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Good practice in Bayesian network modelling

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ABSTRACT

Bayesian networks (BNs) are increasingly being used to model environmental systems, in order to: integrate multiple issues and system components; utilise information from different sources; and handle missing data and uncertainty. BNs also have a modular architecture that facilitates iterative model development. For a model to be of value in generating and sharing knowledge or providing decision support, it must be built using good modelling practice. This paper provides guidelines to developing and evaluating Bayesian network models of environmental systems, and presents a case study habitat suitability model for juvenile *Astacopsis gouldi*, the giant freshwater crayfish of Tasmania. The guidelines entail clearly defining the model objectives and scope, and using a conceptual model of the system to form the structure of the BN, which should be parsimonious yet capture all key components and processes. After the states and conditional probabilities of all variables are defined, the BN should be assessed by a suite of quantitative and qualitative forms of model evaluation. All the assumptions, uncertainties, descriptions and reasoning for each node and linkage, data and information sources, and evaluation results must be clearly documented. Following these standards will enable the modelling process and the model itself to be transparent, credible and robust, within its given limitations.

1. Introduction

Bayesian networks (BNs) represent systems as a network of interactions between variables from primary cause to final outcome, with all cause–effect assumptions made explicit. BNs are often considered suitable for modelling environmental systems due to their ability to integrate multiple issues, interactions and outcomes and investigate tradeoffs. Furthermore, they are apt for utilising data and knowledge from different sources and handling missing data. BNs readily incorporate and explicitly represent uncertain information, and this uncertainty is propagated through to and expressed in the model outputs. BNs are based on a relatively simple causal graphical structure, meaning they can be built without highly technical modelling skills and be understood by non-technical users and stakeholders. This is a very valuable feature of BNs, particularly in the context of natural resource management which benefits from interdisciplinary and participatory processes (Voinov and Bousquet, 2010).

In BNs, variables are represented by nodes, which are linked by arcs that symbolise dependent relationships between variables. The strength of these relationships is defined in the Conditional Probability Tables (CPTs) attached to each node. CPTs specify the degree of belief (expressed as probabilities) that the node will be in a particular state given the states of the parent nodes (the nodes that directly affect that node). Evidence is entered into the BN by substituting the *a priori* beliefs of one or more nodes with observation or scenario values. Through belief propagation using Bayes' Theorem, the *a priori* probabilities of the other nodes are updated. This belief propagation enables BNs to be used for diagnostic ('bottom–up' reasoning) or explanatory purposes ('top–down' reasoning) (Castelletti and Soncini-Sessa, 2007). Therefore unlike black-box models, such as neural networks (Chen et al., 2008), BN users can interrogate the reasoning behind the model outputs as interactions between variables are clearly displayed, providing transparency to users and promoting system learning. BNs can be used for classification and prediction of states or events even when data is partial or uncertain (Newton, 2010), which is a huge advantage over many other traditional statistical models that rely on large amounts of empirical data to be built (Marcot et al., 2006).

There is an enormous scope for the possible applications of BNs in natural resources management including species or community models (Marcot et al., 2001; Borsuk et al., 2006), management models (Bromley et al., 2004; Lynam et al., 2010; Nash and Hannah, 2011), integrated models (Ticehurst et al., 2007; Kragt et al., 2011)

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social models (Ticehurst et al., 2011), and risk assessment models (Pollino and Hart, 2005; Pollino et al., 2007b). The limitations of BNs include their inability to readily represent feedback loops and dynamic relationships (Uusitalo, 2007). However some software packages can handle dynamic models by representing each time slice with a separate network (Kjærulff, 1995) and there has also been some progress in the development of spatial BNs (Smith et al., 2007). The case study presented later in this paper is a spatial BN linked to GIS to model habitat suitability for an endangered species. More details about the advantages and limitations of BNs in environmental modelling can be found in Castelletti and Soncini-Sessa (2007) and Uusitalo (2007). Commonly used BN software platforms include Hugin Expert (Hugin, www.hugin.com), Netica (Norsys Software Corp., www.norsys.com), Analytica (Lumina Decision Systems, www.lumina.com), GeNIe and SMILE (University of Pittsburgh, genie.sis.pitt.edu), BUGS (MRC and Imperial College, www.mrc-bsu.cam.ac.uk/bugs) and BayesiaLab (Bayesia Ltd., www.bayesia.com).

Modelling can be a useful approach to understanding and supporting decisions on environmental systems. However, for a model to be of value, good practice in its construction, testing and application is essential, as is awareness of the purposes, capabilities and limitations of the modelling approach. Without this, there is a risk of the model user misinterpreting or misusing model outputs, and drawing invalid conclusions (Jakeman et al., 2006). Poor modelling practice reduces the credibility of the model and can lead to the model capabilities being 'oversold', potentially causing poor decisions to be made based on models, or where model transparency and testing has not been completed, users mistrusting models and their outputs (Refsgaard and Henriksen, 2004). Models that are not properly evaluated also risk being discredited. Consequently, guidelines for good modelling practice that create standards to help ensure the development and application of credible and purposeful models are essential.

Several authors have developed modelling guidelines (Refsgaard and Henriksen, 2004; Jakeman et al., 2006; Crout et al., 2008), where the key components for good practice include:

- Clearly defining model purpose and the assumptions underlying the model
- Thorough evaluation of the model and its results
- Transparent reporting of the whole modelling process, including its formulation, parameterisation, implementation and evaluation

Good modelling practice will result in better understanding of the development and application of models, benefitting not only the modelling community but also model users.

The objective of this paper is to introduce a good practice framework for developing and evaluating BN models of environmental systems. BN modelling protocols have been published by Cain (2001) and Marcot et al. (2006). Cain (2001) provided guidelines to using BNs for supporting planning and management of natural resources, with a large emphasis on facilitating stakeholder consultation. In the context of natural resources management, stakeholder consultation is seen as essential to ensuring that the management plan is followed through and implemented (Cain, 2001). Marcot et al. (2006) developed guidelines for Bayesian networks applied to wildlife and ecological assessment, with the steps to developing and updating the BNs described at three model levels: alpha, beta and gamma. The alpha-level model is the initial functioning BN, suitable only for internal use and review. The BN is considered a beta-level model after formal peer review and revision is conducted. The gamma-level or final application model, is created by further testing, calibrating, validating and updating the beta-level model (Marcot et al., 2006). This paper presents an updated set of guidelines relevant to the wide scope of possible applications of the modelling approach.

The development and evaluation process of BNs is explored following the generic guidelines for good modelling practice outlined by Jakeman et al. (2006) and demonstrated by Welsh (2008), Robson et al. (2008) and Blocken and Gualtieri (2012). It is envisaged that adhering to the guidelines will enhance the quality and value of BNs in generating and sharing knowledge on environmental systems and providing advice on their management. Good practice in BN modelling is discussed, followed by a case study BN that models the habitat suitability of an endangered invertebrate species, *Astacopsis gouldi*.

