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Assessing whether decisions are more sensitive to preference or prediction uncertainty with a value of information approach☆

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ABSTRACT

In many decisions, we are not only uncertain about the predicted outcomes of decision alternatives but also about stakeholder preferences regarding these outcomes. Further information collection may reduce uncertainties, but is costly. We present and apply a framework to identify the most decisive uncertainties and prioritize data collection efforts based on value of information (VoI) sensitivity analysis. Preference uncertainty is usually not explicitly considered in VoI analysis or in standard utility theory. Based on the expected expected utility (EEU) concept, we consider uncertain predictions and preferences jointly in decisions and subsequent VoI analysis. We focus on the expected value of partially perfect information (EVPPI) and adapt a fast, given-data algorithm for estimating this metric. The framework is motivated by complex environmental decision problems and we apply it to a hypothetical multi-criteria decision regarding coral reef management with conflicting stakeholder perspectives. The results show that better understanding of stakeholder positions can be as relevant as improving system understanding. For one perspective, preference model parameters had the highest EVPPI, while for another predictive uncertainties of the reef system attributes were more relevant. For two perspectives, the decision was largely insensitive. By considering predictive and preferential uncertainty on an equal footing in VoI analysis, we open up possibilities to design data collection for decision support processes more efficiently.

1. Introduction

Uncertain predictions about the outcomes of decision alternatives and uncertain preferences regarding these outcomes complicate decision-making processes. Yet, both uncertainties are prominent in many critical decisions, for instance, about long-term strategy, public planning, or environmental management (e.g., [1–3]). An intuitive response to uncertainties is to ask for more information, better science, or additional studies — expecting this will reduce uncertainties and then allow definitive conclusions about the best alternative to implement. However, this is not always the case. Additionally, collecting more information to reduce uncertainties – for instance, by improving predictive modeling or by more detailed preference elicitation – is often difficult, and thus costly.

A more principled approach to guide the resolution of key decision uncertainties is offered by the value of information concept (VoI; [4]). Value of information analysis can be conceptualized as a form of global sensitivity analysis [5,6], with the aim of determining which uncertainties a decision is expected to be most sensitive to. Understanding this sensitivity is critical to prioritizing further research and data collection efforts. In practice, we want to know whether the use of limited resources to gather additional information is justified by the potential to improve decision making. Value of information analysis is a well-established collection of methods with many applications (see reviews by Bolam et al. [7], Keisler et al. [8], Zhang et al. [9], Viet et al. [10]).

Even though VoI analysis can be applied to any uncertainties in a decision, uncertain preferences have not received much attention in the applications of VoI analysis (see reviews cited above). While the impact that variable preferences can have on VoI conclusions has been recognized before [11,12], VoI analysis usually investigates parameters or inputs of predictions and assumes a known objective function. This was also the setting of a previous study of ours, Haag et al. [12]. In this paper, we extend the framework to uncertain preferences. This is critical, because even perfect information about the outcomes may not help to practically tackle a decision if the uncertainty and conflict is about the (societal) *evaluation* of these predictions (cf. [13]).

One reason for disregarding preference uncertainty may be that standard utility theory assumes preferences to be static and certain

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[14]. Still, various methods for tackling preference uncertainty have been developed, including fuzzy (e.g., [15]) and interval-based approaches (e.g., [16]). Our focus is on preference uncertainty that can be described probabilistically. In this case, uncertain preferences lead to a distribution of expected utilities; a situation for which utility theory makes no provision for rational choice. Common approaches based on stochastic multi-criteria acceptability analysis (SMAA) resolve this by calculating acceptability indices to guide decision-making (e.g., [17–19]). In this study, we instead use an extension of utility theory.

The importance of considering uncertain preferences in utility theory has long been recognized and addressed with the concepts of *adaptive utility* [20–22] and *expected expected utility* (EEU; [23]). These terms can be considered interchangeable and we use "EEU" in the following. While it is possible to determine a rational baseline choice given uncertainty in predictions and preferences in this way [2], we need additional considerations to investigate the sensitivity of this choice.

As has been conceptualized by Chajewska et al. [21] and Houlding and Coolen [22], VoI analysis can be conducted in conjunction with EEU to determine the value of having information on uncertain preference parameters. So far, this idea has been used mostly with regard to adaptive or sequential preference elicitation, in which VoI analysis was proposed to determine queries to ask (e.g, [21,24–26]). We are not aware of practical implementations of VoI analysis to jointly consider preferential and predictive uncertainty in decision cases.

The main question in this study is: How can we assess the sensitivity of complex decisions to preference and prediction uncertainty? Only by looking at uncertainties of preferences and predictions on an equal footing, can we sensibly prioritize our data collection efforts to tackle the most relevant uncertainties.

We develop our answer to this question by combining existing methods in a novel way. First, we propose a framework to model the decision and its preference and predictive uncertainties drawing mainly on multi-attribute value/utility theory (MAVT/MAUT; [14]) and EEU (Section 2.2–2.3). Secondly, we operationalize the VoI concept for use with both types of uncertainties (Section 2.4). This starts from a view of VoI analysis as form of global sensitivity analysis and uses the expected value of partially perfect information (EVPPI) as the sensitivity measure [5,6]. Lastly, we need to estimate the EVPPI practically. For this, we adapt and tune an algorithm by Strong and Oakley [27] for use with EEU (Section 3.1). The algorithm follows a given-data approach that only requires a sample of inputs, parameters, and utilities as commonly obtained from uncertainty analysis.

The motivation for this work comes from environmental management decisions. To validate and critique our approach, we apply it to a hypothetical decision case about coral reef management (Section 4–5). This is a complex decision with large uncertainties and difficult trade-offs to make [28]. This case was already investigated in Haag et al. [12], but we now frame the decision as an iterative decision problem where we start with minimal, and thus uncertain, preference information from diverging stakeholder perspectives. These perspectives were emulated based on assumptions, aiming to reflect potential stakeholder views. With our approach we could efficiently calculate the EVPPI of uncertain variables. We obtain a ranking of key uncertainties – both predictive and preferential – that guides targeted information collection for the next iterative step in decision support.

2. Framework for value of information analysis with uncertain utility

2.1. Conceptual overview

To quantify whether decisions are more sensitive to preference or prediction uncertainty, we need to operationalize these abstract concepts. This requires a framework for representing uncertain predictions and uncertain preferences in decisions. This section summarizes the key concepts that will be developed in a more technical way in the subsequent sections.

Our knowledge about a decision can be captured by a decision model. This model can help select one alternative a (or a subset of alternatives) out of a set A of alternatives. A decision model to choose between management alternatives consists of (1) a predictive model and (2) a preference model. The predictive model quantitatively *estimates* the (uncertain) outcomes of implementing the alternatives in terms of system attributes. The preference model then *evaluates* these predicted outcomes from the perspective of the decision makers or stakeholders involved in the decision.

We care about outcomes because they affect what we value. Therefore, alternatives are evaluated in terms of the objectives of a stakeholder. Typically, multiple objectives are relevant in a decision. These are often structured in a hierarchy with higher-level objectives and sub-objectives ([14]; Fig. 3 as an example).

The aim of the decision modeling process is to help select the alternative that will lead to the most preferred outcomes. One way to determine this alternative is calculating the expected utility (EU) of all alternatives and choosing the one with highest EU [14]. However, this is not possible if preferences are uncertain as well. For this case, we propose to use the EEU concept [21–23] to determine the best alternative (Section 2.2). To evaluate the alternatives, we propose to construct a multi-attribute value or utility function that represents stakeholder preferences ([14,29]; Section 2.3)

Our current state of information about the decision can be encoded in probability distributions of the decision model parameters or inputs. We would like to prioritize the resolution of uncertainties by determining which will have the highest impact on the conclusions of our decision modeling. To this end, we use VoI sensitivity analysis. In Section 2.4, we describe the adaption of this analysis from its established use with the EU as decision criterion (e.g., [30]) to employing the EEU criterion.

In many decisions, it is important to consider the perspectives of multiple stakeholders. How to best address this in decision modeling remains an open question. Belton and Pictet [31] suggest three processes that can be applied to the elements of a decision process with multiple stakeholders: sharing, aggregating, and comparing. In the following, we assume that the alternatives, predictions, and the objective hierarchy are shared among stakeholder perspectives, but the preference models and their parameters differ. In the process, we compare the results obtained for different perspectives, rather than aggregating results or model parameters.

2.2. Decisions based on expected (expected) utility

When our knowledge about the outcomes of an alternative $a \in A$ is certain, or we disregard uncertainty, we can describe it by the resulting levels of the attributes when implementing this alternative, $\boldsymbol{y_a} = (y_{1,a}, \dots, y_{n,a})$. In case our knowledge is uncertain, it is better described by a random vector $\boldsymbol{Y}_a = (Y_{1,a}, \dots, Y_{n,a})$ with a joint probability distribution $p_a(\boldsymbol{y})$ that quantifies the uncertainty about these outcomes. In the following, we assume that we have obtained a probabilistic description of the uncertain outcomes, for instance, from a predictive system model. With $\mathcal{Y}$ we denote all possible outcomes for all attributes that are regarded as relevant for the decision.

A multi-attribute value function $v : \mathcal{Y} \rightarrow [0, 1]$ provides a valuation of potential outcomes with larger values representing preferred states [14]. When the outcomes are certain, the alternatives' ranking can be found by computing the value $v(a) = v(\boldsymbol{y}_a)$ for each alternative a in A. A decision is rational if the alternative with the highest value is selected.

For decisions with uncertain outcomes, a multi-attribute utility function $u : \mathcal{Y} \rightarrow [0, 1]$ returns the utility of potential outcomes [14]. A utility function takes into account not only preferences about outcomes (i.e., the value), but also preferences about risk. If a stakeholder is risk neutral, the utility function is identical to the value function.

Given a utility function, we can calculate the EU for an alternative, conditional on the preferences and the uncertain outcomes. In the case of continuous distributions, the EU of an alternative a is given by:

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

with $p_a(\boldsymbol{y})$ the probability distribution of the outcomes of implementing alternative a, as measured by the system attributes. By calculating the EUs of all considered alternatives, we can determine their ranking. A decision is rational, if the alternative with the highest EU – $\max_{a \in A} \mathbb{E}[u(\boldsymbol{y}_a)]$ – is selected.

We suggest using a parameterized function as utility function $u(\boldsymbol{y}, \theta_s)$ with parameters θ_s for each stakeholder s. As we consider each stakeholder separately, we omit the subscript s in the following notation.

In case the preferences are uncertain, this can be captured by using probability distributions for the parameters $\boldsymbol{\theta}$. Our utility function becomes a random variable u_θ [32]. As a result, we receive a distribution of EUs. Uncertainty about a stakeholder's utility function means they are unsure which EU they will receive when choosing an alternative.

Standard EU theory does not offer a rationale for selecting or ranking alternatives based on such distributions of utilities. However, it seems reasonable to assume that a rational decision-maker will select the alternative with the highest expected value of these expected utilities. This is the rationale behind the EEU, as has been suggested by, e.g., Boutilier [23], Chajewska et al. [21], Houlding and Coolen [22].

For the EEU to be justified as a criterion for rational decision making, all considered utility functions must be commensurate. This is the case, if these functions are extremum equivalent [23]. Specifically, for all utility functions the same most favorable and the same least favorable outcome have to exist and all have to assign the same utility to the best outcome (e.g., 1) and the same utility to the worst outcome (e.g., 0). Since the utilities are only unique up to an affine transformation, this must be restricted if we want to take the expectation over a distribution. We believe this should be possible in most practical applications. Houlding and Coolen [22] provide suggestions for weakening the requirement of extremum equivalence at the expense of making elicitation more difficult.

The EEU of an alternative a, with the probability of outcomes given by $p_a(\boldsymbol{y})$, for a stakeholder with a parameterized utility function $u(\boldsymbol{y}, \theta)$ and a distribution of these parameters $p(\theta)$ is:

$$\begin{aligned}\mathrm{EEU}(a) = \mathbb{E}\left[u(\boldsymbol{y}_a, \boldsymbol{\theta})\right] &= \int_\theta \left(\int_y u(\boldsymbol{y}, \boldsymbol{\theta}) \cdot p_a(\boldsymbol{y})\mathrm{d}y \right) p(\boldsymbol{\theta})\mathrm{d}\theta \\ &= \int_\theta \int_y u(\boldsymbol{y}, \boldsymbol{\theta}) \cdot p_a(\boldsymbol{y}) p(\boldsymbol{\theta})\mathrm{d}y\mathrm{d}\theta \end{aligned} \tag{2}$$

The inner integral is simply the EU for specific parameter values θ (Eq. (1)).

2.3. Parameterized hierarchical multi-attribute utility models

Application of EEU theory to support decision making requires us to have a multi-attribute utility function $u(\boldsymbol{y}, \theta)$ that represents a stakeholder's preferences and estimate its parameters. Directly identifying such a function is difficult. However, it can be constructed in a stepwise and hierarchical manner. In the following we summarize the main suggested steps, further details can be found in, e.g., Reichert et al. [1], Haag et al. [33], Haag et al. [2].

In multi-attribute utility theory, the objectives hierarchy is used to structure the value or utility function [14]. After we have elicited this model structure, we can construct a utility function for evaluating the overall objective in three steps:

(1) For each lowest-level objective, a value function $v_i(y_k, \dots, y_l, \phi_i)$ with parameters ϕ_i is specified to evaluate the objective with respect to its predicted attributes $y_k, \dots, y_l$. As a lowest-level objective refers to a specific concept, its value function commonly only depends on a single attribute or few attributes. The value function represents the trade-offs one would make regarding attribute outcomes. For instance, the additional value one receives from an additional unit of fish catch might diminish.

(2) To evaluate each higher-level objective, the evaluations of its sub-objectives are aggregated. This represents the trade-offs one is willing to make between different objectives. We write the multi-attribute value function over the lower-level objectives $o_p, \dots, o_q$ on a specific hierarchical level as:

$$v_{p,q}(y_1, \dots, y_n, \boldsymbol{\theta}) = F(v_p(y_1, \dots, y_n, \theta_p), \dots, v_q(y_1, \dots, y_n, \theta_q), \theta_{pq}) \tag{3}$$

where θ_i are the parameters of the respective value functions and F is an aggregation function [34] that depends on the values of the sub-objectives. In practical settings, each value function v_i will only depend on a subset of the attributes $y_1, \dots, y_n$.

For a hierarchy with several levels, the evaluations are progressively aggregated level by level along the hierarchy, until an overall evaluation is reached. This means nesting multiple aggregation functions in accordance with the hierarchy [33]. Generally, the hierarchy implies independence conditions between objectives and therefore already is part of a stakeholder's preference structure [2].

The aggregation function predominantly used in practice is the weighted arithmetic mean:

$$F_{add}(v_1, \dots, v_n) = \sum_{i=1}^{n} \omega_i \cdot v_i, \quad \text{with} \quad \sum_{i=1}^{n} \omega_i = 1 \tag{4}$$

Its parameters are weights, $\boldsymbol{\omega}$, also called scaling factors. If we use this aggregation function on all levels of the hierarchy, the resulting preference model is called the additive model or simple additive weighting [14,29]. However, it is only a valid representation of a stakeholder's preferences if independence conditions are fulfilled [14] and many alternative aggregation functions with other premises exist (see [33,34] for discussion).

A useful family of aggregation functions in decision models are weighted generalized means (also called weighted power means). They have the form:

$$F_{pow}(v_1, \dots, v_n) = \begin{cases} \left(\sum_{i=1}^{n} \omega_i \cdot v_i^\tau\right)^{1/\tau} & \text{for } \tau \in \mathbb{R}^* \\ \prod_{i=1}^{n} v_i^{\omega_i} & \text{for } \tau = 0 \end{cases} \tag{5}$$

with weights $\boldsymbol{\omega}$ that sum to unity, as in Eq. (4), and an additional parameter τ that allows us to represent different mean functions and thus different trade-off behavior [2,34]. For $\tau = 1$ the weighted generalized mean is identical with the weighted arithmetic mean.

(3) A value function can be converted to a utility function based on a stakeholder's risk attitude [35]. For example, a stakeholder may be risk averse and prefer avoiding uncertain outcomes despite higher expected value of these. Practically, it is often most feasible to assess a one-dimensional utility function over the value function at the highest hierarchical level (e.g., [1]). In the following, we only consider the case of risk neutrality, as this simplifies VoI calculations (see Section 6.1).

2.4. Value of information for analyzing decision sensitivity

With a fully specified decision model, we can calculate the EEU of alternatives and determine an optimal baseline choice, a^*, given our current uncertain state of knowledge about predictions and preferences. However, for any iterative data collection or decision making approach, we want to determine the sensitivity of our decision to potential new information. This sensitivity can be thought of and measured in different ways [5,36].

