Eawag:
Swiss Federal Institute of Aquatic
Science and Technology

Comprehensive Uncertainty Assessment in Environmental Decision Support

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(virtual contribution)

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Content

- **Environmental Decision Support**
  (state of the art)
- **Problems**
  (deficits of the state of the art)
- **Suggested Approach**
  (to reduce the deficits)
- **Discussion**
  (is this feasible?)
- **Conclusions**

Environmental Decision Support

Structured decision support process:

- Define the problem to be addressed (framing)
- Quantify societal preferences (objectives)
- Identify deficits (fulfillment of objectives by the current state)
- Develop alternatives (measures to reduce deficits)
- Predict consequences of alternatives (and their uncertainty)
- Assess degrees of fulfillment of the objectives by the consequences of all alternatives (risk preferences can be considered)
- Analyze results and communicate transparently
  (identify promising alternatives and identify why they rank high)

Keeney and Raiffa 1976
Keeney 1992
Eisenführ et al. 2010
Reichert et al. 2015

Main source of uncertainty that is typically considered:

- Uncertainty in the prediction of the consequences of alternatives
  (risk attitudes of decision makers or sometimes considered use this uncertainty)

Problems

There are other major sources of uncertainty that or often ignored or only addressed by simple sensitivity or scenario analyses:

- **Societal preferences are very uncertain**:
  - Individual preferences have to be aggregated to «societal preferences»
  - Individuals are uncertain about their own preferences
  - Formalization and elicitation of preferences adds uncertainty
- **Probabilistic descriptions of uncertainty are themselves uncertain**:
  - Results depend on the formulation of prior knowledge in the form of model structures and prior distributions of parameters

Is there a systematic and conceptually satisfying approach to a more comprehensive uncertainty assessment in environmental decision support?

Suggested Approach

1. **Infer parameters of value/utility functions by statistical inference** from elicitation results to get their uncertainty analo-gously as it is done for the outcome predictions of measures.

2. **Extend expected utility theory to expected expected utility theory** to account for the uncertain preferences.

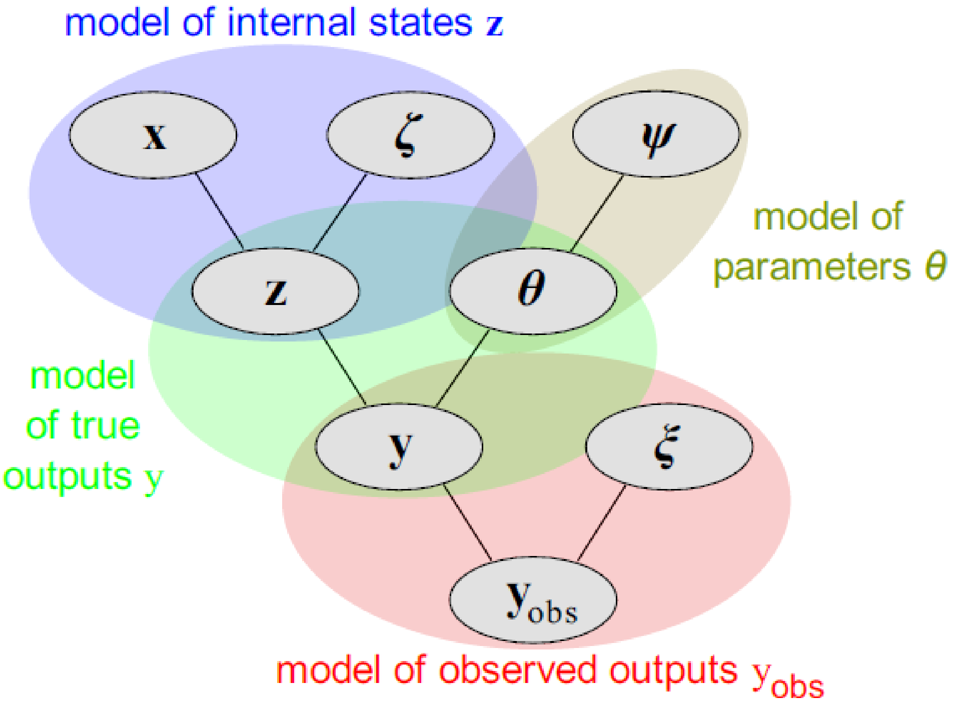
3. **Use imprecise priors** (for preferences and consequence predictions) **to account for ambiguity** and to replace discrete sensitivity analyses by a «nonparametric» approach based on infinite sets of probability distributions.