2. Guidelines to good practice in Bayesian network modelling

2.1. Generic good modelling practice guidelines

This paper is intended to be used in conjunction with the good modelling practice framework by Jakeman et al. (2006), which consist of ten iterative steps:

(1) Define model purpose
(2) Specify modelling context (scope and resources)
(3) Conceptualise the system, specify data and other prior knowledge
(4) Select model features and families
(5) Decide how to find model structure and parameter values
(6) Select estimation performance criteria and technique
(7) Identify model structure and parameters
(8) Conditional verification and diagnostic testing
(9) Quantify uncertainty
(10) Model evaluation and testing

When following these guidelines it is important to understand how the steps should be applied in the context of BNs. The following sections discuss BN Model characteristics (relevant to Steps 1, 2 and 4 from Jakeman et al. (2006)), Conceptual model (Step 3), Model Structure (Steps 5 and 7), Model uncertainty (Step 9) and Model evaluation (Steps 6, 8 and 10).

2.2. Model characteristics

Before proceeding with developing a BN, the modelling approach must be deemed appropriate for the exercise as other modelling approaches may be more suitable. Modelling features of BNs include their:

- transparent nature, such that relationships between variables are made explicit;
- inability to readily represent feedback loops;
- ability to integrate information from a range of sources;
- ability to integrate different sub-models (e.g. social, ecological and economic);
- ability to be easily updated;
- modular structure, which allows parts of the network to be readily extracted and combined with other structures;
- ease of use; and
- limited ability to deal with continuous data.

BNs can be useful for cases:

- involving a high level of uncertainty;
- that have limited/incomplete data on key system variables;
- requiring both qualitative and quantitative information, or data in different forms;

- integrating several system components;
- requiring stakeholder engagement in the modelling process; and/or
- where the relationships between variables are non-linear and complex.

However, other modelling techniques may be more suitable in cases:

- involving feedbacks, particularly if these feedbacks are important with respect to the model outcome;
- that require detailed spatial and/or temporal representation;
- where there is a lot of data; and/or
- where the system processes can be effectively described by mathematical equations.

BNs may not be suitable if accurate predictions are required; however their predictions could be useful for comparing alternative scenarios, such as for tradeoff analysis. To help ensure that the model is built to fulfil the right purpose and captures all relevant ideas, it is essential to clearly define the model purpose and scope in the beginning of the modelling exercise. The model purpose drives many of the choices in the modelling development process, including the variables to include, the level of detail, the scales considered, level of involvement and collaboration with domain experts or stakeholders, uncertainty management and the model evaluation process.

Motives for developing and applying Bayesian network models can include:

- Improving system understanding
- Participatory modelling
- Knowledge discovery
- Synthesizing or encoding knowledge and data
- Prediction
- Exploratory and scenario analysis
- Tradeoff analysis
- Informing and supporting management and decision making
- Identifying knowledge and data gaps

These are not mutually exclusive and a BN can be built for more than one purpose.

If stakeholders are to be affected by decisions based on the BN model, it may be necessary to engage them from this early stage. Model end users (e.g. decision makers, managers) should also be consulted to ensure the modeller and model users have a common understanding of the purpose and design of the model. Involving stakeholders in the design and development of the model also enhances the acceptance of the final decision by strengthening their sense of ownership of the decision process (Bromley et al., 2004). This is facilitated by the straightforward structure of BNs, as all stakeholders, including those without technical skills can readily visualise what factors are being considered and how they are related. If the BN is built to inform science, stakeholder participation may not be necessary, but rather expert review should be conducted.

2.3. Conceptual model

Prior to building the BN, existing knowledge should be synthesized into a conceptual model (i.e. influence diagram) of the system, in the context of the model purpose and scope. More than one conceptual model can be built, for example at different scales, perspectives or levels of detail. The aim of this step is to provide a visual summary of how the drivers (e.g. climate, policy, management intervention) are linked to other variables and the output(s). Therefore it entails identifying the variables that are considered to directly or indirectly influence the final output(s) and describing the assumptions about the system processes that link them. Jakeman et al. (2006) advise to always conduct this conceptualisation step even if the model is not being built from scratch, as it can help to expose weaknesses in the underlying assumptions of the model. Building a conceptual model is valuable for structuring the problem and determining the causal chain, and strongly benefits from input from domain experts and stakeholders. The graphical nature of BNs means that this conceptualisation step can be performed using BN software; the conceptual model can then form the basis of the BN structure (Section 2.4).

After the conceptual model is built, it should be reviewed by a panel of experts and revised if necessary. This feedback may help identify key variables or processes that were overlooked and correct errors in the conceptual model. In some cases it may be appropriate to build the conceptual models together with stakeholder groups, particularly if the model will be used as a management tool whose outcome will affect the stakeholders. Cain (2001) suggests building separate conceptual models with different stakeholder groups to represent each of their perspectives, thereby identifying issues of consensus and conflict between the groups. After joint workshop discussions with the stakeholders, the conceptual models are combined into one (Cain, 2001).

2.4. Model structure

The conceptual model is generally a good starting point for structuring the BN. This structure should then be modified to fit the purpose of the model. In cases where different theories or hypotheses about the system exist, separate BNs can be built for each and then compared, as demonstrated by Pollino et al. (2007a). BNs are capable of structural learning from data by using a score-based algorithm, which searches for a structure that maximises the chosen entropy scoring function (Heckerman et al., 1995), or a constraint-based algorithm, which maps out the model structure based on the conditional dependencies found between each pair of variables (Cheng and Greiner, 2001). Structural learning may be useful for modelling poorly understood systems or those difficult to characterise. However, the learning process requires a large amount of data and is highly sensitive to the settings (e.g. number of bins/states and significance level) chosen by the user (Alameddine et al., 2011). The highly complex and stochastic nature of environmental processes may make it difficult for algorithms to detect an accurate structure. The outcomes of structural learning can be enhanced when combined with expert input; for example the expert specifies some known dependences in the system before the learning algorithm is run (Alameddine et al., 2011).

All nodes included in the model must affect (or be affected by) the final output; if a node does not, it can be left out. The node should also either be: i) manageable, ii) predictable or iii) observable at the relevant scale of the model (Borsuk et al., 2004). The exceptions to this are aggregate nodes (also referred to as latent or intermediate nodes), mentioned below. The inclusion of insignificant variables can increase the complexity of the network and reduce the sensitivity of the model outputs to important variables, not to mention unnecessarily cost extra time and effort, without adding any value to the overall model. Model parsimony is crucial; keep the network as simple as possible. Variables not explicitly included in the model contribute to the unexplained variability or model error, represented by the conditional distributions (Borsuk, 2008).

