Environmental Modelling and Software 158 (2022) 105552

Contents lists available at ScienceDirect

Environmental Modelling and Software

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

Which predictive uncertainty to resolve? Value of information sensitivity analysis for environmental decision models

Fridolin Haag[a,*], Sara Miñarro[b], Arjun Chennu[a]

[a] Leibniz Center for Tropical Marine Research (ZMT), Fahrenheitstrasse 6, 28359 Bremen, Germany
[b] Institute of Environmental Science and Technology (ICTA), Universitat Autònoma de Barcelona, 08193 Bellaterra, Spain

ARTICLE INFO

Dataset link: https://doi.org/10.5281/zenodo.7156065, https://doi.org/10.5281/zenodo.7155783, https://doi.org/10.5281/zenodo.7155948, https://doi.org/10.5281/zenodo.7156015

Keywords:
Sensitivity analysis
Multi-criteria decision analysis
Uncertainty
Agent-based modeling
Coral reef management

ABSTRACT

Uncertainties in environmental decisions are large, but resolving them is costly. We provide a framework for value of information (VoI) analysis to identify key predictive uncertainties in a decision model. The approach addresses characteristics that complicate this analysis in environmental management: dependencies in the probability distributions of predictions, trade-offs between multiple objectives, and divergent stakeholder perspectives. For a coral reef fisheries case, we predict ecosystem and fisheries trajectories given different management alternatives with an agent-based model. We evaluate the uncertain predictions with preference models based on utility theory to find optimal alternatives for stakeholders. Using the expected value of partially perfect information (EVPPI), we measure how relevant resolving uncertainty for various decision attributes is. The VoI depends on the stakeholder preferences, but not directly on the width of an attribute's probability distribution. Our approach helps reduce costs in structured decision-making processes by prioritizing data collection efforts.

1. Introduction

Environmental management decisions need to be made in the face of large uncertainties. Confronted with these uncertainties, an intuitive response is to collect additional information on the reasonable assumption that more information will reduce uncertainty. This in turn may improve our understanding and, ultimately, lead to better management decisions.

However, collecting more information requires time and effort, which could otherwise be allocated to management actions, particularly in countries with limited resources for environmental management. When we know *enough* about a system to make a sensible decision, requesting "more science" rather becomes a technique to delay implementation (Gregory et al., 2006). Faced with the trade-off between researching and managing an ecosystem, it is important to consider: to what extent is the use of limited resources to improve our understanding of a system justified by the resulting potential for improved management?

This question can be approached with the concept of value of information (Howard, 1966; Feltham, 1968). Value of information (VoI) analysis allows us to determine the *value* (in the sense of benefit or utility) of additional information for deciding between different alternatives. We can think of VoI analysis as a form of sensitivity analysis with a focus on the sensitivity of the decision to new information rather than the magnitude of variation in the outcomes (Borgonovo et al., 2016; Felli and Hazen, 1998; Razavi et al., 2021). The analysis supports us in answering the questions: would our decision for a specific management alternative change if we had more information? And if so, which information would most influence our choice? Or conversely, resolving which of the uncertainties would bring more utility? Based on the answers, we can rationally prioritize between research, monitoring, and implementation activities for a concrete decision.

Tackling complex decisions in a rational way and conducting VoI analysis is facilitated by a quantitative representation of the decision and its uncertainties (see Section 2.1). This is achieved by a decision model, which consists of a predictive system model and a preference model (Reichert et al., 2015; Haag et al., 2019b). The predictive system model (also called prediction model, system model, assessment model, or simulation model in the literature) provides measures of various system attributes (e.g., coral cover, crop yield, breeding pairs, etc.) given an input state. This allows us to assess the potential consequences if we implemented different management alternatives (also called options, variants, actions, strategies, or scenarios in the literature). The preference model (also called evaluation or utility model) represents how decision-makers, stakeholders, or society perceive and evaluate the predicted consequences of the system state. In this study, we

* Corresponding author.
E-mail address: fridolin.haag@leibniz-zmt.de (F. Haag).

https://doi.org/10.1016/j.envsoft.2022.105552
Received 9 March 2022; Received in revised form 5 August 2022; Accepted 3 October 2022
Available online 16 October 2022

focus on quantitative preference models based on multi-attribute utility theory (Keeney and Raiffa, 1993).

Value of information analysis is an established approach in health care economics and medical decision making (e.g., Felli and Hazen, 1998; Fumie and Thompson, 2004; Jackson et al., 2022). There is also growing interest in conservation biology (reviewed by Bolam et al., 2019) and environmental management in general (Keisler et al., 2014; Eidsvik et al., 2015). However, many environmental decision problems share characteristics that complicate VoI analysis and at the same time make it especially relevant for these problems.

In this paper we address two research gaps for VoI analysis that emerge from the complexity of environmental decisions. First, we lack an integrative framework for jointly tackling common characteristics of such decisions, including (1) multiple, conflicting management objectives (management criteria), (2) uncertain consequences of management alternatives with continuous distributions rather than discrete states or hypotheses, and (3) probability distributions of consequences that are not independent from each other. Multi-criteria decision approaches (MCDA/MCDM) have been used with VoI analysis before (e.g., Bates et al., 2014; Runge et al., 2011; Eidsvik et al., 2015), but mostly have addressed these aspects separately (see Bolam et al., 2019). VoI analysis for continuous probability distribution remains conceptually straightforward, but can become challenging for (conditionally) dependent probability distributions (e.g., Eidsvik et al., 2015; Myklebust et al., 2020). Second, multiple, conflicting perspectives on an environmental decision problem commonly exist. However, the consideration of multiple stakeholder perspectives in VoI analysis has not been discussed widely in the literature before. We address this issue and investigate the influence of diverging stakeholder perspectives on the results and conclusions from VoI analysis.

The aim of this paper is to develop an integrated approach to conducting VoI analysis given the characteristics of environmental decisions, and highlight relevant considerations when applying the method. The following questions guide our approach:

1. How can we estimate the VoI based on the correlated output of complex system models?
2. How to analyze VoI in decision contexts with multiple, conflicting objectives?
3. What is the influence of diverging stakeholder perspectives on the conclusions of VoI analysis?

To address these questions, we create a framework to conduct VoI analysis for complex decisions, bringing together elements that have been developed previously. Our VoI analysis rests upon a decision model that combines system predictions and stakeholder preferences (see above and Section 2.1). The predictions can come from one or more arbitrarily complex models and can exhibit dependencies in their distributions. To efficiently conduct VoI analysis for dependent probability distributions, we adapt an algorithm by Strong and Oakley (2013) as a replacement for traditional double-loop Monte Carlo procedures. While different measures of the VoI have been proposed (see Eidsvik et al., 2015 and Section 2.2), we use the expected value of partially perfect information (EVPPI; also called EVPXI or EVXI). This measures the expected gain in utility if we would decide based on perfect information about one (or few) variables of interest instead of being uncertain about them.

To implement our framework, we investigate a case study on coral reef fisheries management for islands in the Indo-Pacific. It is a complex decision problem in a region that requires sound management of precious and fragile ecosystems (Eddy et al., 2021). Coral reefs are under intense pressure from various local and global stressors, such as climate change, pollution, fisheries, and other impacts (Burke et al., 2012). A reef's ecological complexity poses substantial challenges for predicting the state of the reef under a management alternative. While different modeling approaches can be helpful (Kelly et al., 2013), we use a spatially explicit agent-based model in our study (Miñarro et al., 2018). Decisions about their local management are not only difficult because coral reefs and their fisheries are intricately linked, but they also fulfill a variety of needs in often resource-constrained socio-economic contexts (Ferse et al., 2014). Therefore, the divergent objectives and perspectives of various stakeholders need to be considered in decision making. Typically, the available data and our ability to collect data is limited, requiring iterative and adaptive management approaches that include targeted efforts for the collection of additional information.

After discussing our framework for VoI analysis (Section 2), we introduce the structure of the reef management decision case (Section 3.1). We describe how to analyze the EVPPI for predictions of fisheries management alternatives and discuss design choices for such efforts (Section 3). Based on the analysis results (Section 4), we discuss the usefulness of VoI analysis and suggest desirable extensions to our implementation (Section 5).

2. Framework for analyzing value of information for decision models

2.1. Decision modeling

Making a rational decision between several alternatives is facilitated by a quantitative representation of the consequences of implementing an alternative and of the stakeholder preferences regarding these consequences. The combination of predictive system models with preference models to evaluate decision alternatives we call a decision model (see Haag et al., 2019b). In the following, we provide the conceptual background to VoI analysis for such models (Fig. 1). A concrete implementation is detailed in Section 3.

After a comprehensive problem structuring phase (e.g., Marttunen et al., 2017), the first step of decision modeling is to predict the consequences $\boldsymbol{y}_a = (y_{a,1}, \dots, y_{a,m})$ for each alternative a on the system attributes $(1, \dots, m)$ that are relevant for decision making according to the stakeholders. These predictions can come from a mathematical model, but also from experts (e.g., Nicol et al., 2019). Given that environmental or socio-ecological systems can neither be completely understood, nor fully observed, nor perfectly represented in a model, it makes sense to conceptualize these predictive system models as probabilistic models with uncertain parameters or inputs (Reichert et al., 2015; Reichert, 2020). Therefore, the consequences for an alternative a are better represented as a random vector Y_a, as we do not obtain a point estimate for the predicted variables, but distributions of predictions p_{Y_a}. The distribution of predictions is a more informative description of our knowledge than a point estimate or aggregated value. The predicted distributions will often not be independent. For instance, the biomass of carnivorous fish may be negatively correlated with biomass of prey species.

The second step is to identify a utility function, u, that quantifies a stakeholder's preferences with regard to the predicted attribute levels and their uncertainties. The utility function represents the trade-offs the stakeholder is willing to make between uncertain consequences. Let Y denote the set of all possible consequences for all attributes considered relevant in the decision. A multi-attribute utility function $u : \mathrm{Y} \rightarrow [0, 1]$ maps from a space of predicted consequence regarding system attributes to a utility space. It returns the utility of potential consequences, with larger utilities representing more preferred system states (Keeney and Raiffa, 1993). Standard utility theory does not consider uncertainty of preferences; in the following we keep to this limitation. A more extensive and rigorous treatment of multi-attribute utility theory than outlined here can be found in textbooks (e.g., Keeney and Raiffa, 1993; French, 1986).