Here, we focus on VoI analysis, which is a type of global sensitivity analysis that measures the expected effect of reducing uncertainty about inputs and parameters on the decision. For determining the sensitivity of a decision, it takes into account the probability of a change in the best alternative and the utility gain of switching to the

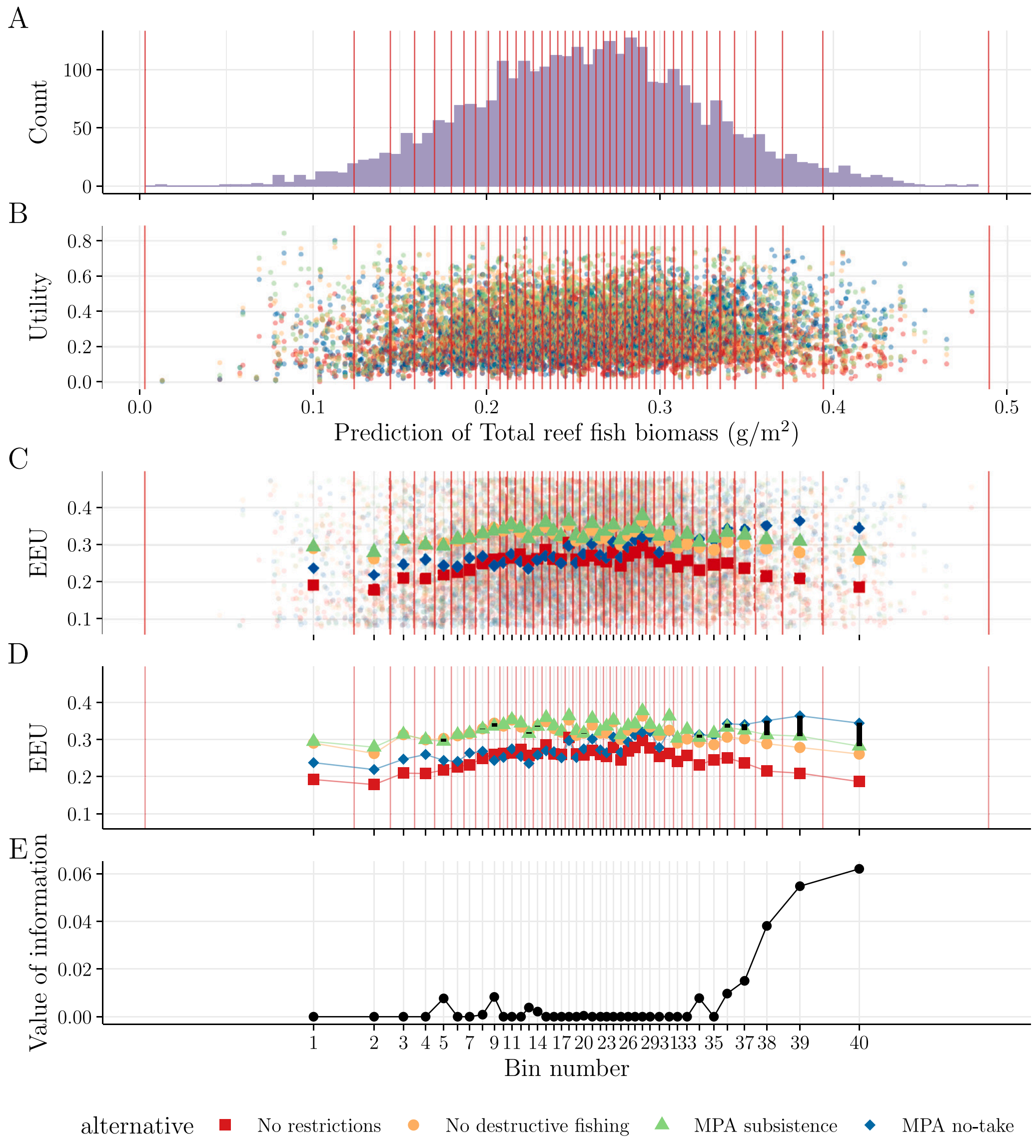

Fig. 1. Visualization of the steps in the given-data algorithm for estimating expected value of partially perfect information (EVPPI), based on the work of Strong and Oakley [27]. (A) The sample of the variable of interest is ordered and partitioned into bins of equal sample size (vertical lines). (B) We create a scatterplot of the random utilities corresponding to these samples. (C) In each bin, we calculate the EEU of the alternatives. (D) In each bin, we calculate the difference between the EEU of the baseline optimal alternative and the alternative with highest EEU in the bin (black bars). (E) This is the value of information, given that the variable of interest is in this bin. By averaging over the bins, we receive the EVPPI.

now better alternative [5,12,36]. Thus, despite its name, VoI analysis does not provide an absolute measure of the value of some information for a practical decision situation. Different measures of VoI exist and are well established for decisions based on EU (e.g., [30]):

- The expected value of perfect information (EVPI) measures the effect of knowing all aspects or parameters of the decision with certainty.
- The expected value of partially perfect information (EVPPI, sometimes abbreviated EVPXI) measures the effect of knowing one or more aspects of the decision with certainty, but remaining uncertain about the rest. The EVPI is thus an upper limit for the EVPPI. In this study, we focus on EVPPI.
- The expected value of sample information (EVSI) measures the effect of obtaining some specified additional data about a decision aspect, as perfect information is usually not achievable. The EVPPI thus is an upper limit for the EVSI.

If we have no further information, the optimal decision is to choose the alternative a^* with highest EEU. The EVVPI quantifies the benefit we can expect if we could choose the optimal alternative after learning about the actual value of an uncertain variable of interest, $V_* = v_*$, instead of staying with the baseline optimal alternative a^*. The value of the additional information, therefore, is the difference between the expected payoff that would be achieved under posterior knowledge and the expected payoff under current, prior knowledge. As V_* is generally not independent of the other variables in the decisions, the posterior knowledge includes the conditional distributions of these variables.

When we are uncertain about preferences and predictions at the same time, this requires a generalization of the classical EVPPI calculation, as additional information about either aspect can change the EEU we expect to receive. As common in EU theory, we assume that preferences are not state-dependent, i.e., additional information about outcomes will not change the preferences regarding the outcomes. Still, the uncertain preferences will affect the EVPPI of predictions and vice versa (see [22] for discussion). If we cannot assume that preference parameters are independent of outcomes, we would also need to condition them on the additional information about the predictions.

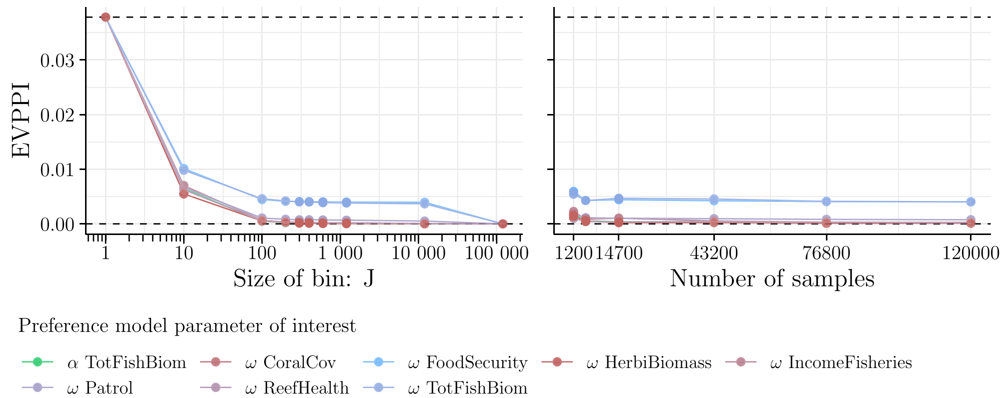

Fig. 2. Dependence of the estimated EVPPI (y-axis) on the bin size parameter J (x-axis; left side) and on the sample size S (x-axis; right side) when using the estimation algorithm. The variables of interest are a subset of parameters of the utility model (colors) for the conservation perspective. The upper dotted line indicates the EVPI, while the lower dotted line at zero indicates the minimum possible EVPPI. The estimation is stable over a range of bin sizes and sample sizes. Figs. SI-6–9 show results for other perspectives and variables of interest, including predictive uncertainties.

Moving from the EU to the EEU setting for VoI calculations can be achieved by replacing the known utility function with a random utility function with parameter distribution $p(\theta)$ and taking the expectation also over this distribution (conditioned on V_*). For the case of risk neutrality, the EVPPI of an uncertain variable V_* based on the EEU (Eq. (2)) can be expressed as:

$$\begin{aligned}\mathrm{EVPPI}(V_*) &= \mathbb{E}\left[\max_{a\in A}\left\{\mathbb{E}[u(\boldsymbol{y}_a,\boldsymbol{\theta}|V_*)]\right\} - \mathbb{E}\left[u(\boldsymbol{y}_{a*},\boldsymbol{\theta}|V_*)\right]\right] \\ &= \mathbb{E}\left[\max_{a\in A}\left\{\mathbb{E}[u(\boldsymbol{y}_a,\boldsymbol{\theta}|V_*)]\right\}\right] - \max_{a\in A}\left\{\mathrm{EEU}(a)\right\}\end{aligned} \tag{6}$$

The VoI of knowing that V_* takes on a specific value v_* then is the difference between the maximum EEU of the decision given this value, $\max_{a\in A}\left\{\mathbb{E}[u(\boldsymbol{y}_{a*},\boldsymbol{\theta}|V_*=v_*)]\right\}$, and the EEU of the baseline optimal alternative given this value, $\mathbb{E}[u(\boldsymbol{y}_{a*},\boldsymbol{\theta}|V_*=v_*)]$. As the values of V_* are unknown, we take the expectation over its distribution to obtain the EVPPI. Importantly, the variable of interest V_* can now be a preference parameter or a parameter or input regarding the predictions.

3. Estimation of the value of information

3.1. Simulation approach to value of information analysis

To obtain VoI analysis results and prioritize uncertainties, we need to calculate the EVPPI of variables. This involves computing the EEU of alternatives. Analytical solutions for both measures are rare for complex decision as we encounter them in practice. Therefore, we present a general simulation approach for estimating EEU and EVPPI. This procedure also allows calculating thresholds for variables of interest where the ranking of alternatives changes.

To estimate the EEU of an alternative, we use a Monte Carlo approach. First, we draw S samples from the joint probability distribution of all predictions, taking into account dependencies between attributes. Since the preference parameters are independent of the predictions, we likewise draw S samples from the joint distribution of the preference parameters. We then pair each prediction sample with its corresponding preference sample based on their draw order. The dimensionality of each paired sample is given by the total number of attributes and preference parameters. Second, for each sample, we calculate the resulting utility. The expectation of these utilities is an estimate of the EEU (Eq. (7)).

$$\mathrm{EEU}(a) = \frac{1}{S}\sum_{i=1}^{S} u(\boldsymbol{y}_{a,i},\boldsymbol{\theta}_i) \tag{7}$$

For estimating the EVPPI, we could similarly follow a nested Monte-Carlo approach (e.g., [5]). It consists of two loops. The variable of interest is sampled in an outer loop and, conditional upon this, the remaining uncertain variables are sampled and the resulting VoI is calculated in an inner loop. By averaging over these values of information, the EVPPI is estimated. However, for real-world problems the number of required model runs and associated computational cost quickly become prohibitive [37]. One suggested alternative approach for estimating EVPPI are surrogate models or emulators [38,39].

Based on work by Strong and Oakley [27] and Borgonovo et al. [6], we propose to use a *given-data* approach as a further alternative. It is a single-loop approach that relies on a probabilistic sensitivity analysis sample. Our aim is to estimate EVPPI of individual variables, such as predictions for an attribute of an alternative, or a preference model parameter. To this end, we adapt and implement a fast algorithm for estimating the EVPPI for decisions with uncertain predictions and uncertain preferences (Fig. 1). The idea and algorithm has been developed by Strong and Oakley [27] using *net benefit* instead of the EEU as decision criterion. An adaption to EU has been provided by Haag et al. [12].

For EVPPI estimation with this algorithm, we first create a sample of all parameters and inputs (see above) and then calculate the resulting utility for each sample with our prediction and preference models. This is a common step in many types of probabilistic sensitivity analysis. We do not require any specific (experimental) design to create the sample [36]. The algorithm then uses this sample of inputs, parameters, and utilities to estimate EVPPI, as detailed below. Hence its characterization as given-data algorithm.

The variable of interest for which we want to calculate the EVPPI we again denote V_*. We construct a matrix with S rows and $n(A)+1$ columns by assigning the S samples of the variable of interest V_* to one column and the corresponding utilities u_a for the $n(A)$ management alternatives to the remaining columns.

Now we sort the rows of this matrix – indexed by $1,\ldots,S$ – such that the values of V_* increase with the row index, i.e., $v_*^{(1)} \le v_*^{(2)} \le \cdots \le v_*^{(S)}$. The superscript denotes the reordered position. This results in a particular sample of the variable of interest being similar to samples with neighboring indices but dissimilar to samples on positions further away.

We partition this reordered matrix into K bins of equal size J, with $J\times K = S$ (panels A and B Fig. 1). For each of these bins, we calculate the EEU for each alternative (analogous to Eq. (7), panel C Fig. 1) and then take the maximum across the alternatives. This approximates the maximum EEU, given that the value of variable V_* falls into this bin. Crucially, this factors in the effect of the conditional distributions of all other inputs and parameters that are part of calculating the EEU.

The arithmetic mean of the maximum EEU in each bin over all K bins is then taken as estimate for the first term in Eq. (6):

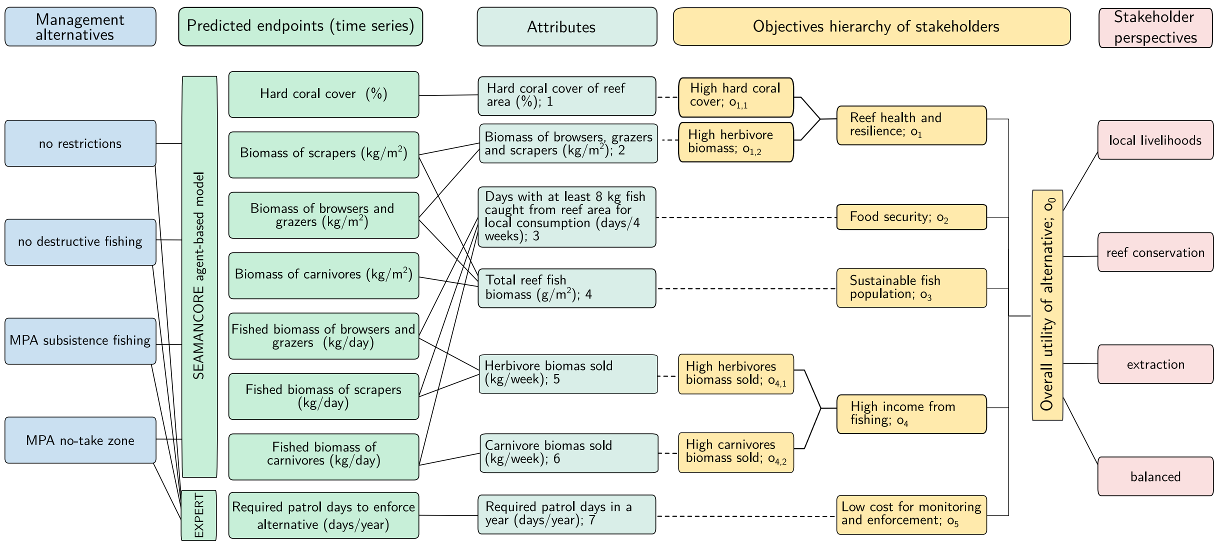

Fig. 3. Scheme of the relevant elements in the coral reef management decision. Alternatives (boxes to the left) lead to different outcomes on a number of attributes. These outcomes are predicted by a mathematical model or expert judgement. Predicted model outputs are transformed to attribute values that measure decision-relevant outcomes of management alternatives (middle). These outcomes are evaluated along a hierarchy of objectives that represents the structure of the preference model. In the evaluation, outcomes that are measured by the attributes are mapped to an aggregated utility. This evaluation was repeated for different stakeholder perspectives (right side). Figure adapted and expanded from Haag et al. [12].

$\mathbb{E}\left[\max_{a\in A}\left\{\mathbb{E}[u(\boldsymbol{y}_a,\boldsymbol{\theta}|V_*)]\right\}\right]$. The second term of Eq. (6), the EEU of the baseline choice, $\max_{a\in A}\{\mathrm{EEU}(a)\}$, has already been estimated when calculating the baseline choice with Eq. (7).

This procedure is repeated separately for all variables of interest. The approximation of the conditional distributions of variables and utilities achieved by the sorting and binning strategy eliminates the need for conditional resampling and recalculation of utilities that we have in the nested Monte Carlo approach. This typically results in a significant speed-up, as additional prediction or preference model computations are eliminated.

In some cases, we are less interested in an aggregate measure, such as EVPPI, but rather in the variation of the alternative's EEU, given variation in a specific variable V_*. This allows identifying threshold values of that variable, where the ranking of alternatives changes, and also regions of stability. Identifying thresholds is often done with local sensitivity analysis approaches. However, they typically do not consider the conditional distributions of the other inputs and parameters given values of V_*. With the presented algorithm we can take these into account and estimate the relationships in a global sensitivity setting [12].

The relationship between specific values of V_* and the EEU of alternatives can be approximated by calculating both the arithmetic mean of the variable of interest and the resulting EEU of the alternatives for the same bin. The calculation of the EEU takes into account the conditional samples of the other variables, given that the values of V_* fall into the bin. We can then create a scatterplot of the relationship (Fig. 7) or fit a statistical model to this data. Additionally, we can identify thresholds for V_*, where the best alternative changes.

