with a panel of four experts, all affiliated with the University of Klaipeda in Lithuania, who volunteered to participate in this study. Those experts worked with the Curonian Lagoon for a period spanning 4 to 33 years. Their fields of specialization range from ichthyology, aquatic ecology, ecological modeling, to food webs. See Appendix 3 for a list of the specific expert's meta-data. The first round of expert elicitation focused

on a discussion of the proposed literature-based BN diagram in order to determine the suitability of the design in cooperation with the experts. This was accomplished via a virtual roundtable discussion.

This first discussion is used to provide an introduction to the case study, the methodology of BN, and clearly define the role of the experts, and resulted in the identification of superfluous nodes, deemed inappropriate in the context of the Curonian Lagoon which were in turn changed, eliminated, or redefined in accordance with the expert panel’s judgements. All nodes, their fate, and the experts’ rationale are provided in Table 1. The feedback provided by the experts’ clarified erroneous conclusions derived from the previous literature review.

An expert-enhanced BN diagram (Fig. 4) is the final output. This BN diagram was re-sent via e-mail to the experts to ask a final confirmation on the applied changes. Simultaneously, a list of proposed states and their definition (for a full description of the states see Appendix 4), for every node, was sent. All changes and proposed states were accepted by the experts.

Next, the conditional probability tables must be populated to transform the BN diagram into a fully functional BN. Therefore, a questionnaire is developed to survey prior probabilities from the same panel of experts involved earlier. The questionnaire combines various approaches derived from the prior examples from literature (Renooij and Witteman 1999; Speirs-Bridge et al. (2010); Kuhnert et al. 2010;

Table 1 Node enhancement by expert elicitation

Original node	Expert decision	New node	Rationale
Physical disturbances	Eliminated	–	The fact that during winter harvesting, the physical disturbance is minor
Reed morphology	Changed	Mosaic nature of lagoon fringe vegetation	key determining factor for the biodiversity of the lagoon fringes; more powerful and meaningful way of propagating information from the input to the output
Reed bed density	Changed	Reed bed perimeter	The length of the reed belt perimeter determines the size of spawning grounds
Reed distribution	Redefined	Reed bed coverage	suggested to reduce the ambiguity of the initial name of the node
Migration corridor	Changed	Lagoon fringe biodiversity	The structure and overall biodiversity of the lagoon fringes play a much more important role.
Fish fry diversity	Redefined	Juvenile fish diversity	Allows for encompassing all development stages of fish; widens the potential sources for empirical data