Increasing the number of nodes between the input and output nodes can dilute the sensitivity of the output to the inputs as well as increase the uncertainty propagated to the final node. To avoid this, Marcot et al. (2006) suggests the BN should have less than five layers of nodes, if possible. However, this depends on the complexity and scale of the modelled system. This can also be a problem if only some of the input nodes have several intermediate nodes between them and the output and the other input nodes have only a few, as this asymmetric structure creates uneven sensitivity of the various input nodes to the output nodes (Marcot et al., 2006). There may be cases where this asymmetric structure is intended.

For large complex systems, it may be possible to split the model structure into modular subnetworks (or network fragments) that represent different components of the system (Laskey and Mahoney, 1997; Borsuk et al., 2004). It is often easier to conceptualise complex systems in terms of smaller, interlinked components (Molina et al., 2010), and this also enables contributions from different research groups (Borsuk, 2008), which is particularly relevant to multidisciplinary problems. A specialised form of BN, Object Oriented Bayesian networks (OOBNs), follows a similar concept, with one of the main differences being that the subnetworks are hidden in the master network and instead represented by instance nodes (Koller and Pfeffer, 1997). OOBNs are particularly suitable for systems containing repetitive or hierarchical structures (e.g. Molina et al., 2010; Carmona et al., 2011).

BNs cannot contain cyclic loops. In cases where the system does contain some feedback, one should consider the relative degree of influence the processes have in the context of the model objectives. If it is found that one direction of flow is of minor importance to the model outcome relative to the other processes, it may be left out. Another option suggested by Borsuk (2008) is to use long-term (rather than short-term) equilibrium responses. Often no data or good knowledge for representation of feedbacks is available. However if such feedbacks require representation, Dynamic Bayesian Networks can be applied (Kjærulff, 1995; Borsuk et al., 2006).

2.5. Model parameters

2.5.1. Minimising probability elicitation

Each node has a set of mutually exclusive states, which can be categorical, Boolean, continuous or discrete. Continuous variables, however, must be discretised into a finite set of states (e.g. <5, 5–10, >10) in most BN software. The strength of the relationships between nodes is quantified in the Conditional Probability Tables (CPTs) attached to each node. Parentless nodes are described by marginal probability distributions, rather than conditional probabilities. For each child node, conditional probabilities are allocated for each combination of states in their parent nodes, so the size of each of these CPTs depends on the number of parent nodes and the number of their states, such that:

$$\text{size(CPT)} = S\prod_{i=1}^{n} P_i$$

where S = the number of states, P_i = the number of states in the ith parent node (Marcot et al., 2006). Therefore, the size of the CPT can increase considerably with the number of parents, which can make the process of populating the CPTs intractable especially if this is done through expert elicitation. Where sensible, it is recommended that each node should have no more than three parent nodes (Marcot et al., 2006).

To keep the size of the CPT manageable, it is also better to have the fewest number of states necessary in each node. It is recommended to select states that describe: 1) the current state that the variable is in, 2) the state it may shift to under the system change scenarios, and 3) if necessary, any intermediate states (Cain, 2001). Unless the modelling exercise is for purposes such as risk assessment or disaster management, a state should not be included if it is unlikely to be reached or is not relevant to the model objectives. The states must also match the logic of the network. To ensure this, check that the states of the parent and child nodes directly affect or are directly affected by the states in each node.

Another possible approach to help keeping the CPT to a manageable size is by 'divorcing' nodes (Fig. 1) (Henderson et al., 2009). This process involves aggregating a few of the nodes by adding a new node (A) that summaries themes. This can only be done if the aggregations are logical and no interactions are lost in the procedure. Although this process adds nodes to the network, it actually reduces the combined size of CPTs in the network (Cain, 2001). It should be noted that divorcing may, to some degree, dilute the sensitivity of the final node(s) to the input nodes and increase the uncertainty propagated through the network (Cain, 2001).

2.5.2. Discretisation of continuous variables

One of the drawbacks of BNs is the potential loss of statistical accuracy through discretisation of continuous variables, thereby neglecting variations within an interval and introducing imprecision and vagueness to the model (Borsuk, 2008; Nash and Hannah, 2011). Choosing the number of intervals requires a compromise between model simplicity and accuracy. Consider what level of detail of the node states may actually affect the final output. For example if the node represents rainfall and we know that annual rainfall below 500 mm is too low for the plant species we are considering, above 1000 mm is too high, and levels in between are adequate, rather than having multiple states which lead to the same result (e.g. <250, 250–500, 500–750, 750–1000, etc), only include states that are relevant to the outcome (i.e. <500, 500–1000, >1000). Ideally, the continuous values are divided at breakpoints or thresholds relevant to the child nodes or model objectives, however if these breakpoints are unknown other discretisation techniques are available.

Two simple and commonly used discretisation techniques are the equal-width and equal-frequency methods, which divide the range of values (minimum to maximum) into a predefined number of intervals of equal-width or intervals containing the same number of data, respectively (Muhlenbach and Rakotomalala, 2005). For many datasets these techniques may generate inappropriate divisions of the data when performed unsupervised. For example the equal-width method is unsuitable if the data values are unevenly distributed or if extreme outliers exist, and equal-frequency method is unsuitable if there are many occurrences of one value (e.g. data of a rare species may contain mostly zeros) as cases with the same value may end up in different intervals. More

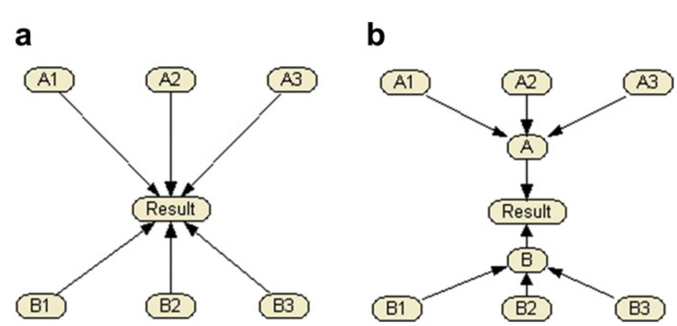

Fig. 1. Divorcing, where nodes 'A1', 'A2' and 'A3' and 'B1', 'B2' and 'B3' in (a) are divorced from the 'result' node by including intermediate nodes 'A' and 'B' (b) (Source: Henderson et al., 2009).

sophisticated techniques apply algorithms that determine the intervals by either starting with one value per interval then progressively merging these (i.e. bottom up) or starting the whole dataset as one interval then progressively splitting these into more intervals (i.e. top down) until a certain criterion is met (Muhlenbach and Rakotomalala, 2005). If possible the discretisation process should include some expert input to ensure the intervals are logical with respect to the model objectives.

2.5.3. Alternatives to discretisation

Few BN software packages (e.g. Hugin and Analytica) do allow continuous and discrete variables to be modelled simultaneously, to produce hybrid BNs. The most common types of hybrid BNs are conditional Gaussian (CG) models and mixtures of truncated exponentials (MTE) models. In CG BNs, continuous variables are assumed to follow a multivariate Gaussian distribution given its discrete parent variables, and discrete nodes cannot have continuous parents (Lauritzen and Jensen, 2001; Cowell, 2005). MTE models provide a more flexible framework without such restrictions about the structure of the network, In MTE models, the probability density function of the data are approximated by linear combinations of exponential functions (Moral et al., 2001; Langseth et al., 2009). There is growing interest in hybrid BNs as they provide an alternative approach that avoids loss of accuracy from discretisation (Aguilera et al., 2010).