3.2. Tuning of the estimation algorithm

In the estimation algorithm for EVPPI we can choose the bin size, J, (or the number of bins) and the sample size S. To evaluate the sensitivity of the proposed estimation algorithm to these parameters, we conducted a step-wise local sensitivity analysis, based on the case study that is detailed in Section 4. For a sample size of S = 120000, we recalculated the EVPPI results for different bin sizes ($J = \{1, 10, 100, 200, 300, 400, 600, 1200, 12000, 120000\}$). In a second analysis, we varied the sample size ($S = \{1200, 4800, 14700, 43200, 76800, 120000\}$). As the sample size restricts the possible bin size, we also changed the bin size under the constraint that $J/K = 4/3$, i.e., $J = \sqrt{3S/4}$, as this seemed a sensible ratio based on the first analysis.

The choice of J can significantly affect the resulting estimate [12, 27]. In our test case, most EVPPI estimates were stable when using from 100 bins with 1200 samples each to 1200 bins with 100 samples each (Fig. 2 and Figs. SI-6–7). However, in specific circumstances, estimates can be sensitive to the bin size (e.g., predicted herbivore biomass sold in Fig. SI–6).

For small bin sizes, the estimator is biased upward due to the maximization step. As $J \to 1$ the estimates converge to the EVPI across all variables. For large bin sizes, the estimator exhibits downward bias. Estimates for EVPPI converge to zero as $J \to S$, since both terms of Eq. (6) become equal.

For the analysis of the sample size S, we also find a large region in which EVPPI estimates are stable (Fig. 2 and Figs. SI-8–9). However, sample sizes lower than 4700 were not always stable. Generally, with low sample size, EVPPI tends to get overestimated. Since the sample size also determines the maximum bin size, this might be an indirect effect. For example, with S = 1200 we used 30 bins with size of only J = 40.

4. Implementation for a coral reef management case

4.1. Decision problem description

To apply and test our suggested framework and simulation approach in a case with realistic complexity, we investigate a hypothetical coral reef management decision for an island in the Indo-Pacific. Decisions about the local management of coral reefs are difficult because they are complex ecosystems and the reefs and associated fisheries contribute to a variety of needs in often resource-constrained socio-economic contexts [28,40]. This case study has been described in detail in Haag et al. [12] and we use the same problem structure and prediction data. However, instead of assuming specific preference profiles, we now explicitly model preference uncertainty (see details in Section 4.2).

The decision aim is improving fisheries management for a local reef area. The decision is made to better fulfill societal objectives. These are captured in an objectives hierarchy (Fig. 3). The outcomes of the four proposed management alternatives (see below) are evaluated from different societal perspectives. In this study, the perspectives we have

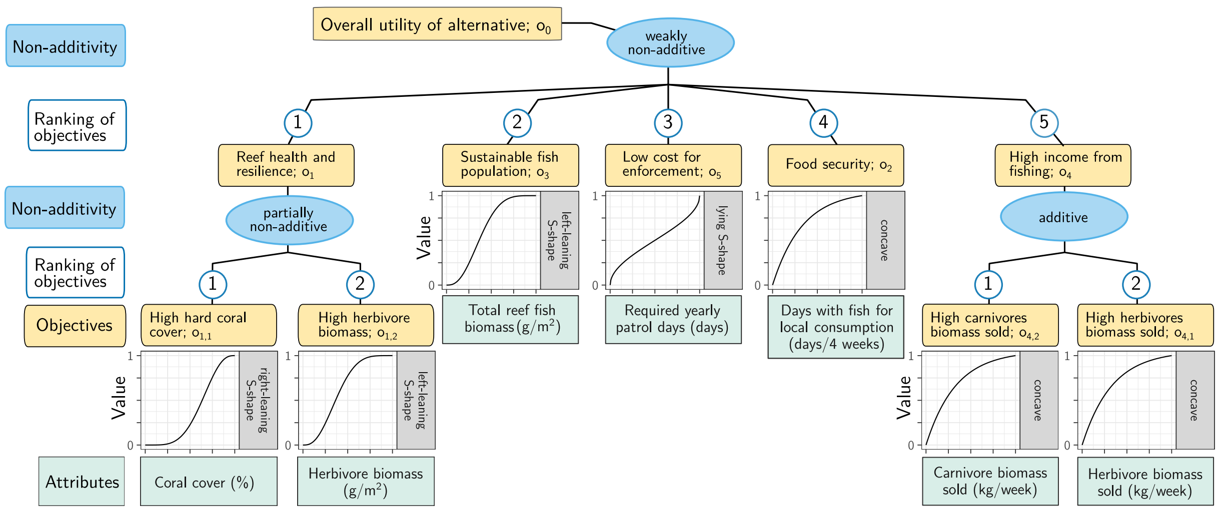

Fig. 4. Scheme of the qualitative and ordinal preference statements of the conservation perspective structured along the objectives hierarchy (Fig. 3). These statements were used to determine the shape and parameter distributions of the utility function (Eq. (8)). On the lowest level of the hierarchy, attribute predictions are mapped to values with value functions that can have different shapes (Fig. SI-2). Descriptive statements about the shapes were mapped to functional forms and parameters (Table 1). The individual values are aggregated to come to an overall evaluation. The aggregation considers the degree of non-additivity (blue ellipses) as well as the ranking of objectives on each hierarchical level (blue circles). The degree of non-additivity was mapped to an aggregation parameter distribution and the ranking to a distribution of weight parameters (Table 1). Specifications for the other perspectives are given in Tables SI-2–3.

Table 1
Mapping of parameter distributions used in the preference model, based on descriptive statements (Fig. 4, Tables SI-2–3). $U(min, max)$: uniform distribution; $B(a, b)$: beta distribution.

Descriptive statement	Functional form	Parameter distributions and constraints
Lowest-level value function shapes		
Linear	Exponential; Eq. (9)	$\gamma \sim U(-1, 1)$
Convex	Exponential; Eq. (9)	$\gamma \sim U(0, 6)$
Concave	Exponential; Eq. (9)	$\gamma \sim U(-6, 0)$
Right-leaning S-shape	CDF Beta; Eq. (10)	$\alpha \sim U(1, 10), \beta \sim U(1, 10)$, constraint: $\alpha > \beta$
Left-leaning S-shape	CDF Beta; Eq. (10)	$\alpha \sim U(1, 10), \beta \sim U(1, 10)$, constraint: $\beta > \alpha$
Lying S-shape	CDF Beta; Eq. (10)	$\alpha \sim U(0.2, 0.8), \beta \sim U(0.2, 0.8)$
Aggregation functions		
Additive	Weighted arithmetic mean; Eq. (4)	
Weakly non-additive	Weighted power mean; Eq. (5)	$\tau \sim B(7.2, 4.8)$
Partially non-additive	Weighted power mean; Eq. (5)	$\tau \sim B(3, 7)$
Weight parameters $\boldsymbol{\omega}$		
Ranking of importance		ω from $n-1$ dimensional simplex $\Omega_n = \{\omega \in \mathbb{R}^n \mid \omega \geq 0 \text{ and } \sum_{i=1}^{n} \omega_i = 1\}$ constraints: order of weights according to ranking

developed do not represent actual stakeholders, but rather elucidate the decision situation from contrasting viewpoints. They differ in their utility model and the uncertain model parameters (see Section 4.2). The perspectives are:

- conservation perspective: focused on ecosystem health,
- extraction perspective: focused on fishery yield and economic benefits,
- local livelihoods perspective: focused on ensuring food security and economic benefit to locals,
- balanced perspective: focused on the balance of different interests.

To achieve the objectives, we developed four management alternatives with decreasing degrees of fishing pressure:

- *no restrictions*: no restrictions and therefore continued intense fishing pressure, including destructive fishing,
- *no destructive fishing*: enforcement of a ban on destructive bomb and cyanide fishing,
- *MPA subsistence*: implementation of a marine protected area (MPA) with only subsistence fishing for locals allowed,
- *MPA no-take*: implementation of a strict MPA, making it a no-take zone.

If the management alternatives were implemented, this would lead to different outcomes regarding various aspects of the island's socio-ecological system (see Section 4.3). Outcomes that are relevant for deciding between the management alternatives are measured by specific system attributes (Fig. 3 and Table SI-1).

Our core question for the case study is: which of the predictive or preferential uncertainties should be most urgently resolved to arrive at a robust management decision? This question is answered by a VoI analysis based on the EVPPI measure.

4.2. Preference models for stakeholder perspectives

For each of the four stakeholder perspectives, we constructed a preference model in the form of a hierarchical multi-attribute utility function (see 2.3) to represent the interests. The hierarchical structure

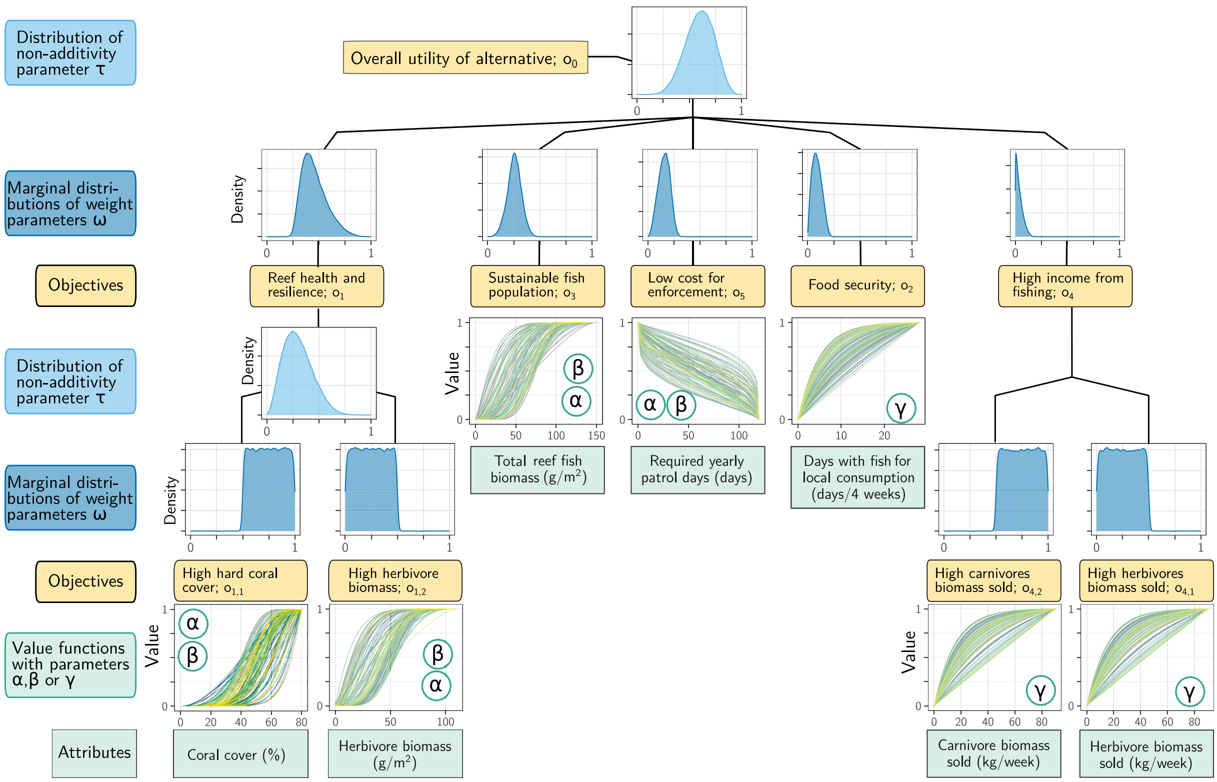

Fig. 5. Parameter distributions of the hierarchical utility function that were obtained by mapping the qualitative and ordinal statements (Fig. 4) to functional forms and parameter distributions (Table 1). Parameters of the lowest-level value functions (α, β, γ; distributions shown in Fig. SI-3) induce different possible value functions (line plots) that map from attribute predictions to values. The individual values are aggregated along the hierarchy by an aggregation function with weight parameters ω (darker distributions) and in the case of non-additive aggregation an additional parameter τ (lighter distributions). Figure shows the parameters of the conservation stakeholder perspective. Results for other perspectives are given in Figs. SI-3–5.

(Fig. 4) is shared between the perspectives, while the specific functional forms and parameters differ. The overall preference model for evaluating the utility of a sample of outcomes of an alternative a can be written as (for indices refer to Fig. 4):

$$\begin{aligned} u(\boldsymbol{y}_a, \boldsymbol{\theta}) = F_0(&F_1(v_{o_{1,1}}(y_1, \boldsymbol{\phi}_{o_{1,1}}), v_{o_{1,2}}(y_2, \boldsymbol{\phi}_{o_{1,2}}), \boldsymbol{\omega}_{F_1}, \tau_{F_1}),\\ &v_{o_2}(y_{3,a}, \boldsymbol{\phi}_{o_2}),\\ &v_{o_3}(y_{4,a}, \boldsymbol{\phi}_{o_3}),\\ &F_4(v_{o_{4,1}}(y_{5,a}, \boldsymbol{\phi}_{o_{4,1}}), v_{o_{4,2}}(y_{6,a}, \boldsymbol{\phi}_{o_{4,2}}), \boldsymbol{\omega}_{F_4}, \tau_{F_4}),\\ &v_{o_5}(y_{7,a}, \boldsymbol{\phi}_{o_5}), \boldsymbol{\omega}_{F_0}, \tau_{F_0}) \end{aligned} \tag{8}$$

The functional forms of F, v and their parameters differ for each stakeholder perspective. To parameterize the model, we did not elicit data from real-world stakeholders, but base it on minimal preference information that could be quickly elicited in practice. For instance, a ranking of the objectives or the general shape of a lowest-level value function (Fig. 4). We translated these qualitative or ordinal statements to value functions and aggregation functions and their uncertain parameters (Table 1). In a practical decision support case, it will be crucial to validate this mapping with the stakeholders.

First, we specified value functions for the seven objectives on the lowest level of the hierarchy (Fig. 4, Table SI-2). These can have various shapes (Fig. SI-2). As functional forms, we use either exponential functions (Eq. (9)) or sigmoid functions based on the cumulative distribution function of the beta distribution (Eq. (10)), depending on the specification (Table 1):

$$v(y_i, \gamma) = \begin{cases} \frac{1-\exp(-\gamma \cdot \tilde{y}_i)}{1-\exp(\gamma)} & \text{for } \gamma \in \mathbb{R}^* \\ \tilde{y}_i & \text{for } \gamma = 0 \end{cases} \quad \text{with } y_i \in [y_i^-, y_i^+] \text{ and } \tilde{y}_i = \frac{y_i - y_i^-}{y_i^+ - y_i^-} \tag{9}$$

$$v(y_i, \alpha, \beta) = \frac{\int_0^{\tilde{y}_i} t^{\alpha-1}(1-t)^{\beta-1} dt}{\int_0^1 t^{\alpha-1}(1-t)^{\beta-1} dt} \text{ with } \alpha, \beta \in \mathbb{R}^+, y_i \in [y_i^-, y_i^+] \text{ and } \tilde{y}_i = \frac{y_i - y_i^-}{y_i^+ - y_i^-} \tag{10}$$

The parameters $\phi = \alpha, \beta$ or $\phi = \gamma$ were assumed to be uncertain (Table 1 and Fig. SI-3). This results in a distribution of lowest-level value functions (Fig. 5 and Fig. SI-4).

Secondly, we specified how to aggregate the obtained valuations along the hierarchy by determining a weighted aggregation function, $F_k(v_p, \dots, v_q, \boldsymbol{\omega}, \tau)$, for each aggregation step. As aggregation function we use either weighted generalized means (Eq. (5)) or the weighted arithmetic mean (Eq. (4)).

The first set of uncertain parameters of the aggregation function are the weights, or scaling factors, $\boldsymbol{\omega}$. We assumed that for each hierarchical level we have information about the ranking of objectives by a stakeholder (Fig. 4). This might, for example, be obtained in the first steps of a SWING elicitation procedure (e.g. [3,41]). We treated this ranking as constraint when sampling the distributions of the weights (see Section 4.4).

The parameter τ of the weighted generalized mean indicates the degree of non-additivity or compensatory behavior that is possible, i.e., to what degree poor achievement of objectives can be compensated by achievement of other objectives [33]. For $\tau = 1$ the generalized mean corresponds to the arithmetic mean, for $\tau = 0$ to the geometric mean. By using values for τ in between, we can model different degrees of *andness* [34]. We mapped qualitative statements about the degree of non-additivity (Fig. 4, Table SI-3) to distributions for τ (Fig. 5, Fig. SI-5).

We obtain a multi-attribute value function across all attributes for each stakeholder perspective. This function gives us an overall evaluation of each sample of outcomes for each decision alternative.

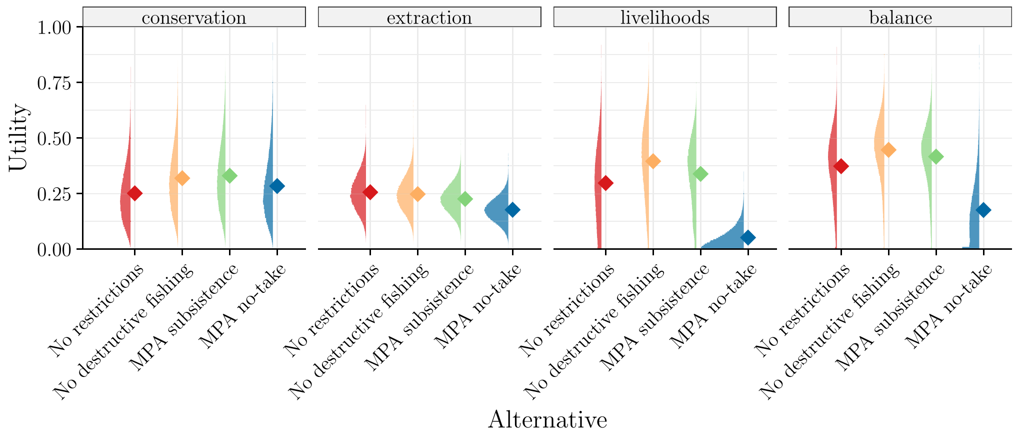

Fig. 6. Histograms of uncertain evaluations (y-axis) of the management alternatives (x-axis, colors) and the resulting EEU (diamond markers). Each stakeholder perspective (panel) is represented by different uncertain parameters of the utility function, which maps the outcomes of the alternatives to a utility between 0 and 1. The distributions result from uncertain predicted outcomes and uncertain parameters of the utility function. As the distributions for different alternatives overlap, the ranking of alternatives may change depending on the realization of the actual outcomes and preferences. Therefore, investigating the sensitivity of the decision is crucial. Hierarchical results for sub-objectives are given in Fig. SI-10.