Once we specified parameters of a utility function based on a stakeholder's preferences, we can calculate the resulting multi-attribute utility $u(\boldsymbol{y}_a)$ for an individual prediction of consequences $\boldsymbol{y}_a = (y_{a,1}, \dots, y_{a,m})$. For instance, y_1 could be the prediction for the coral cover in % and y_m the prediction for herbivorous fish biomass per m^2 three years

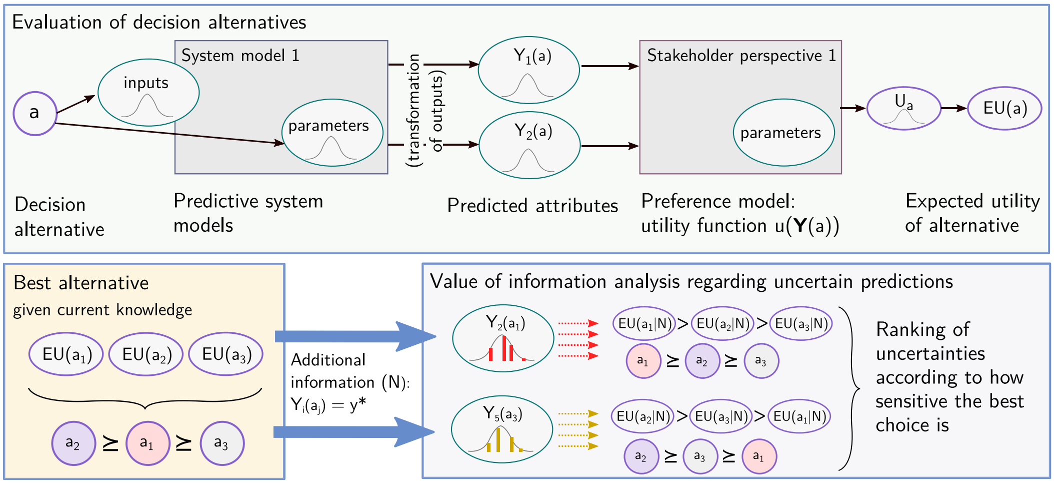

Fig. 1. Scheme of decision modeling and value of information (VoI) analysis followed in this study. The predicted uncertain consequences of alternatives ($Y_i(a)$) are evaluated according to stakeholder preferences to determine an optimal baseline choice by maximizing expected utility (EU). The sensitivity of this choice to new information is then investigated with VoI analysis as a form of sensitivity analysis. For a practical case, more alternatives, several different predictive models, more attributes, and more stakeholders may exist than depicted here.

from now. However, as the predictions are uncertain, we need to evaluate their entire distribution. Given uncertain consequences $\mathrm{Y}(a)$ for an alternative a, we receive corresponding utilities $\mathrm{U}_a = u(\mathrm{Y}(a))$. For a given stakeholder preference profile, we obtain a ranking of the alternatives based on their expected utility (EU):

$$\mathrm{EU}(a) = \mathbb{E}[\mathrm{U}_a] = \int_y u(\boldsymbol{y}) p_{\boldsymbol{Y}_a}(\boldsymbol{y}) \mathrm{d}y \tag{1}$$

with $p_{\boldsymbol{Y}_a}$ the probability distribution of the consequences of implementing alternative a as measured by all of the system attributes. The alternative with the highest EU is then determined by maximizing:

$$\max_{a=1\ldots A} \mathbb{E}[u(\mathrm{Y}(a))] \tag{2}$$

Utility theory is *prescriptive* because a rational decision maker should choose the alternative with the highest EU, a^*, given their preferences (encoded in the function u) and the probability distributions of predicted consequences $p_{\boldsymbol{Y}_a}$.

Utility theory allows determining the optimal choice for individuals or groups with homogeneous preferences. For environmental management decisions, the societal utility of an alternative must be considered from conflicting stakeholder perspectives. Which decision-making criterion should be considered rational or fair for a group or society is an unresolved question (de Jonge, 2012). However, making a number of contested assumptions, such as the possibility for interpersonal comparisons of utility, we can construct a group utility function from the individuals' utility functions (Keeney, 2013). To obtain a group expected utility $\mathrm{EU}_G(a)$ of an alternative a across K stakeholders perspectives, we aggregate individual expected utilities EU_k using the weighted arithmetic mean. The weights w_k with $0 < w_k \leq 1$ are scaling factors for the utility between stakeholders that sum to one (Eq. (3)).

$$\mathrm{EU}_G(a) = \sum_{k=1}^{K} w_k \cdot \mathrm{EU}_k(a) \tag{3}$$

2.2. Value of information sensitivity analysis

The optimal baseline choice in a decision is the alternative a^* obtained by maximizing EU, given the current state of information and the current preferences. However, in practice, we are usually concerned about the sensitivity or robustness of such a conclusion: How bad would it be if we picked this seemingly optimal alternative, but some information turned out to be different in reality?

For illustration, let us consider a decision about a system in which only one among all the variables is uncertain. Following ideas introduced by Felli and Hazen (1998), we consider three perspectives of a decision's sensitivity to that uncertain variable:

- Threshold perspective: If we varied the variable from its lowest to highest value, is there any threshold level at which the optimal choice changes? If not, the decision is insensitive to that variable.
- Probabilistic perspective: Given the probability distribution of the variable, how likely is it that the threshold is crossed? If this is very unlikely, the optimal choice remains insensitive to the variable, even though a threshold exists.
- Utility foregone perspective: How large is the expected difference in utility between our baseline choice and the optimal choice if the threshold would be crossed? If the difference in utility is small enough, the penalty for having chosen a suboptimal alternative will be small enough that we can consider the decision to be insensitive.

Value of information can be thought of as a sensitivity measure that takes both the probabilistic and utility foregone perspectives into account (Felli and Hazen, 1998; Borgonovo et al., 2016). Converse to utility forgone, it measures the gain in utility we can *expect* from knowing a decision aspect, such as a system attribute or parameter, with (more) certainty. With VoI we thus measure how sensitive the optimal choice is to potential new information, before we acquire it. If the VoI is small, it is unlikely that the baseline optimal choice changes with that new information or the difference in utility that this change would bring is small. Thus, VoI supports us in prioritizing which uncertainties should be reduced by further information collection.

Several variants of VoI measures have been proposed. They share the same concept, but differ with regard to the additional information that is considered. The expected value of perfect information (EVPI), measures the sensitivity of obtaining perfect information on all modeled aspects of the decision (Eidsvik et al., 2015). The expected value of partially perfect information (EVPPI, also abbreviated EVXPI or EVXI), measures the sensitivity of obtaining perfect information on parts of the uncertainties, for example, one or several parameters (Eidsvik et al., 2015). This is the measure we focus on in the following.

Given that aleatory uncertainty cannot be reduced by more studies or data collection, EVPI and EVPPI can be thought of as upper bounds for the actual VoI we can expect. In practice, we will always only obtain imperfect information. The expected value of sample information

(EVSI) is a measure for the impact of obtaining additional data, but not perfect information. Estimating EVSI is still difficult in many contexts, but it is an active area of research (e.g., Williams and Johnson, 2018; Kunst et al., 2020).

2.3. The expected value of partially perfect information

The idea of VoI is to calculate the added value of a piece of information before we actually expend the effort and cost to obtain it. In the case of EVPPI, we estimate the expected gain if we knew one or a group of variables of interest (parameters, inputs, or attributes) with certainty. A formal and extensive treatment as well as algorithms to estimate the EVPPI is available in the literature (Brennan et al., 2007; Eidsvik et al., 2015; Borgonovo et al., 2016; Heath et al., 2017). Here, we sketch out the main ideas with the aim to provide an intuitive understanding of the approach. In this study we focus on uncertainties of the predictions of the attributes. However, VoI analysis can be conducted for other variables within the models by following the same approach.

Let us assume we have determined the optimal baseline choice (a^*) for a coral reef management decision, given the current state of data and knowledge. We are now interested to find out how sensitive that choice is to one aspect of the decision: our prediction of the resulting coral cover (cc) under a marine protected area (MPA) alternative. We denote this variable of interest $Y_i = Y_{\mathrm{cc,MPA}}$. If we had perfect information about the resulting coral cover if an MPA were implemented, what would be the expected added value to the decision?

The idea of the analysis is that we pretend we could – with a certain cost and effort – gain clairvoyance on this variable and found, for instance, that $Y_{cc,MPA} = y_{cc,MPA} = 58\%$. This gives us a better estimate for the variable and can have three effects: (a) the conditional distributions of the other variables, $Y_{-i}|Y_i = y_i$, change if they are not independent, (b) the distribution of all utilities U_a change if they are not independent from the variable of interest, and (c) the optimal alternative might change.

We now calculate the maximum utility given this new information, $\max_{a=1\ldots A}\{\mathbb{E}[U_a|Y_{cc,MPA}=58]\}$, and determine the best alternative. If the best alternative is still the baseline optimal choice a^*, the additional information that coral cover under the MPA alternative will be 58% did not help us make a better choice than we would have made anyway. Rather, there is an opportunity cost, if effort was expended towards collecting this information. Consequently, the value of this information would be zero as the EU of the optimal alternative given the information, a^*, and the EU of the baseline choice given the information is identical: $\max_{a=1\ldots A}\{\mathbb{E}[U_a|Y_{cc,MPA}=58]\} - \mathbb{E}[U_{a^*}|Y_{cc,MPA} = 58] = 0$. However, if the new information changed our optimal choice, this difference will be positive and indicates the value of collecting this information.

While this illustrates the VoI for one particular value $y_{cc,MPA}$, we are interested in the *expected* VoI for $Y_{cc,MPA}$ over its entire probability distribution of the coral cover within the predicted range. We can estimate this by sampling from the predicted probability distribution of coral cover, calculating the corresponding EU given that we 'know' this sampled value, and tracking the corresponding change in the optimal choice. If the optimal choice does not change for any of these values, it implies that no matter how much we improve our predictions our conclusions would never change.

More formally, for a risk-neutral stakeholder we calculate the EVPPI about the variable of interest Y_i with:

$$\begin{aligned}\mathrm{EVPPI}(Y_i) &= \mathbb{E}\left[\max_{a=1\ldots A}\left\{\mathbb{E}[U_a|Y_i]\right\} - \mathbb{E}[U_{a^*}|Y_i]\right] \\ &= \mathbb{E}\left[\max_{a=1\ldots A}\left\{\mathbb{E}[U_a|Y_i]\right\}\right] - \max_{a=1\ldots A}\left\{\mathbb{E}[U_a]\right\}\end{aligned} \tag{4}$$

The EVPPI can be viewed as the difference between a "posterior" value of the decision with new information and a "prior" value without the information, as in the second part of Eq. (4) (Eidsvik et al., 2015). If a stakeholders has an exponential utility function (Keeney and Raiffa, 1993), these are the respective certainty equivalents of the situation where information is available for free and where no further information is available (Eidsvik et al., 2015). If a stakeholder is risk-neutral, the certainty equivalents are the expected values, as in Eq. (4).

