METHOD FACTSHEET

Bayesian Belief Networks (BBNs)

Introduction

A Bayesian Belief Network (BBN) starts from a diagrammatic representation of the system that is being studied, developed by pulling together the knowledge of scientists and practitioners (both are stakeholders) about the processes leading to the supply and demand of ES. As a knowledge representation tool, this initial development of a BBN generates a framework of nodes and links, similar to many other representations of an ecological system or a human decision process (Figure 1). Its purpose is to formalise the flows of information through the system (from ecology to economics) and lead to transparency about what is being represented.

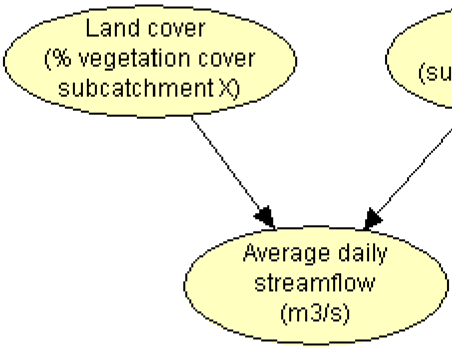

Figure 1: Simplistic representation of a BBN as nodes and linkages.

The next stage is populating the knowledge framework with information, which can include expert opinion, model outputs and empirical measurements (both quantitative and qualitative). If a statement based on that information, for example 'the colour of a leaf is green' compared to alternatives that the leaf could be yellow or brown, is an assertion, then the uncertainty can be seen as the weight of evidence that supports each assertion. Within a BBN there will be values that measure the weight of evidence for each possible assertion being true. Well-known probability theory is then used to provide inferences, i.e. conclusions based on evidence, in the form of the information and uncertainties within the outcome nodes.

The ES and natural capital (NC) concepts are by definition inter-disciplinary and logically fit into the framework of a decision process. The idea of value is only relevant when it is comparable to another value, rather than as an abstract concept, and the BBN can be extended to include decision-relevant information such as preferences and costs[1]. Therefore the BBN is an appropriate decision support tool that can be applied to many of the challenges of ES and NC assessment.

[1] Technically this becomes an influence diagram (ID).

The BBN is very flexible and can also be used to model other methods, such as state and transition models (STM; see Section 2.4) and multi-criteria decision analysis (MCDA; see deliverable 4.3), and can be combined with other model frameworks, such as agent-based models, to improve realism in modelling socio-ecological systems.

Keywords

Object-oriented bayesian networks, influence diagrams, cost-effectiveness, cost-benefit, multi-criteria analysis, decision-support

Why would I chose this approach?

Types of problem

The BBN is a flexible tool that can be used in a number of ways. Particular features of the tool are relevant to its use in ES studies:

- *Compact model knowledge representation* - The BBN can be used directly for simple modelling tasks or represent the simulation output from a more complex model in the form of key input and output variables in a network with conditional probabilities. For example, the detail of a complex hydrological model may not be necessary when assessing the costs of flooding over a 10 year period. The simulated effect, e.g. of land cover and soil type, on run-off over a given area and time span can be summarised in the form of a conditional probability table within a BBN with two conditioning variables.
- *Linking knowledge domains* - The BBN can link diverse types of information, and be used as a meta-modelling tool to link together different models in a causal model chain. Through the use of object oriented BBNs (in a simple case these are hierarchies of nested BBNs) and dynamic BBNs (using time slices to model temporal dependences, feedbacks, etc.), the BBN can be extended and adapted to modelling very complex applications. This is relevant to ES studies, especially implementing the ES cascade or other types of driver-pressure-state-impact-response (DPSIR) model chains. This makes it a good methodological framework for a multi-disciplinary project, as it easily transitions from ecological delivery to social assessment to economic cost, if that is what is required.
- *Knowledge updating* - BBNs can be readily updated with new information, so it is not a static representation of the issues. Existing knowledge on the strength of causal relationships is updated according to how much the new evidence 'weighs' in relation to the old (e.g. how many new observations there are relative to the prior data).