Lastly, this value function can be converted to a utility function at the top level of the hierarchy. As we assumed risk-neutral stakeholders, the utility function is identical with the overall value function.

4.3. Probabilistic predictions for outcomes of alternatives

The complexity of a reef poses considerable challenges to predicting its state under a given management alternative. For this study, we rely on prediction data for this management case from Haag et al. [12], which details the prediction modeling approach. They used a spatially-explicit model to simulate the dynamics of the benthic and fish populations as well as associated fisheries in a coral reef with a cellular automaton and agent-based approach (SEAMANCORE; [42]). For each of the alternatives, the model was run 1100 times with different parameter configurations to capture the uncertainty in the system and in the effects of the management alternatives. Trajectories over six years were simulated and the outcomes 3–6 years in the future used.

Because the predicted system variables are not directly relevant for decision-making, the results were aggregated, compiled, and transformed to arrive at predictions for the attributes [12]. In contrast to the previous study, we applied a rolling mean with 10 day window on the raw fishery data to smooth out short-term fluctuation that result from the modeling approach rather than representing real-world processes. The attribute “number of patrol days required” was assumed to be Poisson distributed for each management alternative. We used our contextual knowledge to estimate a rate parameter for these distributions, expecting stricter restrictions to require more patrols.

Marginal distributions for the predictions are shown in Fig. SI-1. These marginal distributions do not depict the dependencies between the predictions for the attributes and among the alternatives. However, we took these dependencies into account in the VoI estimation with our sampling approach.

4.4. Estimation of EEU and EVPPI

As a form of probabilistic sensitivity analysis, VoI analysis requires knowledge about the distributions of model parameters and corresponding model outputs. We follow a sampling-based strategy for estimation. This required us to first generate a sample of uncertain predictions and uncertain preference parameters and then propagate this uncertainty forward to the model results. We chose a sample size of $S = 120000$.

The sample of predictions was created as described in Haag et al. [12]. For each alternative, we have 120000 predictions of potential outcomes for each of the eight decision attributes. This sample takes into account the dependencies between attributes and alternatives and is an input to the utility model.

For the utility model, we have specified distributions for the parameters. Except for the weights, parameters are all independent, so we can sample directly from the distributions. For the weights, we sampled from a multi-dimensional simplex with ranking as constraints using the method described in Tervonen et al. [43]. As we create a hierarchical utility model, we sample the weights for each branch separately. The resulting distributions are shown in Fig. 5 and Fig. SI-5.

The distributions of predictions and preferences were assumed to be independent. As we use a joint sample of predictions and of preferences to estimate EEU (Eq. (7)), we can combine both and calculate the resulting utilities of the four alternatives for each sample. The expectation over the utility distribution estimates the EEU.

With the sample of inputs and parameters and the corresponding sample of utilities, we calculated the EVPPI as described in Section 3.1. Based on our evaluation of the algorithm (Section 3.2), we used $K = 300$ bins with a bin size of $J = 400$. Likewise, we calculated the data for a threshold perspective on decision sensitivity. We focused on individual parameters and inputs. This means we conducted VoI analysis for 8 attributes $\times 4$ alternatives = 24 uncertain predictions and 16–23 preference model parameters (depending on the perspective). The analysis was conducted separately for each stakeholder perspective to enable comparisons (cf. [31]).

5. Results of the case study

5.1. Baseline EEU of alternatives

Given the uncertain attribute predictions (Fig. SI-1) and our preference models for the different perspectives with uncertain parameters (Section 4.2), we calculated the utility for each sample (histograms in Fig. 6). The expectation over these utilities, the EEU, is the criterion a rational decision should be based on (solid markers in Fig. 6).

The baseline optimal alternative varies depending on the stakeholder perspective. For the conservation perspective, a MPA with only subsistence fishing allowed would be the optimal alternative; for the extraction perspective, the alternative with no restrictions; and for the balance and local livelihoods perspective, a ban on destructive fishing practices would be optimal (Fig. 6). For all except the extraction perspective, the alternative with no restrictions is ranked third or fourth. Even a moderate restriction of fisheries can lead to higher reef fish biomass and fished biomass. A strict MPA with a no-take zone receives

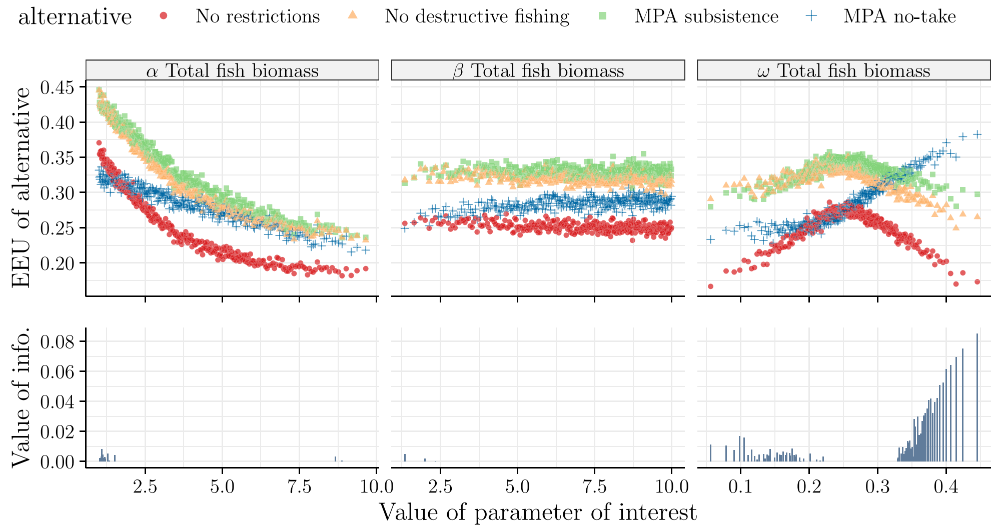

Fig. 7. Upper row: Dependence of the EEU (y-axis) of alternatives (colors) on variation (x-axis) of a specific a preference parameter (panels) while keeping the conditional variability in all other variables and parameters. The alternative with highest EEU is the optimal alternative, given that the variable of interest takes on a specific value on the x-axis. The sensitivity is different for the three shown parameters. Bottom row: Difference between the EEU of the baseline optimal alternative and the alternative with highest EEU. In regions where the EEU of the baseline optimal alternative remains highest, the VoI (y-axis) is zero. The baseline optimal alternative is not sensitive to the precise value of the variable of interest in that region. Value function parameters (α, β) and weight (ω) for the total fish biomass attribute from the conservation preference perspective are depicted. Figs. SI-11–14 show all results.

the third or fourth rank for all perspectives. This is due to the missing fulfillment of socio-economic objectives. Although no consensus for a best management alternative emerged among the perspectives yet, the alternatives may be refined iteratively, taking into account that (1) some reduction in fishing appears to be beneficial for fishery yield even in the short term, and (2) the failure to achieve socio-economic objectives due to a complete ban on fishing cannot be compensated by better conservation outcomes.

The marginal distributions of the alternatives' utilities have large overlaps (Fig. 6), implying that potential realizations of system attributes or preferences could result in different conclusions about the optimal alternative. This ambiguity in the ranking of the alternatives calls for investigating the sensitivity of the decision to both sources of uncertainty. As we will see in Section 5.3, a large overlap of the utility distributions does not directly imply a high sensitivity and vice versa.

5.2. Sensitivity scatterplots and thresholds

First, we consider sensitivity to individual variables of interest from a threshold perspective. Fig. 7 shows a scatterplot of the management alternatives' EEU as a function of three variables of interest, while keeping the probabilistic view and the correlation structure in all other variables. Results for all preference parameters and perspectives are given in Figs. SI-11–14.

We can differentiate three cases that can enlighten our understanding of sensitivity:

1. The EEU of alternatives does not vary much as we vary a variable of interest (e.g., the β parameter of the value function, middle panel Fig. 7). The value sensitivity is low. Consequently, the optimal alternative seldom changes. The decision sensitivity from a threshold view is low — also if we measure it with the VoI (lower middle panel).
2. The EEU of alternatives varies considerably as we vary a variable of interest (e.g., the α parameter of the value function, left panel Fig. 7). However, the baseline optimal alternative – here the MPA with subsistence fishing – remains optimal for (almost) the entire range of the variable of interest. The value sensitivity – as measured by an appropriate index – is high, however the decision sensitivity and thus the VoI are low.
3. Both the EEU of alternatives and the ranking of alternatives change as we vary our variable of interest (e.g., weight parameter ω, right panel Fig. 7). The decision sensitivity from a threshold view is high and therefore knowing that the variable takes on a certain value can have high VoI (lower right panel). This may also mean a high EVPPI, depending on the distribution of the variable of interest.

This analysis is insightful, because we can identify thresholds at which the ranking of the decision alternatives changes. Because our results are based on simulations, the thresholds are not exact points, but rather small regions. The interpretation of thresholds is more direct than aggregate measures such as EVPPI and they allow identifying regions in which results are stable or unstable. For instance, for the conservation perspective, the MPA with subsistence fishing is no longer optimal if the weight parameter for the total fish biomass becomes greater than 0.325. The MPA with no-take zone becomes the best alternative (right panel of Fig. 7). In this region, the VoI is greater than zero (lower right panel).

While thresholds can be informative, this sensitivity analysis falls short in two ways. First, it does not take into account how probable it is that a threshold will be crossed: how likely is it that the weight ω of the total fish biomass will ever be greater than 0.325? Second, once we cross a threshold, we disregard how large the potential gain would be from taking the optimal instead of the now sub-optimal baseline alternative (this difference is shown in the lower panels of Fig. 7). Both aspects are crucial for understanding how sensitive a decision is and motivates the analysis of the EVPPI.

5.3. EVPPI of uncertain preferences and predictions

The EVPPI arguably offers a more comprehensive measure of decision sensitivity and we calculated it for all variables of interest (Fig. 8). The lower the EVPPI of a variable, the less sensitive the decision is to that variable, and vice versa. Ranking the variables based on their EVPPI can then help us determine the key uncertainties to resolve.

The EVPPI varies depending on the variable of interest and stakeholder perspective (Fig. 8, Fig. SI-15). Focusing on the type of parameter or input, we find that with two exceptions the parameters of the lowest-level value functions, α, β, γ, had low EVPPI. This is the case,

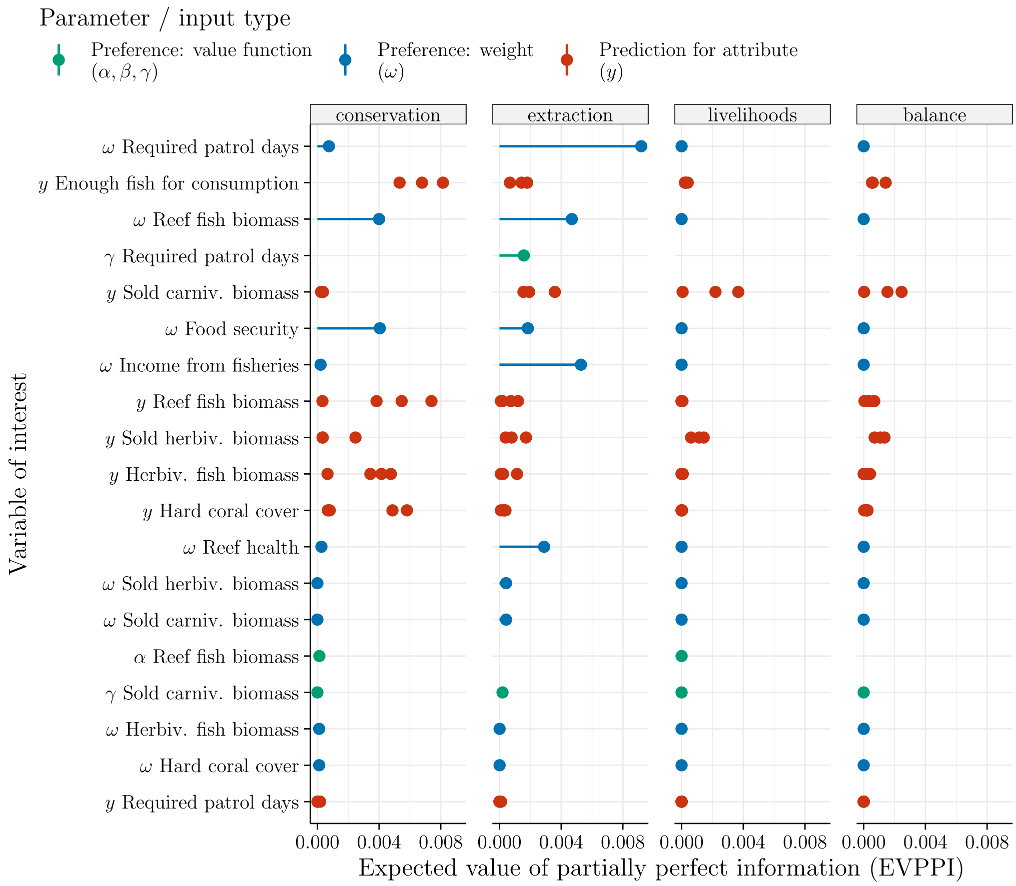

Fig. 8. Expected value of partially perfect information (EVPPI; x-axis) for variables of interest (y-axis) for the different stakeholder perspectives (panels). Colors describe the type of parameter or input; see Fig. 5 for an overview of these. A single point represents the expected gain in utility for a particular stakeholder perspective, if we had perfect information about this variable. Not all stakeholder perspectives share the same parameters, therefore, some entries are missing. The predictions (y) are differentiated by alternative, therefore, four EVPPI values for each predicted attribute exist. Whether preference or prediction uncertainties have higher EVPPI depends on the stakeholder perspective. For the two perspectives on the right, the decision is largely insensitive. Subset of results for variables with EVPPI $\geq$ 0.0001; all results depicted in Fig. SI-15.

even though many value functions they induce look quite variable (Fig. 5 and Fig. SI-4). Of the aggregation parameters, individual weights at the upper hierarchy level had the highest EVPPI. Together with the uncertain predictions, these are the uncertainties that this decision is most sensitive to. The additional aggregation parameters τ or weights of the lowest-level objectives (e.g., ω of herbivore biomass) had negligible EVPPI values in similar ranges than the value function parameters (Fig. SI-15).

Comparing the results for the different perspectives, EVPPI is small for the livelihood and balance perspective, except for one attribute. From these perspectives, the optimal alternative is robust, regardless what additional information we would obtain about the predictions or preferences — within the scope of the model (see Section 6.2). This is the case even though the (marginal) utility distributions have significant overlap (Fig. 6). For the extraction perspective, uncertainties of some preference parameters have higher EVPPI than prediction uncertainties. For this perspective it would be crucial to elicit preferences in more detail. For the conservation perspective, this pattern is reversed.

Looking in more detail into the conservation perspective, we find few key uncertainties, while most are irrelevant for the decision (Fig. 8, Fig. SI-15). Two key predictive uncertainties for this perspective are the total reef fish biomass and the days with fish for local consumption. However, the EVPPI regarding the uncertainty about the weight parameter for these two objectives is similarly high. Perfect information about these predictions or about preferences will have similar benefit. Furthermore, the predictions of coral cover, of the herbivore biomass, and of the sold herbivore biomass are high up in the ranking. Because the determined baseline choice may not remain the best if we received additional information, efforts directed at understanding these seven aspects will be most valuable for decision-making.

In contrast, further investigation of other parameters or inputs is unlikely to change the conclusions regarding the optimal management alternative for the conservation perspective. Their EVPPI appears negligible. Therefore, the sensitivity of the conclusions can be reduced by gathering few key pieces of information. This minimizes the effort required, e.g., for further elicitation of preferences.

6. Discussion

6.1. Improved estimation of the value of information

As we have shown in Section 3.2, the proposed given-data estimation algorithm for EVPPI is relatively stable for different bin sizes and sample sizes. This corroborates findings of Strong and Oakley [27] and Haag et al. [12]. However, occasionally the EVPPI estimates can remain sensitive (Fig. SI-6). This suggests hyperparameter analysis, as we performed, can remain beneficial.

The large sample size we used in this study (S = 120000) would not have been necessary, but about 5000 samples were required in our study set-up to receive stable estimates. This can still be a significant computational cost, especially with complex prediction models, but much lower than with a nested Monte Carlo approach [37]. In our case, a ratio of bin size to bin number of 4:3 tended to give good results.