If we expand our analysis to several variables of interest (e.g., growth rates, herbivore fish biomass, revenue for fishers, etc.), we can determine a ranking of the variables in terms of their EVPPI. This provides a quantitative and transparent prioritization of the most relevant uncertainties. This can serve as the basis for directing study design and deciding about upcoming expenditure of costs and efforts towards collecting data and information.

2.4. Given-data approach to estimating EVPPI and threshold sensitivity

Since analytical solutions can rarely be found, various simulation-based approaches to estimate the EVPPI have been developed. The classical procedure is a two-level nested Monte Carlo simulation (e.g., Felli and Hazen, 1998; Brennan et al., 2007). However, this requires many simulations. In addition, to account for dependencies in the distributions of predictions, Markov-Chain-Monte-Carlo (MCMC) or other conditional resampling procedures with high computational burden are needed with a nested approach (Strong and Oakley, 2013).

The alternative we describe here, is a given-data approach that only requires a single-loop Monte Carlo sample, as one obtains from a probabilistic sensitivity analysis. This procedure has been developed by Strong and Oakley (2013) and is more generally discussed by Borgonovo et al. (2016). The method was originally conceived for VoI calculations based on the *net benefit* of alternatives, here we adapt it to usage with EU for risk-neutral preferences.

We focus on this approach because it can handle the conditional dependencies in the distributions of variables while being computationally more feasible in connection with complex system models, as a single-loop Monte Carlo sample is sufficient. A drawback of the method is that it is only efficient for calculating the EVPPI of single variables. To calculate EVPPI for sets of variables other approaches have been suggested (Strong et al., 2014; Heath et al., 2017).

While we refer the reader to the original publication by Strong and Oakley (2013) for the details, the basic algorithm can be described as follows.

- From a Monte Carlo simulation we receive S samples of the uncertain variables and of the S corresponding utilities for each alternative.
- The vector of samples $\boldsymbol{y}_i$ of the variable of interest Y_i for which we want to calculate the EVPPI, as well as the corresponding utilities $\boldsymbol{u}(a)$ for all management alternatives are now both reordered such that $y_i^{(1)} \leq y_i^{(2)} \leq \cdots \leq y_i^{(S)}$. The superscript denotes the reordered position in the vector of variable samples.
- The reordered samples and the corresponding reordered utilities are partitioned into K bins of equal size J, with $J \cdot K = S$.
- For each bin k, we calculate the EU for each alternative. This is an approximation of the EU conditional on the value of the variable of interest y_i being in this bin. We then take the maximum EU across the alternatives.
- The arithmetic mean of these maxima across all K bins is taken as an approximation to the first term in Eq. (4): $\mathbb{E}\left[\max_{a=1\ldots A}\left\{\mathbb{E}[U_a|Y_*]\right\}\right]$. The second term of Eq. (4), the EU of the baseline optimal choice – $\max_{a=1\ldots A}\left\{\mathbb{E}[U_a]\right\}$ – can be directly calculated as in Eq. (2).

The corresponding estimator for EVVPI can be written as:

$$\begin{aligned}\mathrm{EVPPI}(Y_i) = &\frac{1}{K}\sum_{k=1}^{K}\max_{a=1\ldots A}\left\{\frac{1}{J}\sum_{(s)=1+J\cdot(k-1)}^{J\cdot k} u^{(s)}(a)\right\} \\ &- \max_{a=1\ldots A}\left\{\frac{1}{S}\sum_{s=1}^{S} u^{s}(a)\right\}\end{aligned} \tag{5}$$

We propose that the same algorithm is efficient for threshold sensitivity analysis that takes into account conditional distributions. The aim here is to estimate the EU of alternatives given that a variable of interest Y_* takes on different values and then identify threshold values of Y_* where the optimal alternative changes. This could be achieved by varying Y_* in a one-factor-at-a-time sensitivity analysis. However, to take a regional view on sensitivity and account for dependencies across attributes and alternatives, we need to consider the conditional distributions of all variables given the specific values of the variable of interest.

To understand the relationship between specific values of Y_* and the EU of the alternatives, we can employ the algorithm described above. The relationship can be approximated by calculating the arithmetic mean of the variable of interest in each bin and the corresponding EU for each alternative in this bin. Thresholds can then be determined visually from a scatterplot or by calculating a threshold criterion. As it is sample-based, we may not be able to identify one threshold, but rather a range of Y_* as a threshold region.

3. Implementation for a reef management problem

3.1. Case study description

3.1.1. Problem background

In this case study, we investigated the local reef management for an island that can be considered as typical in the Spermonde archipelago in Indonesia, using the framework described in Section 2. The Spermonde archipelago is a complex of about 70 islands located off Southwest Sulawesi, most of them inhabited and surrounded by coral reefs. The region lies in the center of the Coral Triangle, which is the most biodiverse marine region worldwide (Burke et al., 2012). As for many small islands and island nations in the Indo-Pacific, it is necessary to find a balance between the exploitation and conservation of their natural resources in the face of local and global changes: from livelihoods and ecosystem degradation to climate change and globalized economics.

Major local stressors on the reefs in the area are overfishing and the use of destructive fishing techniques. Fish are consumed for nutrition locally, but mostly sold, partly as live fish (Radjawali, 2012). Target species are diverse and shift with global demands and local supply (Ferse et al., 2014). A wide range of fishing techniques are employed, among them destructive techniques such as bomb fishing or cyanide fishing. For fisherfolk of the islands, alternative livelihoods are often neither attainable nor desired (Ferse et al., 2014). Additionally, fisherfolk are often embedded in elaborate systems of patron–client relationships that provide benefits such as social protection (Glaser et al., 2015). These relationships can influence fishing behavior and may encourage overfishing and destructive fishing (Glaser et al., 2015; Miñarro et al., 2016).

The effects of fishing pressure are exacerbated by pollution from point and diffuse sources as well as sedimentary run-off stemming from the islands and the Makassar urban area (Teichberg et al., 2018). Larger scale pressures such as global climate change are expected to cause ocean warming and sea-level rise, resulting in the decline of reef health.

For this study, we investigated an exemplary reef site of a typical island in the region. The site is 200 × 160 m and part of a larger reef area. The majority of the seafloor is less than 5 m deep, but descends to 15 m depth (Fig. SI-1). To improve the local situation, we focus on fisheries management as a way to mitigate a primary local stressor for the reef.

3.1.2. Societal perspectives and objectives

Different users and interest groups hold varied perspectives on a reef site, its value, and its relevant services. Societal evaluation ultimately determines which form of management is optimal. Therefore, we need to consider different stakeholder perspectives on the issue. For the reef of the inhabited island we investigate, we seek to represent a diversity of views by exploring four archetypal perspectives:

- local livelihoods perspective, focused on ensuring food security and economic benefit to local fishers
- reef conservation perspective, focused on ecosystem health and resilience
- extraction perspective, focused on maximizing fishing yield and economic benefits
- balanced perspective, focused on balancing the different aspects and interests

The values that are implicit in these perspectives can be expressed in the form of an objectives hierarchy (Keeney, 1992) that we developed based on literature (Maynard et al., 2017; Brown et al., 2018; McField and Kramer, 2007) as well as our knowledge of the case and context (Fig. 2). We chose these four archetypal perspectives to illustrate a wide range of views on the management issue, but they are not meant to represent actual individual stakeholders or groups. For real-world decision support, these perspectives and their objectives need to be elicited and co-developed locally. We use these perspectives to guide an analysis for multiple stakeholder perspectives, which can be adapted to a particular decision context.

3.1.3. Management alternatives, attributes, and time scale

At the investigated reef site, fishing occurs for subsistence and commercial reasons and destructive fishing techniques are employed occasionally (see description of the no restrictions alternative in Table SI-1). To define management alternatives, we first developed a strategy generation table (Gregory et al., 2012). We identified three management factors: (1) gear and technique restrictions, (2) access restrictions, and (3) fishing quotas. Based on the strategy generation table, we developed four management alternatives expected to result in decreasing degrees of fishing pressure (see Table 1):

- *no restrictions*: no restrictions with continued intense fishing pressure including destructive fishing
- *no destructive fishing*: enforcing a ban of bomb and cyanide fishing
- *MPA subsistence*: implementing a marine protected area, which allows only subsistence fishing for locals
- *MPA no-take*: implementing a strict marine protected area, making it a no-take zone

The management alternatives, if implemented, will have consequences for very different aspects of the socio-ecological system of the island reef. The consequences that are relevant for deciding between the management alternatives are captured by attributes of the system (Fig. 2 and Table SI-2). The attributes should describe the consequences in a way that is understandable and useful for decision-makers and stakeholders (Keeney and Gregory, 2005). The degree of fulfillment of the decision objectives can then be quantified based on the attribute levels. For instance, the attribute "total biomass of browsers, scrapers, and grazers in g/m^2" can be used to determine the achievement of the objective of having a high biomass of herbivorous fish in the reef.

The considered time scale of consequences can make a large difference in decision-making. Short-term and long-term consequences can diverge. For instance, an over-exploitation of fishing resources can be advantageous in the short term, but detrimental in the long term. In this study, we consider consequences three to six years in the future.

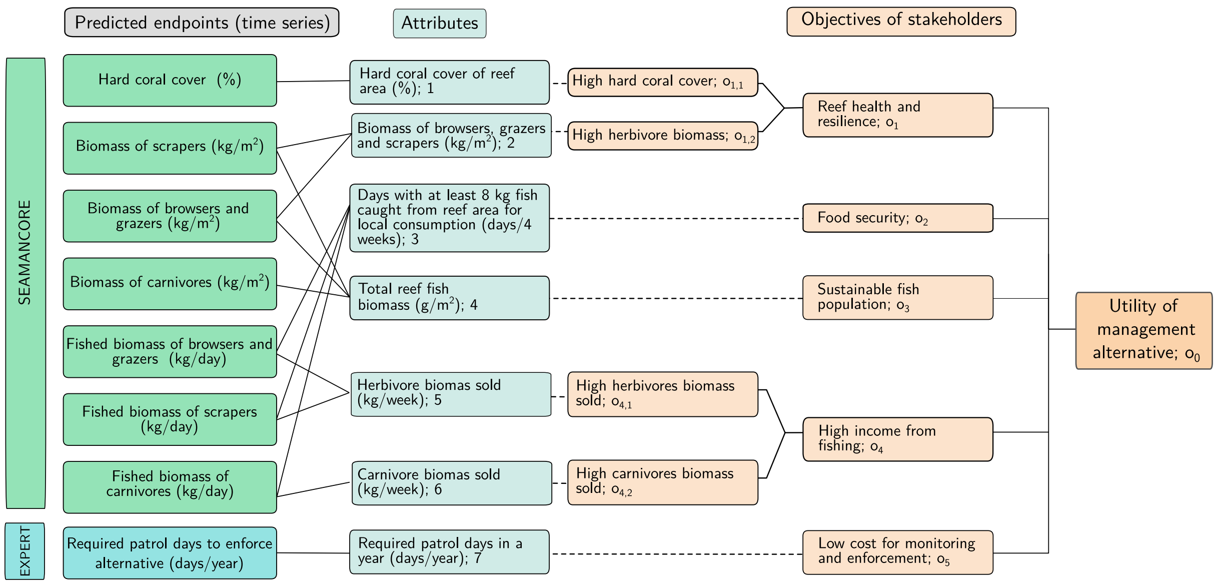

Fig. 2. Scheme of predicted model outputs (boxes on the left), their transformation/aggregation to attributes that measure decision-relevant consequences of management alternatives (middle, also see Table SI-2), and the hierarchy of objectives (right side) used in evaluating these alternatives based on the attribute predictions. The objective hierarchy is also the structure of the preference model based on utility theory that is used for evaluation. Consequences that are measured by the attributes are mapped to an aggregated utility.

