



The conceptual foundation of environmental decision support



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ABSTRACT

Environmental decision support intends to use the best available scientific knowledge to help decision makers find and evaluate management alternatives. The goal of this process is to achieve the best fulfillment of societal objectives. This requires a careful analysis of (i) how scientific knowledge can be represented and quantified, (ii) how societal preferences can be described and elicited, and (iii) how these concepts can best be used to support communication with authorities, politicians, and the public in environmental management. The goal of this paper is to discuss key requirements for a conceptual framework to address these issues and to suggest how these can best be met. We argue that a combination of probability theory and scenario planning with multi-attribute utility theory fulfills these requirements, and discuss adaptations and extensions of these theories to improve their application for supporting environmental decision making. With respect to (i) we suggest the use of intersubjective probabilities, if required extended to imprecise probabilities, to describe the current state of scientific knowledge. To address (ii), we emphasize the importance of value functions, in addition to utilities, to support decisions under risk. We discuss the need for testing “non-standard” value aggregation techniques, the usefulness of flexibility of value functions regarding attribute data availability, the elicitation of value functions for sub-objectives from experts, and the consideration of uncertainty in value and utility elicitation. With respect to (iii), we outline a well-structured procedure for transparent environmental decision support that is based on a clear separation of scientific prediction and societal valuation. We illustrate aspects of the suggested methodology by its application to river management in general and with a small, didactical case study on spatial river rehabilitation prioritization.

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1. Introduction

Two main problems make decisions in environmental management difficult (McDaniels et al., 1999; Kiker et al., 2005; Clemen and Reilly, 2013). First, the society consists of individuals with a high diversity of perspectives, opinions, and interests. This makes it impossible to formulate “societal objectives” in any strict sense. Societal objectives may be defined as objectives with which a majority of people would agree. Still, such objectives may be conflicting and they are difficult to formulate and quantify. Second, environmental or coupled socio-environmental systems are complex. Therefore, it is difficult to reliably predict the consequences of decision alternatives. However, as the desirability of alternatives depends on the degree to which their consequences fulfill the

objectives, it is very important to derive such predictions and consider their uncertainty in decision making.

To account for these difficulties, different decision support techniques have been suggested and applied in environmental management (Salminen et al., 1998; Lahdelma et al., 2000; Kiker et al., 2005; Mendoza and Martins, 2006; Mahmoud et al., 2009; Huang et al., 2011; Gregory et al., 2012; Linkov and Moberg, 2012). All of them structure the decision making process into procedural steps and assess the degree by which decision alternatives fulfill the objectives. Some techniques rely on qualitative assessments, while others quantify preferences and predictions and rank alternatives based on scores of the expected fulfillment of objectives.

Important elements contributing to the success of environmental decision support are: transparency of the procedure, a good representation of stakeholders, the willingness of stakeholders to participate constructively and make their objectives explicit, guidance by a good facilitator, and a good conceptual basis of the underlying methodology (Howard, 1988; Belton and Stewart, 2001;

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Hajkowicz, 2008; Eisenführ et al., 2010). This multiplicity of elements explains, why decision support in environmental management can be successful for different underlying approaches (Hajkowicz, 2008). An excellent facilitator, for instance, may compensate for a poorer conceptual basis, or uncooperative stakeholders may hinder the success even if a conceptually sound procedure is used.

Thus, a good conceptual basis of the decision support methodology is only one important element that contributes to success. It is particularly relevant to support the use of scientific knowledge in societal decision making that has to be justified to the public. This is a key element of environmental management. Important conceptual requirements of good environmental management decision support can thus be summarized as follows:

1. Use of a mathematical formalism to describe scientific knowledge that
 - a) can deal with uncertainty (to consider poor predictability),
 - b) is able to represent conditional knowledge (for given driving forces, future scenarios, or decision alternatives),
 - c) can consistently describe a learning process based on new data (consistent means here that learning in two steps with partial data leads to the same result as learning in one step with all data).
2. Use of a mathematical description of preferences that
 - a) imposes as few constraints as possible to allow large freedom for specifying individual preferences,
 - b) considers risk attitudes to account for uncertainty in predictions in addition to describing preferences for certain outcomes,
 - c) avoids unreasonable results, such as rank reversals of top scoring alternatives if inferior alternatives are added or removed.
3. Use of a structuring and quantification process that
 - a) is relatively easy to understand and supports transparent communication of the reasons for a decision to the public,
 - b) supports identifying causes of disagreement and separates scientific predictions from societal valuations,
 - c) stimulates the generation of better alternatives and supports including them without re-elicitation of preferences.

As argued previously, procedures that violate some of these criteria can still lead to a successful decision support. However, we are convinced that a generally recommendable technique for bringing scientific knowledge into environmental management must be defensible against criticism. How can we convince stakeholders, if the chosen technique can lead to strange results that do not reflect common sense?

In the following, we first discuss which choices of methodologies these requirements imply. For each of these choices, we suggest modifications to established procedures to better adapt them for environmental management. In Sections 2 and 3, we do this for the mathematical representation of scientific knowledge and of societal preferences, respectively. Then, in Section 4, we discuss how these concepts can be applied in practice and explain key aspects of their use for river management. In Section 5, we illustrate the suggested procedure more concretely with a small, didactical case study on spatial prioritization for river rehabilitation. Finally, we summarize our conclusions in Section 6.

2. Representing and acquiring scientific knowledge

It is reasonable to base environmental management on the best available scientific knowledge. Scientific knowledge is always incomplete, dispersed in the scientific community, and it is difficult

to identify the most relevant knowledge for a given decision. To support the transparent use of scientific knowledge, it is crucial to think about how to represent it mathematically, how to acquire it, and how to use it to get scientific predictions that optimally support environmental management (Reichert, 2012).

2.1. Representing scientific knowledge

2.1.1. Philosophical interpretations of probability

The history of scientific reasoning is closely related to the mathematical framework of probability. The correct interpretation of probabilities as a philosophical basis of (natural) science (see Hájek, 2012 and references therein) has been much more intensively discussed than any of the suggested alternative concepts. In our brief outline of different interpretations of probability we roughly follow Gillies (2000), particularly concerning the historic development (see Chalmers, 1999 for a broader coverage of the philosophy of science).

The most important distinction is between *objective* and *epistemic* interpretations of probability. Objective interpretations use probabilities to describe features of the material world that are independent of humans, whereas epistemic interpretations use probabilities to quantify human knowledge or belief.

Important objective interpretations are the *frequency* and *propensity* interpretations. The frequency interpretation (e.g. Von Mises, 1928) defines probability as the limit of relative frequencies of events in a repeatable experiment. It assumes underlying physical laws that guarantee that this limit exists. The propensity theory (Popper, 1959; see also Gillies, 2000) intends to make objective probabilities applicable to single events by emphasizing the circumstances or causes of a single event that could in principle make it repeatable.

In contrast, epistemic interpretations use the same mathematical construct of probability to describe degrees of belief of individuals. The *logical* theory (e.g. Keynes, 1921) assumes that different individuals will independently come to the same degree of belief given the same evidence. Doubts about the possibility to uniquely derive probability statements based on logical reasoning lead to the development of the *subjective* interpretation of probability (e.g. Ramsay, 1926; De Finetti, 1931). Here, probabilities describe degrees of belief of individuals. Such probabilities can be different for different individuals facing the same evidence.

In the subjective interpretation, probabilities are operationalized by lotteries about which an individual is indifferent. Assume a lottery provides a gain proportional to $(1 - p)$ for a statement to be true and a loss proportional to p otherwise. If an individual is indifferent between this lottery and the lottery with the reverse outcomes, then his or her belief that the statement is true is defined to be p . It can be shown that if an individual agrees to operationalize his or her beliefs in this sense and wants to avoid sure loss if someone makes a choice among lotteries the individual is indifferent, then these quantities, p , must be probabilities in the sense of fulfilling the axioms of probability theory (see Howson and Urbach, 1989 for a careful discussion and proof of this Ramsey–De Finetti theorem).

There are other, complementary arguments for using probabilities to describe subjective beliefs. Cox (1946) shows that conditional beliefs that fulfill minor requirements must follow the laws of probability theory. Lindley (1982) proves that any scoring rule to quantify uncertainty that fulfills some reasonable properties can be transformed to probabilities. The argument of Cox is particularly important for environmental management since we are often confronted with questions as “which are the expected consequences, given a management alternative or future scenario?” This requires specifying conditional beliefs. Interestingly, several,

independent rational justifications exist for the use of probabilities to describe subjective beliefs.

Finally, Gillies (1991) introduced the *intersubjective* interpretation of probability by extending the Ramsey–De Finetti argument to groups of individuals sharing a common interest. He advocates a *pluralist view* of probability that uses different interpretations in different contexts (Gillies, 2000). He suggests to use epistemic probabilities in the social sciences and objective, propensity-based probabilities in the natural sciences.

2.1.2. Ideal representation of scientific knowledge by intersubjective probabilities

We agree with Gillies (2000) on the need of a pluralist view of probability with different interpretations in different contexts. The subjective interpretation is important when describing individual beliefs and human behavior, whereas objective interpretations are fundamental to the natural sciences. To support environmental decision making, we need a description of the best available scientific knowledge. This knowledge is usually not perfect enough that intrinsic randomness, characterized by objective probabilities, is the only source of uncertainty. Therefore, ideally, we would like to describe the best available scientific knowledge by intersubjective probabilities about which the scientific community agrees.

As it is impossible to ask all scientists, reasonable approximations are probability distributions about which several experts agree, or which are constructed from the individual beliefs of different experts. When constructing intersubjective knowledge from beliefs of different experts, the individual beliefs become “observations” of the current state of knowledge. To minimize the “observation error”, the individual beliefs can be averaged.

Such an intersubjective interpretation conforms to standards of best scientific practice, such as the peer-review system of scientific journals, by which articles are only accepted upon positive assessment by several independent experts (Bornmann and Daniel, 2010). It also agrees with practices of knowledge integration in modeling as represented particularly clearly by Bayesian belief network modeling (e.g. Borsuk et al., 2004).

Given this agreement with current scientific standards, it is surprising that a discussion of the conceptual basis of intersubjective probabilities is largely missing in the scientific literature (but see Gillies, 2000; Rowbottom, 2008). Although usually not discussed explicitly, the research field of combining expert opinions (Clemen and Winkler, 1999) also builds implicitly on an intersubjective interpretation of probability (see also Section 2.2.2).