2.5.4. Specifying conditional probabilities

The approach to obtaining conditional probabilities depends on the type and amount of accessible data. These can include:

- Datasets, from field monitoring or laboratory studies
- Process equations, derived from peer-reviewed studies or models
- Datasets, derived from models
- Information elicited from experts or stakeholders

Each of these data sources has their advantages and limitations, and it is crucial that the modeller is aware of these and conveys them to the user.

When using datasets collected by direct measurements, the data must represent how the node changes according to changes to the states of the parent nodes. Each of these data samples or events is referred to as a case. The inherent stochasticity and uncertainty of environmental systems is likely to be reflected in the dataset, with cases varying despite the same combination of parent states. Accordingly, the accuracy of the conditional probabilities increases with a larger number of cases. It has been recommended there be at least 20 cases for each combination of states of the parent nodes to avoid overfitting the model (Cain, 2001), but this recommendation has not been tested. The conditional probabilities can be learnt from data using algorithms such as the Lauritzen–Spiegelhalter algorithm (a basic representation of Bayes' theorem), Gibbs sampling, Expectation Maximization (EM) or Gradient Descent (GD), which are built into most BN software. These algorithms estimate the conditional probabilities based on the network structure and dataset. The Gibbs sampling, EM and GD algorithms can approximate probability distributions for datasets containing missing values (Pollino et al., 2007b).

If available, another alternative is to use datasets generated from models, including those calibrated by measured data. Sampling methods are suitable for generating cases from models. Monte Carlo sampling performs repeated runs of the model with different sets of inputs and model parameters, which are randomly varied within defined limits (Cain, 2001). A case is produced with each run and conditional probabilities can be learnt from these cases using learning algorithms.

If no appropriate datasets or models are available to parameterise the BN model, expert judgement, based on past observation, knowledge and experience can be used to estimate conditional probabilities. The ability of BN models to be parameterised using expert opinion is an advantage particularly for environmental systems that simply do not have the quantitative data necessary for statistical modelling approaches (Smith et al., 2007). However the inherent subjectiveness of expert opinion must be considered. Numerous factors can limit a person's judgement and estimation of quantities (regardless of their expertise) including heuristics, biases, values, attitudes and motivations (Morgan and Henrion, 1990). See Burgman et al. (2006) for a comprehensive review of techniques for eliciting expert judgement. It is also possible to combine expert elicitation with data or model outputs, to specify the CPTs (Pollino et al., 2007b). Expert judgement can be used to provide an initial estimate of the probabilities (i.e. prior probabilities), which are then updated using the available observed data.

2.6. Model uncertainty

Uncertainties in a BN model can originate from: incomplete understanding of system processes; the stochastic nature of environmental systems; incomplete, finite or imprecise data; or subjective biases of expert elicitation of probabilities. Uncertainties are expressed in BNs through the distribution of probabilities assigned to the states of nodes. Probability theory is a widely used formalism for quantifying uncertainty, understood to at least some extent by most people, which allows relatively straightforward communication of model uncertainties to stakeholders and other users. Uncertainties associated with the input nodes and parameters are propagated through the network to the final model endpoints. BNs therefore provide a coherent framework for representing and reasoning with uncertainty (Mead et al., 2006). The explicit representation of uncertainty can be valuable if the BN is used to support management, as it can help decision makers identify risks of undesirable outcomes associated with management alternatives (Cain, 2001).

Although BNs explicitly express uncertainties; no distinction can be made between the different types and sources of uncertainties. Different sources of uncertainty in models are often highly interlinked; for example uncertainties associated with input data, structure and calibration, collectively influence the model parameter values (Deletic et al., in press). Therefore this makes it very difficult to distinguish and independently assess the sources of uncertainties, regardless of modelling approach. One type of uncertainty not accounted for in BN models concerns the causal structure of the network and its adequacy in representing the system and processes. Another type of uncertainty unaccounted for pertains to the confidence in the uncertainty values (i.e. probabilities) themselves. For the latter type of uncertainty, if an adequate amount of data is available, it is possible to estimate approximate credible intervals or 'Bayesian error bars' around the model outputs (Van Allen et al., 2008).

Structural uncertainty is often neglected in modelling, resulting in underestimation of the uncertainty of model outputs (Mead et al., 2006; Lindenschmidt et al., 2007). Structural uncertainty is potentially large in ecological models and other models of complex systems, due to the need to drastically simplify reality (Reichert and Omlin, 1997). In such situations, some researchers have rejected the concept of an 'optimal' model in favour of the equifinality thesis, which asserts the existence of several different models and parameter sets that adequately describe the system (Reichert and Omlin, 1997; Beven and Freer, 2001). Therefore a possible approach in addressing structural uncertainty involves developing and evaluating multiple models based on different hypotheses about the system (Pollino et al., 2007a). Expert review of the conceptual model and BN model can also help reduce structural uncertainty, and sensitivity analyses can identify where linkages need to be inserted or removed.

2.7. Model evaluation

Model evaluation helps ensure the model's interactions and outcomes are feasible and defensible. The performance criteria depend on the model purpose and objectives. The behaviour of parts of or the whole model can initially be tested by applying different scenarios (i.e. combinations of inputs) and examining whether the resulting probabilities are reasonable and logical. The desired outcome of the modelling exercise can include an acceptable prediction performance or the model exhibiting realistic/plausible behaviour. Ideally, the accuracy of the model should be tested with empirical data, but in many studies that use BNs these data are not available, at least not voluminously.

Data independent from that used to parameterise the model should be used for testing. The simplest form of such Cross-Validation is to randomly split the dataset into two parts, one for training, and the other for testing (e.g. 80%/20%). Many BN software platforms have a function that allows a set of data to be tested against model predictions or diagnosis. The software updates the probability values of all samples within the case, except the 'unobserved nodes' (i.e. the nodes you have selected to be predicted/diagnosed), and then generates beliefs for each unobserved node. This generated value is then compared with its true value, and this is repeated for all given cases. One of the outputs for the test is a Confusion Matrix, which compares the predicted with actual outcomes. The most likely state is chosen as the model's prediction for that case. The columns in the matrix represent the instances in a predicted state and the rows represent the instances in the actual state and the number of cases is tallied up accordingly. In this case the performance criterion can be a certain error rate (e.g. $<5\%$).