The suggested algorithm is only feasible for individual parameters or inputs. This is a constraint when we are interested in groups of parameters, for instance, what the VoI of knowing all weight parameters at once would be. Statistical surrogate models or emulators are an alternative approach for EVPPI estimation which could overcome this limitation [39]. Emulators are also suitable for efficiently estimating the value of sample information (EVSI; [38]). Further research into the EVSI sensitivity measure is a promising direction for the presented decision modeling approach. In practice we will usually not obtain perfect information, but rather generate more data.

A limitation of our approach lies in the assumption that stakeholders are risk-neutral. This is often not warranted in practice, especially in environmental and conservation decisions where stakeholders may exhibit risk-averse or risk-seeking preferences. In such cases, we would not want to define the VoI directly in terms of EU differences, because these differences are conceptually difficult to interpret. Instead, we may measure the VoI based on the difference of the certainty equivalents of the situation with and without additional information (see [30,44]). Practical implementations of such an approach seem to be rare, however. Assuming risk neutrality greatly simplifies these issues because of the equivalence of certainty equivalent, expected utility, and expected value under this assumption.

6.2. Lessons from applied value of information sensitivity analysis

Our case study is one of few published cases considering both preferential and predictive uncertainty on equal footing. Combining VoI analysis with the EEU concept [21,22] is a promising way to prioritize among all key decision uncertainties, not just predictive uncertainty. We obtained a ranking of both predictive and preferential uncertainty. Thus, our analysis allows assessing which of these uncertainties are more relevant for a concrete decision situation.

The reef management decision was sensitive to few parameters and inputs, while many were irrelevant. As already discussed by Gould [45], there is no simple connection between the degree of uncertainty about a parameter and its VoI. The conclusions from VoI analysis are also dependent on the stakeholder preferences profile; a general, preference-independent VoI does not exist [12]. For the livelihoods and balance perspectives none of the investigated inputs and parameters had high EVPPI — from these perspectives additional information collection is not necessary to arrive at a robust conclusion. For the other two perspectives, the two aspects the decision was most sensitive to were the uncertain system attribute predictions and the weight parameters for the upper level in the hierarchy of objectives. The shape of the lowest-level value function had limited influence, with one exception. While such a conclusion is case-specific, this is consistent with literature indicating insensitivity to shapes of lowest-level value functions (e.g., [2,41,46]).

The EVPPI results provide important clues to the analyst or other actors in the decision process about the next steps to take. By eliciting only few preference parameters in more detail – the weight parameters for the upper level of the objectives hierarchy from the conservation and the extraction perspectives and the shape of the lowest-level value function for the patrol days from the extraction perspective – we would efficiently address the key preference uncertainties in the presented case. For the predictive uncertainties, most remain relevant to further study. These conclusions may not be valid outside the scope and structure of the decision model (see Section 6.3). For example, adding a "tourism revenue" objective could change the baseline ranking of alternatives and the EVPPI results.

The case study can be viewed as the first step of an iterative approach to decision support. For static decisions, a natural connection between VoI analysis and sequential information gathering approaches exists, e.g., in a Bayesian framework [47]. Using VoI results to design the next round of information collection is an active research field [21,24,26]. Value of information analysis also lends itself to approaches for dynamic or iterative decision making, such as adaptive management where it could help decide about monitoring efforts (e.g., [48,49]).

When using EVPPI results for making decisions about which information collection activities to pursue, this requires trade-offs between the costs of acquiring the information against the benefits. The EVPPI is a measure of the benefit of reducing uncertainty. In single-objective cases, VoI can be expressed in the units of this objective (e.g., reduction of species decline as in Bal et al. [50]). However, in our study VoI is expressed in units of EEU that indicate relative performance of alternatives. This abstract unit can make trade-offs with cost challenging. A pragmatic approach is to start with information collection activities that have the least cost for a given VoI, i.e., Pareto-optimal activities.

6.3. How to navigate decision uncertainties?

Two interconnected challenges exist for decisions in which uncertainties are large, as in our case of coral reef management: (1) how to represent or model the uncertainties and (2) how to handle them in decision-making. This study focused on the latter challenge: given that we have a representation of decision uncertainties in the form of probability distributions of inputs and parameters, how sensitive is the decision to these uncertainties?

We showed that the combination of VoI analysis and the EEU concept can help identifying key uncertainties. However, the conclusions from VoI analysis depend on the answer of the former challenge, as they are answered in the "small world" of our model [51]. Assuming that decision-specific VoI results apply to the larger problem setting may lead to discounting the value of data as historical record or for long-term management [52]. From a broader perspective, the VoI concept also ignores that information that increases our confidence in the ranking of alternatives can be of great practical value even if the best alternative does not change.

Representing the uncertainty of predictions through probabilistic estimates is a well-established standard, although many predictive models – especially those based on simulation – have yet to adopt it [53]. Representing the uncertainty of preferences by assigning probability distributions to utility model parameters is practically still an underused approach (but see, e.g., [2,3,20,25]). As discussed, the EU is not a sufficient decision criterion to arrive at a unique ranking of alternatives when preferences are uncertain. However, with adaptive utility and the EEU criterion a conceptually straightforward and practically feasible extension exist [20,23].

Assigning probability distributions to utility model parameters can be a challenge. In this study, we based the distributions on qualitative and ordinal preference information that would be easy to elicit from stakeholders. For the weight parameters, we treat the ordinal ranking of objectives as a constraint in estimating their joint distribution [43]. For the other parameters, our translation of qualitative statements to distributions would need to be verified with stakeholders, for example, by asking validation questions. Conceptually more satisfying would be to estimate these parameter distributions from data by fitting the model to preference statements, such as choices or indifference statements [54]. Probability distributions can be found by Bayesian inference or bootstrapping (e.g., [24,33,54]). However, this approach needs to be balanced with practical constraints regarding cognitive load and time of stakeholders for data elicitation.

A common way to deal with uncertain preferences in decision analysis is by different forms of one-factor-at-a-time local sensitivity analysis, i.e., varying a parameter and observing changes (e.g., [55,56]). Alternatively, SMAA approaches offer various methods to investigate uncertain information (e.g., [17–19,46]). One component of SMAA that addresses decision sensitivity is to determine the space in which a parameter may change until the decision would change [17,57]. This has similarities to the threshold sensitivity analysis we conducted. Some of these methods avoid specifying distributions for parameters and thus the challenges discussed above. However, this limits VoI analysis to examining discrete scenarios. We cannot calculate an expectation as in our EVPPI analysis.

7. Conclusions

In decision making, we are confronted with large uncertainties about the future state of the world if a management alternative was implemented, as well as large uncertainties about the social evaluation of these yet-to-manifest states. Commonly, this evokes calls for more data or more science to reduce these uncertainties [13]. However, data acquisition and additional studies can be costly and, therefore, need to be balanced with the expected benefit towards reaching a timely and reasonable decision. Value of information analysis was developed as a type of global sensitivity analysis to estimate the impact better knowledge can have on a decision [5,6].

We have presented a structured, decision analytic framework to consider uncertainty of preferences on equal footing to predictive uncertainties using expected expected utility. This allows VoI analysis to be extended to consider both uncertainties at once. We have focused on the expected value of partially perfect information (EVPPI) as a sensitivity measure, but the framework can be adapted to other metrics such as the expected value of sample information. Although, estimation of EVPPI can be a hurdle for complex decision models, we adapted a given-data algorithm by Strong and Oakley [27] for efficiently estimating EVPPI in the context of EEU. In our case study, this estimation was robust over a wide range of sample and bin sizes.

For a reef management case study, we demonstrated how the proposed methods can be implemented and allow determining key uncertainties for the decision. In this way, it can also support more targeted elicitation of stakeholder preferences. The effort for quantifying stakeholder preferences prevents these approaches in many practical projects. We have shown how we can start with coarse information, such as a ranking of objectives, and identify few target parameters for which more detailed information would be beneficial.

If quantitative decision support procedures will gain wider adoption in the future, our presented approach will decrease the efforts and costs of data collection, as we can start with uncertain prior information and then determine the key uncertainties to resolve. Having this explicit understanding will – so we hope – support better-reasoned and robust decision making in practice.

CRediT authorship contribution statement

Fridolin Haag: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Visualization. **Arjun Chennu:** Conceptualization, Resources, Investigation, Writing – review & editing, Visualization.

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 availability

The workflow to reproduce the analysis is available at https://doi.org/10.5281/zenodo.7970672. It depends on an R package with functions for VoI analysis, https://doi.org/10.5281/zenodo.8135705. The dataset of predicted simulation results from SEAMANCORE is available at https://doi.org/10.5281/zenodo.7156015.

Acknowledgments

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.omega.2023.102936.

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Supporting Material to

Assessing whether decisions are more sensitive to preference or prediction uncertainty with a value of information approach. Omega 102936.

https://doi.org/10.1016/j.omega.2023.102936

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Contents

SI-1 Information about attributes

Table SI-1: Attributes and objectives used in the case study. With a value function we can then quantify the degree of achievement of the objectives as a function of the attributes. Adapted from the supporting information of: Haag, F., Miñarro, S., Chennu, A., 2022. Which predictive uncertainty to resolve? Value of information sensitivity analysis for environmental decision models. Environmental Modelling & Software 158, 105552. `https://doi.org/10.1016/j.envsoft.2022.105552`.

Category	Objective	Attribute	Unit	Prediction by	Explanation
Reef health and resilience	High herbivore biomass	Herbivorous fish biomass	g/m^2	SEAMANCORE model	Sum of the biomass of scrapers and browsers fish functional groups. Weekly averages over the whole model area were calculated.
	High hard coral cover	Hard coral cover	%		Weekly averages over the whole model area were calculated.
	Food security	Days with enough fish for local consumption	days/4 weeks		We assumed that 8kg fish/day from this reef area will cover local demand. We counted the days within 4-week periods when at least 8kg of fish was caught. Only some elements of food security are captured by this proxy attribute.
	Sustainable fish population	Total reef fish biomass	g/m^2		Sum of the biomass of all fish functional groups. Weekly averages over the whole model area were calculated.
High income from fishing	High sales of herbivore fish	Carnivore biomass sold	kg sold/week		Fished carnivore biomass from all fishery types after satisfying the local demand of 8kg/day. We assume that all fish biomass can be sold. Carnivorous fish will generally have a higher market value than herbivorous fish.
	High sales of carnivore fish	Herbivore biomass sold	kg sold/week		Fished herbivore biomass from all fishery types after satisfying the local demand of 8kg/day. We assume that all fish biomass can be sold.
	Low cost for monitoring and enforcement	Required patrol days in a year	days/year	Expert judgement	More patrol days will mean higher expenses for fuel and personnel. Only some elements of the total management cost are covered by this attribute.

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SI-2 Predicted outcomes

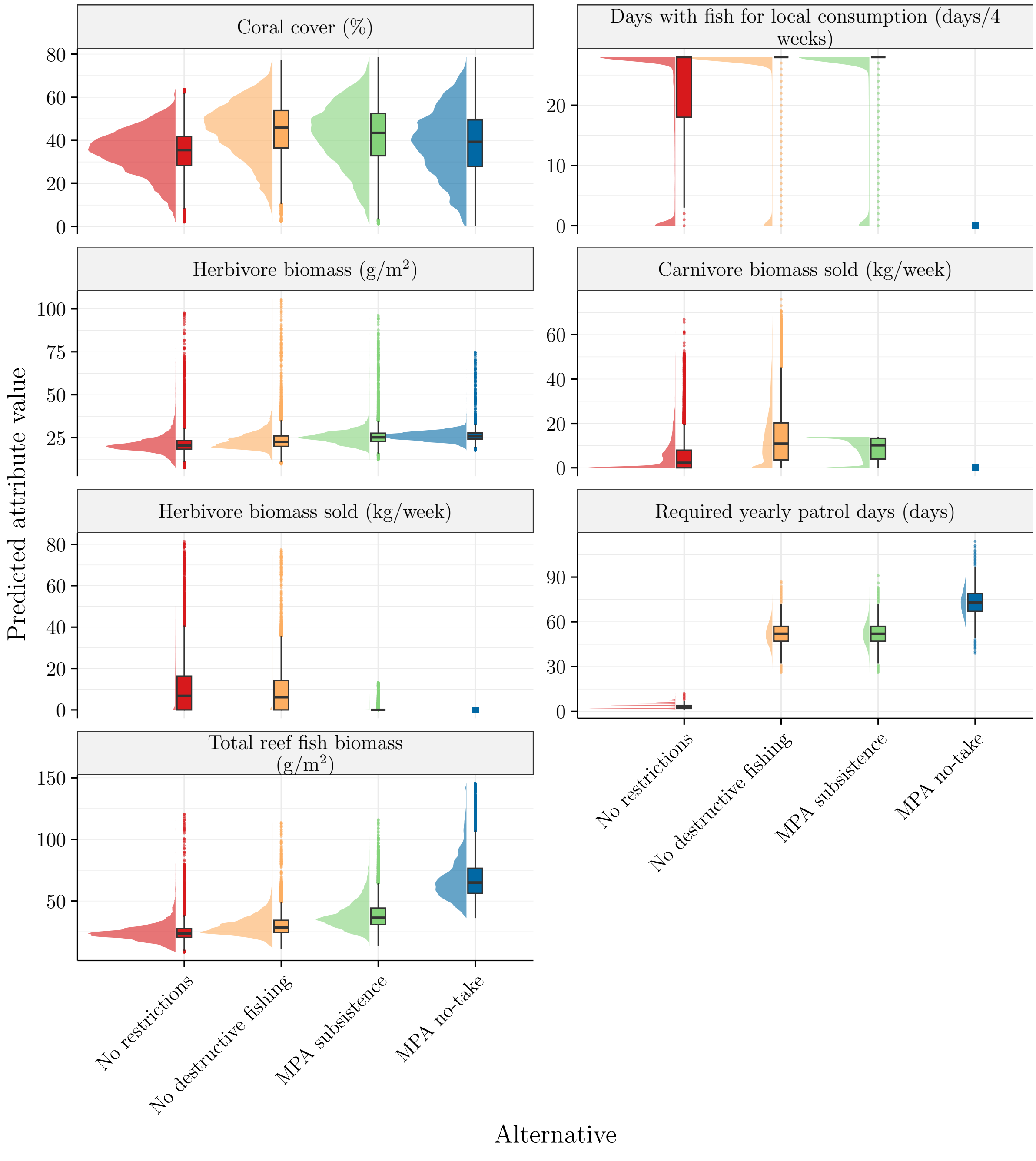

Figure SI-1: Marginal distributions and boxplots of predictions (y-axis) of the attributes (panels) of a coral reef area under four management alternatives (x-axis). Boxplots show the 0.25, 0.5, and 0.75 quartiles of these data, and whiskers extend to the maximum and minimum points within 1.5 times the interquartile range. Only a proportion of outliers is visualized. The distributions for each alternative are based on 120000 samples. They were derived from 1100 independent simulations of the SEAMANCORE reef model, which were transformed, aggregated, and subsampled. 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.

SI-3 Preference parameters

Table SI-2: Qualitative descriptions of the shape of the lowest-level value functions for each objective and the different perspectives. The shapes are visualized in Fig. SI-2. These qualitative statements were then mapped to equations with uncertain parameters, see Table 1 in the main text.

	Perspective			
Attribute	Conservation	Extraction	Livelihoods	Balance
Coral cover	right-leaning S-shape	concave	left-leaning S-shape	concave
Herbiv. biomass	left-leaning S-shape	linear	left-leaning S-shape	concave
Reef fish biomass	left-leaning S-shape	linear	left-leaning S-shape	concave
Required patrol days	lying S-shape	convex	left-leaning S-shape	left-leaning S-shape
Days with fish for consumption	concave	concave	lying S-shape	linear
Carniv. biomass sold	concave	linear	concave	linear
Herbiv. biomass sold	concave	linear	concave	linear

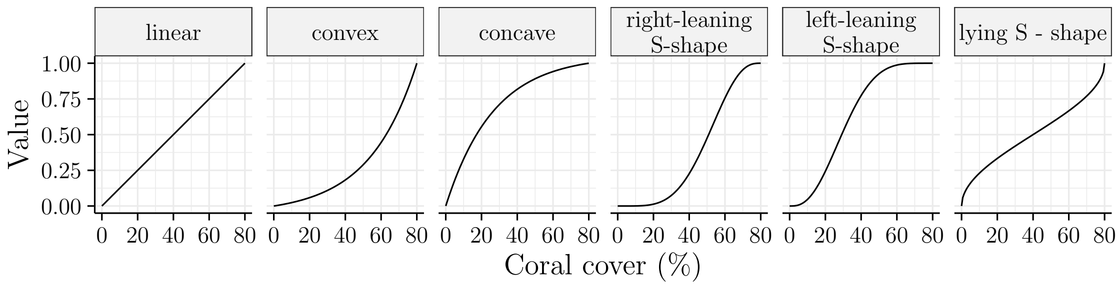

Figure SI-2: Potential shapes of lowest-level value functions that were used in the study. An attribute (x-axis), here the coral cover, is mapped to a value (y-axis) that specifies the degree of achievement of the objective of having a healthy coral cover. The underlying equations are given in Eq. 9 and 10 in the main text.

Table SI-3: Ranking of the objectives in terms of their relative importance per hierarchical level (upper part of table) and specifications of aggregation model (degree of compensation; lower part) for the different perspectives. The model is build hierarchically (see Fig. 4 in the main text for an example). Specifically, Reef health and Income fisheries are first aggregated.