3.2. Prediction of management consequences

Predicting the consequences of management alternatives on complex systems is a difficult task. To predict the ecological consequences of management alternatives on reef fishes, reef benthos, and fisheries yield, we adapted a previously developed model of the system (SEAMANCORE; Miñarro et al., 2018). This model combines an agent-based model of fish stocks and fishing behavior with a corresponding model for benthic community dynamics. The implementation is detailed in the next sections. To account for the often neglected cost of implementing and enforcing management alternatives (McCrea-Strub et al., 2011), we used the “required patrol days” as a proxy attribute for these costs (Brown et al., 2018). We used our contextual knowledge to estimate this attribute’s distribution for each management alternative. These were assumed to be Poisson distributions with different rate parameters.

3.2.1. Model of reef and fishery dynamics under management alternatives

SEAMANCORE is a spatially-explicit 2D model that simulates the dynamics of the benthic and fish populations as well as fisheries in a coral reef through an agent-based simulation (Miñarro et al., 2018). We used SEAMANCORE to predict the temporal dynamics of the reef benthos and fish community in a 200 × 160 m area. The predicted entities consisted of four benthic functional groups (hard coral, macroalgae and turf, hard substrate and cropped algae, non-stabilized substrate), stocks of three functional fish groups (carnivores, browsers and grazers, scrapers), and different fisheries (Table SI-3).

The aim for prediction is to capture the inherent stochasticity of the system as well as the directed effects of the management alternatives. We achieve this by differentiating between *core parameters* and processes of the SEAMANCORE model that are unaffected by the alternatives and *alternative-specific parameters* and processes. If we intend to understand the effect of the alternatives, it is only meaningful to compare the set of predictions where the core parameters are shared. One model parameterization of the natural processes can be viewed as one potential configuration of the world. The four management alternatives then lead to four different futures. Therefore, for one core parameterization, we created four simulations with the alternative-specific parameters set in addition.

The difference between the four management alternatives was represented by modified inputs and parameters in the fishing module (e.g., number of boats). Four types of fisheries were considered: (1) bomb fishing, (2) cyanide fishing, (3) non-destructive commercial fishing, and (4) non-destructive subsistence fishing (see Table SI-2 for their specification in SEAMANCORE). The different management alternatives allowed specific combinations of these types of fishing to occur in the reef, from all types in the no restrictions alternative to none in the no-take alternative (Table 1).

For each simulation run, we specified the initial conditions in a spatially explicit manner: the water depth (Fig. SI-1), the benthic cover, biomass of fish functional groups, and the fishery modes to apply (Table 1 and Table SI-3). Additionally, we set over 100 other core parameters that govern the model behavior (Miñarro et al., 2018). For each simulated time step, the model outputs a 10 × 10 cm resolution map of benthic cover, a 20 × 20 m resolution map of biomass of fish functional groups, and the total fishery yield differentiated by depth, target species, and fishery type. We simulated at a temporal resolution of 1 day for both the benthic and the fish grids.

The management alternatives were assessed against the background of an uncertain environment in which most aspects are beyond management control. For instance, biological processes, such as death rates or feeding rates, were assumed to be independent of management alternatives at the considered scale. However, these processes are usually variable and our knowledge about them is incomplete. We represented this with two approaches. Firstly, the rules governing the cellular automaton and model agents have a stochastic element. For example, rules to change a hard substrate cell to an algae cell are triggered only with a certain probability at each time step. Secondly, we used probability distributions instead of point estimates for the core parameters.

We used the calibration of Miñarro et al. (2018) as a basis for the model parameterization. We then defined probability distributions for 37 of the models parameters (e.g., reproduction rates, feeding rates, time for colonization; Fig. SI-2) and 15 input variables (initial benthic cover and initial fish biomass; Fig. SI-2). Other parameters, such as the probability of transition between benthic substrata, remained the same across all simulations. Parameter distributions were identified based on literature values and judgment by the authors, guided by natural constraints (e.g., a death rate cannot be negative), plausibility of the simulation results, and using maximum entropy distributions. Distributions of model parameters were assumed to be independent,

Table 1
Fishing types allowed under the management alternatives.

Name of alternative	Subsistence fishing	Commercial fishing	Dynamite fishing	Cyanide fishing
(1) No restrictions	Yes	Yes	Yes	Yes
(2) No destructive fishing	Yes	Yes	No	No
(3) MPA, subsistence	Yes	No	No	No
(4) MPA, no take zone	No	No	No	No

except for initial benthic coverages which were assumed to come from a multivariate normal distribution. We assumed all parameters to be constant across the modeled temporal and spatial dimensions. By propagating this prior information through the model with Monte-Carlo simulation, we received a corresponding distribution of model outputs.

An external stressor we modeled explicitly were coral bleaching events (Eddy et al., 2021). We included strong bleaching that turn coral cells into hard substrate and mild bleaching that resets the age of coral cells. Bleaching affects coral cells with a certain probability depending on the depth of their location. The effects of other external stressors – such as temperature change, eutrophication, or loss of connectivity to other reefs – are captured indirectly by the distributions of the parameters — such as colonization rates of coral and algae, growth rates of functional groups, or external recruitment.

3.2.2. Obtaining of decision-relevant predictions

To predict the uncertain consequences of management alternatives, we used Monte-Carlo simulations to obtain a population of predictions from independent runs of the SEAMANCORE model. We drew 1100 samples from the probability distributions of the model core parameters (Fig. SI-2). These were combined with the definitions of each alternative. The SEAMANCORE model was thus run for 1100 samples$\times$4 alternatives = 4800 times in total. For five of the 1100 parameter combinations the model produced nonsensical results: either the model returned an undefined value for biomass of a fish functional group or scraper biomass was continuously above a threshold of 95 $\mathrm{g/m^2}$ for more than 60 days. These runs were excluded.

As we focus on the situation three to six years after implementing a management alternative, we ran the model for 2280 time steps (days) and then took the values for years four to six into the future as the basis for the attribute predictions. To smooth out short-term, noisy fluctuations due to asynchronous updating of fish and benthos grids, we used a 42-day (6 weeks) rolling mean of the time series for the benthos cover and a 14-day (2 weeks) rolling mean for the time series of fish biomass.

The system model outputs are not directly of interest as attributes in the decision. We therefore transformed and aggregated model outputs to obtain predictions for attributes that would be understandable to interested stakeholders (Fig. 2 and Table SI-2). For instance, the daily time series of fish biomass for the three functional groups was aggregated to arrive at weekly average total fish biomass. The variability in time thus became part of the prediction uncertainty. From the perspective of strategic management, the spatially explicit output of the model was also not relevant. Therefore, we aggregated the model outputs for the entire area.

The empirical joint distribution of the aggregated and transformed model outputs was the basis for the decision-relevant attribute predictions. We aimed for a sample of size $S = 120\,000$ for each attribute of each alternative. To ensure equal sample size, attributes measured on a weekly scale were downsampled (from 170 820 samples) and attributes with monthly scale were upsampled with replacement (from 42 705 samples). For the attribute “required patrol days”, we directly drew S samples from the specified Poisson distributions.

A crucial consideration when creating this sample of attribute predictions is that dependencies exist across attributes and alternatives. This should be considered in VoI analysis. For instance, if coral cover correlates with herbivore biomass, having better information about coral cover will also inform us about herbivore biomass. For an estimation approach of VoI that is based on sampling, we therefore need to create a sample that retains the relevant (conditional) dependencies in the predictions. Given the way we set up our simulations, we obtain these dependencies from the SEAMANCORE modeling. For other modeling approaches this can be less straightforward.

Such dependencies exist within the predictions from a simulation run for one alternative. Firstly, the parts of the ecological system are connected. For example, high carnivore biomass will often coincide with lower biomass of herbivorous fish. Secondly, predictions are correlated in time, as the future system state depends on previous time steps. In the resampling of predictions for a management alternative, we retained relations between samples for different attributes regarding points in time and simulation parameterization. This means for one alternative a particular sample of all attributes comes from the same simulation run and time point.

Dependencies also exist between the consequences of different alternatives because they are predicted based on shared core parameters, as described above. Across the alternatives, we retained relations regarding the core parameter samples. This represents system properties or shared external influences that are the same for all alternatives. However, we randomized the resulting predictions regarding time. In this way, we represent different time points at which the effects of the alternatives are assessed in the future. This means a particular attribute sample across the alternatives comes from a model run with the same core parameters, but potentially different time points. We illustrate the effect of retaining different correlations in Fig. SI-7.

3.3. Evaluation of management alternatives

3.3.1. Preference model structure and parameters

To understand the differences in utility that the management alternatives would bring to different societal actors, we specified a hierarchical utility model for each of the four archetypal stakeholder perspectives. Each model encodes an assumed preference profile for a stakeholder perspective and is meant to represent specific interests for that stakeholder. Based on the evaluations of management alternatives with these models, we can then identify areas of conflicts and consensus. As outlined in Section 2.1, we can also calculate aggregate results across stakeholder perspectives.

In the following, we outline our approach to hierarchical utility models, a detailed treatment can be found in Haag et al. (2019a) and Reichert et al. (2015). The structure of the preference models is given by a hierarchy of objectives (Fig. 2). We assume that all stakeholder perspectives share the same set of objectives but differ in their preferences; for instance, the trade-offs they are willing to make between the objectives.