Another form of quantitative evaluation is a sensitivity analysis, which can be conducted to identify sensitive parameters. Sensitivity analyses typically apply variance reduction calculations to continuous variables, and entropy reduction calculations to discrete or categorical variables. These analyses rank the variables in order of importance relative to the variable of interest, typically the final output. A commonly used approach to sensitivity analysis involves varying the value of uncertain factors one-at-a-time (OAT) while keeping all other factors fixed. This OAT approach is deemed inadequate (except for linear models) as it fails to detect interactions among factors and only partially explores the parametric space of the model (Saltelli and Annoni, 2010). Sensitivity analysis can be used to verify whether the model's response correctly conforms to expectations. Sensitivity analysis can also identify which variables have the most influence on the final outcome, and subsequently these variables indicate priority risks or key knowledge gaps (Pollino et al., 2007b).

If data on the system is limited or unavailable, qualitative forms of model evaluation, such as peer review, are valuable. By applying different combinations of inputs, and examining the resulting probabilities throughout the network, reviewers can test whether the behaviour of the model is consistent with current understanding about the system. Other forms of model evaluation include: critique of assumptions; critique of the model development process; and ability to perform under a range of conditions including unexpected scenarios (Jakeman et al., 2006). As stressed by Jakeman et al. (2006), model evaluation should go beyond the traditional attitude of validation based only on model accuracy, to also include subjective criteria such as fitness for purpose and transparency of the modelling process. In a review of over 100 BN applications related to environmental sciences, Aguilera et al. (2011) found that over a third (38%) did not perform any model validation. This may be linked to the fact that BNs are commonly applied in situations of scarce data, although this by no means is an excuse not to perform this step. Model evaluation can and should be performed even with limited data; this will be in the case study below.

If the model results are not plausible or if the model does not behave in a manner that is feasible or defensible, it may be necessary to reassess the model structure and assumptions. This may involve readjusting the network structure, fine-tuning the questionable CPTs, or combining, separating or redefining nodes or states (Marcot et al., 2006). There must be a thorough analysis of how well the model achieves the modelling purpose and objectives. It is important that the entire modelling process is well documented; this includes specifying the rationale for the modelling approach, the definition and rationale of all nodes and states in the network, citations of information and data sources and reporting the limitations and capabilities of the model. Every stage of the modelling process should be open to critical review and revision.

The development of a BN is often seen as an ongoing process. One of the major advantages of BN models is their ability to be easily updated with new information. This can be especially valuable in the context of environmental systems, where data and knowledge on processes is often limited. It provides modellers the opportunity to proceed with building a BN even with poor or incomplete knowledge. The BN can then be updated when new data or improved system knowledge becomes available. The models can be updated using case files by applying data learning algorithms. BN modelling shells such as Netica, allow users to specify the weight of single or sets of cases (Marcot et al., 2006). Alternatively, if the model evaluation results suggest that the entries of certain CPTs are poor, then those individual CPTs can be repopulated without having to repopulate the entire model. Similarly, if only part of the model needs rebuilding this can be done without having to rebuild the entire model, thanks to modular architecture of BNs. BN models are therefore suitable for supporting the iterative process of learning and updating that serves adaptive management. The easily updatable nature of BNs also gives them a longer life span than most other models.

3. Case study: juvenile *A. gouldi* habitat suitability model

This section presents a habitat suitability model for juvenile *A. gouldi*, the giant freshwater crayfish to demonstrate good practice in BN modelling. *A. gouldi* is the largest known freshwater invertebrate, and is endemic to Tasmania, Australia. The model is linked to GIS, thereby attempting to overcome BNs' weakness in representing spatial relationships. The integration of GIS with BN has gained considerable interest in recent years. Examples of such applications include BNs used to model the effects of environmental variables on woodland distribution to support reforestation planning (Galan et al., 2009), to map habitat suitability of the endangered Julia Creek dunnart (*Sminthopsis douglasi*), based on very limited expert knowledge and empirical data (Smith et al., 2007), to analyse the risk of disasters such as avalanches or wildfires in a spatially-explicit manner (Gret-Regamey and Straub, 2006; Dlamini, 2010), and to spatially assess the impact of human activities on marine habitat to support planning and management (Stelzenmüller et al., 2010). Environmental variables typically have a spatial dimension of interest; therefore it is often useful to manage environmental problems with an understanding of their spatial distribution and relationship.

3.1. Model purpose and context

The purpose of this juvenile *A. gouldi* model was to demonstrate the approach and value of spatial BNs. This was a desktop study based on mapping rules for juvenile *A. gouldi* by Davies et al. (2005b), which discriminate high, medium and low classes of habitat suitability based on riparian vegetation condition, mesohabitat and other habitat variables. These rules were developed by Davies et al. (2005b) to identify habitat highly suited to *A. gouldi*, as such locations require protective measures from forestry operations under current legislation. Mesohabitat consists of habitat features in the stream channel, such as large rocks, cavities and logs. The other variables considered were macro-habitat characteristics including elevation, stream class, slope and whether the area is within a geological contact zone (where the boundaries of two or more geological groups meet). Survey work by Davies et al. (2005a) found very low abundances of juvenile *A. gouldi* in non-perennial Class 4 streams, but significantly higher incidences in perennial Class 4 streams fed by groundwater discharge, such as those found in geological contact zones.

The mapping rules from Davies et al. (2005b) for discriminating stream habitat suitability for juvenile *A. gouldi* within the species range were interpreted as follows (rules are applied in numerical sequence):

1. All stream reaches >400 m elevation → unsuitable
2. Class 4 streams not within a geological contact zone → low suitability
3. Stream reaches with poor riparian condition, i.e. Conservation of Freshwater Ecosystem Values native riparian vegetation index (CFEV ripveg index) < 0.2 → low suitability
4. The habitat suitabilities of all remaining reaches (i.e. Class 1, 2 and 3 streams <400 m with CFEV ripveg index > 0.2, and Class 4 streams in geological contact zones < 400 m with CFEV ripveg index > 0.2) are defined in the matrix below (Table 1)

The scope of this study is limited to the work by Davies et al. (2005b) and Davies et al. (2007), with an aim to encode the mapping rules into a BN. The model endpoint will be 'habitat suitability', and the model inputs will be stream class, geocontact, elevation, slope, mesohabitat and riparian condition. The data on the input variables (macro-habitat characteristics and riparian condition) will be derived from GIS layers. Data on mesohabitat is currently unavailable, however mesohabitat has been included as a model input as it is considered an important variable determining habitat suitability. For this study, the value of mesohabitat in the model will be 'unknown', but this can be updated as data becomes available.

The geographical area to be modelled is limited to the *A. gouldi* range, over northern Tasmania. As the model considers habitat suitability given spatial data, no temporal aspect is built in. Many of the nodes (except mesohabitat and riparian condition) are unlikely to change with time. The riparian condition data (CFEV) was collected in 2003. A subsequent validation study found that the CFEV scores for condition correlated reasonably well with real data from surveyed river sections (Davies et al., 2007), thus the CFEV data is considered to be a good surrogate for riparian vegetation condition.