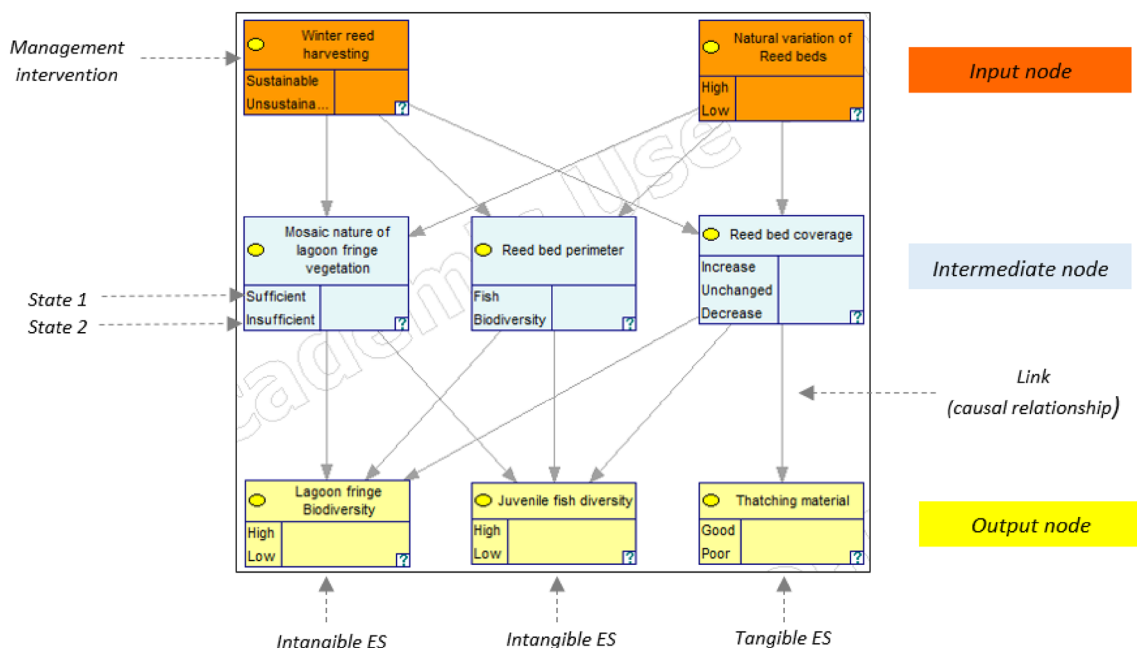


Fig. 4 Expert informed BN showing the final agreed up on input, intermediate, and output nodes and states per node that was developed through consultation with experts at Klaipeda University

Ban et al. 2014, 2015; Hamilton et al. 2015). To overcome potential difficulties of the experts not being accustomed to the methodology of BN and to minimize biases, a thorough introduction to the concept of BNs is provided with the questionnaire together with a summary of the case study’s topic and detailed example of what is expected of the expert when assigning their best guess and 95% BCI. For eliciting the prior probabilities, all conditional probability tables are translated into short verbal scenarios, to facilitate the elicitation process, for which the experts are asked to assign their best guess estimate, and 95% BCI. Figure 5 shows an excerpt of the questionnaire where the written descriptions linked to the percentage values are stylized after Renooij and Witteman (1999) who developed such a scale based on experiments. Using a scale linking a description to the percentage value is beneficial to provide a common understanding of what the percentage assigned represents, among the experts. Experts are further encouraged to contact the facilitator when in doubt or unsure about any part of the questionnaire.

Upon receipt of the completed questionnaires from the expert panel, all prior probabilities underwent a quality control and reviewed for peculiarities. It is found that in some cases, the experts indicated very similar beliefs into the likelihood of a node being in a certain state, however, this was not always the case. When comparing the expert responses, contradictory likelihoods were provided by members of the expert panel as well. The differences within the 95% BCIs were checked for diverging levels of certainty assigned to the best guess estimates. It is observed that in some cases, the 95% BCIs differed noticeably between the experts.

No pattern regarding years or field of expertise could be detected, though this may be resultant of the small sample size. In some individual cases, the respondent assigned prior probabilities of which the sum exceeds 100%, contrary to the style of the questionnaire. In such circumstances, the expectations and requirements are clarified to the expert and estimates adjusted, respectively.

Different versions of the BN are tested. Rise to this decision gave the previously mentioned observed variance among the elicited expert’s 95% BCIs. The BN was run using different combination of the elicited priors as described in the methodology. By considering the various configurations of the BN derived from diversifying the elicited data, an analysis was performed producing results that account for a wider picture. Consequently, five models per expert are tested. Each model utilizes a different combination of the elicited prior probabilities of each expert. In addition, three models are generated by merging all four expert’s prior probabilities via different methods. Table 2 provides an explanation of how the prior probabilities are configured for each model. All models were run using four different input scenarios. The input scenarios are defined by the four possible combinations of the states assigned to the input nodes as seen in Table 3.

3.3 Site application

Figure 6 depicts an example of the generated outputs. It represents the posterior probabilities computed for the node *Lagoon fringe biodiversity* using the information provided

Fig. 5 Exemplar confidence interval questionnaire utilized for expert elicitation probability query. A series of similar queries were developed for each of the nodes and states within the network and used for expert elicitation to populate the probabilities with confidence intervals

Please, consider following scenario	<u>Fish</u>	<u>Biodiversity</u>
<p>Scenario:</p> <p>Imagine a situation in which the NATURAL VARIATION within the reed beds is LOW, and at the same time REED is HARVESTED in a sustainable fashion during the WINTER.</p> <p>What proportion of the lagoon fringe area will demonstrate an elongated reed bed perimeter benefiting the state FISH? What proportion of the lagoon fringes do you estimate to have a shortened reed bed perimeter aiding the state BIODIVERSITY?</p> <p>Please, also indicate your 95% Bayesian credible interval</p>	certain — 100	certain — 100
	probable — 85	probable — 85
	expected — 75	expected — 75
	fifty-fifty — 50	fifty-fifty — 50
	uncertain — 25	uncertain — 25
	improbable — 15	improbable — 15
	impossible — 0	impossible — 0
	Upper limit: ___%	Upper limit: ___%
Best guess: ___%	Best guess: ___%	
Lower limit: ___%	Lower limit: ___%	