Decision support

- *Constructing a shared causal model* - A BBN is readily adaptable to accommodate stakeholders' belief about the structure of causality and the amount of knowledge/uncertainty about each outcome. BBNs are easily used 'live' for exploring scenarios with stakeholders because model run time is instantaneous once compiled. Here, BBNs are used to construct a common understanding of the problem.
- *Expected utility of decisions* - No decisions are taken with true certainty. The BBN can be used as a decision support tool with a consistent treatment of uncertainty. Decision alternatives can be

associated with costs and multiple end-points can be associated with benefits. BBNs will compute the expected utility (net benefits) of decision alternatives. BBNs with multiple outcomes can also be set up as a multi-criteria analysis, using multi-attribute value functions with utility weights on each outcome (instead of monetary utility).

- *Value of information* - BBNs include diagnostics such as the value of information of each variable in the network in relation to a specified outcome. With information on the cost of additional observations, BBNs can help decision-makers determine whether the cost of information is justified by the net benefits of making a better decision.
- See also Factsheet on 'Object-Oriented Bayesian Networks for Decision Support'.

Scale relevance

The BBN is developed at the temporal and spatial scales chosen by the knowledge engineer (person responsible for constructing the BBN), and these must be defined clearly at an early stage in each study. Explicit choices on temporal and spatial scale follow automatically once the ES under study have been properly defined with geographical boundaries and time frames. There is also a scale of complexity so the BBN delivers sufficient detail without overloading the model with irrelevant information; this has to be appropriate to the individual study and can be tested through formal analysis and stakeholder interactions. The BBN is specific to the scales chosen, so any change of scale will often lead to a change in BBN structure or quantification.

The inputs and outputs are also linked to the scales of the BBN, and there is a significant challenge to upscale and downscale data from a variety of sources to make the information appropriate at the correct scales for the BBN.

Spatially-explicit

The BBN operates on the domain that is specified by the knowledge engineer using the scales of space and time, and these should identify the unit that is appropriate to make the decision. For a regional government looking at the decision of whether or not to increase the area of forestry, the BBN would model one regional decision process, which will often rely on summaries of supplementary spatially-referenced data such as maps to inform the process. The decision is not to plant a specific tree at a particular location; it is to provide a policy of increasing forestry by a certain amount across the region. The decision process itself is not spatial, and neither is the BBN.

A BBN can be embedded within a GIS where it does become spatially-explicit, but it also inherits the constraints of a GIS system in terms of representing spatial dependence. Here, the BBN models the functional relationships between the states of nature represented by the GIS layers, and these are generally based on a raster or polygon with uniform information across the geographical unit. There is a possibility of capturing local spatial dependence by using information from neighbouring geographical units, but it is more difficult to include correlations or dependences that occur across longer distances.

What are the main advantages of the approach?

- Easy to use once some experience has been gained;
- Quick to use;
- Recognised and established approach;
- Advanced state-of-the-art method;

- Draws on existing data, can handle missing data, and expert knowledge can be included;
- Useful in a participatory approach with stakeholders;
- Naturally an integrative/holistic approach;
- Spatially-explicit where required;
- Covers a wide range of ES;
- Trade-offs can be evaluated in terms of expected utilities of alternative decisions;
- Temporal capability through dynamic BBNs;
- Naturally set up for use in scenario analysis;
- Uncertainty can be managed;
- Can be constructed incrementally;
- Easily updated with new data as it becomes available;
- Easy to deploy a model on a website to enable stakeholder interactions with the model, also useful during model construction.

What are the constraints/limitations of the approach?

- The detail within a BBN is restricted by the use of classes or states to record information;
- Continuous variables must be discretised when BBNs are used with utility nodes for decision support; this discretisation may lead to some information loss / loss of resolution;
- Uncertainty is defined by the chosen spatial and temporal scale, the complexity of the causal structure of the network and the resolution/discretisation in the model; experience is required in finding the right balance between these sources of uncertainty, given the purpose of the BBN.

What types of value can the approach help me understand?

BBNs are incredibly flexible and can be used to provide information on most kinds of value.

How does the approach address uncertainty?

All inputs and outputs in a BBN have an associated uncertainty which is propagated throughout the network using Bayesian conditional probabilities.