	Objective	Conservation	Extraction	Livelihoods	Balance
Ranking of objectives	Reef fish biomass	2	3	4	2
	Required patrol days	3	4	5	4
	Food security	4	5	2	3
	Income fisheries	5	1	1	2
	Carniv. biomass sold	1	1	1	1
	Herbiv. biomass sold	2	2	2	2
	Reef health	1	2	3	1
	Coral cover	1	2	2	1
	Herbiv. biomass	2	1	1	2
Degree of non-additivity	Overall	weakly non-additive	additive	weakly non-additive	partially non-additive
	Income fisheries	additive	additive	additive	additive
	Reef health	partially non-additive	additive	weakly non-additive	partially non-additive

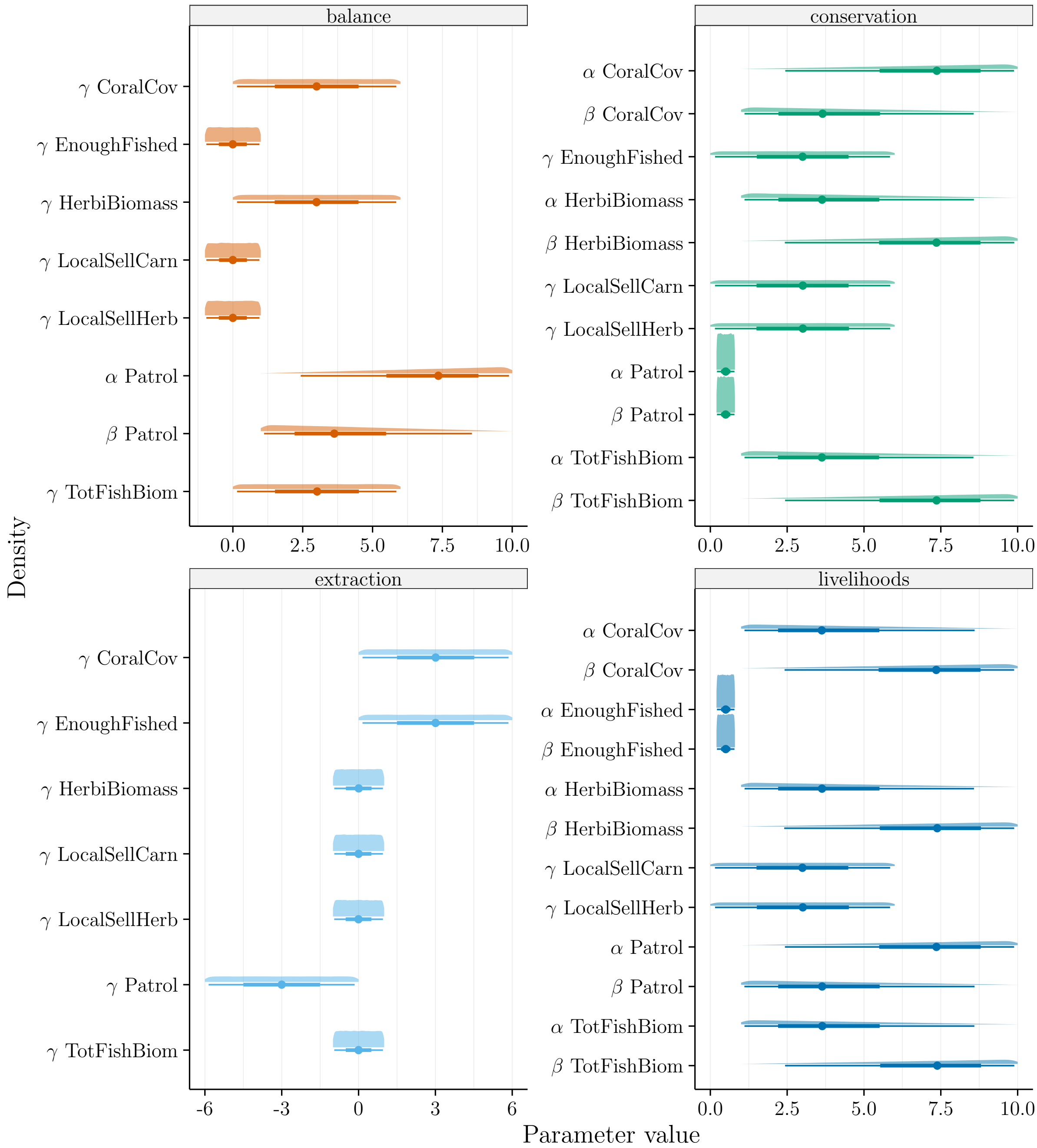

Figure SI-3: Distributions of marginal value function parameters (x-axis) for the objectives (y-axis) for the different stakeholder perspectives (panels).

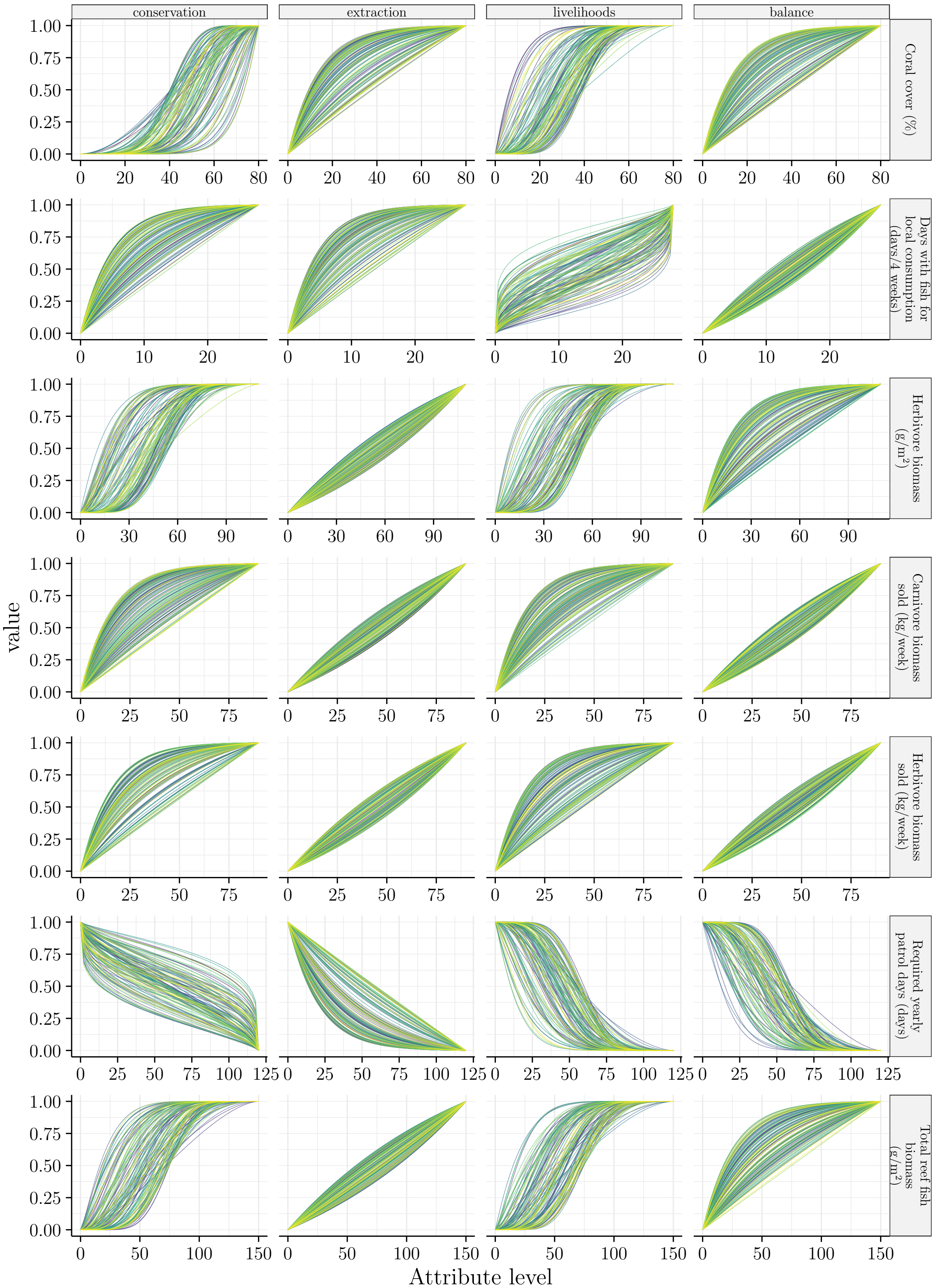

Figure SI-4: 120 exemplary value function for each lowest-level objectives (rows) and stakeholder perspective (columns) that result from 120 parameter draws of the full distributions shown in Figure SI-3.

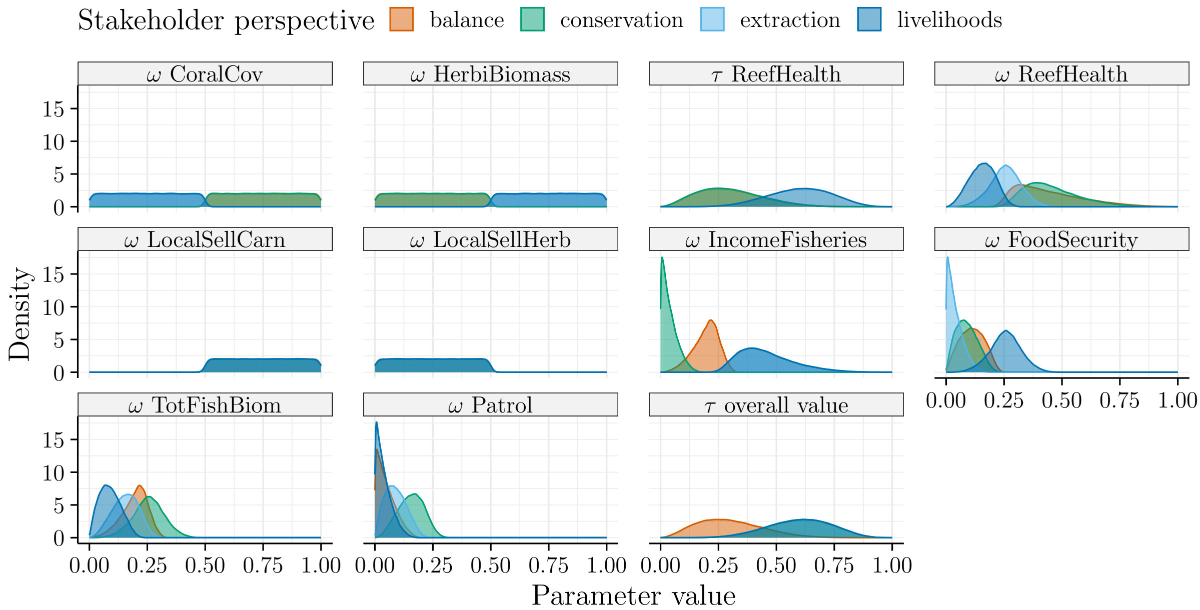

Figure SI-5: Distributions of samples for the different aggregation function parameters (panels) for different stakeholder perspectives (color). Attribute weights, ω, together with the "non-additivity" aggregation parameter, τ, represent which trade-offs stakeholders would be willing to make between the achievement of different objectives.

SI-4 Tuning of the EVPPI estimation algorithm

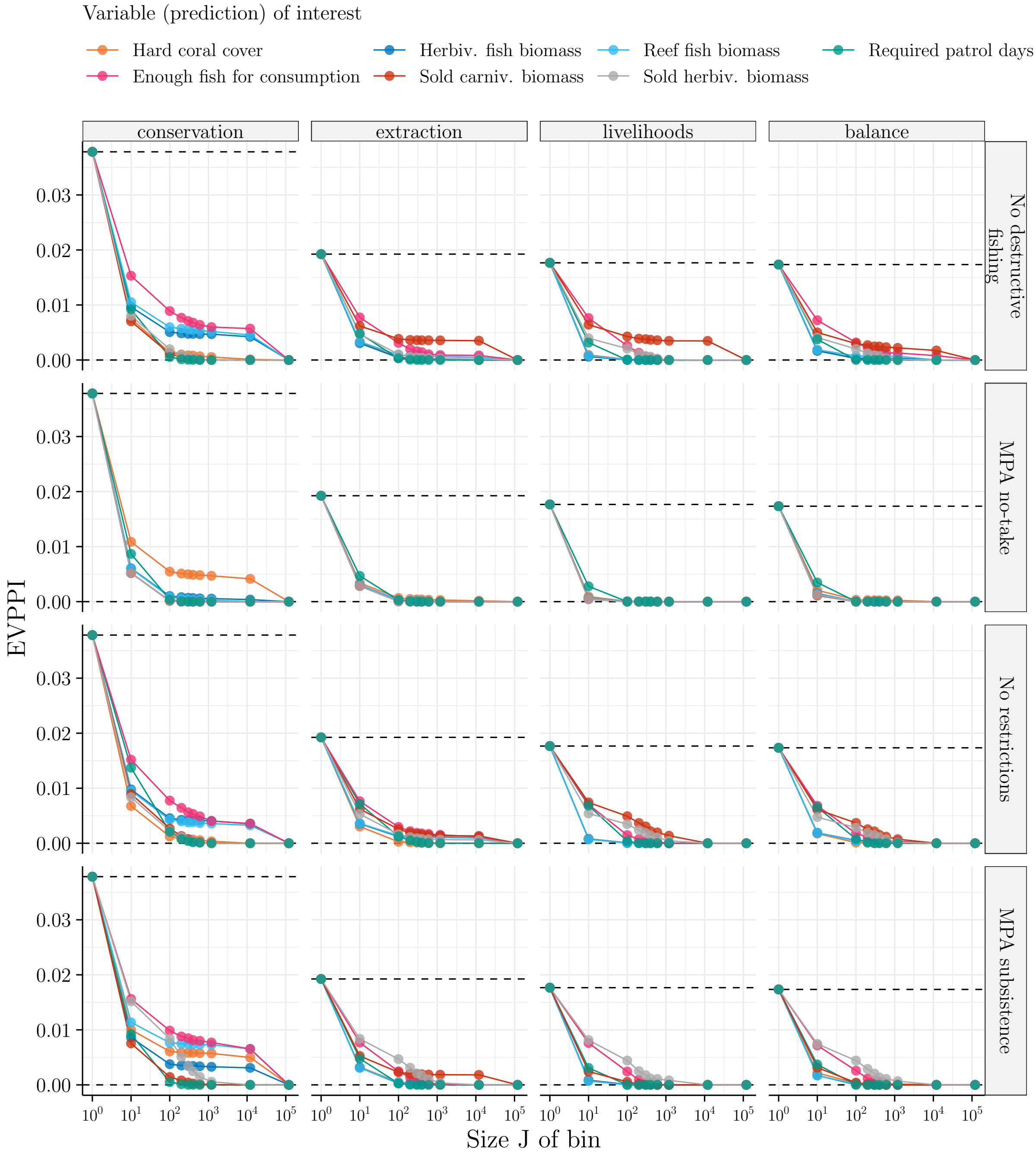

Figure SI-6: Dependence of the EVPPI estimate (y-axis) on the bin size parameter J (x-axis) of the estimation. The variables of interest deptiched are the attribute predictions (colors) for the different alternatives (panel rows). Results for the different stakeholder perspectives are shown in the four panel columns. The upper dotted line indicates the expected value of perfect information (EVPI), the lower dotted line is at zero, the minimum possible EVPPI.