To build the model, we first specify a marginal value function for each of the seven objectives on the lowest level of the hierarchy, $v_{o_p}(y_p)$ (Fig. SI-3). These map from the attribute space to a relative degree of achievement for each of these objectives. Then, we aggregate these valuations along the hierarchy with nested aggregation functions, F_k, that we specify for each aggregation step. We arrive at a multi-attribute value function over all attributes, $v(y_1, \ldots, y_m)$. With this function we receive an overall evaluation of each decision alternative. Lastly, as discussed by Dyer and Sarin (1982), this multi-attribute value function is converted to a utility function $u(v(y_1, \ldots, y_m), r)$ at the highest objective in the hierarchy, given the risk attitude r. As we assume stakeholders to be risk neutral, the EU of an alternative is its expected value based on the evaluation with the value function. The preference model used to evaluate one set of consequences of alternative a can therefore be written as (for the indices refer to Fig. 2):

$$
\begin{aligned}
u(\boldsymbol{y}_a) = F_0(&\\
&F_1(v_{o_{1,1}}(y_{1,a},\boldsymbol{\theta}_{o_{1,1}}), v_{o_{1,2}}(y_{2,a},\boldsymbol{\theta}_{o_{1,2}}), \boldsymbol{w}_{F_1}, \gamma_{F_1}),\\
&v_{o_2}(y_{3,a},\boldsymbol{\theta}_{o_2}),\\
&v_{o_3}(y_{4,a},\boldsymbol{\theta}_{o_3}),\\
&F_4(v_{o_{4,1}}(y_{5,a},\boldsymbol{\theta}_{o_{4,1}}), v_{o_{4,2}}(y_{6,a},\boldsymbol{\theta}_{o_{4,2}}), \boldsymbol{w}_{F_4}, \gamma_{F_4}),\\
&v_{o_5}(y_{7,a},\boldsymbol{\theta}_{o_5}),\\
&\boldsymbol{w}_{F_0}, \gamma_{F_0})
\end{aligned} \tag{6}
$$

As aggregation functions F_k for the values v on each hierarchical level we chose functions of the family of weighted generalized means (also called power means) with the form:

$$
F_k(v_1,\ldots,v_n,\boldsymbol{w},\gamma) = \left(\sum_{i=1}^{n} w_i \cdot v_i^{\gamma}\right)^{1/\gamma}, \gamma \in \mathbb{R}^* \tag{7}
$$

with weight parameters (scaling factors) $0 < w < 1$ and $\sum_{i=1}^{n} w_i = 1$.

The parameters of the preference model (Eq. (6)) were changed for each of the stakeholder perspectives based on assumed preferences in line with their concerns (see Section 3.1.2). These parameters are:

- how they evaluate changes on the attribute scales, such as diminishing returns regarding fish catch or coral cover (shapes of marginal value functions, $\boldsymbol{\theta}$, Fig. SI-3).
- how they trade off changes in one objective relative to the other objectives (weight parameters, $\boldsymbol{w}$, Table SI-3)
- to what degree a poor achievement of objectives can be compensated. For example, can a high enough fished biomass compensate for a very low coral cover, or is a "one out all out" view appropriate (degree of non-additivity, $\boldsymbol{\gamma}$, Table SI-3).

As the aim in this study was to explore the space of potential perspectives, the preference profiles were designed by the authors according to the archetypes (see 3.1.2). For a practical decision problem, the parameters should be inferred from stakeholder data. These data can be collected by choice experiments (Hensher et al., 2015) or other forms of preference elicitation (Haag et al., 2019a).

3.3.2. Estimation of expected utility

Based on the empirical distributions of attribute predictions, we first calculated the optimal baseline choice. Each stakeholder preference profile was treated separately. For each sample $y = y_1, \ldots, y_7$ of the 7 attributes, we calculated the utility of each alternative using the respective preference model. Since we have $S = 120\,000$ samples, we obtained 120 000 utilities, the set of which we denote U_a for alternative a. By taking the arithmetic mean of U_a we received the EU for each alternative assuming risk neutrality: $\mathbb{E}[\mathrm{U}_a]$. The rational imperative is to pick the alternative with the highest EU: $\max_{a=1\ldots4}\{\mathbb{E}[\mathrm{U}_a]\}$. This is the optimal baseline choice for a stakeholder preference profiles, given our current information about the system attributes.

Based on the evaluation of management alternatives with the four preference profiles associated with the stakeholder perspectives, we can identify areas of conflicts and consensus. For also providing an aggregated view across the stakeholder perspectives, we followed the approach outlined in Section 2.1. Using Eq. (3), we calculated the EU of an alternative across perspectives giving all perspectives equal weight.

3.4. Sensitivity analysis using value of information

Value of information analysis can be conducted for any uncertain inputs or parameters of a decision model. For this case study, we focused on exploring the EVPPI with regard to uncertain attribute predictions. The aim was to understand the impact of better knowledge of the predictions of specific attributes. To identify whether the uncertainty of an attribute prediction was more relevant for some alternatives than others, we focused on individual variables for each of the alternatives and calculated the EVPPI of 4 alternatives for 7 attributes, resulting in 28 variables of interest. That is, if we had perfect knowledge of some attribute's predictions $\mathrm{Y}_i(a)$ for alternative a, how much additional utility would this be expected to provide to a stakeholder?

To estimate EVPPI, we implemented the algorithm as described in Section 2.4 and ran the analysis separately for each of the 28 variables of interest and each stakeholder perspective. We also calculated the EVPPI across perspectives based on averaging the EUs of the perspectives in each bin and on the EU of the baseline optimal alternative across the perspectives. For the main analysis, we chose values of $K = 300$ and $J = 400$ to mitigate the chance of bias. We also investigated the dependency of EVPPI on these choices (Fig. 7, Fig. SI-9).

To understand the added value of EVPPI over a simpler threshold view on sensitivity (see Section 2.2), we conducted a threshold sensitivity analysis. This means, we estimated the EU of alternatives given that a variable of interest Y_* takes on different values as described in Section 2.4. We repeated this analysis for all 28 variables of interest and each stakeholder. To identify thresholds visually, we normalized the EU values to the baseline optimal alternative for a stakeholder and estimated a smoothing spline model for this relationship.

4. Results

4.1. Predicted consequences of reef fishery management

The inputs and parameters of the predictive system model were described by probability distributions. Together with the stochastic processes in the model, this led to distributions for the obtained outputs and, consequently, for the derived predictions of the relevant attributes (Fig. 3). If we would only consider point predictions in our decision making (e.g., median lines in Fig. 3), we would disregard a lot of relevant information.

The distributions of attributes that describe the state of the reef – coral cover, herbivore biomass, and total fish biomass – are wide. This means, the predictive uncertainty about their future is high. The differences between alternatives appear less pronounced when considering the marginal distributions. This suggests the alternative had relatively less effect on the outcome compared to the stochasticity of the system. As expected, decreased fishing pressure generally leads to increased fish biomass, especially of carnivores. Increases in herbivore biomass are smaller due to the increasing predation pressure from carnivores. Coral cover increases when destructive fishing is stopped, but decreases slightly when fishing is stopped completely as feeding pressure by scrapers increases.

The distributions of attributes connected with fishery yield – carnivorous and herbivorous biomass to sell, fish for local consumption – exhibit long tails (Fig. 3). With the high fishing pressure in the no restrictions alternative, few carnivorous fish can be sold due to over exploitation and hence stock depletion in the considered 3–6 year time frame. The carnivorous fishing yield is higher in total with less intense fishing. On the other hand, when only subsistence fishing occurs there is little surplus of (especially herbivorous) fish to be sold. With the high fishing pressure of the no restrictions alternative, it is more likely that not enough fish can be caught for local consumption in comparison to the alternatives with no destructive fishing or with a protected area that allows subsistence fishing. With a strict no-take zone, no fishing is assumed to occur. Therefore the attributes related to fishery yield are always zero.

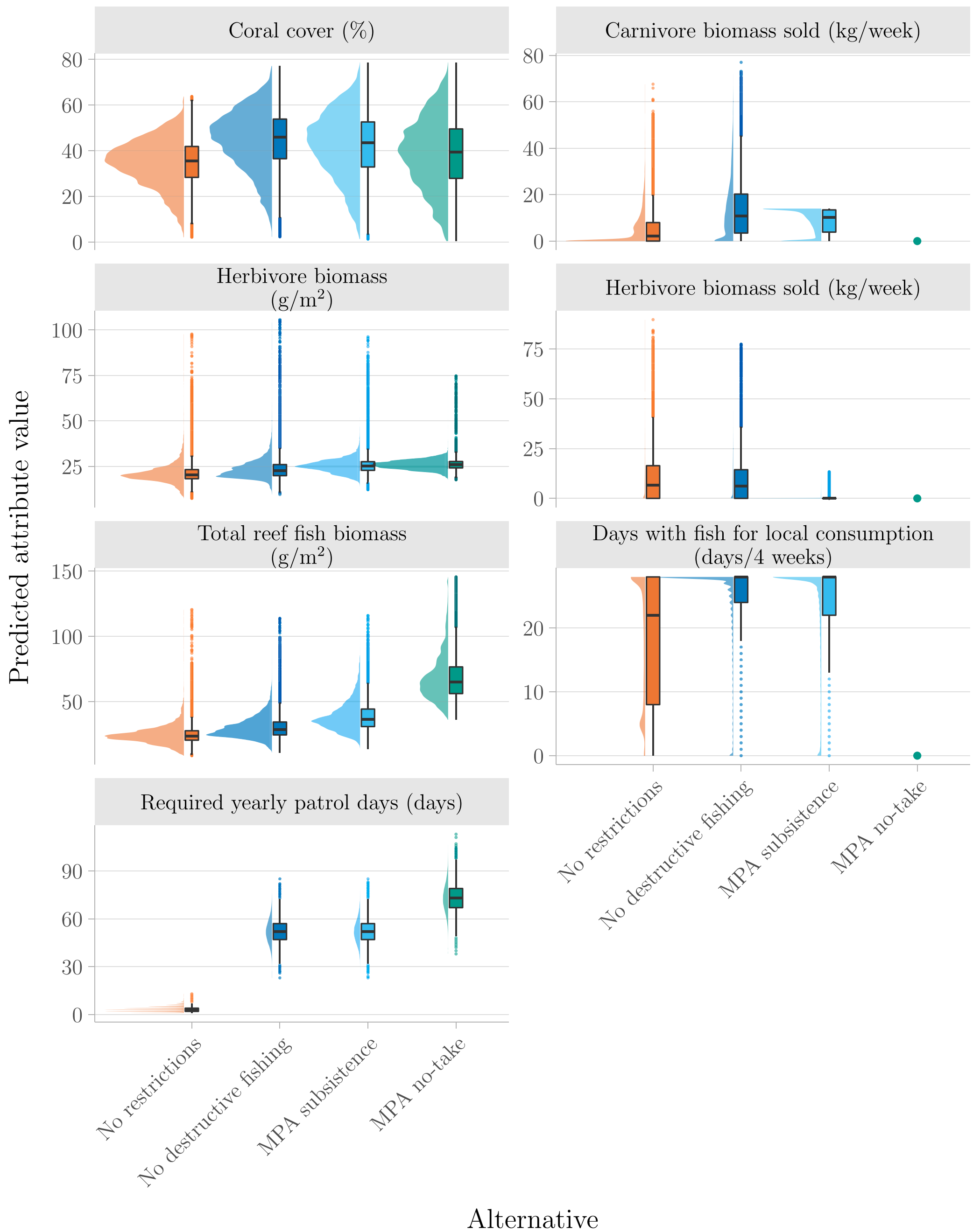

Fig. 3. Marginal distributions and boxplots of predictions (y-axis) of the attributes (panels) of a coral reef area under four management alternatives (x-axis). Distributions per alternative are based on 120 000 samples derived from 1100 independent simulations of the SEAMANCORE reef model, which were transformed, aggregated, and resampled. The predictions cover the time 3 to 6 years after the management alternatives were activated in the model. Required patrol days were directly sampled from Poisson distributions. Boxplots show the 0.25, 0.5, and 0.75 quartiles of these data, and whiskers extend to the maximum and minimum points within 1.5 times the interquartile range. Only a proportion of outliers is visualized.