How do I apply the approach?

There are three generic steps in setting up a BBN: (i) identify the structure (nodes and links); (ii) parameterise the structure (using conditional probability tables (CPTs), equations, and/or learning from data cases); and (iii) run options and scenarios including tests on the structure, sensitivity analyses, etc. These three steps are interspersed with a number of stakeholder consultations, as illustrated by the flow diagram shown in Figure 2.3.2. One advantage of using a BBN is that it can be set up to allow stakeholder consultations to interact with the program, so options suggested at these meetings can be explored in real time and stakeholders can engage fully with the development of the structure. The BBN could be embedded within a GIS but the process of construction and testing remains the same.

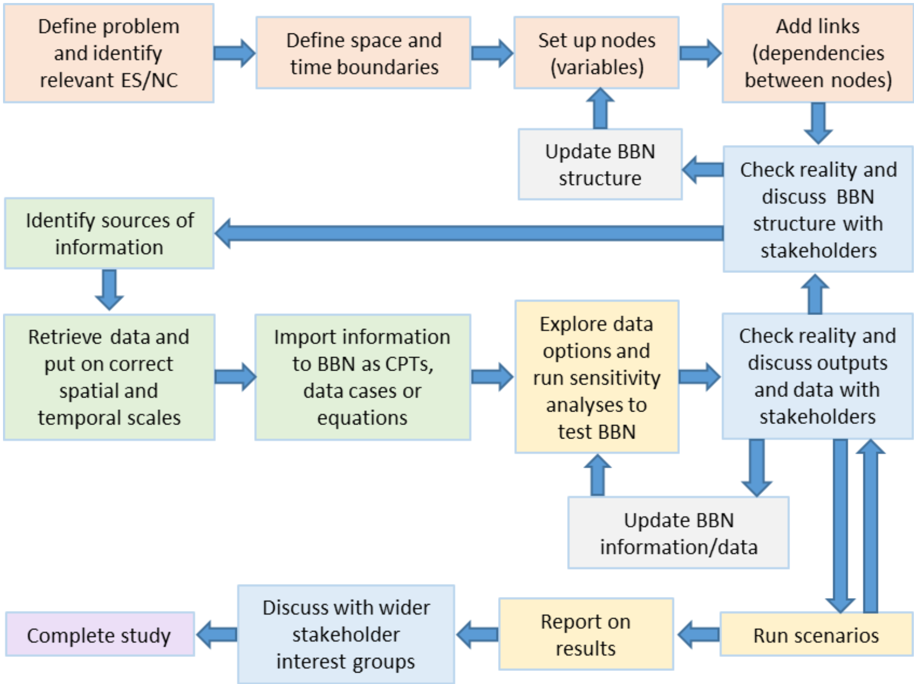

Figure 2: Flow diagram showing the steps required to develop and apply a BBN.

Requirements

Data	☑ Data is available ☐ Need to collect some new data ☐ Need to collect lots of new data	Data are always available through the use of expert knowledge, so there is never a need to wait for new data before exploring possibilities. BBNs are excellent at integrating knowledge by providing a framework to combine expert opinion and data within a single model.
Type of data	☑ Qualitative ☑ Quantitative	Handles all types of input information, but internally the software holds it as qualitative data.
Expertise and production of knowledge	☑ Work with researchers within your own field ☑ Work with researchers from other fields ☑ Work with non-academic stakeholders	Very useful in an inter-disciplinary study and where working with stakeholders (of all backgrounds) is important.
Software	☑ Freely available ☑ Software licence required ☐ Advanced software knowledge required	Software is available either free or on licence.
Time resources	☑ Short-term (< 1 year) ☐ Medium-term (1-2 years) ☐ Long-term (more than 2 years)	Short-term to get models working, explore potential frameworks, and get the most out of available data.

Economic resources	☑ < 6 person-months ☐ 6-12 person-months ☐ > 12 person-months	<6 person-months, longer time will be required if there is a lot of stakeholder interaction and/or there is no initially agreed model structure.
Other requirements		

Where do I go for more information?

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Factsheet prepared by Ron Smith, Anders L. Madsen & David N. Barton