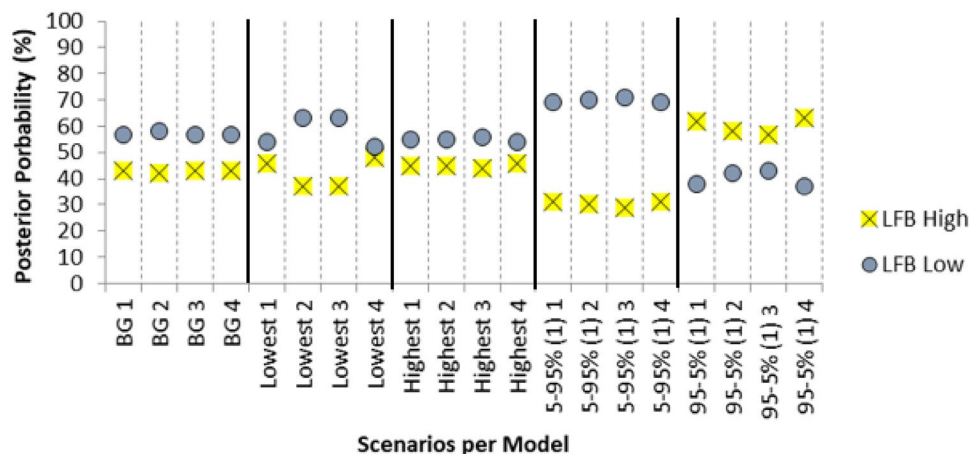
Table 2 Different types of BBN models and their conditional probability tables

Name of the BBN model	Conditional probability table
Best Guess (BG) model	Best guess estimate of every expert
Lowest model	5% BCI estimate for all states
Highest model	95% BCI estimate for all states
5–95% model	5% BCI for the 1st state and 95% BCI for the 2nd state
95–5% model	95% BCI for the 1st state and 5% BCI for the 2nd state
Weighted average Best Guess (BG) model	Best guess estimate of all experts weighted according to the assigned 95% BCI
Absolute minimum Best Guess (BG) model	Absolute minimum Best Guess estimate of all experts for the 1st state and absolute maximum BestGuess estimate of all experts for the 2nd state
Absolute maximum Best Guess (BG) model	Absolute maximum Best Guess estimate of all experts for the 1st state and absolute minimum Best Guess estimate of all experts for the 2nd state

Table 3 Combination of input node states for all scenarios, e.g., Best Guess (BG)

Input scenario	State of the input node
BG1	Winter reed harvesting = sustainable; natural variation = high
BG2	Winter reed harvesting = sustainable; natural variation = low
BG3	Winter reed harvesting = unsustainable; natural variation = low
BG4	Winter reed harvesting = unsustainable; natural variation = high

Fig. 6 Posterior probabilities derived from E1 for Lagoon Fringe Biodiversity (LFB) showing the probabilities for all four input scenarios (description see Table 2) for the five different models, where each model represents a different strategy of populating the conditional probability tables of the input nodes (description Table 3)



by Expert 1 (E1). Indicated are the results for all four input scenarios of all five models. The input scenarios refer to each possible combination of the input nodes' states (Table 3). The five models represent the different strategies of combining the prior probabilities of each individual expert to populate the conditional probability tables. *Lagoon fringe biodiversity* has two states assigned, "High" (blue bars) and "Low" (yellow bars). Several observations are made. Four out of five models populated for E1, BG to 5–95%, compute a marginally greater posterior probability for the *Lagoon fringe biodiversity* (LFB) being in a "Low" state, only the 95–5% Model predicts a slightly larger posterior probability of the node being in the state "High." The almost equally dispersed posterior probability of the node being in either

of its two states (~ 60/40% favoring "Low"), suggests high uncertainty into how the *Lagoon fringe biodiversity* will be impacted by winter reed harvesting. This uncertainty is further highlighted by the fact that the 95–5% Model predicts a marginal higher posterior probability of the *Lagoon fringe biodiversity* being in a "High" state, thereby contradicting the findings of the other models. Only posterior probability distributions calculated by the 5–95% Models showed more distinct tendencies, representing a large gap between the 5% and 95% interval estimates, which further signals uncertainty. Another observation is that the four input scenarios all result in nearly equal predictions. This suggests that under the current setup, the implications of winter reed harvesting are potentially the same.