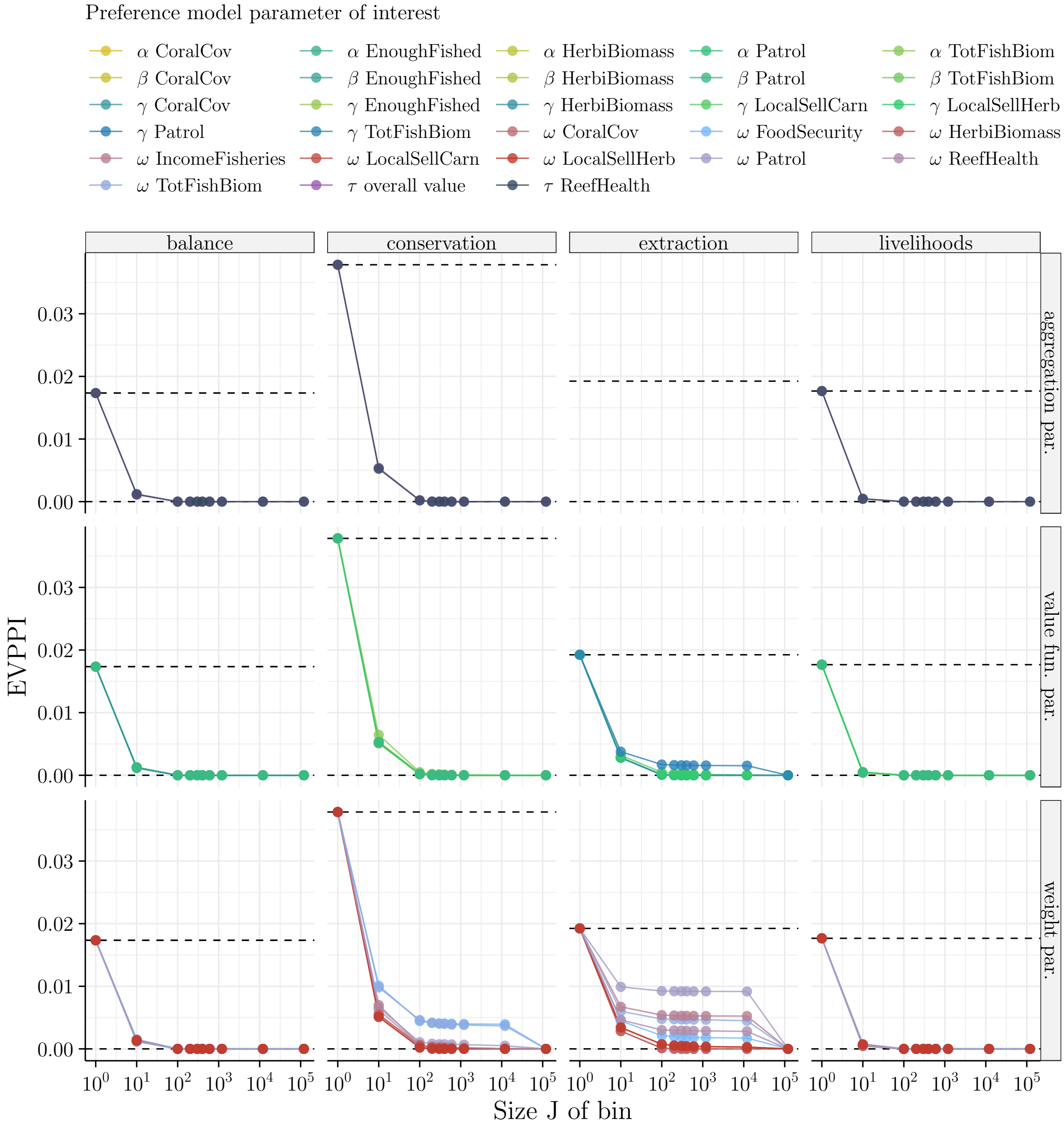

Figure SI-7: Dependence of the EVPPI estimate (y-axis) on the bin size parameter J (x-axis) of the estimation. The variables of interest depicted are the parameters of the utility model (colors), categorized by parameter type (panel rows). The upper dotted line indicates the expected value of perfect information (EVPI), the lower dotted line is at zero, the minimum possible EVPPI.

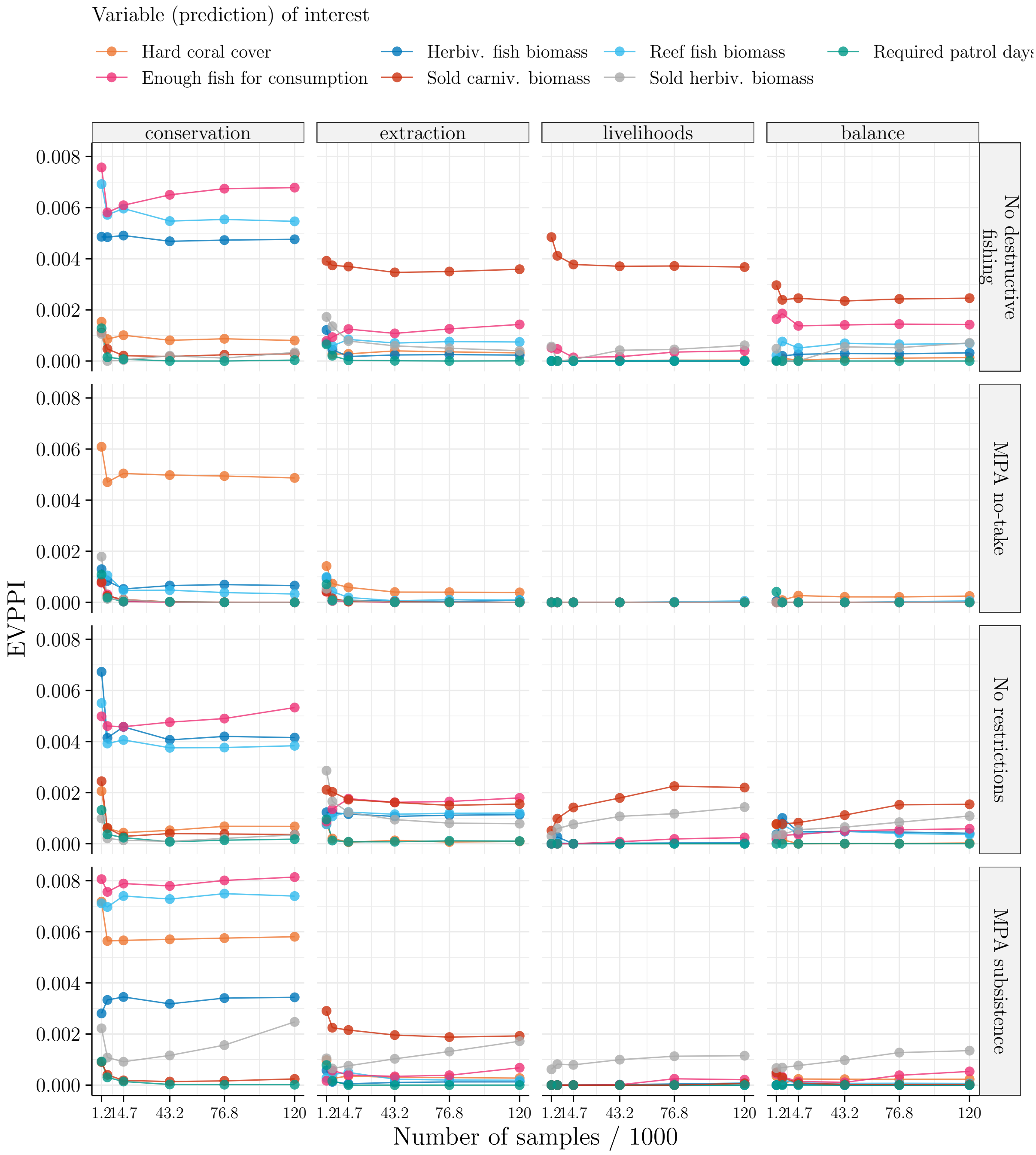

Figure SI-8: Dependence of the EVPPI estimate (y-axis) on the sample size S (x-axis). The depicted variables of interest are the attribute predictions (colors) for the different alternatives (panel rows). Results for the different stakeholder perspectives are shown in the four panel columns.

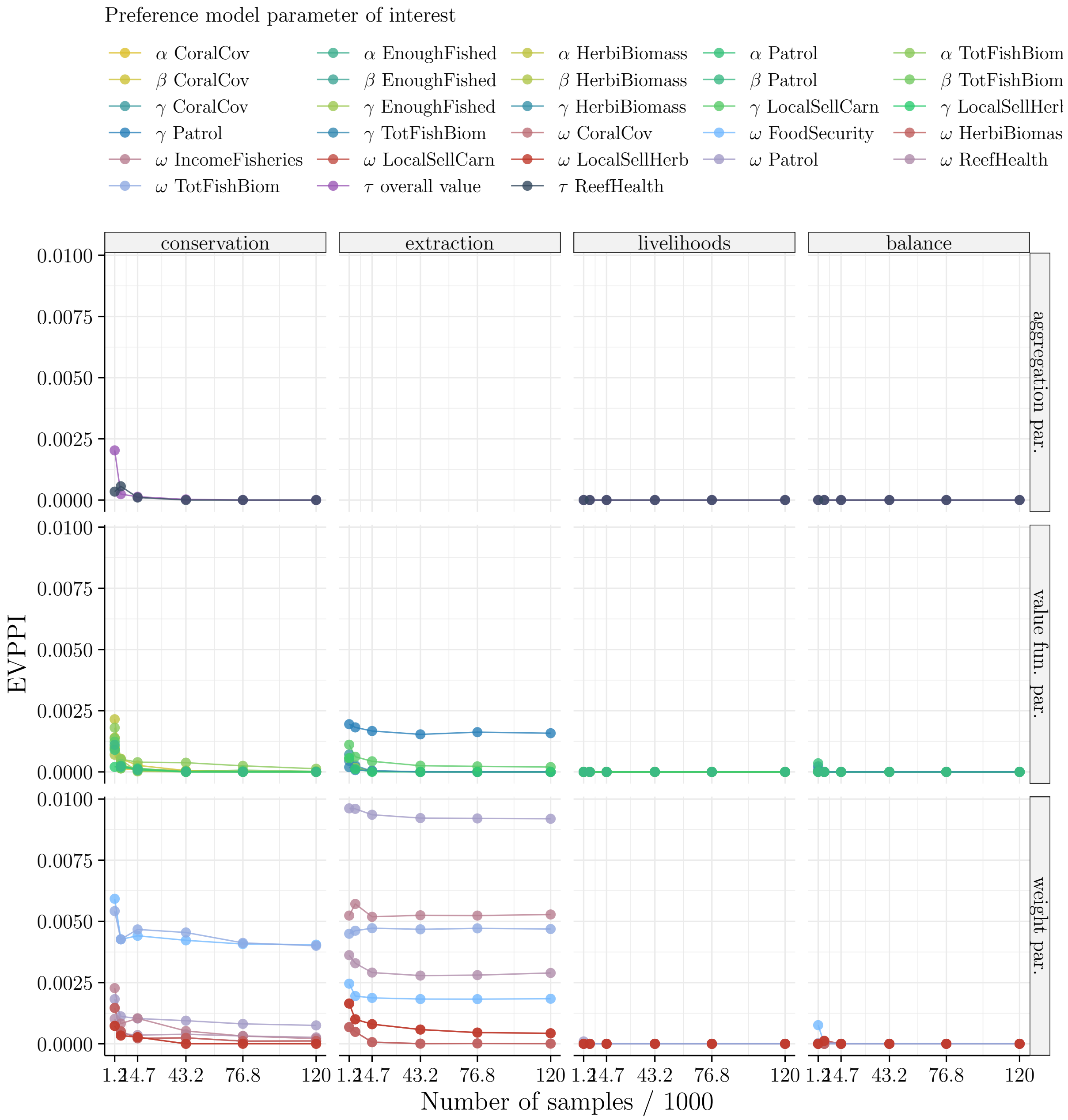

Figure SI-9: Dependence of the EVPPI estimate (y-axis) on the sample size S (x-axis). The depicted variables of interest are the parameters of the utility model (colors), categorized by parameter type (panel rows). Results for the different stakeholder perspectives are shown in the four panel columns.

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SI-5 Case study results

SI-5.1 Baseline results

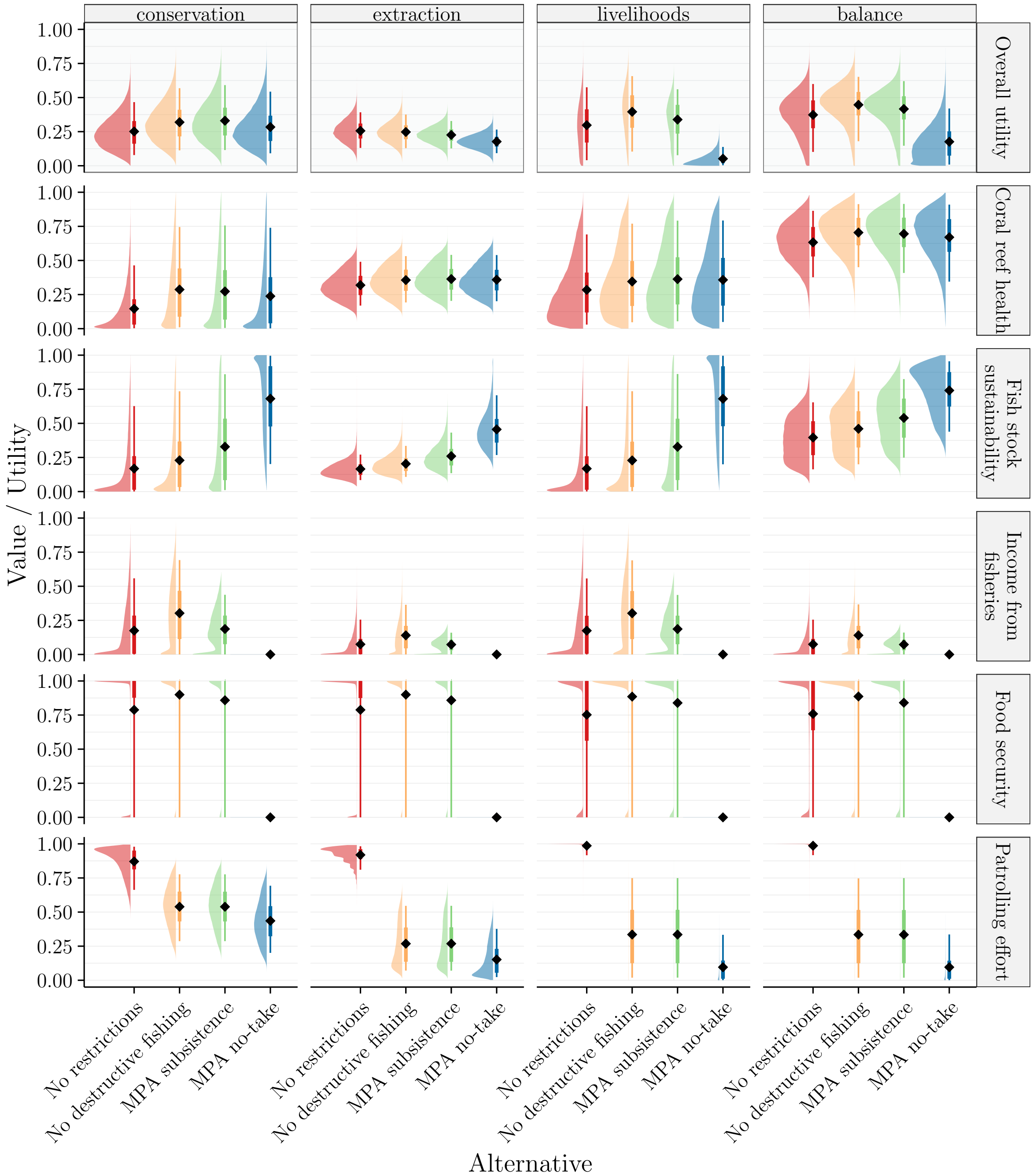

Figure SI-10: Distribution of uncertain evaluations (y-axis) for the management alternatives (x-axis, colors) along the objectives hierarchy. Panels show the top-level objectives and the overall objective (top row). The evaluations are uncertain values and black markers indicate the expectation. For the overall objective the evaluations are uncertain utilities and the black markers indicate the EEU. The distributions results from uncertain predictions and uncertain parameters of the value/utility functions. Distributions are normalized within each panel, so they are not directly comparable.

SI-5.2 Sensitivity of aggregation parameters

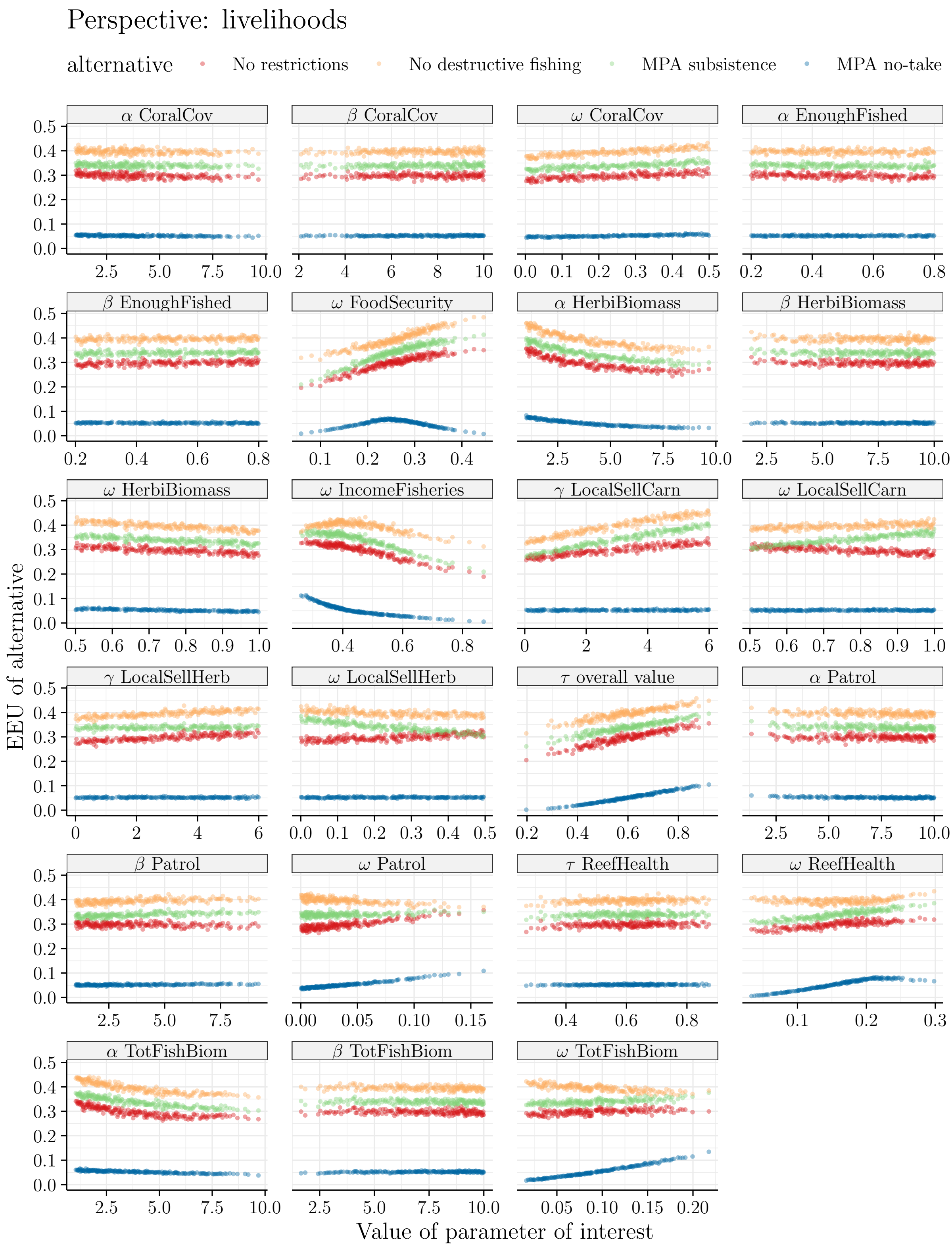

Figure SI-11: Dependence of the expected expected utility (EEU; y-axis) of alternatives (colors) on variation (x-axis) of a specific a preference parameter (panels) while keeping the conditional variability in all other variables and parameters.