Another important argument for using intersubjective probabilities to describe scientific knowledge is rarely discussed. Uncertainty of the outcome of a perfectly known system affected by randomness can be characterized by objective probabilities. Once the random event is realized, but the outcome has not yet been observed, uncertainty becomes epistemic. Here, the underlying objective probability serves as the natural, intersubjective characterization of the epistemic uncertainty of the outcome (it seems reasonable to believe with a probability of 1/6 of each possible outcome of a dice that has been thrown but not yet observed, as this is the underlying objective probability before the dice was thrown). This adoption of objective probabilities as intersubjective, epistemic knowledge is only possible if the same mathematical framework is used to quantify randomness (with objective probabilities) and uncertain knowledge (with intersubjective, epistemic probabilities).

A final argument for using the probabilistic framework to describe knowledge is that Bayesian inference provides a consistent description of an iterative learning process: updating prior information iteratively with partial data leads to the same result as updating once with all data.

2.1.3. Considering imprecision

Intersubjective probability distributions, representing scientific knowledge, can be based on consensus within a group of scientists or by aggregating their individual beliefs.

In practice, scientists may be uncertain about their own beliefs and a group may not reach consensus. Therefore, we may have to account for the scientists' ambiguity about the current state of knowledge. A conservative way of considering uncertain knowledge is to ask experts for intervals of provided probabilities or quantiles instead of precise estimates (Meyer and Booker, 2001; O'Hagan et al., 2006). Alternatively, intervals can be constructed from the replies of different experts. For continuous variables, this information can be used to construct sets of probability distributions instead of a single, precise distribution. Such sets are also known as imprecise probabilities (Walley, 1991; Rinderknecht et al., 2012b; <http://www.sipta.org>). When used as prior distributions in Bayesian inference, this leads to so-called robust Bayesian analysis (Berger, 1984, 1994; Pericchi and Walley, 1991; Rinderknecht et al., 2014). The density-ratio class (DeRobertis and Hartigan, 1981; Berger, 1990) is particularly interesting, as it is invariant under updating, marginalization, and propagation through a deterministic model (Wasserman, 1992; Rinderknecht et al., 2014).

2.1.4. Combination with scenarios

In some cases, due to a too high degree of ambiguity, scientists may even hesitate to formulate predictions as imprecise probabilities. Here, alternative future scenarios may be developed, often for driving forces or external influence factors (Schoemaker, 1995; Ringland, 2006). If external influence factors are formulated as scenarios, probabilistic predictions for the system of interest can be formulated conditional on these scenarios. This combines future scenario and probabilistic prediction approaches (Lienert et al., 2014; Scholten et al., 2014a,b).

2.1.5. Alternative theories for describing uncertain knowledge

The use of probability theory as the most adequate framework for describing epistemic uncertainty has been challenged (Helton and Oberkampf, 2004; Colyvan, 2008). The main criticism is that typically insufficient knowledge is available to specify a precise probability distribution. Alternative approaches to consider this ambiguity (Helton et al., 2004) are evidence theory (Dempster, 1967; Shafer, 1976), possibility theory (Zadeh, 1978; Dubois and Prade, 1988; Dubois, 2006), and interval analysis (Moore, 1979). Similar to imprecise probabilities, evidence theory uses lower and upper probabilities, but evidence is combined by different rules (Dempster, 1967). Possibility theory is based on fuzzy sets, where potential elements have a “degree of membership” between 0 and 1. 0 indicates not to be an element, 1 to be an element. Values in between formulate partial degrees of membership. Membership functions seem to be similar to probability densities, but they use a different normalization and a different calculus. Interval analysis characterizes unknown quantities by intervals without specifying probability distributions within the intervals. These intervals are then propagated through functions allowing for all possible combinations of values in the intervals. This theory is particularly important for exact maximum error analysis of digital computers.

In our view, none of these alternative theories has a similarly good axiomatic foundation as probability theory for ideally representing uncertain scientific knowledge. However, the argument that ambiguity about the correct probability distribution can hardly be represented by probabilities (Colyvan, 2008) is justified. For this reason we suggest the use of intersubjective probabilities to describe scientific knowledge in the absence of significant ambiguity (see Section 2.1.2), and imprecise, intersubjective probabilities otherwise (see Section 2.1.3). This approach can easily be

combined with future scenarios.

2.2. Acquiring scientific knowledge

Integrating scientific knowledge for environmental decision support can best be done by experts in the respective fields. Such integrated, intersubjective knowledge can be gained by eliciting consensus probability distributions of a group of experts (in the sense of Gillies, 1991, 2000) or by constructing an aggregated probability distribution from subjective distributions of individual experts (extending intersubjective probabilities as introduced by Gillies, 1991, 2000; see Section 2.1.2). Below, we comment on elicitation and aggregation procedures.

2.2.1. Eliciting knowledge as probability distributions

There exist standard procedures for eliciting subjective beliefs of individuals as probability distributions (e.g. Morgan and Henrion, 1990; Meyer and Booker, 2001; O'Hagan et al., 2006). Continuous distributions are usually elicited by asking the expert(s) for selected quantiles or cumulative probabilities and then fitting a parametric distribution through the elicited points. Known biases of probability elicitation should be avoided by carefully designed elicitation protocols (Tversky and Kahneman, 1974; Kynn, 2008). Recently, these techniques have been extended to elicit imprecise probability distributions as density-ratio classes (Rinderknecht et al., 2012a).

2.2.2. Aggregating subjective probability distributions of experts

Many techniques for combining probability distributions to aggregate expert opinions have been proposed (Winkler, 1968; French, 1985; Genest and Zidek, 1986; Clemen, 1989; Clemen and Winkler, 1999). We suggest to use the linear opinion pool (Stone, 1961), which calculates the weighted average of individual distributions. There are the following reasons for this choice: It has reasonable properties for the combination of information from multiple experts (compromise between disagreeing opinions, but no narrowing of the distribution if experts agree), it supports transparency as it is easy to understand, and there is empirical evidence that simple aggregation techniques are successful (Clemen, 1989). Weights can be used to quantify different degrees of expertise of different experts. This approach accounts for the fact that the scientific uncertainty does not decrease with asking more experts, but the confidence in its correct description increases.

Considering ambiguity by imprecise probabilities offers new perspectives for aggregating subjective probability distributions. Quantiles or cumulative probabilities stated by experts can be used to construct quantile or cumulative probability intervals, either by including all stated values or by using a quantile interval that excludes extreme views. Then, a set of probability distributions can be constructed that is compatible with these intervals analogously to Section 2.2.1. Note that this is a conservative approach that may lead to very high uncertainty in predictions.

2.3. How to get scientific predictions?

To support decisions in environmental management, we need probabilistic predictions of the outcomes for management alternatives and scenarios of driving forces. We can thus either a) acquire conditional predictions of the outcomes for all management alternatives and driving force scenarios directly, or b) acquire mechanistic knowledge on the structure and function of the affected systems to derive predictions through modeling.

Approach b) is more universal as outcomes for new alternatives can be predicted without re-elicitation. However, developing mechanistic models requires a considerable effort. For generic problems for which the model can be re-used or can even become a

permanent management tool, this is certainly preferable. Approach a) can be implemented more quickly; it corresponds to acquiring expert advice in a traditional sense, but it emphasizes the prediction of outcomes rather than the selection among alternatives. In practice, the approaches are often combined. Option b) is used for predicting the consequences for those sub-systems for which models are available or can be developed efficiently and option a) for the other sub-systems.

Whenever possible, probability distributions elicited from experts should be updated by Bayesian inference with new, often local data. This can narrow the distributions or lead to the identification of prior-data conflicts that have to be resolved.

2.4. Summary of arguments in favor of the suggested approach

In summary, the following arguments favor using (possibly imprecise) intersubjective probabilities gained from experts to describe the current state of scientific knowledge:

1. Despite good reasons for the existence of objective probabilities in the real world, the incomplete state of **scientific knowledge can only be described by intersubjective beliefs**. This is compatible with established techniques of scientific quality control, such as peer review.
2. Operationalization of (inter-)subjective beliefs based on indifference between lotteries clarifies their meaning (as far as possible). The rationality argument of avoiding sure loss supports the use of probabilities for describing uncertain knowledge and becomes even stronger when formulating justifiable, intersubjective knowledge rather than subjective beliefs. Other reasons for this choice are based on assumptions regarding conditional beliefs, the formulation of scoring rules, compatibility with objective probabilities, and the existence of a consistent updating technique. According to these arguments, **intersubjective beliefs would ideally be described by probabilities**.
3. **The extension to imprecision allows us to consider ambiguity** induced by uncertain knowledge of experts or disagreeing opinions. In case of negligible ambiguity, imprecise probabilities degenerate to precise ones that we argued for in the ideal case.
4. **The suggested approach can easily be combined with future scenarios of external influence factors**. This is done by using conditional probability distributions based on the scenarios.

Thus, the description of the current state of scientific knowledge by potentially imprecise, intersubjective probabilities fulfills requirements 1a, 1b and 1c formulated in the introduction. Alternative approaches are built on a weaker conceptual basis and do not seem to compensate this with other advantages.

3. Describing societal preferences

In addition to acquiring the best scientific knowledge for predicting the outcomes of decision alternatives, we need a representation of societal preferences to support environmental decision making. We can then evaluate to which degree the predicted outcomes of management alternatives fulfill the societal goals. Even more importantly, the insights gained through this process can stimulate the generation of better alternatives. We adopt the framework of *value-focused thinking* (Keeney, 1992), which emphasizes thinking about what one would like to achieve and being open for any kind of measures to reach this goal rather than focusing on given alternatives.

The first difficulty of quantifying societal goals is that “societal preferences” are even harder to tackle than individual preferences.