Empirical data on juvenile *A. gouldi* occurrence was not available to test and validate a model at the time that this paper was published. This would prohibit us from modelling habitat suitability with most modelling approaches. The data on the variables affecting *A. gouldi* habitat are from multiple disciplines and are in different forms (quantitative and qualitative). Therefore BN modelling was considered a suitable approach for this case study. This model was intended to be a prototype to form the basis for future iterations.

3.2. Review of existing knowledge

A. gouldi is only found in northern Tasmania, with its natural distribution including the Arthur River system and all river systems flowing into Bass Strait, except the Tamar system (Horwitz, 1994). Females take approximately 14 years to reach sexual maturity, after which they breed every two years with gestation taking about nine months (Hamr, 1992; Hamr, 1996). The diet of *A. gouldi* includes decaying wood, leaves, detritus, aquatic insects and gastropods, algae, nematomorph worms, small fish and rotting flesh (Hamr, 1996; Threatened Species Section, 2006).

A. gouldi occur in both flowing and still waters, including lakes, and streams of various sizes. They seem to have an altitudinal range of up to 400 m, with the majority of observations of the species recorded below 200 m (Horwitz, 1994). The species prefer relatively low temperatures, and seem to be intolerant of long periods of water temperature above about 20 °C (Threatened Species Section, 2006). They tend to inhabit waters shaded with native riparian vegetation, which also provides instream woody debris (snags) and food such as leaf litter (Walsh, 2002). Individuals inhabit cavities, formed instream by snags or rocks in riffles, runs or pools, or by undercut banks. These refuge cavities, particularly riffle zones are vulnerable to silt deposition, and surveys have found that the crayfish is scarce in heavily silted sites (Walsh, 2002; Davies and Cook, 2004). Mesohabitat preference tends to vary between age groups, with adults favouring snags submerged in deep pools, and juveniles favouring shallower sections within the stream (Davies et al., 2005a).

The major threatening processes attributed to causing the decline in *A. gouldi* populations include: the clearance of riparian vegetation; habitat disturbance through channelization or des-nagging; the construction of instream barriers to movement; the use of potentially toxic chemicals such as pesticides; forestry operations; and fishing (Horwitz, 1994; Threatened Species Section, 2006). The removal of native riparian vegetation can lead to a loss of suitable habitat due to reduced shading and thus increased water temperature, increased bank erosion which can lead to siltation of potential refuge cavities, and a reduction in organic debris entering

Table 1
Rules for discriminating habitat suitability for juvenile *Astacopsis gouldi* in reaches below 400 m altitude with CFEV ripveg index >0.2 in stream Classes 1, 2 and 3 and in Class 4 streams in geological contact zones.

		Mesohabitat & riparian vegetation Condition			
		Optimal mesohabitat CFEV ripveg index >0.8	Optimal mesohabitat CFEV ripveg index <0.8	Sub-optimal mesohabitat CFEV ripveg index >0.8	Sub-optimal mesohabitat CFEV ripveg index <0.8
Elevation and slope	<250 m Elevation <10% slope	High	Medium	Medium	Low
	<250 m Elevation >10% slope	Medium	Low	Low	Low
	250–400 m elevation <10% slope	Medium	Low	Low	Low
	250–400 m elevation >10% slope	Low	Low	Low	Low

the water, which can be a source of food and shelter for *A. gouldi* (Horwitz, 1994). Forestry activities adversely impact *A. gouldi* by increasing sedimentation and runoff, reducing riparian cover, and increasing accessibility for fishing (Horwitz, 1994; Threatened Species Section, 2006). The threats to *A. gouldi* are exacerbated by the species' slow growth rate and long breeding cycle.

The key factors influencing *A. gouldi* populations and their habitat is summarised into the conceptual model in Fig. 2. The arcs indicate the general direction of cause–effect. Although the species requirements have become better understood over the years, some uncertainty remains about the interactions between factors and the extent of their effects. The conceptual model provides the foundation of the BN. Even though most factors will not be included in the BN model, it is important to appreciate the intricacy of the system and acknowledge the drivers and processes that will not be accounted for in the habitat suitability model.

3.3. Model structure and parameters

The model structure and parameters were determined by the habitat suitability mapping rules (Table 1). Descriptions of the variables, including their data source are in Table 2. The BN model was built using the Netica software (Norsys Software Corp.). The BN model is shown in Fig. 3. An aggregate node 'suitable stream class' was added to reduce the size of the 'habitat suitability' CPT from 432 combinations of parent states to 144 combinations. The mapping rules in Davies et al. (2005b) were deterministic functions and therefore the relationships in the BN were also conditionally deterministic rather than probabilistic.

GIS was linked to the BN model following the process outlined by Smith et al. (2007), where each node in the BN was a GIS layer. The GIS layers for each of the input nodes were combined into one layer using the 'intersect' operation in ArcMap 9.3 (ESRI). The data for 'mesohabitat' were marked as missing (*). The attribute table for the combined GIS layer (containing approximately 626,000 polygons) was exported from ArcMap and saved as a database file. This exported file was processed by the BN as a case file ('process cases' operation in Netica), whereby the data were entered into the model as findings. The model then updated the probabilities for the nodes without findings (i.e. 'suitable stream class' and 'habitat suitability'). The output file contained the most probable 'habitat suitability' state for each polygon and an ID number. This ID number allowed 'habitat suitability' data to be imported back into ArcMap and joined to the GIS layer containing the input data. The resulting map is shown in Fig. 4. It is also possible to process the cases in BN to produce outputs other than most probable state. For example, other outputs can include the probabilities of state '*A*' or '*B*' of the final node given the findings of the input nodes, although this is not applicable to this study due to the deterministic nature of the relationships.

3.3 1. Model evaluation

Due to the lack of *A. gouldi* occurrence data, performance accuracy cannot be measured. Therefore the model remains as a belief system only, with the reliability of its predictions unknown (Marcot et al., 2006; Smith et al., 2007). The model was evaluated by sensitivity analysis to identify the variables that have the most influence on habitat suitability. The model was tested to ensure it generates the same habitat suitability values as the mapping rules it was based on (Davies et al., 2005b). In order to verify this, more than 12 polygons from each habitat suitability class (except 'High' suitability, as there were none) were randomly selected from the map and the corresponding variables were applied to the mapping rules to derive habitat suitability values. The habitat suitability values produced by the BN and derived from the mapping rules were consistent, so it was concluded that the BN satisfactorily reproduced the mapping rules.