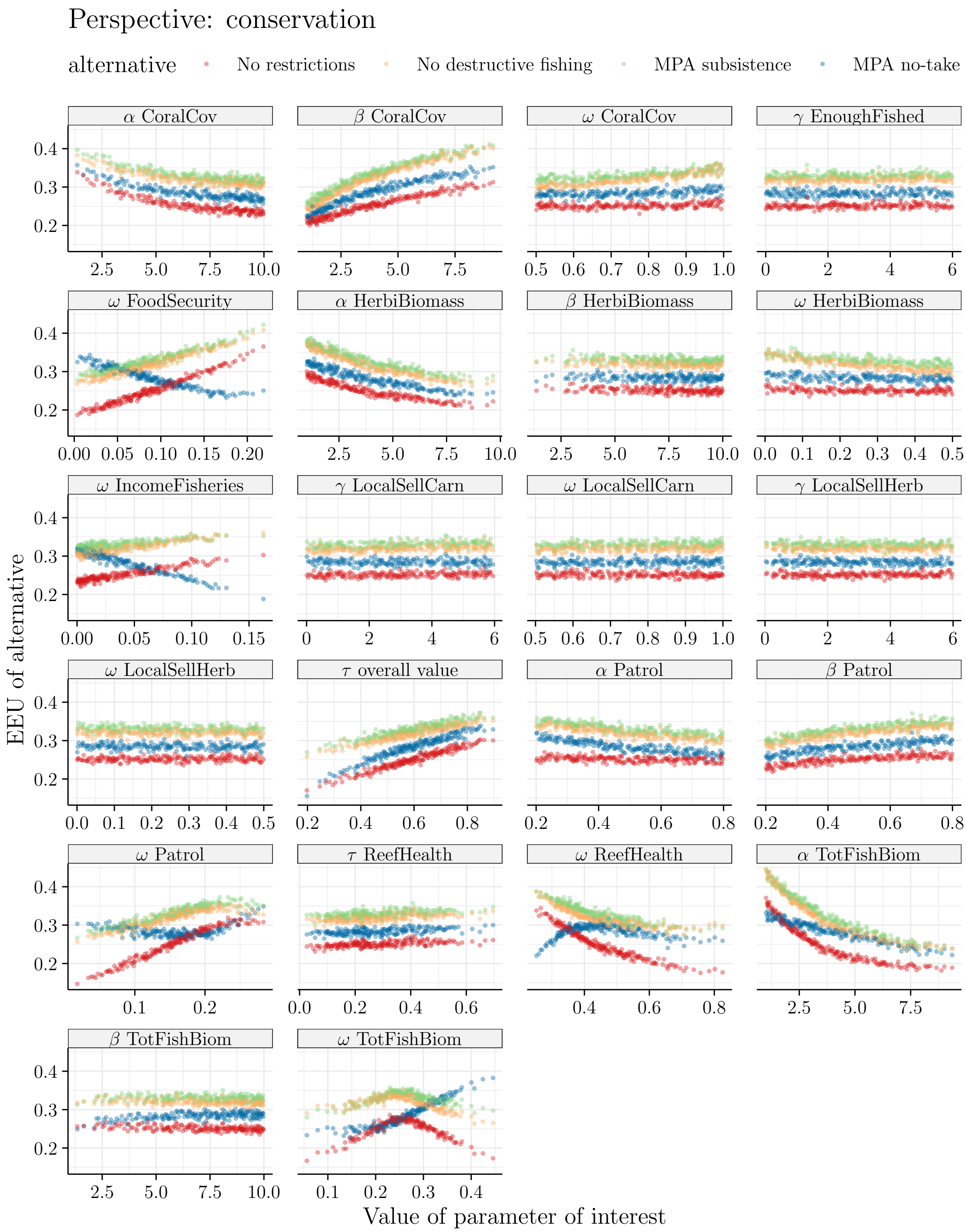

Figure SI-12: Dependence of the expected expected utility (EEU; y-axis) of alternatives (colors) on variation (x-axis) of a specific a preference parameter (panels) while keeping the conditional variability in all other variables and parameters.

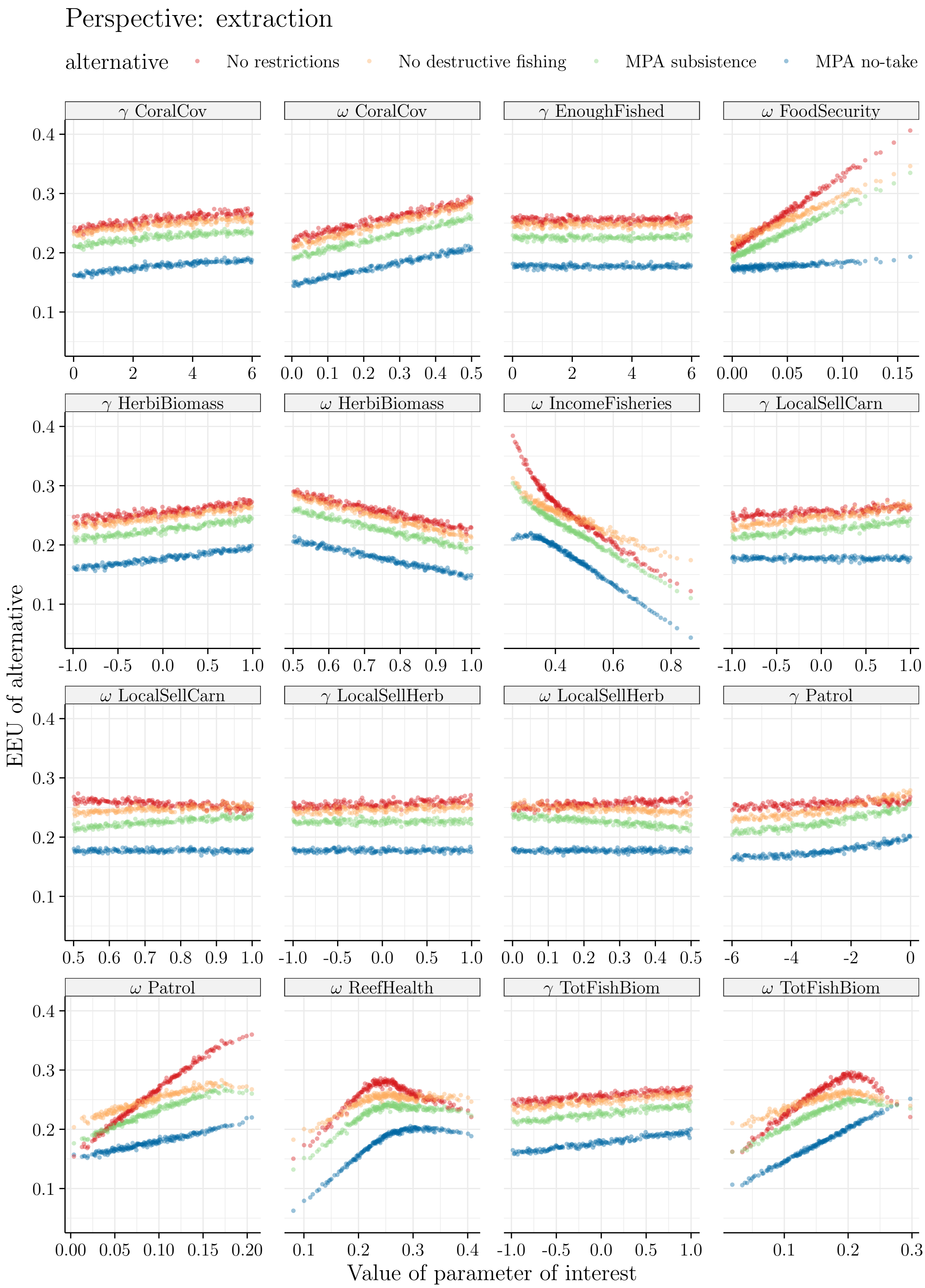

Figure SI-13: Dependence of the expected expected utility (EEU; y-axis) of alternatives (colors) on variation (x-axis) of a specific a preference parameter (panels) while keeping the conditional variability in all other variables and parameters.

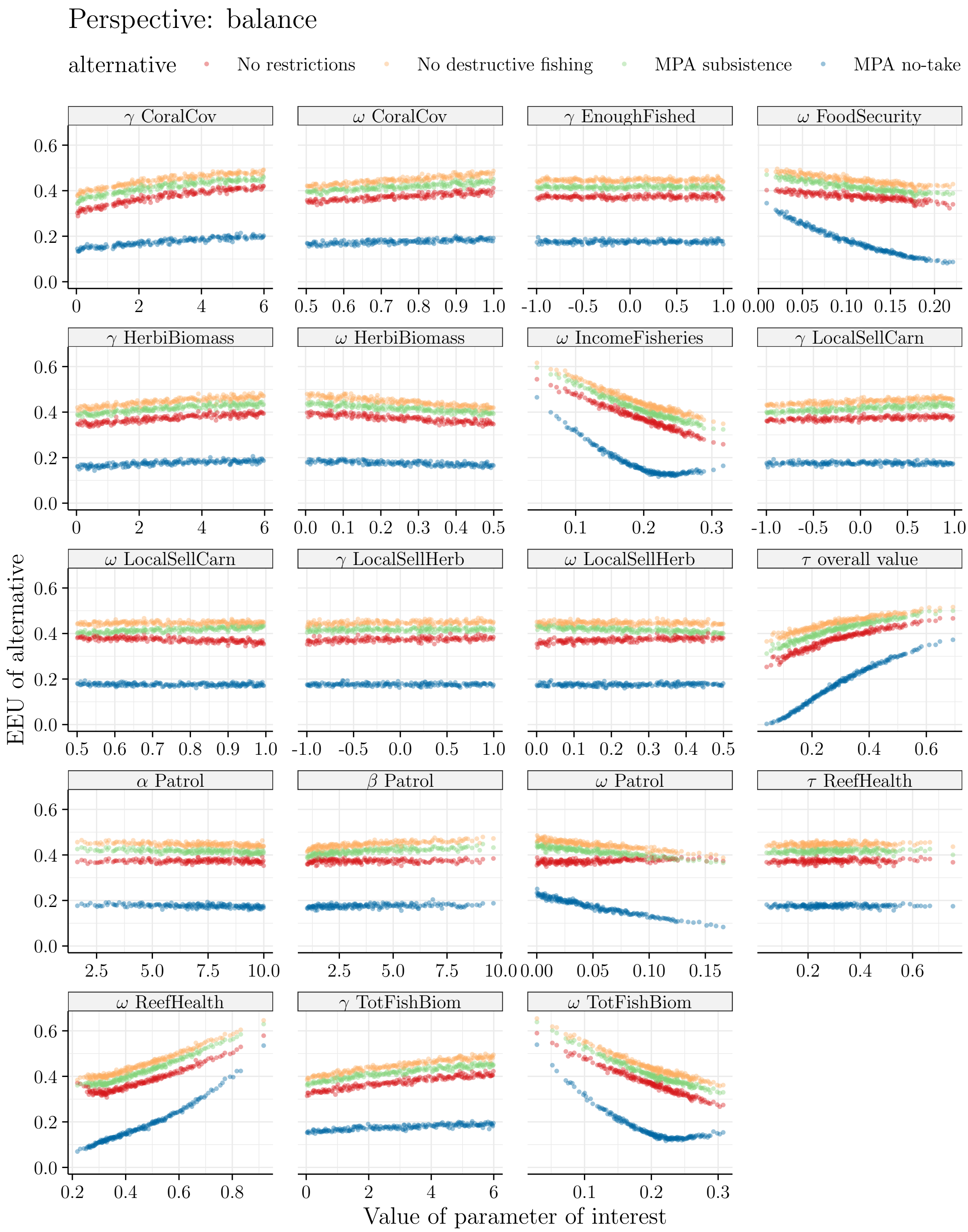

Figure SI-14: Dependence of the expected expected utility (EEU; y-axis) of alternatives (colors) on variation (x-axis) of a specific a preference parameter (panels) while keeping the conditional variability in all other variables and parameters.

SI-5.3 EVPPI of variables

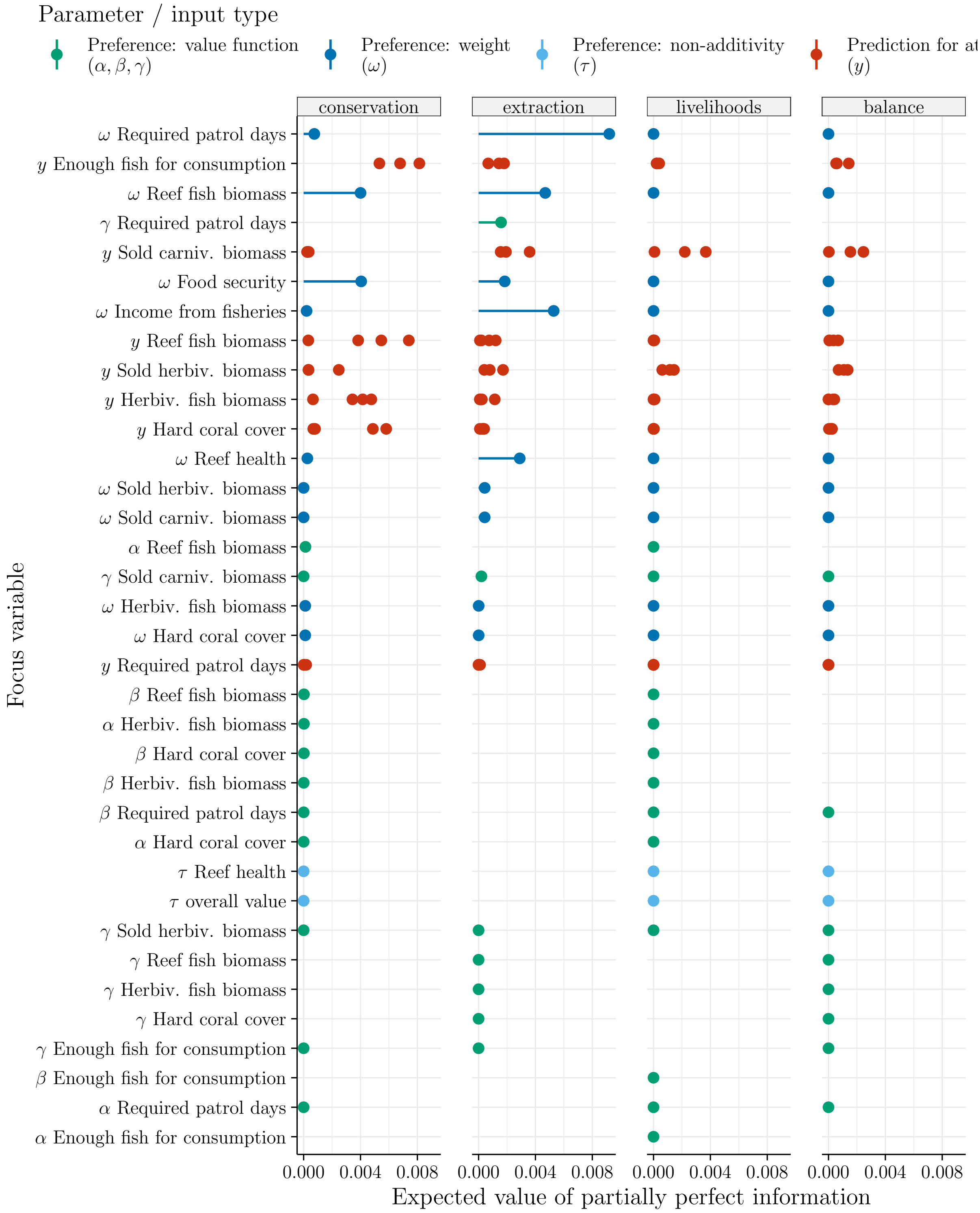

Figure SI-15: Expected value of partially perfect information (EVPPI; x-axis) for variables of interest (y-axis) for the different stakeholder perspectives (panels). Colors describe the type of parameter or input. A single bar represents the expected gain in utility for a particular stakeholder perspective, if we had perfect information about this variable. The predictions (y) are differentiated by alternative, therefore, four EVPPI values for each predicted attribute were calculated. Not all stakeholder perspectives share the same parameters, therefore, some entries are missing. Whether preference or prediction uncertainties have higher EVPPI depends on the stakeholder perspective.