The development of preferences of individuals requires them to think hard about the problem and often preferences become more concrete during the elicitation process (Belton and Stewart, 2001). This problem is aggravated when preferences have to be formulated by laypersons, who are unfamiliar with environmental systems and their management. Additionally, because of the heterogeneity of people and their interests and perceptions, “societal preferences” do not exist in a strict sense. Therefore, we are searching for a description of preferences either of multiple, less heterogeneous (stakeholder) groups or of a representative, large sample of the population. The first type of preferences can show the plurality among groups and resulting differences can stimulate the process of finding “compromise” alternatives (Hostmann et al., 2005a). The second type may help to check whether an alternative could reach acceptance in a public vote. The same mathematical formalism can and should be used for both cases, but elicitation techniques may differ. In the first case, face-to-face interviews can be performed with a (relatively small) number of representatives of the groups. Here, it may even be possible to address technical or scientific issues related to the decision problem. In the second case, simpler, possibly online surveys of a larger set of persons are required. These can only cover objectives at a relatively general level and have to rely on summary assessments at lower levels. In both cases, we are interested in intersubjective preferences that are representative of the (stakeholder) group or the whole society.

3.1. Conceptual basis for representing preferences in multi-attribute value and utility theories (MAVT/MAUT)

Decisions in environmental management have to be communicated and justified to the public. This is facilitated by transparently conveying objectives and rational arguments of how these can best be achieved. This is the core of decision analysis or the theory of rational decision making (Keeney and Raiffa, 1976; Keeney, 1982; Eisenführ et al., 2010) which is built on relatively simple rationality axioms.

The concepts of rational decision making are often violated in actual human decision making. Alternative models have been suggested to better account for human behavior (Simon, 1955, 1956, 1982; Gigerenzer and Goldstein, 1996; Gigerenzer and Gaissmaier, 2011). Nevertheless, to structure the decision making process and to justify public decisions, rational arguments are important as they make the decision transparent and plausible. Thus, despite the deficiencies of rational decision theory as a behavioral theory, it is still preferable to behavioral theories when applied to support justifiable decision making in environmental management.

Following the concept of *value-focused thinking* (Keeney, 1982), it is crucial to start decision support by discussing which objectives should be achieved. Hereby, the overall objective is hierarchically broken down into sub-objectives each of which is more focused and concrete and all together cover all important aspects of the objective at the higher level. Then, the degree of fulfillment of the objectives must be quantified, as a function of observable properties, so-called attributes, $\mathbf{y} = (y_1, \dots, y_n)$, of the system affected by the decision. If we assume that the preferences of a decision maker or stakeholder over outcomes are complete and transitive, then an *ordinal value function*, $v(\mathbf{y})$, exists that has larger values for preferred alternatives (there are minor additional technical requirements; see Keeney and Raiffa, 1976 or Eisenführ et al., 2010 and literature cited therein). Complete preferences means that for any pair of outcomes the decision maker or stakeholder can decide which one he or she prefers, or whether he or she is indifferent between the two outcomes. Transitivity requires that if someone prefers an outcome $\mathbf{y}^{(a)}$ over an outcome $\mathbf{y}^{(b)}$ and $\mathbf{y}^{(b)}$ over $\mathbf{y}^{(c)}$, then he or she prefers $\mathbf{y}^{(a)}$ over $\mathbf{y}^{(c)}$. An ordinal value function is unique

up to a strictly increasing (possibly nonlinear) transformation. It can be scaled to the interval $[0,1]$, where 0 represents the worst and 1 the best outcome. As mentioned above, these assumptions are hardly questioned as a basis for a procedure to guide rational decision making for decisions that have to be justified to the public, although they are sometimes violated by actual human behavior.

More information about the preferences of the decision maker or stakeholder can be included in two ways: First, as we are also interested in quantifying preferences regarding transitions from one state to another, we assume that these are also complete and transitive. Under these assumptions a *measurable (or cardinal) value function* exists for which larger differences between values of outcomes imply stronger differences in preference (e.g. Keeney and Raiffa, 1976 or Eisenführ et al., 2010). A measurable value function is unique up to a linear, increasing transformation. It can thus be made unique by specifying the value for the worst outcome under consideration as 0 and the best outcome as 1. This is the basis of multi-attribute value theory (MAVT). The second option is to include information about risk attitudes of the decision maker or stakeholder. This leads to a *utility function* (note that in economics the term “utility function” is often used for what in decision analysis and in this paper is called “value function”). In this case, probabilistic outcomes can be ranked according to their expected utility. The axioms of expected utility theory, also called multi-attribute utility theory (MAUT), were first derived by Von Neumann and Morgenstern (1947) (see e.g. Keeney and Raiffa, 1976). A utility function can be directly elicited as a function of attributes by asking for relative preferences between lotteries of outcomes (see e.g. Keeney and Raiffa, 1976 or Eisenführ et al., 2010). Alternatively, it can be expressed as a function of value after having first elicited a value function (Dyer and Sarin, 1982). The latter option has the advantage of providing preference and risk attitude information separately. Moreover, it minimizes the need for eliciting preferences between lotteries, as this is only needed for the overall value instead of the values of each sub-objective (see Section 3.2).

The few axioms of MAVT, essentially completeness and transitivity, will hardly be questioned as guiding principles for rationally evaluating alternatives and justifying decision to the public. Utilities, the axioms of which may be more difficult to communicate and agree with, will often not change the results. This can be tested by sensitivity analysis (see Sections 3.2 and 4.4 and Schuwirth et al., 2012). As there are no further constraints or rules for the formulation of preferences, MAVT/MAUT is based on a minimal set of assumptions and leaves the decision maker or stakeholder as much freedom as possible for formulating his or her beliefs.

3.2. Implementation of MAVT and MAUT

To implement the description of societal preferences as value and utility functions, we need to construct these functions based on interviews with decision makers or stakeholders, or based on population surveys. We distinguish preference elicitation based on objectives hierarchies and preference construction using discrete choice experiments. The first technique is better suited to obtain preference information from a small group of people, whereas the second is better suited to survey the population. As utility functions confound preferences and risk attitudes, and value functions are easier to elicit, we prefer eliciting value functions and transfer them to utilities later (Dyer and Sarin, 1982).

3.2.1. Preference elicitation based on objectives hierarchies

When eliciting preferences with interviews, it is recommendable to first elicit an objectives hierarchy, then construct a value function based on this hierarchy, and finally convert the overall value into a utility.

An objectives hierarchy can be constructed by iteratively breaking down each objective into a set of mutually complementary and collectively comprehensive sub-objectives (Keeney and Raiffa, 1976; Eisenführ et al., 2010). This helps to clarify what one would like to achieve.

Constructing a value function is complex, because value judgments are difficult and because the overall value may depend on many attributes. The structure offered by an objectives hierarchy considerably simplifies the construction of a multi-attribute value function.

First, for the lowest level sub-objectives, adequate attributes must be chosen that can be used to quantify the degree of fulfillment of each objective as a measurable value function. As the lowest level sub-objectives are relatively narrow in scope, one or a few attributes may be sufficient for each of these sub-objectives. There are established techniques for eliciting such value functions (see e.g. Keeney and Raiffa, 1976; Eisenführ et al., 2010).

The next elicitation step requires constructing value functions for objectives that combine lower level sub-objectives. Such a value function is formulated as an aggregation function of the values at the lower level, and it thus depends only indirectly on the attributes. The top row of Fig. 1 shows examples of aggregation functions of two values, v_1 and v_2 : additive aggregation (weighted arithmetic mean) with equal (Fig. 1A) and unequal (Fig. 1B) weights given to the two sub-objectives, geometric aggregation (weighted geometric mean) with equal weights (Fig. 1C), and mixed additive-minimum aggregation (Fig. 1D) with equal weights (see Langhans et al., 2014a for a more thorough discussion of value aggregation techniques).

Elicitation of the correct aggregation function and its parameters should be done by trade-off questions. This is illustrated in the bottom row of Fig. 1 for the same aggregation functions as in the top row. The horizontal and vertical line segments starting from nine value combinations indicate the change in the value on the corresponding axis required to get a gain in the aggregated value of 0.05.

For additive aggregation with equal weights, the same increments in v_1 and v_2 are required to reach outcomes between which the decision maker or stakeholder is indifferent (Fig. 1E). These increments are independent of the values v_1 and v_2 (the shape remains the same when moving from the trade-offs marked in red to those in green or blue). Different weights lead to different increments in v_1 and v_2 (Fig. 1F), but they still do not depend on v_1 and v_2 . Although in many studies such an additive aggregation technique is assumed, this assumption should be tested carefully by eliciting trade-offs for different values of v_1 and v_2 . As an example, geometric aggregation and mixed additive-minimum aggregation lead to the dependence of the trade-offs on v_1 and v_2 (Fig. 1G and H). When eliciting such trade-offs, the values v_1 and v_2 must be communicated by associated attributes, because the attributes characterize the state of the system and the value function is just a tool to represent the preferences mathematically.

Trade-offs are best elicited by keeping one of the endpoints of the lines in Fig. 1E–H fixed and asking for the attributes corresponding to indifference along the other line. Instead of asking for this/these attribute(s), discrete choices of the attributes could be given and the decision maker would be asked for preferences of these given, discrete choices. This could be used for bracketing the attributes for which the decision maker would be indifferent to the reference state. To aggregate more than two values, this elicitation step can be done by either keeping some values fixed or by asking for indifference between two states differing in multiple values.