Fig. 7 Results of the Best Guess Model showing all four scenarios starting with Scenario 1 upper left graph, Scenario 2 upper right graph, Scenario 3 lower left graph, Scenario 4 lower right graph for all experts. Indicated are all three output nodes (Lagoon Fringe Bio-

diversity, LFB; Juvenile Fish Diversity, JFD; Thatching Material, TM) and the computed posterior probabilities for each output node being in either of its two pre-defined states

After performing this initial functional analysis, the results for all BG Models were investigated for trade-offs between the three output nodes. Figure 7 illustrates the probabilities for the BG Models of all four experts, and for all three output nodes. Each expert is indicated by one color and symbol. Every point indicates the computed posterior probability per input scenario. It can be observed that the BG Model suggests trade-offs between the *Lagoon Fringe Biodiversity* (LFB) and *Juvenile Fish Diversity* (JFD) for two of the experts, E1 (blue dot) and E3 (black square). In contrast, for E2 (orange asterisk) and E4 (yellow triangle), the results suggest that harvesting reed during the winter does not result in trade-offs between the LFB and JFD. For trade-offs between Thatching Material (TM) and either of the other two nodes, no concrete statement can be made. This is because the posterior probabilities for the node itself suggest almost an equal probability for both states to occur. Thus, the produced results reveal a lot of uncertainty about the potential implications of winter reed harvesting on the three chosen ESs. There is also very little variation between the four input scenarios, indicating either high uncertainty about the effect of reed harvesting, or very similar impacts of reed harvesting on the ESs regardless of the harvesting quantity.

The above-discussed results can be translated into the following exemplary narrative for the Curonian Lagoon, describing the first input scenario (BG1) of E1:

Given a situation in which winter reed harvesting is done sustainably and natural variation of the reed beds is low, the BN predicts a 57% posterior probability of the Lagoon fringe biodiversity being in a low state. The Juvenile fish diversity has a 70% posterior probability of being in a “High” state. This indicates a trade-off between the two ESs. For Thatching material, a posterior probability of 59%, indicating a “Good” state, was computed. According to this scenario, there is a small possibility of trade-offs to occur between the Lagoon fringe biodiversity and Juvenile fish diversity if winter reed harvesting would be implemented sustainably while the natural variation is low. Furthermore, a marginally higher posterior probability is indicated for Thatching material and the Lagoon fringe biodiversity to experience trade-offs; however, the magnitude of it is very small forbidding a concrete conclusion.

While the developed BN can respond to single expert inputs, its key ability is to combine and integrate multiple experts is of interest, as this could provide a more holistic use of BNs. Keeping this in mind, this study further tested three different ways of merging the surveyed expert’s

priors into one joint BN. Combining the priors is achieved by applying a weighting approach based on the elicited 95% BCI as described in Appendix 1. The computed outputs resemble much of the results found for E2 and E4, as introduced in Fig. 7. This finding indicates that applying a weighting method based on the assigned confidence levels, results in outputs reflecting more the knowledge of the experts with higher confidence into their provided priors. In other words, weighing converges the knowledge of the individual experts and skews the results towards the view of the experts with the higher confidence in their estimates.

4 Discussion and conclusion

This study looked at the capacity of a BN in depicting trade-offs between tangible and intangible ESs within one model in information-restricted environments. Such trade-offs are potentially influenced by ES management and/or utilization. It is demonstrated how expert knowledge greatly enhances the value of a BN solely created based on available literature.

4.1 Setting-up of a BN

Building a BN based on existing literature as a preparatory exercise prior to expert involvement and elicitation has been deemed beneficial in facilitating the latter. Performing an extensive literature review to develop a BN helps to identify knowledge gaps; those gaps arise from a lack of information, partially from the fact that certain research has yet to be published or made available in English, which is true for this study (personal communication, Adrasiunas et al. 2016). Identifying areas subject to a lack of (published) knowledge can be useful in defining future research priorities, and has also been suggested by Douglas and Newton (2014) and was done by Smith et al. 2017. Thus, it can be said that developing system understanding via a literature review is key for BN modeling, and facilitates expert elicitation. Also, it helps identifying future research priorities.

Though it is found that a BN diagram may be developed based solely on existing literature, expert elicitation highlights the necessity of validating any BN diagram to avoid false representation of the system under investigation, as is also described by Aguilera et al. (2011). Especially in information-restricted circumstances, literature-based BNs seem increasingly prone to misconceptions. A finding from this research in line with both Douglas and Newton (2014) and Landuyt et al. (2013) is the value added by including experts into the BN development process, particularly in regard to informing and refining the choice of nodes, also further supported by the findings of Marcot et al. (2006), Chen and Pollino (2012), Douglas and Newton (2014), Uusitalo et al. (2015), Marcot (2017), and Smith et al. (2017).

