

## Object-Oriented Belief Networks (OoBN)

### Introduction

Bayesian belief networks are not a valuation method per se, but an approach to synthesising valuation and ecosystem function knowledge for decision support. Bayesian belief networks (BBNs) are useful for:

- (i) Eliciting stakeholders understanding of cause-effect linkages in a visual network and formalising their knowledge of the strength of effects as a series of conditional probabilities.
- (ii) Linking biophysical and socio-economic model input-outputs together in a consistent ecosystem services cascade or driver-pressure-state-impact-response chain, handling cumulative uncertainty consistently using a series of conditional probability tables making reasoning with uncertainty possible, and
- (iii) Analysing costs and benefits of decisions in terms of cost-effectiveness analysis (CEA), cost-benefit analysis (BCA) and multiple criteria analysis (MCA).

Sub-networks representing sub-model input-outcomes can be represented as model 'objects' within another BBN – producing a hierarchical model called an Object-Oriented Bayesian Network (OOBN). Other fact sheets address OOBNs in the context of (i) and (ii) while this fact sheet addresses (iii). When variables (nodes) for costs and benefits (utilities) are added to chains of conditional probability tables (representing ecosystem functions) BBNs are called "influence diagrams" (Kjærulff and Madsen 2007).

### Keywords

Object-oriented Bayesian networks; Influence diagrams; Cost-effectiveness; Cost-benefit; Multi-criteria analysis; Decision-support.

### Why would I chose this approach?

OOBNs make it possible to link 'upstream' costs of decisions to 'downstream' benefits of those decisions, making use of all available information, and accounting for the cumulative uncertainty of using information sources of different quality. This makes it well-suited for operationalising the ecosystem services cascade framework (Haines-Young 2011, Landuyt, Broekx et al. 2013). OOBNs for decision-making are useful where more than one biophysical model needs connecting to costs and benefits of decisions (Barton, Kuikka et al. 2012). In principle, any ecosystem service can be addressed by this generic tool. In practice it has seen many applications to watershed management, looking at model chains from upper catchment to downstream impacts in water bodies (Barton, Saloranta et al. 2008). As the interface between BBNs and GIS improves OOBNs are seeing greater use in studying ecosystem service impacts spread over a landscape – these are spatially disaggregated BBNs. This means that applications for, e.g., cultural ecosystem services, are likely to increase in future.

OOBNs are useful for 'priority-setting' under uncertainty, combining information from different approaches to valuation. OOBNs are generic and can be applied to any spatial scale.

## What are the main advantages of the approach?

### Methodological advantages

- Trans-disciplinary;
- A knowledge integration tool that integrates qualitative and quantitative data;
- Draws on existing data (monitoring, modelling);
- Formalises expert judgement;
- Explicit modelling focus on the relationships between model resolution and uncertainty;
- Manages missing information.

### Governance advantages

- Integrated valuation modelling tool;
- Covers wide range of ecosystem services;
- Can address a wide range of impact/values types;
- Participatory approach with stakeholders;
- Trade-offs can be evaluated;
- Uncertainty can be addressed (diagnose 'garbage-in-garbage-out' problems).

## What are the constraints/limitations of the approach?

### Methodological constraints

- Discretization of data can lead to information loss (but this is a common features of all models, while in BBNs it is directly observable);
- GIS integration is limited but improving;
- Handling of time series and feedback effects is limited, but improving (time sliced models).

### Governance constraints

- Information loss in each modelling link and cumulative uncertainty analysis leads to a bias towards 'no action' or status quo decision alternatives.

## What types of value can the approach help me understand?

Bayesian belief networks are suitable to most value categories independent of which value typology we take into account. Because it is a generic method it has limitations common to other quantitative methods in eliciting non-anthropocentric values of nature, as well as bequest and existence values.

## How does the approach address uncertainty?

A BBN is a representation of a joint probability distribution where uncertainty is represented as conditional probability distributions in a network diagram. In a graphical user interface (example in Figure 1, below) posterior distributions given observations are shown for each variable. OOBNs strength lies in describing uncertainty – variance that is generated from spatial heterogeneity and temporal variation - meaning that OOBNs spatial and temporal resolution is often coarse and they are most useful for synthesising 'large data' problems. If high-resolution modelling of ES is required – it is better to use bespoke biophysical models. OOBNs makes them ideal for the kind of synthesis that is needed for assessing decision alternatives across landscape variation.