As a last step, the value function of the overall objective must be converted to a utility function to derive a unique ranking also for uncertain outcomes (Dyer and Sarin, 1982). This can be done by applying standard techniques, such as the certainty equivalent method with a representation of the values by corresponding attributes (e.g. Eisenführ et al., 2010). It may be worth checking for an effect on the resulting ranking of alternatives beforehand by a sensitivity analysis within a range of plausible risk attitudes. Changes in the ranking only occur if the expected utilities of two

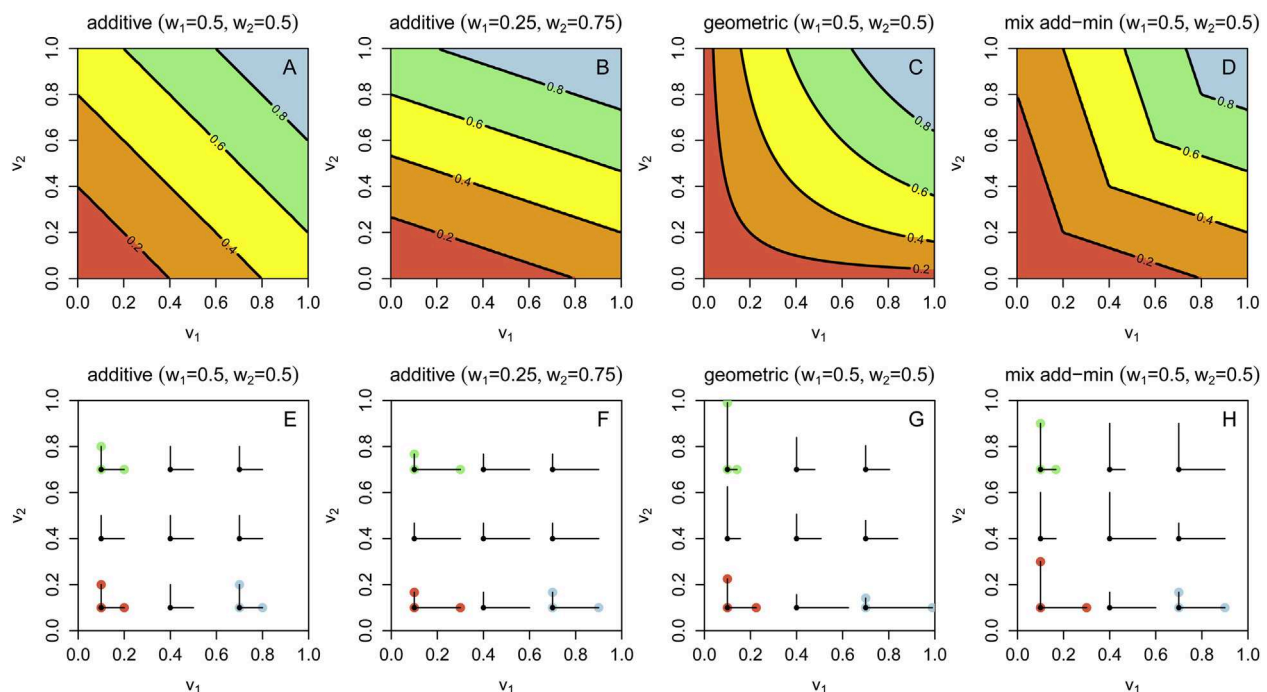


Fig. 1. Iso-value lines and color-coding of additive (for different weights), geometric, and mixed additive-minimum aggregation techniques (top row), and trade-offs for the same aggregation techniques (bottom row). Horizontal and vertical lines indicate the change in the value on the corresponding axis required to get a gain in the aggregated value by 0.05. See text for more explanations (modified from Langhans et al., 2014a).

alternatives are close and the distributions of the utilities are significantly different. If this sensitivity analysis indicates no rank reversals, this last elicitation step can be omitted. A conversion from values to utilities can also be done at lower levels. In this case, different risk attitudes can be present in different branches of the objectives hierarchy. This is still compatible with a single risk attitude at the final level of aggregation, but the aggregation rules for values and utilities must fulfill consistency requirements.

3.2.2. Construction of preference representations using discrete choice experiments

An alternative to the hierarchical construction of value functions is the fit of a parameterized value function to results of discrete choice experiments (Ben-Akiva and Lerman, 1989). Typical statistical techniques applied for such a fit from discrete data are logistic and probit regression (Agresti 2012). To apply these techniques, many discrete choices are required. Therefore, these techniques are particularly well-suited to construct a societal value function that describes “average” preferences of the whole population, which is represented by a large, representative sample of people. These techniques are also applied to extract monetary trade-offs for cost-benefit analysis in environmental economics (see also Section 3.3).

3.3. Alternative approaches

Many alternative approaches to value and utility functions for supporting rational decision making have been developed (see e.g. Belton and Stewart 2001). Frequently applied techniques in environmental management are outranking techniques, such as ELECTRE (Roy, 1991; Figueira et al., 2013) and PROMETHEE (Brans et al., 1986; Klauer et al., 2006; Behzadian et al., 2010), and the Analytic Hierarchy Process, AHP (Saaty, 1977; Saaty, 1994). Despite many successful applications, we prefer MAVT/MAUT because of the following conceptual deficiencies of the other techniques: (i) the potential for rank reversals when removing a lower ranked alternative (Wang and Triantaphyllou, 2008; Mareschal et al., 2008; Dyer, 1990), (ii) the use of “ad hoc” aggregation schemes that were not elicited from the decision maker or stakeholder, and (iii) the difficulty of considering uncertainty and risk attitudes. Even if these deficiencies can be addressed, MAVT/MAUT provides the broadest coverage of potential preferences so that the other techniques are not needed.

Cost-benefit analysis is another methodology often applied in environmental decision support (Hanley and Spash, 1993; Brouwer and Pearce, 2005; Pearce et al., 2006). It is based on similar principles as MAVT; in particular, discrete choice experiments are often used to extract willingness to pay for ecosystem services (see also Section 3.2.2). To keep them feasible, such discrete choice experiments usually have to be limited to high levels of the objectives hierarchy. This makes them suitable for analyses at the societal level (as discussed in Section 3.2.2 for MAVT/MAUT), but does not make it possible to consider details of the underlying mechanisms. With a higher resolution of the objectives hierarchy, MAVT/MAUT can provide a more detailed view on complex, multi-faceted decision problems (Chee, 2004) while still also providing the overview at the highest levels.

3.4. Summary of arguments in favor of the suggested approach

In summary, the following arguments favor the use of value and utility functions for the representation of societal preferences:

1. MAVT/MAUT is based on a **small number of axioms** that define “rational choice”. Although individuals often violate these axioms in their personal decisions, these axioms make sense to

support decisions which have to be justified transparently and with rational arguments to the public.

2. Value functions are **very flexible regarding the representation of preferences**. In contrast to other decision support methodologies, there are hardly any formal constraints to quantifying preferences.
3. The representation of preferences under uncertainty by utilities makes it possible to consider **risk attitudes** of decision makers or stakeholders in a consistent framework that fits to the probabilistic description we chose in Section 2 for representing scientific knowledge. Formulating utilities as functions of values facilitates elicitation and makes it possible to test the sensitivity of the results to risk attitudes. If the resulting rankings are insensitive to a reasonable range of risk attitudes, utilities are not needed.
4. The elicitation of value and utility functions is (largely) **independent of the outcomes of specific alternatives**. This makes it possible to evaluate new alternatives without re-eliciting preferences, except if it is necessary to extend the attribute ranges.
5. The framework of MAVT/MAUT **avoids artefacts** such as rank reversals when adding or removing alternatives or the use of ad-hoc procedures for evaluating results.

Thus, the description of societal preferences by value and utility functions fulfills the requirements 2a, 2b and 2c formulated in the introduction.

4. Making the theory accessible for practical decision support

Satisfying concepts for representing scientific knowledge and societal preferences, as developed in the Sections 2 and 3, respectively, are an important basis of good decision support. However, successful implementation additionally requires that the concepts are understandable to the decision makers and stakeholders and that the decision support process is well structured and moderated. In this section, we discuss how the practical application of the concepts discussed in the Sections 2 and 3 can be facilitated.

To make the discussion more concrete, we illustrate the key elements with the example of river management. Many of the elements discussed above have been applied to decision support regarding different aspects of surface water management. Examples are river rehabilitation (Reichert et al., 2007; Beechie et al., 2008; Corsair et al., 2009; Convertino et al., 2013), environmental flow requirements (Richter et al., 2003, 2006), fisheries management (McDaniels, 1995), and lake water quality management (Anderson et al., 2001).

4.1. Structuring the decision making process

The most important element to support practical application of the techniques outlined in Sections 2 and 3 is their embedding into a structured decision making process (Gregory et al., 2012). Fig. 2 shows the key elements of such a process.

The decision making process starts with a clear definition of the problem (step 1 in Fig. 2) and an analysis of stakeholders (Grimble and Wellard, 1997; Lienert et al., 2013) to be included in the process (step 2). This is followed by the explicit formulation and structuring of the objectives to be achieved (step 3), including the identification of observable system properties (attributes) that can be used to quantify the degree of fulfillment of the objectives and the ranges of these attributes. Next, the preferences regarding these objectives can be elicited quantitatively in the form of a value function as outlined in Section 3 (step 3). This value function can then be confronted with observations of the attributes of the system to be

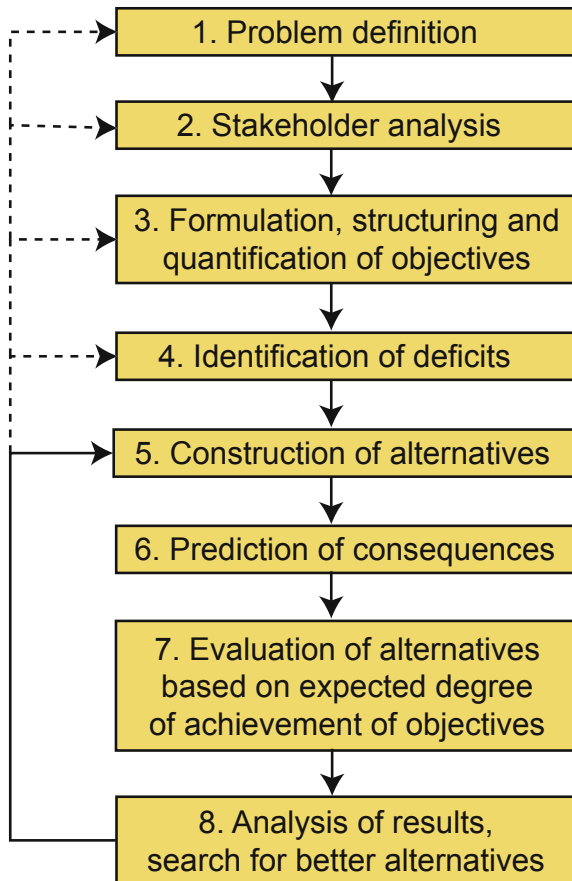


Fig. 2. Structure of the decision making process (modified from Schuwirth et al., 2012).

managed to check the degree of fulfillment of the objectives and to identify deficits (step 4). This deficit analysis can inspire the creation of management alternatives which improve the fulfillment of the objectives (step 5). Depending on the nature of the alternatives, it may often be a purely natural scientific or engineering problem to predict the consequences of the alternatives (step 6). However, some alternatives, such as establishing incentive systems to change the behavior of social actors, may need predictions for social systems (this may require using behavioral decision theories). Confronting the predictions with the quantified preferences leads to an evaluation of the alternatives (step 7). In the most detailed execution of this decision making process (see Section 4.2), this step consists of ranking the alternatives according to decreasing expected utility. The insights into the decision problem gained through this process will often help to design better alternatives (step 8, solid arrow) or lead to a revision of the objectives and/or even of the problem definition and involved stakeholders (dashed arrows).