4. **Derive an incomplete ranking of the decision alternatives** and discuss results with stakeholders.

Approach: 1. Model formulation and Bayesian inference

Prediction of consequences of measures or alternatives

Probabilistic model for the prediction of consequences of decision alternatives (the graphical structure supports the decomposition into submodels):



$$
\begin{aligned}
p(\mathbf{y}_{obs}, \mathbf{y}, \mathbf{z}, \zeta, \theta, \psi, \xi \mid \mathbf{x}) \\
= \quad & p(\mathbf{z} \mid x, \zeta)\, p(\zeta) && \text{model of internal states } \mathbf{z} \\
& \times p(\mathbf{y} \mid \theta, \mathbf{z}) && \text{model of true outputs } \mathbf{y} \\
& \times p(\theta \mid \psi)\, p(\psi) && \text{model of parameters } \theta \\
& \times p(\mathbf{y}_{obs} \mid \mathbf{y}, \xi)\, p(\xi) && \text{model of observed outputs } \mathbf{y}_{obs}
\end{aligned}
$$

Approach: 1. Model formulation and Bayesian inference

Bayesian inference:

Given the probabilistic model (prior knowledge) and the observations, the posterior of parameters and states is proportional to the joint probability distribution with the observations substituted for $\mathbf{y}_{\mathrm{obs}}$.

$$p(\mathbf{y},\mathbf{z},\zeta,\theta,\psi,\xi \mid \mathbf{x}, \mathbf{y}_{\mathrm{obs}}) \propto p(\mathbf{y}_{\mathrm{obs}},\mathbf{y},\mathbf{z},\zeta,\theta,\psi,\xi \mid \mathbf{x})$$

This allows us to consider observations in addition to prior knowledge.

Numerically, this can be done using Markov Chain Monte Carlo (MCMC).

Model requirements:

To be useful for decision support, the model has to predict the variables required for the formulation of preferences and it has to depend on inputs and/or parameters that can be used to quantify the measures underlying the decision alternatives.

Schuwirth et al. 2020

Approach: 1. Model formulation and Bayesian inference

Stakeholder preferences can be described by a value function

$$v(\mathbf{y})$$

that quantifies the degree of fulfillment of an objective as a function of system attributes, $\mathbf{y}$, on a scale from 0 to 1.

Similarly to the graphical visualization of cause-effect relationships in the predictive model of consequences of decision alternatives, a hierarchical decomposition of the main objective into sub-objectives can support the construction of a value function as shown on the next slide.