4.2. Optimal baseline choice under uncertainty

Given the uncertain predictions of the attributes and our preference models for the different perspectives (Section 3.3), we calculated the utility for each predicted sample of the alternatives (distributions in Fig. 4). The expectation over these utilities, the expected utility (EU), is the criterion that a rational decision should be based on. This EU integrates over the predictive uncertainties and is therefore a single number (solid markers in Fig. 4).

For the balance and local livelihoods preference profile, a ban of destructive fishing practices would be the optimal alternative, for the conservation profile a marine protected area (MPA) with only subsistence fishing, and for the extraction profile the alternative with no restrictions would be most desirable (Fig. 4). Except for the conservation profile, a strict MPA with a no-take zone receives the lowest EU in all profiles; for the conservation profile the no restrictions alternative results in sightly lower EU. This can be explained by the missing fulfillment of any socio-economic objectives by an alternative that enforces a no-take zone. The alternative with no restrictions is not optimal for most preference profiles. Even a moderate restriction of fisheries can lead to higher fish biomass and also fished biomass, especially of carnivorous fish, even in the short time frame studied.

Based on these results, no clear consensus for a best management alternative emerges between the different perspectives. However, we can identify two aspects that might help come to such a consensus in

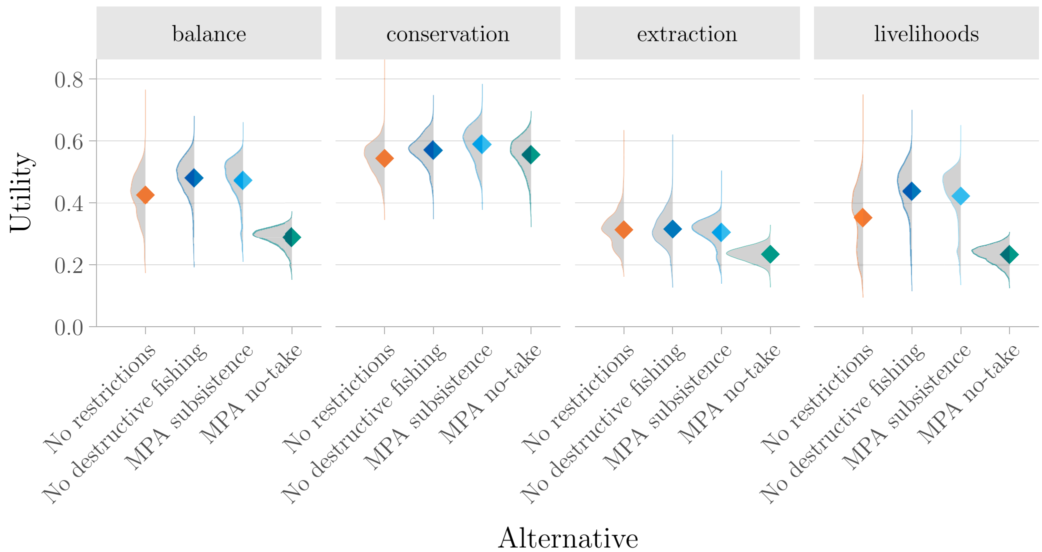

Fig. 4. Distribution of utilities (y-axis) and the EU (solid markers) for the management alternatives (x-axis). Each stakeholder preference profile (panel) is represented by a different utility function which maps the consequences of the alternatives into a utility between 0 and 1. Utilities are relative and allow ranking of alternatives within a perspective.

an iterative process: (1) some reduction in fishing seems beneficial for fishery yield even in a short time horizon and (2) the lack of fulfillment of socio-economic objectives due to a complete ban of fisheries can hardly be counterbalanced by better conservation outcomes.

4.3. Threshold view on decision sensitivity

There are large overlaps in the distributions of the alternatives' utilities (Fig. 4). This means, we might see future system states in which different conclusions about the optimal alternative would be drawn. Therefore, we need to investigate the sensitivity of the decision. Before considering the VoI view of sensitivity analysis, we identify thresholds for individual variables of interest – here the attribute predictions for one alternative – that lead to changes in the optimal alternative.

In Fig. 5 we see the resulting EU of the management alternatives relative to the baseline optimal alternative as we vary a variable of interest along its range. This relative EU is given as a function of a variable of interest, while retaining a probabilistic view and the correlation structure in all other variables.

Based on this we can identify thresholds at which the ordering of the decision alternatives changes. Since our results are based on simulations, the thresholds are small regions rather than exact points. As an example, the baseline optimal alternative for the conversation perspective is the MPA with subsistence fishing. We can now investigate the decision's sensitivity to the predicted coral cover of the MPA with subsistence fishing alternative (lower left panel of Fig. 5; results for all variables and perspectives are given in Figs. SI-5–8).

There are two thresholds. If we knew the coral cover of the MPA with subsistence fishing alternative would turn out to be below 23%, the no restrictions or no destructive fishing alternatives would now provide higher utility. If we could be certain that the coral cover of the MPA with subsistence fishing alternative would be between 23% and 62%, it would be the optimal choice. In this region, the VoI is zero, as the best alternative is not sensitive to the precise value of the coral cover prediction.

If the coral cover of the MPA with subsistence fishing alternative would be higher than 62%, the no-take MPA would be optimal. This may seem counter intuitive as, all else being equal, the utility of the MPA with subsistence fishing alternative should increase with increasing coral cover as higher cover is preferred. It is, however, a consequence of the correlation structure in the predictions. Either the high coral cover for that alternative coincides with less preferred consequences on its other attributes or it coincides with even more preferred consequences for the no-take MPA alternative.

The analysis falls short in two regards. First, we do not take into account how probable a crossing of a threshold would be: how probable would it be that we actually see coral cover greater than 62% under the MPA with subsistence fishing alternative? Second, once we crossed a threshold, we disregard how large the potential gain in utility would be from taking the optimal instead of the now sub-optimal alternative: if coral cover was above 62%, how much higher would the utility of deciding for the no-take MPA alternative be in comparison to sticking with the MPA with subsistence fishing? Both aspects are crucial for understanding the sensitivity of a decision. This is the point of the analysis of the VoI.

4.4. Results of the value of information analysis

To have a more comprehensive measure of decision sensitivity than the threshold view, we calculated the EVPPI of the variables of interest. The lower the EVPPI of a variable is, the lower the sensitivity of the decision to it and vice versa. If we had perfect information about that variable, this either would seldom change the optimal alternative, the gain in utility due to choosing the new optimal alternative would be small, or both. A ranking of the variables of interest based on their expected VoI can then support us in identifying the key uncertainties and prioritizing their resolution.

The EVPPI varies by variable of interest and stakeholder preference profile (Fig. 6, Table SI-5). Comparing all stakeholder perspectives, two commonalities exist. The attribute of required patrol days had relatively low EVPPI, while the attribute regarding fish available for local consumption had high EVPPI. Otherwise the results are more nuanced. Across variables, the livelihoods perspective often receives lower EVPPI than the other perspectives; the decision is less sensitive for this perspective. This demonstrates how the VoI depends on the stakeholder preference models and how far away (in terms of probability of change) the baseline optimal alternative is from the others (see Fig. 4).

The EVPPI is not directly linked to the width of the probability distributions of the variables (Fig. 3). The herbivore biomass of the no restrictions alternative has a markedly narrower distribution than the total fish biomass of this alternative. Yet, for all profiles as well as across profiles both have a similar EVPPI. As expected, for variables that are known with certainty, for instance, fisheries variables in the no-take MPA alternative, the EVPPI is zero.