While the order of the steps (Fig. 2) bears internal logic, the benefit of a structured decision making process largely results from interactions among them. Therefore, the diagram is intended to guide an iterative decision support process. Depending on the application, detailed processing of some steps may be skipped in a first iteration and be taken up later. For example, if deficits are apparent and some measures are already suggested, it may be useful to proceed to the prediction of their consequences (step 6) before quantifying preferences in step 3. The ranges of predicted attributes may then be useful when returning to step 3 to quantify the preferences and an a priori sensitivity analysis regarding

different preference parameters may help to distribute the elicitation effort to the most important parameters (see also the alternative flow diagrams in Schuwirth et al., 2012; Lienert et al., 2014).

4.2. Choice of appropriate application level

The required degree of detail for environmental decision support and the availability of resources vary considerably between decision problems. The procedure outlined in Section 4.1 can guide decision support at different levels of detail regarding the implementation of the steps shown in Fig. 2:

- A. The steps of the procedure (Fig. 2) can be used to structure the discussion among stakeholders and decision makers and stimulate *value-focused thinking* (Keeney, 1992) without quantifying objectives and predictions (Gregory et al., 2012).
- B. Objectives hierarchies and the fulfillment of sub-objectives for different alternatives can be assessed with stakeholders, decision makers, and experts without formally quantifying predictions and valuations.
- C. Value functions can be constructed and applied to observed attributes for deficit analysis. Expert predictions can be used to assess the improvement expected from different alternatives.
- D. Utility functions can be applied to probabilistic predictions of the consequences of decision alternatives obtained through expert elicitation and/or mathematical modeling.

It is important that needs and resources are carefully considered to find the appropriate degree of detail for decision support in any specific case. Moreover, the sample of stakeholders or of the population to elicit the preferences from and the elicitation techniques depend on the application. To gain insight into the decision problem and find better alternatives, it may be useful to elicit separate value function from representatives of different stakeholder groups (Hostmann et al., 2005a,b; Lienert et al., 2011). The effect of the diversity of opinions on final rankings of alternatives can be analyzed, and causes of poor rankings may be eliminated by modified alternatives. Alternatively, for a better overview of the valuation by the society, the fit of a parameterized value function through the results of a discrete choice experiment performed with a representative population sample may be more suitable.

4.3. Structuring objectives and quantifying preferences

Carefully thinking about objectives and structuring them hierarchically is a crucial step of any decision support procedure (Fig. 2, step 3). The resulting objectives hierarchy can be used to facilitate the quantification of preferences (Fig. 2, step 3; see Section 3.2.1). Here, we outline some elements of these steps for which we suggest to deviate from standard decision analysis practice when applying it to environmental management. We illustrate these steps with an example from river management.

4.3.1. Generating and structuring objectives

Fig. 3 shows the upper levels of an objectives hierarchy for a good river management strategy. At the highest level, the decision maker or stakeholder has to weigh the objectives of a good ecological state of the river network, good ecosystem services, low costs, conformity with regulation, and a robust design of the alternatives that allows for corrections. In this example, only “direct” services are listed under ecosystem services. The objective of achieving a good ecological state of the river network is kept as a separate branch of the hierarchy and is not included in the

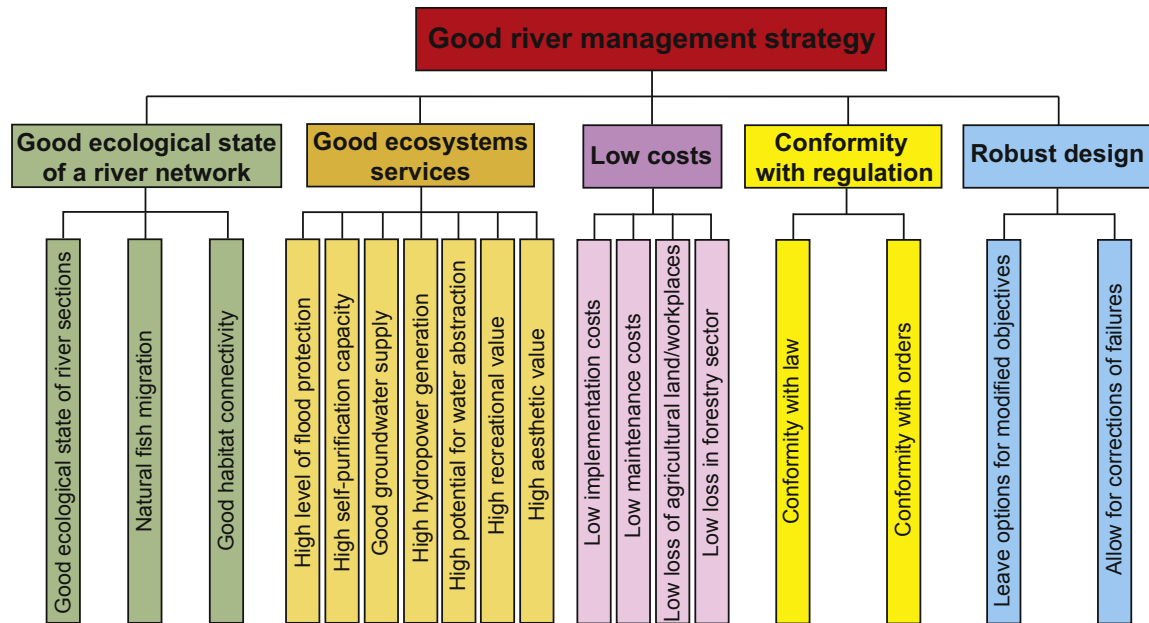


Fig. 3. Example of an objectives hierarchy for a good river management strategy (modified from Reichert et al., 2011).

ecosystem services. This is advantageous as we can translate conventional ecological river assessment procedures into a generic value function for the good ecological state (see also Section 4.3.2). In addition, this separation of the ecological state from the other

ecosystems services allows us to better account for the complexity of the valuation problem (Chee, 2004). Note that this is usually not done in environmental economics where all benefits are formulated as ecosystem services (MEA, 2005; TEEB, 2010).

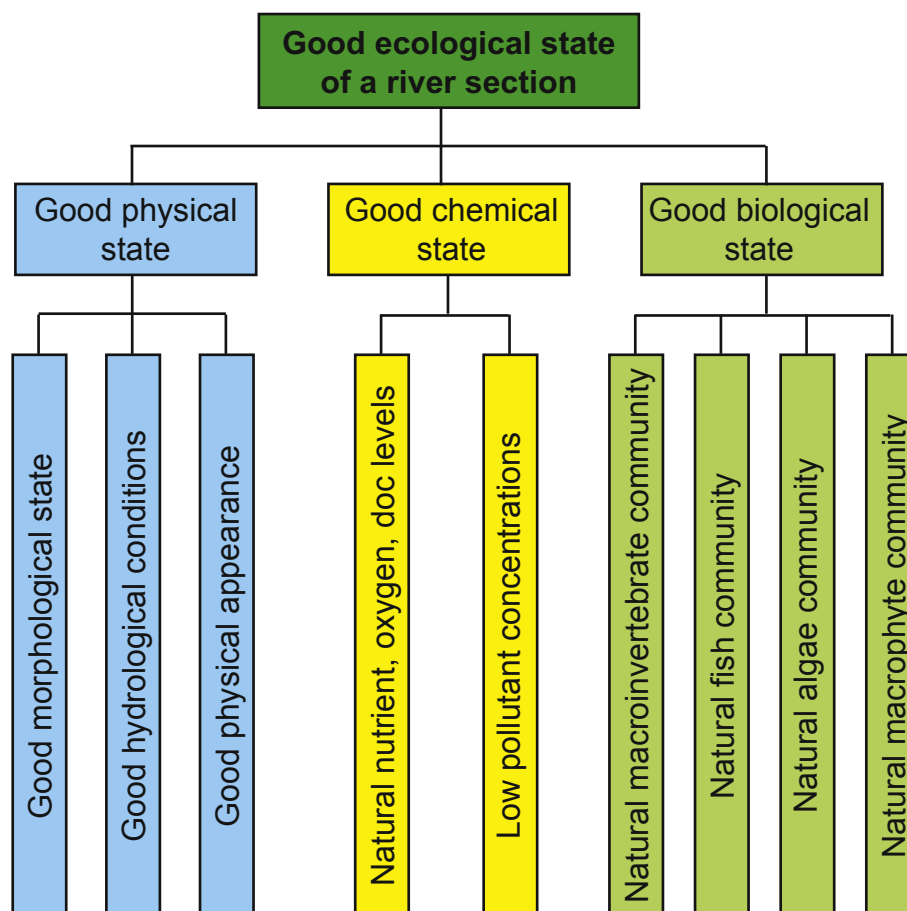


Fig. 4. Example of an objectives hierarchy for the good ecological state of a river section (modified from Reichert et al., 2011).

4.3.2. Constructing generic value functions

Representing preferences through value functions requires a demanding elicitation procedure either by interviews, group discussions, or surveys (see Section 3.2). This process cannot be performed easily for a large objectives hierarchy with many attributes. An additional difficulty can be that some branches of the objectives hierarchy require technical knowledge for their assessment. To address both of these problems, the value functions for some branches of the objectives hierarchy may be elicited from experts, and used as input to the societal value function at higher levels of the objectives hierarchy. In many cases, such branches can even be formulated generically for a given type of assessed systems. Typically, the highest level of the hierarchy, representing the major societal trade-offs, will remain case-specific and must be elicited from stakeholders or a sample of the population.

In river management, existing ecological river assessment procedures developed generically with experts (Bundi et al., 2000; Hering et al., 2004, 2006) can be translated into value functions of the good ecological state of a river section (Fig. 4; Langhans et al., 2013). Such value functions can then be used as branches of the value function for river management, constructed on the basis of an objectives hierarchy as shown in Fig. 3. The value function elements corresponding to the higher hierarchical level will have to be elicited from stakeholders.