Keeney and Raiffa 1976
Keeney 1992
Eisenführ et al. 2010
Reichert et al. 2015

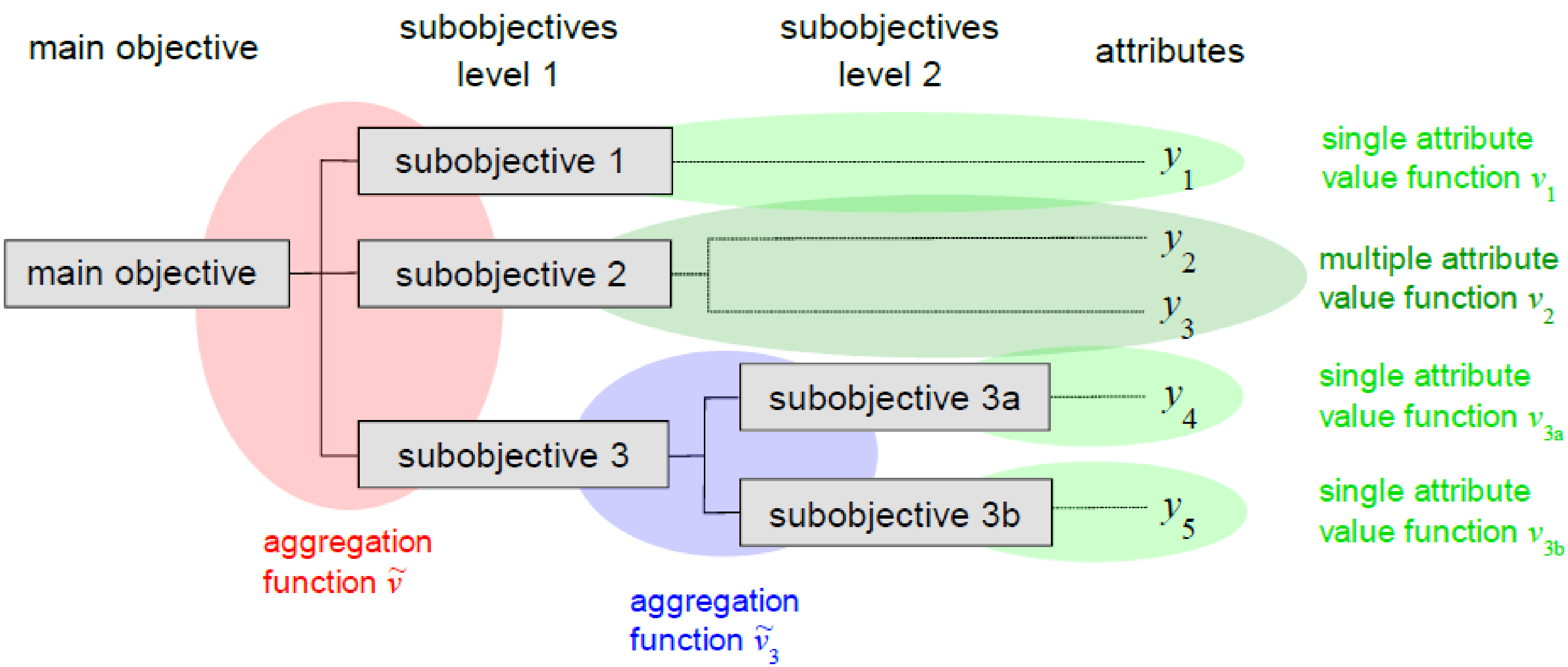
Approach: 1. Model formulation and Bayesian inference

Value function for quantifying preferences:

aggregation functions

$$v(y_1,y_2,y_3,y_4,y_5) = \tilde{v}\left(v_1(y_1),\ v_2(y_2,y_3),\ \tilde{v}_3\left(v_{3a}(y_4), v_{3b}(y_5) \right) \right)$$

end node value functions



Approach: 1. Model formulation and Bayesian inference

The parameters of value and aggregation functions can again be estimated based on a probabilistic model of stakeholder replies (building on the parameterized value function) and on actual, elicited replies.

Haag et al. 2019a

These replies can be in the form of discrete choice or indifference state-ments. In the former case the stakeholder has to express his or her prefe-rence among a small set of hypothetical outcomes, in the latter case he or she has to adjust one of the attributes of one of the hypothetical outcomes to achieve indifference between two outcomes. These replies are taken as observations for inferring the parameters of the value functions.

Using elicited risk attitues of the stakeholders, the value function of the overarching goal can be converted into a utility function. Dyer and Sarin 1982

This leads to a utility function with uncertain parameters:

$u(\mathbf{y},\boldsymbol{\vartheta})$ $p(\boldsymbol{\vartheta})$

Approach: 2. Expected expected utility

Using precise utilities alternatives are ranked according to decreasing expected utilities:

$$\mathrm{EU}(a) = \int_{\mathbf{y}} u(\mathbf{y}) p_a(\mathbf{y}) \mathrm{d}\mathbf{y}$$

Keeney and Raiffa 1976
Keeney 1992
Eisenführ et al. 2010

If the uncertainty of preferences are considered by probability distributions of the parameters, $\boldsymbol{\vartheta}$, of the utility function, alternatives are ranked according to expected expected utilities:

$$\mathrm{EEU}(a) = \int_{\boldsymbol{\vartheta}} \mathrm{EU}(a, \boldsymbol{\vartheta}) p(\boldsymbol{\vartheta}) \mathrm{d}\boldsymbol{\vartheta} = \int_{\boldsymbol{\vartheta}} \left(\int_{\mathbf{y}} u(\mathbf{y}, \boldsymbol{\vartheta}) p_a(\mathbf{y}) \mathrm{d}\mathbf{y} \right) p(\boldsymbol{\vartheta}) \mathrm{d}\boldsymbol{\vartheta}$$