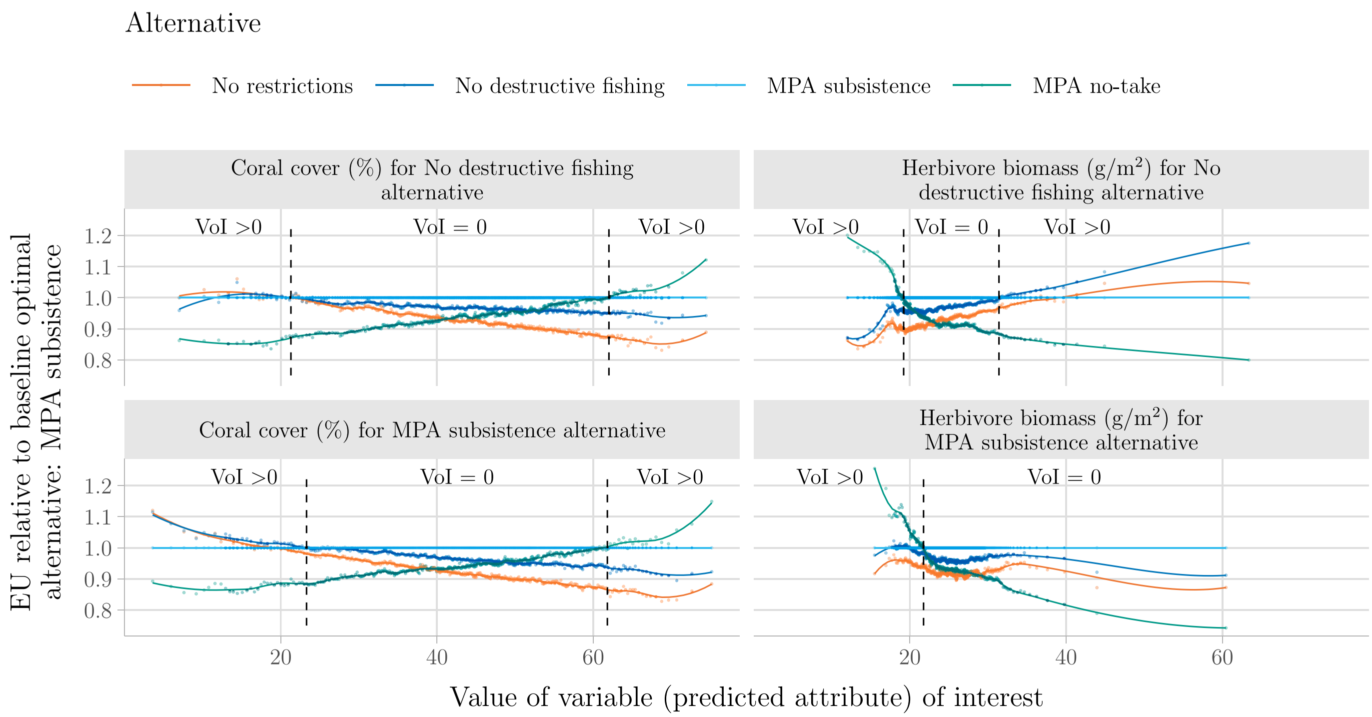

Fig. 5. Visualization of a threshold view on sensitivity for the conservation perspective. Each panel shows the variation of expected utility (EU) of alternatives (y-axis) when one variable of interest, meaning one attribute of one alternative, takes on different values (x-axis) while keeping the conditional variability in all other attributes. For clearer presentation, the EU of alternatives is divided by the EU of the baseline optimal alternative; thus, the y-axis shows ratios relative to this alternative. The lines are a loess smoothing of these data points (dots). The alternative with highest relative EU is the optimal alternative given that the variable of interest takes on a specific value on the x-axis. At the threshold values of this variable the optimal alternative changes (dotted vertical lines). In regions between thresholds where the EU of the baseline optimal alternative is higher, the value of information (VoI) is zero, as the best alternative is not sensitive to the precise value of the variable of interest in that range. A subset of the results for the conservation stakeholder preference profile is depicted. Figs. SI-5–8 show the other results.

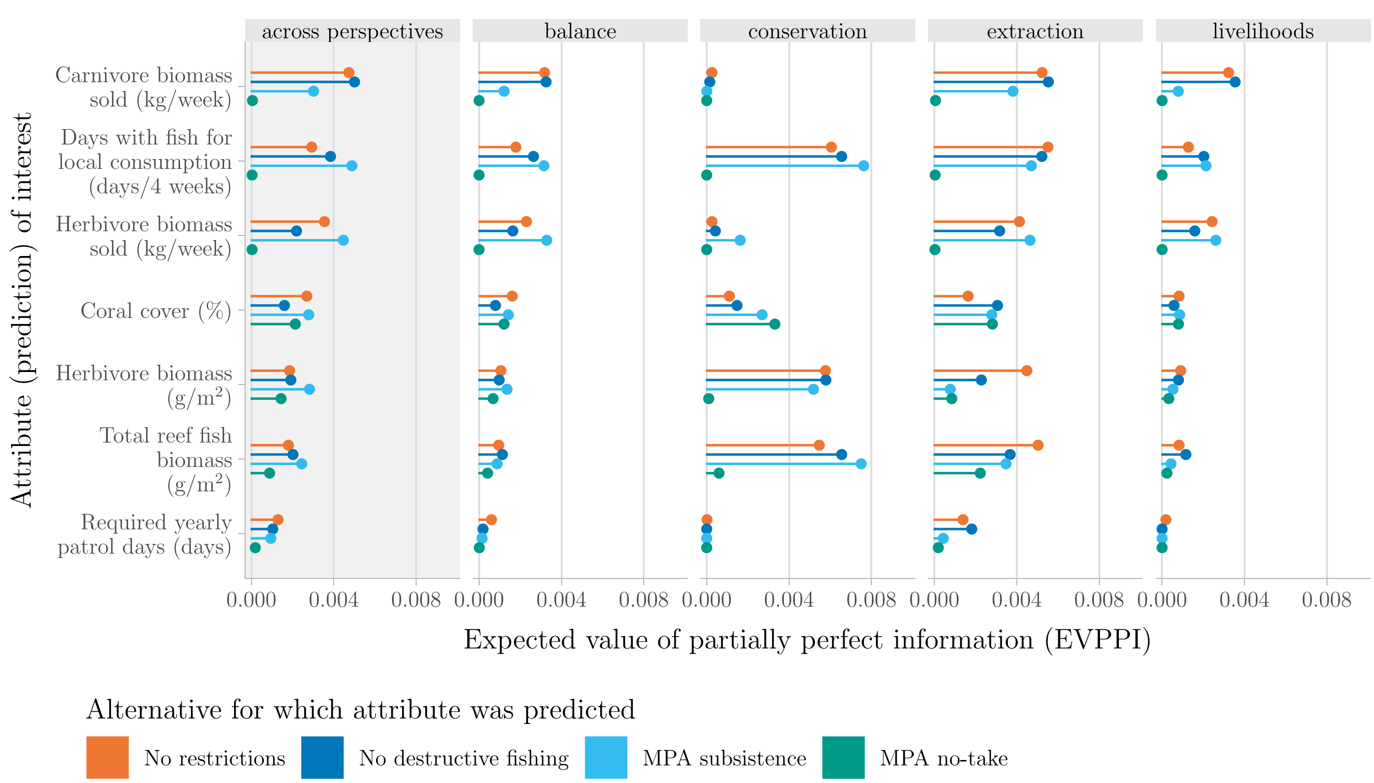

Fig. 6. Expected value of partially perfect information (EVPPI; x-axis) of uncertain attribute predictions of interest (y-axis) differentiated by alternative for which they were predicted (colors). Results for different stakeholder perspectives are shown in panels, with the leftmost shaded panel showing the result of an aggregated view across the perspectives. A single bar represents the expected gain in units of utility for a particular preference profile if we had perfect information about the prediction of the attribute of interest of a specific alternative. For variables that are known with certainty, such as fish catch under a no-take zone, the VoI is zero by definition.

For the conservation perspective, we can summarize our analysis as follows (for brevity, we do not discuss the other perspectives here, but they can be similarly analyzed). The optimal baseline choice given our current state of knowledge would be implementing an MPA with subsistence fishing (Fig. 4). However, this choice is sensitive to the actual realizations of the predicted attributes. Thresholds exist that would make a different choice optimal (Fig. 5 and Fig. SI-6). We expect the optimal choice to be sensitive to the days with food for local consumption, herbivore biomass in the reef, and total fish biomass (Fig. 6). We expect it to be insensitive to the number of patrol days and the actual fished biomass for selling. For any variable, except the coral cover, better knowledge about the true consequences when implementing the no-take MPA alternative is hardly relevant for the decision (green bars in Fig. 6). This alternative is unlikely to become the best one for the conservation perspective.

Based on the EVPPI analysis, the conclusion for the conservation preference profile would be that understanding the trajectory of the reef and its organisms better should be a priority. However, the uncertainty about the fish for local consumption is also relevant. Further efforts directed at improved understanding of these aspects will be most critical for decision-making as the determined baseline choice may not be the best if our knowledge about the respective attributes was improved. On the other hand, further investigation of the patrolling effort or the sold fish biomass is unlikely to change the conclusions regarding the optimal management alternative. For the other preference profiles, the list of priorities differs, with some commonalities as described above.

The estimation algorithm for EVPPI that we propose in Section 2.4 has a hyper-parameter, the size of the bins, J. The choice of J can have a significant effect on the resulting estimate (Fig. 7 and Fig. SI-9). For small bin sizes the estimator is upwardly biased due to the maximization step. As $J \to 1$ the estimates converge to the expected value of perfect information across all variables (EVPI). If each sample is placed in its own bin, i.e., $J = 1$, the estimated EVPPI is equal to the EVPI. The estimated EVPPI converges to zero as $J \to S$, as both terms of Eq. (5) become equal. Thus, for large sizes of the bins, the estimator is downwardly biased.

In our case, most EVPPI estimates are relatively stable, using from 100 bins with 1200 samples each to 12 000 bins with 10 samples each (Fig. 7). This confirms our choice of a bin size of 400 for the analyses above. However, in specific cases, estimates can also be sensitive to the bin size (e.g., days with fish for local consumption in Fig. 7 or Fig. SI-9).

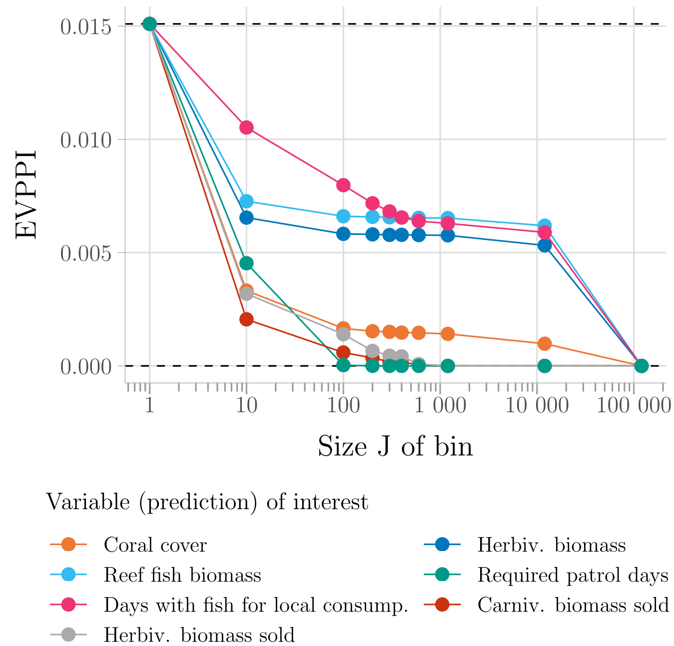

Fig. 7. Dependence of the EVPPI (y-axis) on the bin size parameter J (x-axis) of the estimation algorithm. The variables of interest are the attribute predictions (colors) for the no destructive fishing alternative. Only results for the conservation perspective are shown. The upper dotted line indicates the expected value of perfect information, the lower dotted line is at zero, the minimum possible EVPPI. Results for other perspectives and variables of interest are given in Figure SI 9. For our case study we used a bin size of 400.

5. Discussion

5.1. Relevance of value of information analysis for the case study

In the case study on coral reef fisheries management, we found that the attributes measuring consequences related to fish biomass, food security, and sales of fish groups had the highest EVPPI for at least one stakeholder preference profile. On the other hand, better estimates for the required patrolling effort had low EVPPI for any single and across stakeholder perspectives. Likewise, hard coral cover, which is routinely monitored and prominently reported, was not among the top three variables in terms of EVPPI for any perspective.