In this study, experts were introduced to the case via a virtual roundtable discussion and later provided with a pre-defined BN diagram during the elicitation, an approach found beneficial as it shortens the overall development process, and provides a common point of reference to seed the discussion. However, this approach appears to create a source of uncertainty during the elicitation process. Reasons for this uncertainty might include ambiguity about the name, and definition of the states, potentially enhanced by only using verbal rather than numerical descriptions (Marcot et al. 2006; Pollino and Henderson 2010; Uusitalo et al. 2015; Marcot 2017). Also, limited communication exchange has the potential to exacerbate the ambiguity, as pointed out by Hamilton et al. (2015). Therefore, this study shows that pre-defining states may create high level of ambiguity in contrast to the finding of Chen and Pollino (2012) and Ban et al. (2014); thus it has been found it is better to define states in close cooperation with the experts involved. This is particularly true when the model developer is not an expert either on the study area or the specific field of study wherein the BN is being applied. This issue could be overcome both through in-person workshops or also a web front-end, both being equally viable options (Smith et al. 2017). In summation, under the given experimental framework, the increased uncertainty outweighs the benefits of shortening the approach, though it did provide a basis for future work on the topic.

Insights into the layout of the expert survey are gained. As aforementioned, there is no one optimal method available for surveying experts on BN prior probabilities. In this case, an expert survey was compiled based on examples derived from Kuhnert et al. (2010), Speirs-Bridge et al. (2010), and Hamilton et al. (2015). It appears that the questionnaire's phrasing and instruction can cause misunderstandings. Ambiguity in the wording has been mentioned as one source of complication by Speirs-Bridge et al. (2010) and was found to also be an issue in this case. Further complications to this fact are a lack of a common language for BN application (Aguilera et al. 2011) or confusion over applied (statistical) terms (Marcot, 2017). Another issue arises from the overall survey's length, potentially having caused expert fatigue (Ban et al. 2014). Therefore, simplified BNs not only ensure meaningful connections, but also serve to limit the demand placed on experts. These findings are in line with those of Chen and Pollino (2012) stressing the need to keep the number of elicited probabilities to a minimum, which can directly correspond to the complexity of the network. Performing expert elicitation in a more interactive way, e.g., during a workshop, could have helped to avoid the problems experienced. Marcot (2017) provides solutions to some of the problems experienced in this study, however, Smith et al. (2017) stress the importance of more guidelines, especially

for populating the conditional probability tables, which would also have benefitted this study.

It is concluded that, for information restricted applications, literature-based BNs are prone to contextual uncertainty, especially when the modeler is unfamiliar with the study site and new to the methodology. Developing a BN is comparatively easy but not trivial, as also experienced by Smith et al. (2017). Including experts as an additional channel of system specific knowledge is found to be highly beneficial, as was evident from the need to adjust the literature-based BN given expert inputs in this study. Using literature-based BNs provides a great means of developing system understanding, and both opening and facilitating the subsequent expert elicitation processes. This study concludes that it is of utmost importance to pay close attention to the length of the expert survey, and to use easily understandable, clear and ambiguity-free language, particularly when communicating in the non-native language of both surveyor and surveyee. There is still a need for the further refinement of proper structure and applicable guidelines in developing expert surveys and subsequent promotion of the wider uptake of such an approach in ES trade-off analysis.

4.2 Applicability of BN

During the site application, the expert-informed BN was populated using five different combinations of the elicited prior probabilities and ran by manipulating the state of the input nodes. The likelihood of trade-offs to appear between the output nodes for each input scenarios was investigated. The generated outputs reveal occasional variations between the results of the five different expert-specific models. This variance between the results suggests a high degree of uncertainty allocated to the priors elicited from the experts. High levels of uncertainty are further identified by the contradicting results of the models using a combination of the upper and lower 95% BCIs (Hamilton et al. 2015). One factor intensifying uncertainty may result from an under-confidence of the experts as also suggested by Uusitalo (2007). Another reason might be a bias of the experts, particularly for nodes not falling directly into their field of expertise (Douglas and Newton 2014). To become aware of these uncertainties, it is found to be crucial to elicit also for the 95% BCI in addition to the best guess estimates. Also, new research published strongly suggest starting with eliciting the outer boundaries rather than the best guess estimate. This finding agrees with Kuhnert et al. (2010) who described the utility of investigating intervals rather than point estimates. To avoid erroneous interpretation of the results produced by a BN, experts should always be surveyed for their certainty (e.g., Marcot 2017) about the point estimate, enabling executing a sensitivity analysis, also described by Uusitalo et al. (2015). New research by O'Hagan (2019) elaborates on