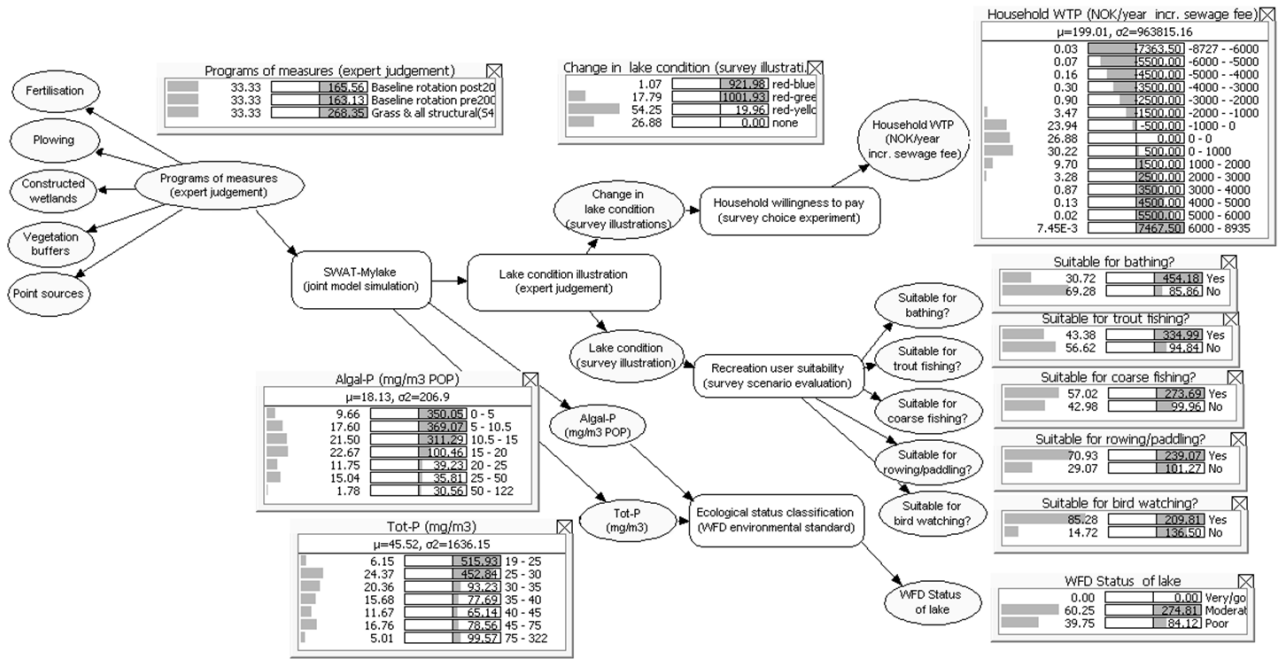
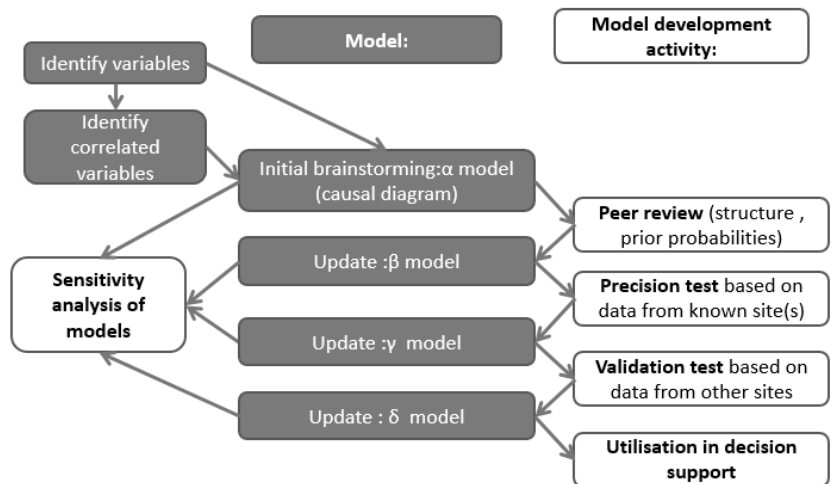


Figure 1. Graphical user interface of an Object-oriented Bayesian Network. Rectangles are sub-models ‘objects’ that are linked together in a joint probability distribution. Ovals are conditional probability distributions with their information displayed in monitors; bars on the left are probability distributions, bars on the right are expected utilities of each state of the variables. Source: Barton et al. 2016.

## How do I apply the approach?

The generic modeling steps for setting up a BN for decision support are briefly as follows:



Source: adapted from p. 207 chapter 13 – Étude de cas no.5... (Naim et al. 2008)

Figure 2. Stepwise approach to OOBNs. Source: Naim, Wullemin et al. (2007)

## Requirements

Requirements		Comments
<b>Data collection requirement</b>	<input type="checkbox"/> Data is available <input checked="" type="checkbox"/> <b>Need to collect some new data (e.g. participatory valuation)</b> <input type="checkbox"/> Need to collect lots of new data (e.g. valuation based on surveys)	
<b>Type of data required</b>	<input checked="" type="checkbox"/> <b>Quantitative</b> <input type="checkbox"/> Qualitative	
<b>Expertise and production of knowledge needed</b>	<input type="checkbox"/> Working with researchers within your own field <input checked="" type="checkbox"/> <b>Working with researchers from other fields</b> <input checked="" type="checkbox"/> <b>Working of non-academic stakeholders</b>	
<b>Software requirements</b>	<input type="checkbox"/> Freely available <input checked="" type="checkbox"/> <b>License required</b> <input type="checkbox"/> Advanced software knowledge required	HUGIN, Netica, Bayesia, BayesFusion, Quicksan
<b>Time requirements</b>	<input checked="" type="checkbox"/> <b>Short-term (less than 1 year)</b> <input type="checkbox"/> Medium-term (1-2 years) <input type="checkbox"/> Long-term (more than 2 years)	When data and parametrised models are available
<b>Economic resources</b>	<input type="checkbox"/> Low-demanding (less than 6 PMs) <input checked="" type="checkbox"/> <b>Medium-demanding (6-12 PMs)</b> <input type="checkbox"/> High-demanding (more than 12 PMs)	
<b>Other requirements</b>		

## Where do I go for more information?

Contact: [david.barton@nina.no](mailto:david.barton@nina.no)

BBN examples applied in OpenNESS can be found at <http://openness.hugin.com/>

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