The analysis provided a reasoned and prescriptive focus for the design of future investigations for the decision case. The effect of the management alternatives on the reef fish, their catch, and livelihood impacts should be a focus of future data collection efforts to reduce decision uncertainty. However, this conclusion depends on the stakeholder perspective considered. For the conservation perspective, better knowledge about the amount of fish sold had low expected informational value, whereas for the livelihoods perspective better knowledge about the biomass of fish functional groups in the reef was not very relevant (Fig. 6).

Importantly, the EVPPI is not directly linked to the extent of uncertainty in the predictions (Fig. 3). Even though the coral cover had a wide distribution for each management alternatives, having perfect information on it did not have high informational value. Consequently, to improve decision robustness, it is not always the largest uncertainties that require addressing. Rather, it is the most decision-relevant uncertainties, which can be identified through the analysis of VoI.

This is in line with several studies that have investigated the factors that influence the VoI in a decision, but found it can vary in unexpected and sometimes counter intuitive ways (e.g., Eeckhoudt and Godfroid, 2000; Gould, 1974). Dependencies between alternatives can be one influencing factor: while we may be very uncertain about the future coral cover, we may be quite certain that one alternative results in higher coral cover than another (cf. Reichert and Borsuk, 2005).

Delquié (2008) has shown that under quite general assumptions the VoI is highest when a stakeholder's baseline choice is indifferent between two alternatives. The VoI decreases with increasing utility difference between the alternatives in the baseline case. Our results show the same pattern, as for the livelihoods and extraction preference profiles, which have a larger spread among the utility of alternatives (Fig. 4), the EVPPI is generally lower than for the other two preference profiles (Fig. 6).

Value of Information is specific to the investigated decision. If the informational value of a variable, e.g., coral cover, is low in a particular decision this does not imply we should stop regular monitoring. Historical baselines and operating protocols remain important and can be of great value in another decision and for improved understanding of the complex system dynamics.

5.2. Evaluation and outlook of VoI framework

This study showed how VoI analysis, and specifically the EVPPI, is a useful form of sensitivity analysis for decision models. Based on the approach in this study, we highlight three key directions for further development that we consider relevant in the context of environmental management decisions.

The first direction is extending the approach to uncertainty of preference model parameters. Standard utility theory (e.g., French, 1986; Keeney and Raiffa, 1993) does not consider uncertainty of preferences nor do any VoI applications we are aware of. However, in practice the stakeholder preferences are also uncertain and we have shown in this study that the preference model can make a substantial difference for the VoI analysis results. The uncertainty of stakeholder preferences could be included in VoI analysis by using the *expected expected utility* concept (Chajewska et al., 2000; Haag et al., 2019b). Considering the uncertainty about the consequences of management alternatives and the uncertainty about the societal evaluation of these consequences on equal footing in VoI analysis will allow us to differentiate better where further studies are actually needed. Depending on the case, the uncertainty about the social evaluation could be the primary cause for decision uncertainty (Gregory et al., 2006).

The second direction for development is improving uncertainty quantification of the variables of interest (e.g., the predictions). Quantitative VoI analysis is only meaningful to the degree that we can specify or infer probability distributions for these variables, ideally derived from empirical sources. The question of a variable's VoI is only ever addressed in the "small world" (Savage, 1954) of our specified model. However, the assessment of uncertainties in predictive system models is usually limited, especially regarding structure and dependencies. We also disregarded crucial structural uncertainties in the predictive reef model. Missing processes, such as changes in fish population structure might entail larger uncertainties than all the included parametric uncertainty. More comprehensive uncertainty assessments are a large task for the environmental modeling community, but there are many advances in this direction (e.g., Uusitalo et al., 2015; Reichert, 2020).

A way to address large uncertainties that are difficult to quantify – examples for reef systems are crown-of-thorns starfish outbreaks or powerful storms – are scenarios (e.g., Walker et al., 2003; Wright et al., 2019). Scenarios can be modeled by repeating the analysis for different possible futures – in the form of constraints or modified ecosystem processes – and qualitatively evaluating the differences in the conclusions. This would be possible without fundamental changes to the presented approach.

The third direction for development is advancing methods to estimate EVPPI more efficiently. Especially with environmental models that often entail significant computational effort, simulation-based approaches that rely on many model runs and resampling from conditional distributions, such a nested Markov-Chain-Monte-Carlo (Brennan et al., 2007; Felli and Hazen, 1998), are infeasible. The algorithm we implemented based on Strong and Oakley (2013) and Borgonovo et al. (2016) is fast, only requires a given probabilistic sensitivity analysis sample, and can handle conditional dependencies. On the other hand, it can only be sensibly used for investigating the EVPPI of single variables, and it still requires a large sample size.

An important consideration when using the proposed algorithm is the choice of the bin size J as this can lead to bias, as investigated in Section 4.4. As Strong and Oakley (2013) have also shown before, the upward and downward biases appeared for extreme values of J with a large region of stability in between these. However, in our case there were few estimates where such a stable region was small (Fig. SI-9). The conditions under which the algorithm can reliably be used thus require further investigation.

5.3. Value of information analysis to support iterative environmental management

VoI analysis is most useful if we can take actions to address the key uncertainties and improve the information state before or after decision making. Thus, it fits well with decision contexts that have an iterative aspect, such as the regular strategic considerations of environmental monitoring programs. For the case study, we presented the first steps of such an iterative approach. Based on the analysis results, we can decide to (a) move forward with implementation of the baseline optimal alternative, (b) gather more information if we deem the decision too sensitive to potential new information, or (c) conduct implementation and information gathering in parallel.

In the environmental domain, adaptive management is a common iterative approach and VoI analysis has been used to improve adaptive management decisions (e.g., Moore and Runge, 2012; Williams et al., 2011; Runge et al., 2011). In adaptive management, we plan monitoring and data collection activities in parallel to implementing a management alternative. There will be feedback processes in the system after implementing a management alternative that we need to take into account in long-term management. Therefore, the idea of revisiting the same decision context and updating our state of knowledge is key. This can include (1) updating changed stakeholder perspectives, (2) monitoring how the predicted trajectories have played out, (3) updating the future model predictions, and (4) coming up with the plan in terms of what to focus on for the next monitoring phase. In modeling approaches that optimize over iterative management problems, such as Markov decision processes, VoI analysis can also play an important role (Chadès et al., 2017; Williams et al., 2011; Williams and Johnson, 2018).

Using VoI in environmental management and conservation practice is still at an early stage, though its value is increasingly recognized (see studies in Bolam et al., 2019; Keisler et al., 2014). Along structured decision-making approaches (Gregory et al., 2012), many opportunities for broader application of VoI analysis beyond local management or conservation decisions exist. For example, VoI analysis can be of interest when designing large-scale research programs (Rushing et al., 2020) or monitoring programs (Bal et al., 2018).

The long-term benefits of investing in VoI analysis include a well-reasoned allocation of resources as it provides a ranked list of the expected benefit of addressing uncertainties. For VoI measures that are based on utility, this relative benefit can be difficult to interpret. If costs and benefits of additional information are not measured in the same units, we cannot directly determine which uncertainties we *should* resolve. Any practical decision about information collection requires making trade-offs with the (opportunity) cost of acquiring this information (e.g., Maxwell et al., 2015). A straightforward approach to this issue is a cost–benefit analysis to find the Pareto optimal set of cost-efficient information seeking activities (Marchese et al., 2018).

6. Conclusions

Difficult environmental decisions can benefit from structured approaches (Gregory et al., 2012) and the conceptual foundation of rational decision making under uncertainty is well established (Keeney and Raiffa, 1993; Reichert et al., 2015). Understanding the sensitivity of a decision to uncertainties remains a key challenge to support better decision making. Our intuitions about the benefit of more information may not be correct, but the costs of additional data acquisition are often high. We propose that sensitivity analysis known under the umbrella term value of information (VoI) analysis is useful to estimate the robustness of current conclusions and indicate where to focus future data collection.

The complexities of environmental issues make the practical application of VoI analysis challenging. In this study, we tackled VoI analysis in the framework of multi-attribute value/utility theory (MAVT/MAUT) with: (1) a continuous uncertain prediction space, (2) dependencies in the distribution of these predictions, (3) multidimensional objective functions that include trade-offs between objectives, and (4) divergent stakeholder perspectives. This included adapting a fast algorithm for estimation based on a probabilistic sensitivity analysis sample. We analyzed expected value of partially perfect information (EVPPI) for a decision model of local coral reef fishery management. This led to a ranking of the sensitivity of predictive uncertainty of management alternatives. Our framework can be used as a template for other decision cases.

Two simple, but practically relevant, conclusions were corroborated in our case study. First, the EVPPI of a variable cannot directly be mapped to the extent of uncertainty in that variable. Large uncertainties in predictions do not prevent robust decision making per se (cf. Reichert and Borsuk, 2005). More data collection is not always the answer. Second, the results of VoI analysis depend on the preference models used to evaluate the predicted consequences (cf. Delquié, 2008). The variables that stakeholders require more information on can differ. If we disregard the variety in stakeholder perspectives, any VoI analysis will give an incomplete picture of the actual value of a piece of information in a specific context.

Value of information analysis fits into many structured and iterative approaches to decision-making and assessment, such as adaptive management. It facilitates identifying and ranking (Fig. 6) key uncertainties and thus key aspects for further investigation and data collection. While the extent and intricacy of a quantitative modeling approach, as employed in this study, will need to be aligned with the concrete needs and resources available, any practical decision case can benefit from a deliberation about the value of new information. Which information – if any – would likely change our conclusions?

CRediT authorship contribution statement

Fridolin Haag: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Review & editing, Visualization. **Sara Miñarro:** Methodology, Resources, Writing – review & editing. **Arjun Chennu:** Conceptualization, Methodology, Resources, Writing – review & editing, Visualization, Supervision, Funding acquisition.

Declaration of competing interest

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

Data and software availability

The workflow to reproduce the analysis is available at https://doi.org/10.5281/zenodo.7156065. It depends on two submodules: the SEAMANCORE simulation model (https://doi.org/10.5281/zenodo.7155783) and an R package with functions for VoI analysis (https://doi.org/10.5281/zenodo.7155948). The dataset of simulation results from SEAMANCORE used in the analysis is available at https://doi.org/10.5281/zenodo.7156015.

Acknowledgments

We thank Daniel Schürholz for coding advice. This project benefited greatly from the resources of the ZMT Datalab; we are thankful to Miroslav Shaltev and Joscha Schmiedt for support. We also thank the three reviewers and the editor for their excellent comments and suggestions.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.envsoft.2022.105552.

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