a protocol of how to minimize expert's biases recommending to elicit first the upper and lower limit of the total interval and only afterwards narrowing down on the median. According to O'Hagan's (2019) findings, this strategy reduces the bias of anchoring. Bias of anchoring means that if the expert is asked to first give a best guess, this value acts as an anchor and any further values elicited are adjusted to match the anchor. These adjustments are often insufficient resulting in a distorted representation of the actual situation. Thus, it is suggested to follow the protocol of O'Hagan (2019) for further research to minimize expert biases and to utilize a standardized elicitation method, allowing to more readily compare BNs. Though, O'Hagan stresses that for a high-quality elicitation it is essential for the facilitator to be experienced, a requirement not fulfilled in this study.

The expert-specific models in themselves, as well as the results among the experts, show variances. Consistency among experts may be interpreted as supporting the result's reliability (Douglas and Newton 2014); however, dissimilarities may indicate honest variation in the expert's beliefs as further described by Hamilton et al. (2015) as the "plurality of expert opinions" or experts' personal experience (Marcot 2017). Considering this, the observed variance among the expert's results does not necessarily mean the results are erroneous. Rather, it highlights the benefit of surveying multiple experts over a single expert in producing reliable results, a conclusion in line with the findings by Landuyt et al. (2013). Therefore, eliciting multiple experts for BNs prior probabilities seems beneficial in validating the model's outputs. It allows to investigate for varying understandings and helps avoiding making false conclusion based on only a single expert's knowledge. Consequentially, it is advised to include multiple experts when populating a BN.

This study further tests the possibility to combine multiple expert's prior probabilities into one BN model. Provided prior probabilities were merged by assigning a weight to every expert's best guess estimate according to the indicated certainties (the 95% BCIs). The produced results indicate similar posterior probabilities to the individual expert's BNs. This demonstrates the ability to combine multiple knowledge sources, and expert's priors into one BN model while simultaneously accounting for the indicated uncertainty ascribed to each estimate, supporting findings by Douglas and Newton (2014). Being able to combine multiple expert's responses into one BN model is of interest especially in situations with larger sample sizes where it is inappropriate to populate the BN for every single expert. However, as Uusitalo (2007) describes, just because some experts have a very distinct experience about a situation does not make it automatically truer. Therefore, the objective of the study must be clearly stated to decide which approach is suitable, as has been suggested by Marcot (2017). On this insight, it is concluded

that when done with care, BNs are suitable to combine multiple sources of knowledge into one functional model operationalizing scenarios.

Despite having identified sources of uncertainty within the BN development process, outputs looking at trade-offs between the exemplar ESs were generated. These results show that based on the input of two experts, trade-offs between the state of the Lagoon fringe biodiversity and Juvenile fish diversity may occur. For the other two experts, the model's output do not suggest any trade-offs between these two ESs. The discussed BN model is an alpha-level model (Marcot et al. 2006), developed solely on expert knowledge and literature, and only applicable in the explorative decision context (Smith et al. 2017). However, the possibility of quantifying trade-offs is (partially) demonstrated; indicating an applicability of BNs in ES trade-off analysis. Nevertheless, there is still need to further define and improve this approach as attempted by Landuyt et al. and explored in their (2016) study.

Furthermore, this study has demonstrated the ability of BNs to combine tangible and intangible ESs into one model. Previous research by Fisher et al. (2009) has identified the inability of traditional ESs valuation in combining tangible and intangible ESs, as a key issue. This inability has further been identified by Folmer et al. (2010) and Gee and Burkhard (2010) as one reason for underestimating the value of, especially intangible ESs. Therefore, being able to utilize BNs to incorporate a variety of ESs into one model appears promising. Particularly, by being able to operationalize scenarios founded on qualitative and quantitative data making the scenarios more realistic, also mentioned as a key advantage of BNs by Landuyt et al. (2013). In combination with the demonstrated ability of BNs to transparently represent uncertainties throughout the development process, a finding stressed by Uusitalo et al. (2015), adumbrating the value this approach can add to ES trade-off analysis. This study suggests that BNs may be a promising tool in ES trade-off analysis, as they appear to be able to bridge the gap between qualitative and quantitative approaches, a finding corroborated by recent studies (e.g., Landuyt et al. 2016; Marcot 2017; Smith et al. 2017), and may potentially aid in the traditionally problematic quantification of ESs by a reduction in underestimation.