The sensitivity analyses were conducted using the 'sensitivity to findings' function in Netica; the key results are presented in Table 3. The function works by systematically varying the evidence entered into each of the nodes to simulate 'habitat suitability' and records the probability distribution for the states of this output node. The resulting mutual information statistic (also referred to as entropy reduction) indicates the variance in the 'habitat suitability' node

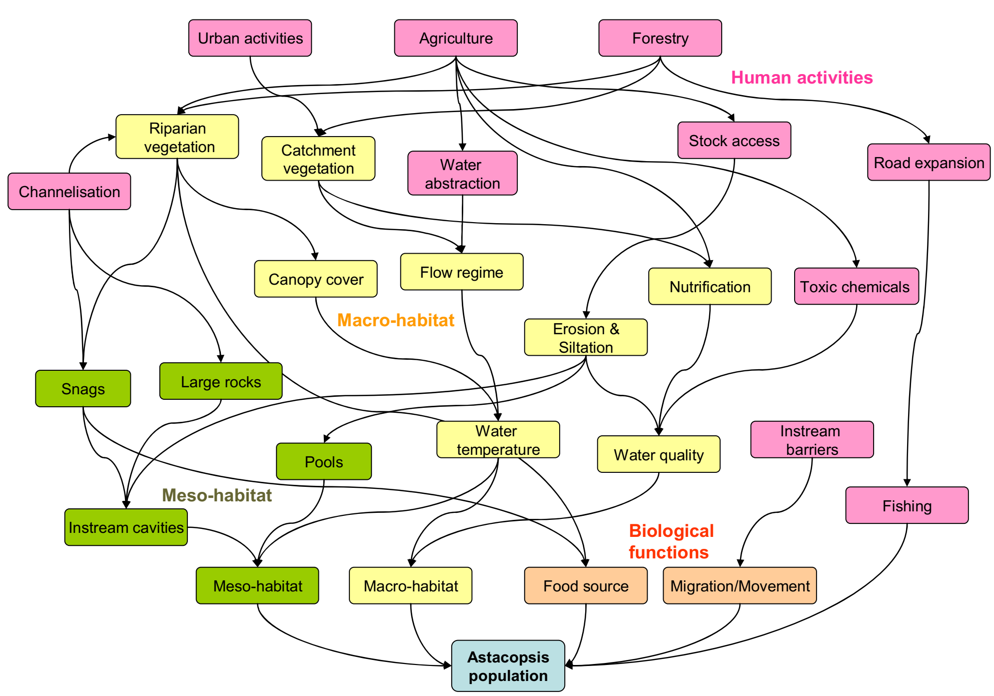

Fig. 2. Conceptual model of the key factors affecting *Astacopsis gouldi* populations.

Table 2
Description of nodes and their data sources.

Input node	Description	States	GIS layer/Data
Stream class	Stream size classes as defined in the Tasmanian Forest Practices Code.	Class 1 Class 2 Class 3 Class 4	Forest Practices Board
Geocontact	Geological contact zones. Is the area within the zone where two or more geological groups meet?	Yes No	Derived from geological polygons (as in Davies et al., 2007) from Mineral Resources Tasmania
Elevation	Metres above sea level	0–250 250–400 >400	Digital Elevation Map of Tasmania
Average Slope	Drainage section average slope (%)	<10 10–30 30–100	Derived from the DEM
Mesohabitat	Geomorphic mosaics that represent optimal mesohabitat	Optimal Sub-optimal	Not available
CFEV riparian vegetation	Conservation of Freshwater Ecosystem Values (CFEV) native riparian vegetation index	<0.2 (poor condition) 0.2–0.8 >0.8 (good condition)	CFEV Data – Catchments, River Section Catchments (Tasmanian Department of Primary Industries and Water, 2008)

that is explained by changes in the respective input nodes (Norsys Software Corp., 2006). As the BN is a direct translation of the mapping rules (Davies et al., 2005b), these sensitivity analysis results are a reflection of the relationship between the variables and the output node implicitly defined in the rules. The sensitivity analysis results indicate that elevation has the strongest influence on habitat suitability, followed by riparian condition, slope and mesohabitat. From a management perspective, of the variables that can be controlled, riparian condition is likely to be the priority risk or key knowledge gap, and therefore requires further monitoring and research.

In this prototype model, mapping rules from Davies et al. (2005b) were used directly, and consequently relationships are represented as being deterministic rather than probabilistic. Therefore the uncertainties in the model are not expressed in the final node's probabilities. One potential approach to testing uncertainties involves adjusting levels of certainty to find out at what level of uncertainty the predictions change; in other words determining how wrong the probabilities can be. Another approach involves asking experts to estimate uncertainties around the mapping rules. We would consider the BN to contain high levels of uncertainties. This is compounded by the lack of juvenile *A. gouldi* occurrence data to validate the model. The model in its current state is therefore considered to discriminate habitat suitability for *A. gouldi* at a low level of confidence. This is an area of future development. Further modelling has been done exploring different expert beliefs and predictions of habitat suitability for *A. gouldi*, which will be published at a later date.

The BN derived habitat suitability map was compared to the habitat suitability map used by Forestry Tasmania (Davies et al., 2007). The maps were based on different sets of rules, with the Forestry Tasmania map showing the habitat suitability for *A. gouldi* under pre-development conditions. As expected, the two maps were very different, with the Forestry Tasmania map showing a much larger area of medium to high habitat suitability. Current conditions would render many potentially highly suitable areas to be less suitable habitat. The advantage of the GIS-linked BN modelling approach compared to the mapping rules approach is that the framework is more interactive in that users can investigate how variables affect the final output. Furthermore there is potential for the model to be expanded in the future to incorporate uncertainties and variables that represent different management alternatives to provide decision support or other species' habitat suitabilities to create a multispecies model.

The BN was qualitatively evaluated in a meeting involving domain experts where the model and its results were presented

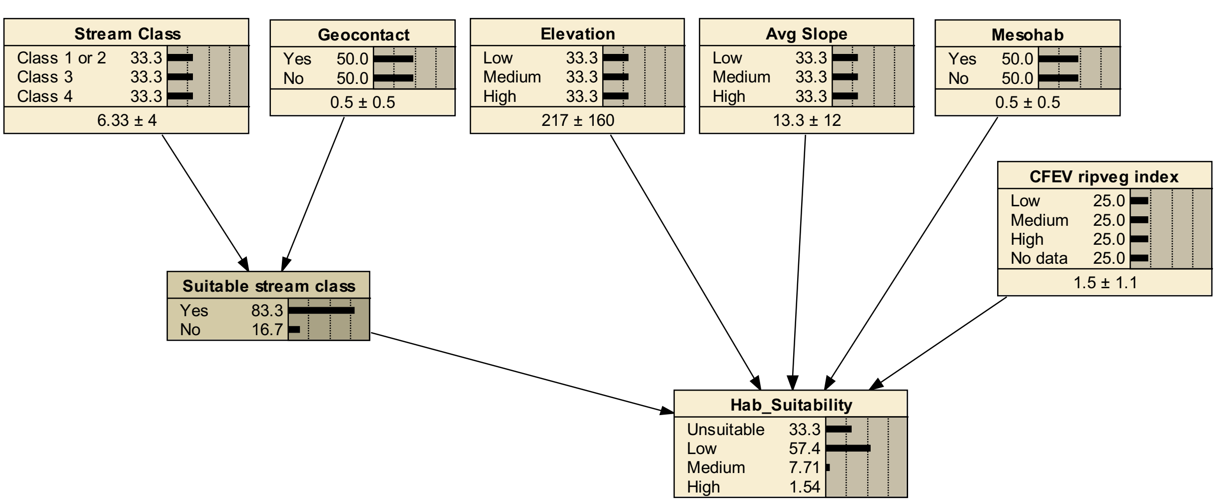

Fig. 3. Bayesian network of juvenile *Astacopsis gouldi* habitat suitability.