The sub-objectives of reaching a good ecological state of a river network (Fig. 3) consist primarily of assessing spatial configurations of reaches in a good state. Not much research has been done so far at this level of assessment (Bernhardt and Palmer, 2011); most existing approaches are in systematic conservation planning (Margules and Pressey, 2000; Linke et al., 2008, 2011; Erös et al., 2011). Besides the goal of having as many river sections in a good state (leftmost sub-objective in Fig. 3), we formulate the objectives of having the natural potential for fish migration and a high connectivity of habitats in a good ecological state. The last of these objectives is targeted towards other organisms than fish, particularly invertebrates and riparian flora and fauna which have different dispersal requirements (see e.g. Tonkin et al., 2014). See Section 5 for an example of how these criteria can be applied.

4.3.3. Making value functions redundant and flexible

According to decision analysis textbooks (Keeney and Raiffa, 1976; Keeney, 1982; Eisenführ et al., 2010), objective hierarchies should divide objectives at each hierarchical level into complementary sub-objectives that cover all relevant aspects of the higher-level objective. This requirement excludes redundancy of sub-objectives. Contrarily, we argue in favor of allowing redundancy of sub-objectives and corresponding value functions in the context of environmental management. The concept is to divide an objective into (partly) redundant sub-objectives, adopt additive aggregation, and allow for an evaluation of the higher-level value, irrespective of how many values at the lower level are available (through a re-normalization of the weights of the available values at the lower level). The main advantages are that the statistical significance of the result increases if redundant data are available, but that some missing data within a redundant branch can be accepted. Both advantages are important in environmental management because ecosystem valuation is typically uncertain and data are often scarce. If the aggregation parameters at higher levels are not changed, this does not lead to biased results (with higher weight of the redundant sub-objectives) irrespective of data availability. However, minimum data requirements must be defined to keep the assessment reliable.

In river management, this technique is particularly useful for the branch of the objectives hierarchy that assesses the ecological state. Here, different assessments of similar aspects of the ecological state can be included and if data availability allows, their results can be

averaged to increase the confidence (see Langhans et al., 2013 for an example regarding the morphological state of a river section).

4.3.4. Accounting for uncertainty in elicited preferences

Due to the imprecision of the preferences of individual people and of the elicitation process, utility functions are uncertain. When merging individual utility functions into intersubjective utility functions that represent the preferences of a group or the population, differences between individual utility functions also contribute to the uncertainty of the aggregated utility. This uncertainty is not considered in expected utility theory, but it can be relevant. Therefore, it may be worthwhile to analyze the robustness of results to changes of preference parameters with scenario analyses (Schuwirth et al., 2012; Scholten et al., 2014a,b) and to perform sensitivity analyses of the resulting ranking to the parameters of the utility function (Scholten et al., 2014b).

4.4. Deficit analysis and generation of alternatives

If the value function is applied to the current state of the system, deficits can be identified. This can stimulate the creation of alternatives. Visualization of the fulfillment of all (sub-)objectives of the objectives hierarchy can facilitate the identification of deficits (Reichert et al., 2013). Including stakeholders may be important to increase the creativity of the process. Their *power of judgment* (Klauser et al., 2013) can be important to generate reasonable alternatives.

In river management, deficits are mainly identified by analyzing the ecological objectives that may have been derived from ecological assessment procedures (Langhans et al., 2013).

4.5. Predicting outcomes

A crucial element for any decision support methodology is the prediction of the consequences of the alternatives. This can be done by

- transferring knowledge from similar systems,
- eliciting expert opinions about effects of alternatives,
- applying mathematical models (elements of which may also have been elicited from experts).

Predictions of outcomes can be visualized analogously as the current state (Reichert et al., 2013). Probability network models can be useful for aggregating information from more detailed, mechanistic models, data analyses, the literature, and experts, while considering uncertainty (Reckhow, 1999; Borsuk et al., 2004; Reichert et al., 2007).

In river management, using expert advice has a long tradition. Often experts were asked to select an alternative. However, this confounds their prediction with their preferences. To avoid this problem, we strongly recommend to get their predictions for the outcomes and include them in the formal valuation process. This has the additional advantage to learn from the comparison of observed and predicted outcomes to improve future predictions.

4.6. Analyzing results and generating new alternatives

It is important to benefit from insights of the decision support procedure (Fig. 2) to improve aspects of alternatives or create new alternatives. Separate evaluation for different stakeholder groups helps identifying reasons for different ranks of alternatives for different stakeholders.

In river management, initial value functions can be constructed based on preference information from governmental authorities

involved in river management. A first iteration of the decision support procedure (Fig. 2) can be based on these value functions. In a second iteration, values from stakeholders can be considered. The reasons for different rankings of stakeholder groups can then be analyzed to construct better alternatives (Hostmann et al., 2005a).

4.7. Summary of techniques to facilitate the application of the approach in practice

In summary, the application of the concepts suggested in the Sections 2 and 3 can be facilitated through:

1. the structure shown in Fig. 2, which **divides the decision making process into clearly separated, transparent steps** of lower complexity;
2. the **explicit discussion of societal values and their clear separation from scientific predictions** to support constructive interaction between decision makers and stakeholders;
3. the transparency of the approach that supports **communication of the reasons for a decision to the public**;
4. some extensions to generally applied methodologies, as the use of **generic value functions for parts of the objectives hierarchy, redundant and flexible value functions**, and the **consideration of uncertainty in value assessments**, which make the application of MAVT/MAUT more robust;
5. insights gained through the structured decision making process and, particularly, the deficit analysis, which **stimulate the process of generating new alternatives** that can easily be incorporated into the value assessment.

Thus, the proposed practical aspects make the suggested methodology fulfill the requirements 3a, 3b and 3c formulated in the introduction.

5. Illustrating example: river rehabilitation prioritization

We illustrate our methodology with an application to spatial planning of river rehabilitation at the catchment scale. We follow the structure introduced in Fig. 2. Note that the value functions used for the network assessment in this example are still at a preliminary stage. They serve for illustrating the methodology and stimulating further development, rather than for quantitative decision support at this stage of the project. All calculations and visualizations in this sections were done with the packages “utility”, “ecoval” and “rivernet” of the software environment for statistical computing and graphics R (<http://www.r-project.org>).

5.1. Problem definition

River rehabilitation is a global priority driven by the loss of freshwater biodiversity and of services that humans receive from

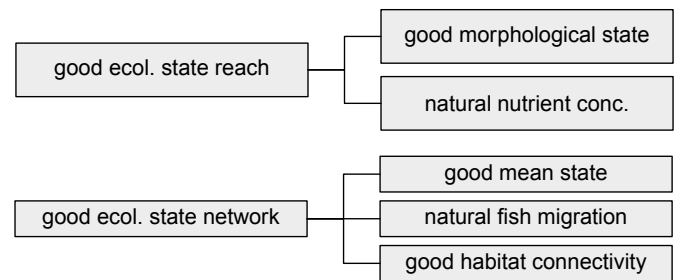


Fig. 6. Simplified objectives hierarchy for assessing the ecological quality of a river reach (simplified from Fig. 4).

freshwater ecosystems (Bates et al., 2008; Roni et al., 2008). The importance of river rehabilitation was also recognized by recent legislations, such as the Water Framework Directive (European Commission, 2012) or the Swiss water protection law (Göggel, 2012). The benefits of rehabilitation projects regarding the improved state of the ecosystem and the increase in the provision of (other) ecosystem services must be traded-off against the costs of rehabilitation, or, if a budget has already been assigned to rehabilitation projects, the ecological gain achieved with planned rehabilitation measures has to be maximized for a given budget. Both of these objectives require the valuation of the ecosystem state at the catchment scale. This is challenging, because river assessment programs, which quantify the ecological state, so far focused on the river section scale only. In this example, we provide a first suggestion of how to evaluate the ecological gain, ecosystem services, and costs at the catchment scale and how to support finding a trade-off between these criteria. The goal is to screen potential spatial arrangements of rehabilitation projects, while detailed planning of local rehabilitation measures would be done later based on more detailed local information. For this example, we focus on the Mönchaltorfer Aa catchment (51 km²) in Switzerland (see Langhans et al., 2014a).

5.2. Stakeholder analysis

In Switzerland, preliminary suggestions for rehabilitation strategies are usually made by regional water authorities. Only when planning becomes more concrete, multiple stakeholders are involved (e.g. governmental agencies, residents, local interest groups, NGOs, etc.). This example represents a first analysis that aims at supporting regional and national authorities in prioritizing rehabilitation projects that will subsequently enter the political decision making process.

5.3. Formulation, structuring and quantification of objectives

To account for data availability at the catchment scale, we simplify the objectives hierarchies shown in Figs. 3 and 4

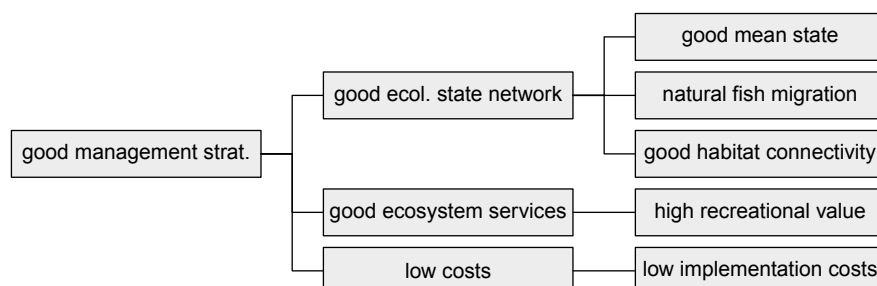


Fig. 5. Simplified objectives hierarchy for a good river management strategy at the catchment or regional scale (simplified from Fig. 3).

considerably. However, we still consider the branches of the objectives hierarchy that are most important for the prioritization or are most strongly affected by rehabilitation (Figs. 5 and 6).

To formulate the “good river management strategy” we include the three branches “good ecological state of a river network”, “good ecosystem services” and “low costs” from Fig. 3 at the highest level of the objectives hierarchy (Fig. 5). We only consider alternatives that conform to regulation and all considered alternatives are similar regarding robustness to later adaptations; therefore, we can omit those two branches. We limit the lower level of the branch “good ecosystem services” to “high recreational value” which is the service most strongly affected in our study catchment (note, however, that other ecosystem services may be more strongly affected in other catchments). We limit the branch “low costs” to “low implementation costs” assuming the maintenance costs to be similar before and after rehabilitation.