The BN in its current state cannot confidently provide a basis upon which a conclusion on the potential trade-offs is imposed by winter reed harvesting. The results of sustainable and unsustainable harvesting are too similar, as well as uncertainties imposed on and propagated through the BN model are too great at this stage. In order to better represent the full spectra of the system in question, the inclusion of a “no harvesting” state, something not actively being pursued but a potential state nonetheless, would introduce a greater contrast between the possible management strategies and better reflect the flexibility of the system.

This study demonstrates the potential to use BNs in operationalizing ESs trade-off analysis and how tangible and intangible ESs may be combined within one model. Furthermore, utilizing experts as an additional channel of knowledge is found beneficial, especially in information-restricted circumstances, underpinning the potential of BNs to support ES valuation. Nonetheless, thorough model validation must be performed before applying a BN in real-life decision-making contexts which require either a deeper pool of experts or, optimally, data sets with which such a network can be tested against. Despite not being able to derive a conclusive decision on the potential impacts of winter reed harvesting in the Curonian Lagoon, it is demonstrated how the BN development process supports identifying future research priorities. Being able to combine qualitative and quantitative data derived from the literature and multiple experts may positively support any protected area park manager in making informed decision. Additionally, the potential to continuously update BNs in regard to newly available data appears to support the application of this approach and further advertises ES trade-off analysis in decision and management applications.

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Software availability The software used is called GeNIe 2.1 Academic developed by BayesFusion, LLC. This software can be run on Windows as well as (with Wine) OSX and Linux. The required software can be downloaded from the website listed in the contact box to the right, this is where `genie_academix_setup.exe` is provided. All contact details are provided here. Software Name: GeNIe 2.1 Academic; Developer: BayesFusion, LLC; Hardware required: Windows or OSX and Linux; Software required: `genie_academix_setup.exe` (<https://download.bayesfusion.com/files.html?category=Academia>). Contact: 5448 Darlington Road, Pittsburgh, PA 15217, USA, Tel: +1-412-444-5476, Skype: bayesfusion, Sales: sales@bayesfusion.com, Support: support@bayesfusion.com.

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Appendix 1

The following formula was used to determine the weight for every individual expert's response per state for each node.

$$BGW_{avg} = \frac{\sum_{i=1}^n w_i x_i}{\sum_{i=1}^n w_i}$$

where BGW_{avg} = average of weighted Best Guess estimates, w = weight, x = Best Guess estimate, n = number of experts

$$w_i = 100 - BCI$$

where BCI = assigned 95% Bayesian Credible Interval

Appendix 2: Literature-based BN

Figure 8 shows the BN developed on the basis of the extensive literature review and knowledge structuring. This BN was provided to the experts during the introduction

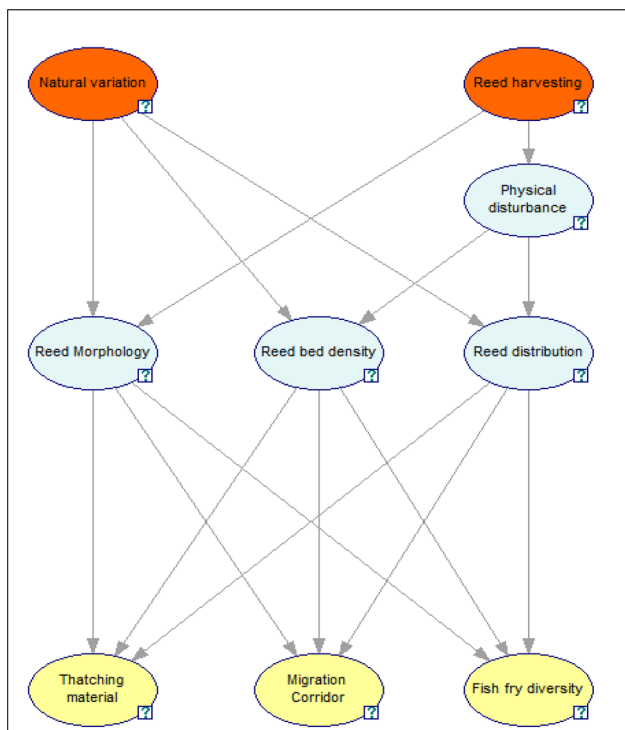


Fig. 8 Literature based winter reed harvesting BN

presentation and used as a basis to develop the expert-informed BN utilized in the later process.