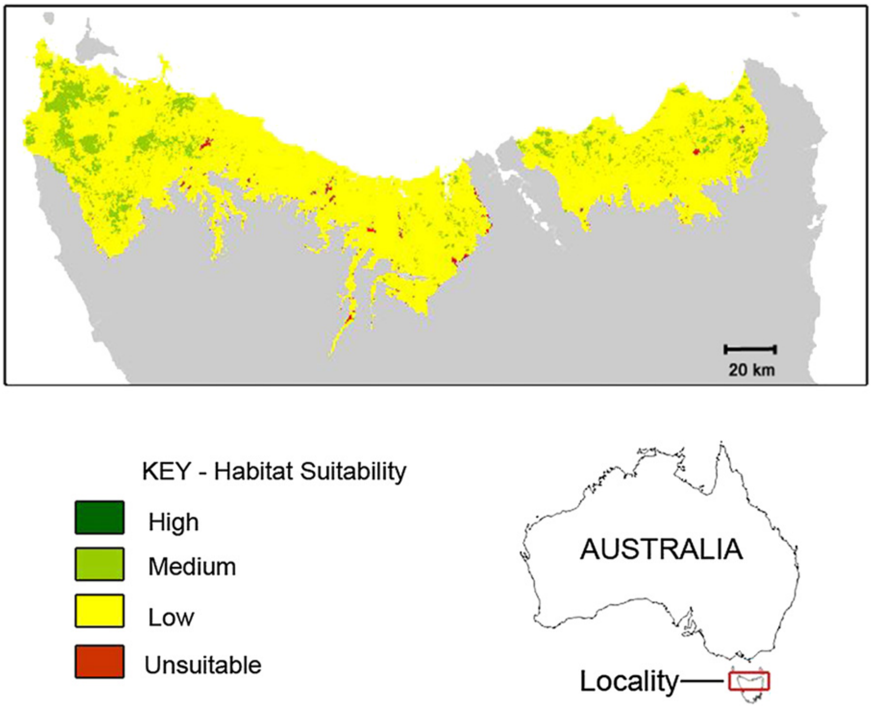

Fig. 4. Map showing the habitat suitability of juvenile *Astacopsis gouldi* produced from the GIS-linked Bayesian network model. *A. gouldi* range is indicated by the coloured areas on the map. Model input 'mesohabitat' was unknown.

and discussed. The reviewers were satisfied that the model represented the mapping rules as intended. Suggestions about how to improve the model included the inclusion of sedimentation and the removal of the geological contact zone variable. While geological contact may be important for juvenile *A. gouldi* in Class 4 streams, it was considered to be less significant than other environmental variables and possibly introduced unnecessary complexity into the model. It was also suggested that the riparian condition variable described the condition of riparian vegetation upstream and not just adjacent to the reach. This feedback will be taken into account in future iterations of the model.

The model was evaluated according to the objectives of the modelling exercise, which were to represent existing information on juvenile *A. gouldi* habitat suitability. The current understanding of *A. gouldi* habitat suitability is limited and occurrence data were not available. Subsequently the BN model contained a high level of uncertainty and its performance accuracy could not be tested. This BN is considered to be a part of an ongoing iterative model development process, which will be advanced as more knowledge and data about the *A. gouldi* habitat becomes available. Marcot et al. (2006) described BNs at three model levels: alpha, beta and gamma. Using this classification, the *A. gouldi* BN presented would be considered an alpha-level model, which is the initial functioning BN, suitable only for internal use and review (Marcot et al., 2006).

Table 3
Sensitivity of 'habitat suitability' due to a finding at another node. The nodes are ranked according to their degree of influence on the 'habitat suitability' node.

Node	Mutual info
Habitat suitability	1.367
Elevation	0.960
CFEV riparian vegetation	0.078
Slope	0.047
Mesohabitat	0.042
Stream suitability	0.026
Stream class	0.007
Geocontact	0.003

4. Conclusion

The ability of BNs to integrate data and knowledge from different sources and handle uncertainty and missing data, makes the approach appealing for modelling environmental systems. Furthermore the logical and visual nature of BNs enables non-experts to understand the model structure and contribute to parts of the model development with relative ease, making the approach highly suitable for participatory modelling. The modular architecture of BNs facilitates their application in integrated modelling and adaptive management. Regardless of the approach, good modelling practice is essential in developing meaningful and credible models. Because of their features as mentioned above, BNs are often employed in cases involving limited data and knowledge and a high level of subjectivity and uncertainty, such as the *A. gouldi* habitat suitability model. Despite the data and knowledge available for this modelling exercise being far from ideal, the case study demonstrated that good practice can be applied in all situations. The emphasis of good practice is transparent and honest reporting of the model's capabilities.

In summary, good practice in BN modelling involves firstly clearly defining the model objective and scope, followed by a compilation of knowledge about the modelled system and articulation of this knowledge into a conceptual model. This conceptual model can help form the structure of the BN, which should be parsimonious. The states for each node should be meaningful and also kept to as few as possible, especially if the CPTs are populated through expert elicitation. All assumptions used to build the BN must be documented, including uncertainties, descriptions and reasoning for each node and linkage, and information and data sources. This provides transparency in the modelling process, and enables model users to fully understand the basis of the model and its assumptions. It also makes the process of evaluating the model, as well as reconstructing, reproducing or altering it, much easier (Refsgaard and Henriksen, 2004). Furthermore, it is important for the modeller to be able to defend the model, and details such as information sources can easily be lost or forgotten over time. BNs are commonly used for modelling systems with limited data, where model validation is not possible; qualitative forms of model evaluation are especially important in these cases. BNs should be evaluated using a mix of quantitative and qualitative forms of evaluation and the results of the evaluation should also be properly documented.

BNs provide a logical and flexible framework for reasoning that is widely applicable to many problems and situations. Uncertainties in data can to some extent be overcome by expert judgement, and vice versa. Although BNs can be built entirely from expert elicitation or data learning, applications are more meaningful and valuable when both expert judgement and data are incorporated (e.g. expert elicited prior probabilities updated with data, supervised learning, etc). Choices made during the modelling process, for example the model structure, discretisation of continuous variables and evaluation approach, must be relevant to the model objectives defined in the beginning of the process. Following protocols in good modelling practice will help ensure that the modelling process and the final model itself is transparent, credible and robust, within its given limitations (i.e. knowledge, data limits).

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