To make the sub-objective of a “good ecological state at the river network scale” more concrete, we divide it into the three sub-objectives “good mean ecological state of river sections”, “natural potential for fish migration”, and “good habitat connectivity” (see Figs. 3 and 5). The first of these expresses the objective of having as many reaches in a good state as possible irrespective of their spatial arrangement. The second emphasizes the importance of fish as an integrative indicator of ecosystem health. Finally, the third sub-objective favors long river corridors in a good state to increase biodiversity and resilience (see more extensive discussion in Sections S1 and S2 of the supporting information).

To assess the ecological state of the river sections, we consider the branches “good morphological state” and “natural nutrient concentrations” from the more comprehensive objectives hierarchy in Fig. 4 (Fig. 6). While we do not expect the nutrient concentrations to significantly change due to rehabilitation measures at small and intermediate spatial scales, the nutrient state serves as a rough estimate of the chemical state. Consideration of the chemical state is important as a poor chemical state may hinder the biological success of rehabilitation. It would be desirable to directly consider the biological state as well. However, predicting biological effects at the catchment scale is much more difficult than the morphological state and nutrient levels; we therefore use these as proxies.

Value functions for the ecological state at the river reach level (in our case based on the assessment of the morphological state and nutrient levels, see Fig. 6), were constructed by converting the procedures of the Swiss concept for stream assessment (Bundi et al., 2000; Hütte and Niederhauser, 1998; Liechti, 2010; <http://www.modul-stufen-konzept.ch>) into value functions (Langhans et al., 2013). We aggregated the value functions for the morphological state and nutrients by the additive-minimum aggregation shown in the rightmost panel of Fig. 1 (see also discussion in Langhans et al., 2014a).

There are no similar assessments available for the ecological state at the river network level. Therefore, we suggest preliminary value functions at this level and hope that this stimulates a broader discussion of this topic. To formulate the degrees of fulfillment of the sub-objectives “good mean ecological state of river sections”, “natural potential for fish migration”, and “good habitat connectivity” we first have to find reasonable attributes. We suggest the attributes “meanval” (length- and stream order-weighted mean of the ecological value of the river sections), “fractmig” (fraction of reachable headwaters for fish of those which would be reachable without artificial barriers), and “fractconn” (sum of total length of adjacent reaches in good ecological state weighted by the inverse of their rank regarding this length) (see section S1 in the supporting information for details). We then formulated preliminary value functions for the sub-objectives assessed by these attributes and aggregated them again with the additive-minimum aggregation

technique (for two values illustrated in the rightmost panel of Fig. 1; see also Langhans et al., 2014a) (see Section S2 in the supporting information).

The degree of fulfillment of the objective of a “high recreational value” was formulated as a function of the attribute “fractgood-morph” (fraction of river length in good morphological state) (see Section S2 in the supporting information for more details). This is again a very crude approach used to illustrate our concepts. Refinements would be necessary, particularly if this approach is applied to larger catchments.

Finally, we assumed a linear value function for costs and additive aggregation at the highest level of sub-objectives in the objectives hierarchy shown in Fig. 5. Additive aggregation seems appropriate at this level to represent the trade-off between costs and improved ecosystem state and (other) services. The range of the value function for costs and the weights of the additive aggregation were estimated from the legislation process stimulated by a public initiative (see Supporting information for details). To account for the high uncertainty in this willingness-to-pay estimate, we considered uncertainty of the weight of costs by a factor of 2 (with a uniform distribution) and renormalized the weights to unity.

5.4. Identification of deficits

Morphological data are available for the entire catchment. As shown in Fig. 7, a major part of the river network is not in a good morphological state. Additionally, a considerable number of artificial and natural barriers (> 50 cm) prevent brown trout migration to upstream river sections (Fig. 7).

Water quality data are only available at 10 sites. We used these to estimate nutrient pollution using the area fractions of intensive agricultural land use and the amount of treated waste water discharged per area of the sub-catchment as explanatory variables. As this fit had a quite good predictive capability at these 10 sites (see Fig. S2 in the supporting information), and the explanatory variables are available for the entire catchment, this linear regression model could be used to extrapolate the state of nutrient pollution to the catchment. The results indicate that large parts of the river network are in moderate to bad conditions (Fig. 8).

5.5. Construction of alternatives

The decision support framework illustrated in this example can be used for an automatic screening of a large number of rehabilitation alternatives. Such sets of alternatives could be generated and evaluated automatically by an optimization algorithm. However, for this example, we demonstrate the use of the procedure by comparing only eight manually suggested rehabilitation alternatives. Each alternative is defined by the reaches to be rehabilitated, the barriers to be removed, and the maximum fraction of intensive agricultural land use allowed in all sub-catchments. River sections with traffic infrastructure, buildings, or groundwater protection zones within a range of 15 m from the river at both banks were excluded from alternatives to avoid extremely high costs and conflicts with legislation. This made it possible to use a universal cost estimate per river length throughout the catchment. The deficits identified from Figs. 7 and 8 motivated a comparison of the following alternatives to discuss complementary rehabilitation strategies:

Alt 1 Keep the current state.

Alt 2 Open and rehabilitate all culverts.

Alt 3 Rehabilitate river morphology of a main branch with no natural barriers and remove the artificial barriers (e.g. replace them by bed ramps that can be passed by fish).

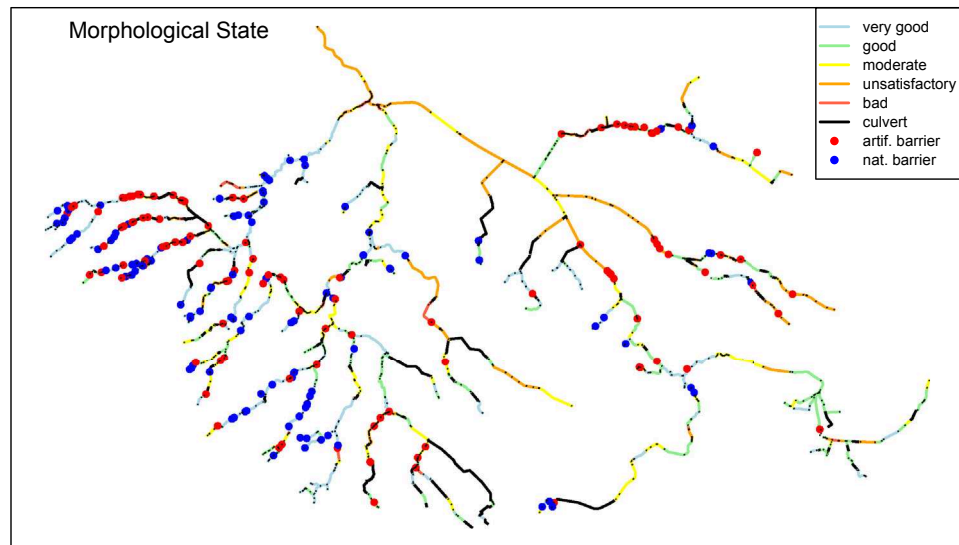


Fig. 7. Morphological state of the river sections in the Mönchaltorfer Aa catchment.

- Alt 4 Same measures as in alternative 3 but additionally reduce intensive agriculture to a maximum of 40% for all sub-catchments.
- Alt 5 Rehabilitate the morphology of reaches which form gaps in a branch which already has many reaches in a good morphological state.
- Alt 6 Rehabilitate the morphology of a tributary with few natural barriers and remove artificial barriers.
- Alt 7 Combine measures from alternatives 4, 5 and 6.
- Alt 8 Rehabilitate approximately the same river length and remove the same number of artificial barriers as in alternative 7, but choose the reaches and barriers randomly.

Note that alternatives 2–7 illustrate alternative management strategies, whereas alternative 1 is used to compare the other alternatives with the current state. Comparing alternatives 7 and 8 illustrates the different effects of strategic or random selections of rehabilitation activities. The alternatives are explained and visualized in Section S5 in the supporting information.

5.6. Prediction of consequences

For morphologically rehabilitated river sections at sites without rehabilitation constraints within 15 m (see Section 5.5) we assumed 50% probability for the best and 50% probability for the second best level of discrete attributes and uniform distributions from 10 to 15 m for the riparian zone width. For sections with rehabilitation constraints on one side, we assumed uniform distributions from 2 to 5 m for the riparian zone width at the constrained side of the river. For barriers, we assumed that they were removed or replaced by a construction that can be passed by fish, e.g. a bed ramp with large blocks. If not otherwise mentioned, agricultural land use and thus water quality remained the same as in the current state. For alternatives 4, 7 and 8 in which land use by intensive agriculture was limited to 40%, current land use fractions were modified accordingly. In both cases, water quality valuation and its uncertainty was predicted based on the linear regression model considering parameter and residual uncertainty. Median costs were estimated to be CHF 2'000 per m of morphologically rehabilitated

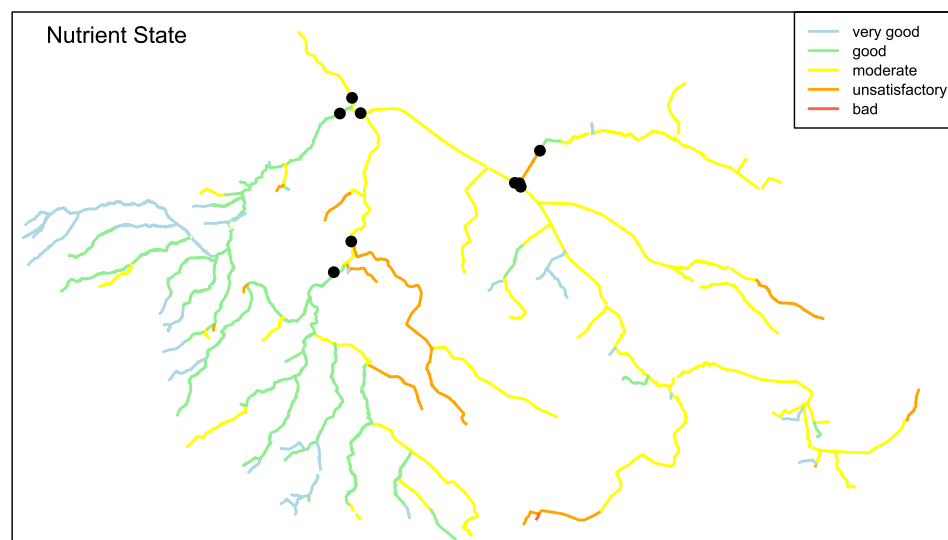


Fig. 8. Extrapolated state regarding nutrient pollution of the river sections in the Mönchaltorfer Aa catchment. Black dots represent observation sites.