Appendix 3: Expert details

In addition to elicit the experts for their priors they were also asked to provide some personal details for the meta-data.

In the following you are kindly requested to provide some personal information. This information serves solely the documentation of the type of experts and level of expertise surveyed. Your information will not be linked to your survey answers in any way.

- (1) What is your affiliation (i.e., University, company, protected area manager/park)?
- (2) What is your educational background (i.e., post-doc, researcher, etc.)?
- (3) What is your field of specialization (i.e., fisheries, macrophytes, etc.)?
- (4) For how long have you been working in your field (length of specialization)?
- (5) Do you have any cross-disciplinary background? If yes, which ones?
- (6) How long have you been involved in the work with the Curonian Lagoon?

Table 4 holds the meta-data of all experts included in the elicitation process. The order of the information per expert is random and not affiliated to the identifier (E1–E4).

Table 4 Expert meta-data

Affiliation	Educational background	Field of specialization	Length of specialization	Cross-disciplinary background	Time worked with Curonian Lagoon
University	PhD student	Fisheries; Ichthyology	5 years	Ecology; biology; botany; etc.	4 years
University	Lead researcher	Aquatic ecology; ecological modeling; food webs	33 years	No	33 years
University	PhD student	Aquatic ecology; food webs; birds	6 years	No	Appr. 4 years (discontinuously)
University	PhD student	Ichthyology; spatial modeling	8 years	System ecology; population ecology; biology; etc.	8 years

Appendix 4: States' definition

See Table 5.

Table 5 Definition of the utilized states

Node	State	Definition of state
Natural variation	High/low	<i>High</i> ≥ 50% of observed variation (size and distribution of reed beds) has natural causes (i.e., differences in ice sheet thickness and coverage period, type of flood, temperature, diseases) <i>Low</i> ≤ 50% of the observed variation origins from natural factors
Reed harvesting	Sustainable/unsustainable	<i>Sustainable</i> = the amount of reed harvested is in balance with the carrying capacity of the system <i>Unsustainable</i> = reed beds are overexploited for raw material, creating negative spin-offs
Mosaic nature of lagoon fringe vegetation	Sufficient/insufficient	<i>Sufficient</i> = reed beds are non-continuous, alternating regularly with other native vegetation; a mosaic nature of habitat dominates the lagoon fringes <i>Insufficient</i> = reed beds occur in large, monospecific beds; other native flora only occurs sporadically at the edge of the reed belts
Reed bed coverage	Increase/unchanged/decrease	<i>Increase</i> = the total area (ha) covered by reed beds increased after introducing reed harvesting in comparison the current coverage <i>Unchanged</i> = there are no noticeable changes in the overall reed bed coverage detected <i>Decreased</i> = the area covered by reed beds declined after introducing reed harvesting in comparison to the area covered currently
Reed bed perimeter	Fish/biodiversity	<i>Fish</i> = the length of the perimeter provides abundant space for phytophilic fish to spawn and juvenile fish to dwell <i>Biodiversity</i> = the combined length of reed bed perimeters is reduced, exhibiting a multitude of vegetation and is supporting the lagoon fringes biodiversity (plants and birds)
Thatching material	Good/poor	<i>Good</i> = the total amount of reed harvested (tons) yields sufficient & qualitative appropriate raw material to promote selling reed as thatching material, creating an alternative income source for local communities <i>Poor</i> = the amount of reed harvested fulfilling the required attributes to be used as thatching material is low and benefits do not compensate for the required efforts
Lagoon fringe biodiversity	High/low	<i>High</i> = lagoon fringes are very diverse habitats, they show a healthy variety of plant species heterogeneity, host a variety of bird species & exhibit an overall well-balanced state <i>Low</i> = reed is the dominant plant species by far; lagoon fringes exhibit a low variety of native fauna and only a few distinctive bird species are dwelling around the lagoon
Fish fry diversity	High/low	<i>High</i> = reed beds are characterized by a high variety of fish fry/larvae/y-o-y of different fish species with an abundant number of individuals <i>Low</i> = lagoon fringes are home to a small number of fish fry/larvae/y-o-y with a low variety in individual species

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