Cyert and de Groot 1979
Boutilier 2003
Haag et al. 2019b

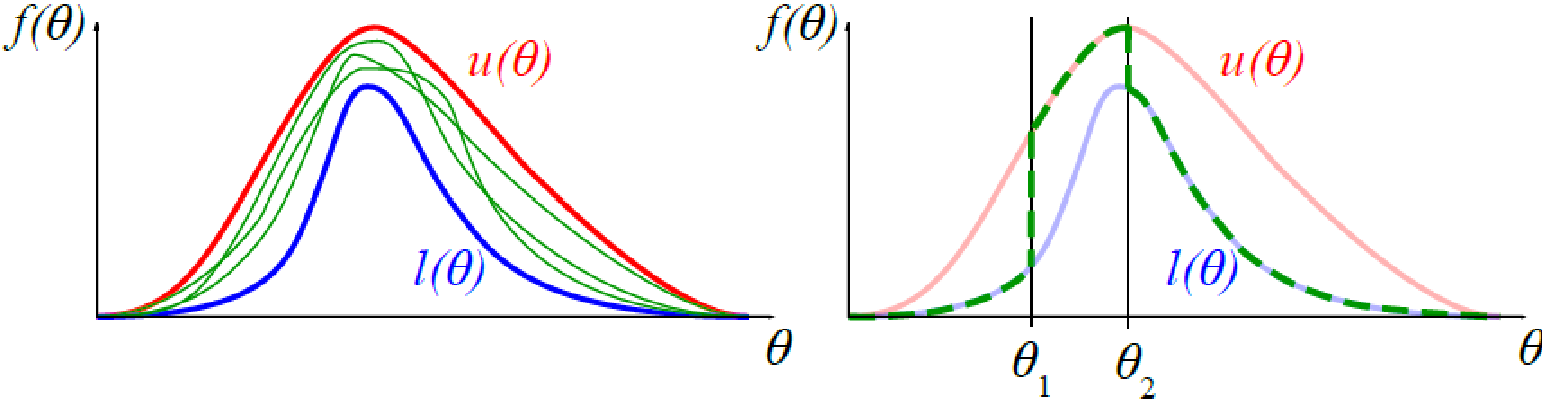
Approach: 3. Imprecise prior probability distributions

Imprecise probabilities: **Use sets of proability distributions** rather than just one specific probability distribution.

Density ratio class:

DeRobertis and Hartigan 1991
Berger 1990

$$\Gamma_{l,u}^{\mathrm{DR}} = \left\{ f(\boldsymbol{\theta}) = \frac{\tilde{f}(\boldsymbol{\theta})}{\int \tilde{f}(\boldsymbol{\theta}')\,\mathrm{d}\boldsymbol{\theta}'} \,\middle|\, l(\boldsymbol{\theta}) \leq \tilde{f}(\boldsymbol{\theta}) \leq u(\boldsymbol{\theta}) \;\forall \boldsymbol{\theta} \right\}$$



Approach: 3. Imprecise prior probability distributions

Advantages of the density ratio class of imprecise probabilities over alternative approaches:

- **Invariance under Bayesian updating**
  → this allows for a consistend iterative learning process
- **Invariance under marginalization**
- **Invariance under propagation through deterministic functions**

Rinderknecht et al. 2014

Density ratio class priors can be elicited by slightly extending usual probability distribution elicitation techniques

Rinderknecht et al. 2011

Approach: 4. Incomplete Ranking of Alternatives

The use of imprecise priors leads to ranges of expected expected utilities and thus to an incomplete ranking of the alternatives.

The usefulness of such results depends strongly on the degree of imprecision in the expected utilities.

Practical experience with typical cases is needed to learn how strongly this affects the decision support.

Discussion

Is this feasible?

- **Practical and numerical tractability?**
  not much more expensive than with precise priors;
  easy to use software would facilitate application considerably
- **Understandability and acceptance by stakeholders?**
  to be tested for typical cases
- **Realistic for real applications?**
  maybe; also depends on the degree of ambiguity

Conclusions

- All elements for a more comprehensive uncertainty assessment in environmental decision support are there (partly for decades).

- Let's go ahead and gain experience in the application of these concepts.

- We will do this in a project funded by the Swiss National Science Foundation but more experience also by other groups is always useful.

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