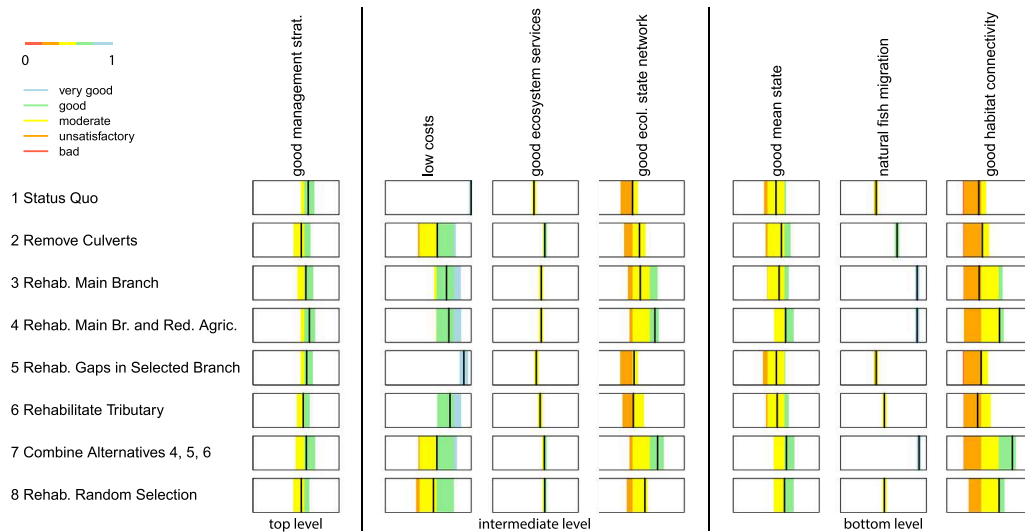


Fig. 9. Valuation of rehabilitation alternatives for all relevant nodes of the objectives hierarchy (Fig. 5). The black lines in the boxes refer to the median values of probabilistic predictions plotted on a scale from 0 to 1 on the lower boundary of the boxes. The colored range represents the 5–95% quantile range using colors that are commonly used for ecological quality classes (see legend in the top left corner). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

river (Langhans et al., 2014b) and CHF 100'000 per replacement of an artificial barrier by a bed ramp (Bernier, 2006). We used normal distributions with standard deviations of 33% around these estimates to account for uncertainty. We did not account for costs for the reduction of intensive agriculture, as we assumed that farmers can earn a similar salary by organic farming.

5.7. Evaluation of alternatives based on expected degree of achievement of objectives

Fig. 9 shows the predicted value distributions of the relevant nodes of the objectives hierarchy shown in Fig. 5 for all decision alternatives.

5.8. Analysis of results

Removing culverts (Alt. 2) or choosing rehabilitation sections randomly (Alt. 8) leads to a considerably smaller gain in the ecological state of the river network than a strategic choice of sections and nodes (Alt. 7) at similar costs (Fig. 9). The importance of integrative planning is demonstrated by the comparison of rehabilitation of a main branch with and without accompanying water quality improvements (Alt. 3 and 4). It is remarkable, that the significant differences in the valuation of outcomes at lower levels of the objectives hierarchy are strongly decreased at the highest level. This is a consequence of two mechanisms: First, cheaper alternatives tend to have less effect (but see the importance of a strategic choice of rehabilitation sites discussed above). Second, the high uncertainty about willingness to pay for river rehabilitation tends to make still existing differences less significant. Only two alternatives, 4 and 7, lead with some confidence to a good ecological state of the river network (green values). Of these two, 7 is more expensive, but leads to better results in particular regarding connected habitats. Given these results, further steps would be to acquire more local information at the rehabilitation sites of these alternatives and try to find better alternatives starting with modifications of these two alternatives. This process could be stimulated by the detailed geographical outline of the alternatives and their consequences as shown in Section S5 in the supporting information.

6. Summary and conclusions

We argue for combining probability theory and scenario planning with multi-attribute utility theory as a conceptual framework for environmental decision support. We discuss the need for adaptations, extensions, and didactical support of these theories to improve their applicability in environmental management. This partially accounts for weak points criticized by developers and users of alternative approaches.

In the following sub-sections we briefly summarize the most important suggested adaptations and extensions and conclude with final comments.

6.1. Intersubjective probabilities

Depending on the context, knowledge may be described by objective or subjective probabilities. In decision making for environmental management, probabilities should represent the state of knowledge of the scientific community about outcomes of decision alternatives. We argue that intersubjective probabilities (Gillies, 1991, 2000) provide the best framework for this purpose. This is rarely discussed explicitly, although combinations of probability statements of multiple experts are often used for scientific prediction, and multiple opinions in peer review processes are the basis of scientific quality control.

6.2. Imprecise probabilities

Although there are convincing arguments for using (intersubjective) probabilities to describe scientific knowledge, the limited capability of experts to quantify these probabilities and disagreements between experts can call for an extension to imprecise probabilities. The degree of imprecision can then be used to quantify the transition from cases in which quantitative decision support is suitable to cases in which the knowledge is insufficient (e.g. Rinderknecht et al., 2012b). In the latter case, other criteria, such as the precautionary principle or probability distributions of the predicted change instead of absolute predictions (Reichert and Borsuk, 2005) may be used to support decisions.

6.3. Scenarios

In some cases, due to too large ambiguity, scientists may even hesitate to formulate their predictions as imprecise probabilities. Here, it may be useful to combine alternative future scenarios with conditional probabilistic predictions and search for decision alternatives that are robust regarding the scenarios.

6.4. Emphasis on value functions (rather than utilities)

Although utility and not value functions are the basis for rational decision support under risk (based on probabilistic predictions of outcomes of decision alternatives), we emphasize the importance of value functions. Eliciting values and transforming them to utilities only at high hierarchical levels (Dyer and Sarin, 1982) has several advantages compared to eliciting utilities directly throughout the objectives hierarchy: (i) elicitation of a hierarchical, multi-attribute value function is easier than of a utility function (because preference elicitation can be done with outcomes instead of lotteries of outcomes); (ii) this avoids confounding the strength of preference for outcomes with risk attitudes (Dyer and Sarin, 1982) and makes it possible to analyze the degree of fulfillment of (sub-)objectives to stimulate the improvement of alternatives; (iii) the probability distribution of values can already give relevant insights into the decision problem under risk, even if finally utilities are required to generate the ranking of alternatives; (iv) if the ranking of alternatives does not change in a sensitivity analysis that includes strong risk attitudes, utilities do not even have to be elicited.

6.5. Importance of the value aggregation scheme

More attention should be given to the elicitation of the aggregation scheme, instead of assuming additivity when calculating the degree of fulfillment of an objective based on the degrees of fulfillment of its sub-objectives. Particularly in ecological valuations, the importance of the joint fulfillment of goals regarding complementary aspects of an ecosystem leads to the need for non-additive aggregation (Langhans et al., 2014a).

6.6. Redundancy of sub-objectives and allowing for flexibility in data availability

Contrary to standard decision theory, we argue that redundancy of sub-objectives can be an advantage for ecosystem assessment. As long as aggregation schemes at higher hierarchical levels are not changed, redundant sub-branches do not bias the overall assessment but increase confidence in the assessments and flexibility in data availability. Additive aggregation seems appropriate for this case.

6.7. Combination of value functions elicited from different groups

An important sub-objective in environmental management is to achieve a good state of an ecosystem affected by management alternatives. Quantifying the degree of fulfillment of this objective as a function of (typically many and partly technical) attributes is difficult for laypersons. Therefore, it may be useful to elicit this branch of the value function from experts or to construct it based on existing ecological assessment procedures. It may even be possible to achieve a certain universality of such assessments among ecosystems of the same type so that a generic value function can be applied across similar systems. When relying on expert value functions, it is important to explain and visualize the meaning of these values to allow the stakeholders to formulate their

aggregation rules at higher hierarchical levels.

6.8. Consideration of uncertainty in preference representation

The elicitation of preferences from individuals is affected by imprecision of the elicitation procedure and, potentially, by imprecision of the person's preferences. If value functions of several individuals are merged into a single, intersubjective value function, differences between the aggregated functions can even increase imprecision. This imprecision is not accounted for in "standard" expected utility theory. Unless this imprecision is small, it may be important to do a sensitivity analysis of the resulting ranking of alternatives (Scholten et al., 2014a,b).

6.9. Final comments

Many of the ideas summarized in the sections 6.1–6.8 could be illustrated with the example of river rehabilitation prioritization in a small catchment in Switzerland. This is in particular the case for the formulation of uncertain knowledge with probabilities, value functions and their aggregation, combination of expert and societal value functions, and uncertainty regarding preference representation. This illustrative example also demonstrated the need for assessing river ecosystems at larger spatial scales than this has typically been done in the past.

In this paper, we emphasized the importance of a solid conceptual foundation of a decision support methodology for environmental management. This is a crucial aspect to guide the transfer of scientific knowledge into societal decision making. However, the practical implementation is another key element of successful decision support. A well-structured decision support procedure, high transparency by a good didactical presentation of scientific results and elicited values, and a good facilitation of the discussion among scientists, stakeholders, and decision makers are important aspects of practical implementation. In our view, combining a conceptually satisfying decision support procedure as outlined in this paper with a careful implementation can contribute significantly to societal decision making. However, it has also to be kept in mind that such quantitative analyses are always incomplete and only cover "technocratic" aspects of the decision problems. For this reason, it is essential to see them as tools to support and not replace appropriate evaluations by specialists and negotiations at the political level.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at <http://dx.doi.org/10.1016/j.jenvman.2015.01.053>.

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