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The belief index: An empirical measure for evaluating outcomes in Bayesian belief network modelling

L. Vilizzi[a,b,*], A. Price[a,b], L. Beesley[c], B. Gawne[a,b], A.J. King[c], J.D. Koehn[c], S.N. Meredith[a], D.L. Nielsen[a], C.P. Sharpe[b,d]

[a] Murray-Darling Freshwater Research Centre, PO Box 991, Wodonga, Vic 3689, Australia
[b] La Trobe University, Wodonga, Vic 3689, Australia
[c] Arthur Rylah Institute for Environmental Research, Heidelberg, Vic 3084, Australia
[d] Murray-Darling Freshwater Research Centre, PO Box 3428, Mildura, Vic 3502, Australia

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ABSTRACT

Bayesian belief networks (BBNs) are a widespread tool for modelling the effects of management decisions and activities on a variety of environmental and ecological responses. Parameterisation of BBNs is often achieved by elicitation involving multiple experts, and this may result in different conditional probability distribution tables for the nodes in a BBN. Another common use of BBNs is in the comparison of alternative management scenarios. This paper describes and implements the 'belief index' (BI), an empirical measure for evaluating outcomes in BBN modelling that summarises the probabilities (or beliefs) of any one node in a BBN. A set of four species-specific BBNs for managing watering events for wetland fish is outlined and used to statistically assess between-expert and between-species variability in parameter estimates by means of the BI. Different scenarios for management decisions are also compared using the % improvement measure, a derivative of the BI.

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1. Introduction

Bayesian belief networks (BBNs) are increasingly being used to model the effect of management decisions and activities on a variety of environmental and ecological responses (e.g. Borsuk et al., 2004, 2006; Pollino et al., 2007a; Uusitalo, 2007; Renken and Mumby, 2009; Johnson et al., 2010; Nicholson and Flores, 2011). BBNs provide for a transparent tool in which complex relationships amongst variables can be clearly articulated, knowledge gaps identified, alternate management scenarios compared, and the most important drivers for ecological responses determined (e.g. Varis and Kuikka, 1997; Marcot et al., 2006; McCann et al., 2006; Uusitalo, 2007; Stewart-Koster et al., 2010). The high level of flexibility of BBNs, and especially their ability to cope with little and/or missing data (Uusitalo, 2007) as well as to incorporate empirical data, expert opinion or a combination of both (Pollino et al., 2007b), makes them well suited to an adaptive management framework (Prato, 2005; Nyberg et al., 2006). For this reason, BBNs have become an integral part of probability-based decision support tools (Marcot et al., 2006), which represent an effective means of synthesising and applying ecological knowledge to management decisions (Castelletti and Soncini-Sessa, 2007).

BBNs are graphical representations of mathematical models in which each variable is represented as a node with the directed links forming arrows amongst the nodes. BBNs are acyclic, that is they do not support feedback loops. Each node in a BBN consists of states that are independent, mutually exclusive and exhaustive propositions about the values that the variable represented by the node can assume. A node that has no incoming arrows and is therefore not dependent on any other node is an input parent (or root) node; a node with both incoming and outgoing arrows is a summary child node; and a node with incoming but no outgoing arrows is an output child node (McCann et al., 2006). Each node in a BBN has associated a probability table, which is unconditional for input nodes and conditional for child nodes. A conditional probability table (CPT) consists of as many conditional probability distributions as there are combinations of states of the parent nodes and describes the probability of each state occurring given the states of the connecting nodes. BBNs use therefore probability as a measure of uncertainty, with beliefs about variables expressed as probability distributions (Uusitalo, 2007).

Development and analysis of a BBN has been represented as a three-stage process involving (i) structural development and evaluation, (ii) parameter estimation, and (iii) quantitative evaluation (knowledge engineering approach, Pollino et al., 2007b). Parameter

* Corresponding author at: Murray-Darling Freshwater Research Centre, PO Box 991, Wodonga, Vic 3689, Australia. Tel.: +39 393 5852484; fax: +61 2 6059 7531.
E-mail address: lorenzo.vilizzi@gmail.com (L. Vilizzi).

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estimation (i.e. the development of CPTs) can be achieved by elicitation from experts and/or from expert literature, by automated learning from data, or by a combination of both methods (Pollino et al., 2007a,b). In the case of expert elicitation, a panel of experts is usually involved in the parameter estimation process, with the result that different probability distributions may arise because of discordances amongst the experts themselves (Uusitalo, 2007). Probability distributions from multiple experts can then be combined by either behavioural or mathematical aggregation methods, the latter including the simple average (or equal-weighted linear opinion pool) of distributions from a number of experts (Clemen and Winkler, 1999; O'Hagan et al., 2006).

A common use of BBNs is in 'top-down' reasoning for descriptive/explanatory purposes, in which the probability of an effect is computed once the evidence for one or more of its causes has been provided (Castelletti and Soncini-Sessa, 2007). In this case, different management scenarios may be evaluated by first compiling the BBN and then entering different sets of evidence for the parent nodes, following a 'what-if' analysis approach (Nyberg et al., 2006). By comparing alternative scenarios, management decisions can then be made on how to maximise one or more target response variables (e.g. Borsuk et al., 2004, 2006; McNay et al., 2006; Chan et al., 2011; Shenton et al., 2011).

The aim of this study is to describe and implement the 'belief index', an empirical measure for evaluating outcomes in BBN modelling that summarises the probabilities (or beliefs) of any one node in a BBN (usually an endpoint or query node, Pollino et al., 2007b). To this end: (1) a set of related species-specific BBNs, developed for managing watering events for wetland fish, is outlined and employed in a series of sample applications; (2) computation of the belief index, along with a derivative, is described; and (3) applications are provided on how to statistically assess between-expert and between-species variability in parameter estimates as well as to compare different scenarios for management decisions.

2. Description of the BBNs

As part of the outputs of a project whose primary objective was to provide managers with improved knowledge and tools for the effective delivery of environmental water to wetlands for the benefit of native fish assemblages (Beesley et al., 2011), a 'fish in wetlands' (FW) decision support tool was developed (Gawne et al., in press). This decision support tool consisted of a set of four species-specific BBNs (CARP, GOLDEN PERCH, GUDGEON and SMELT) which were based on a common conceptualisation of the relationships between wetlands, water flow and fish (Gawne et al., in press). The four fish species, common carp (*Cyprinus carpio*), golden perch (*Macquaria ambigua*), carp gudgeon (*Hypseleotris* spp.) and Australian smelt (*Retropinna semoni*) were selected to represent a diversity of life-history styles (Humphries et al., 1999), and because there was sufficient ecological knowledge to construct BBNs for these species.

Structural development and evaluation of the FW BBNs was achieved through the engagement of both experts and managers (Meredith and Beesley, 2009), whereas parameterisation was based on expert elicitation (Beesley et al., 2011). Experts were instructed on how to describe the CPT for each node as a graphical relationship amongst the parent node variables. This involved consideration of both the mean response and the level of response uncertainty (95% credible intervals, Pollino et al., 2007b) for a specific combination of parent inputs (Marcot et al., 2006). Graphical relationships were converted first into estimated probability ranges, then into probability distributions, and eventually combined into a node's CPT. Only expert knowledge was therefore used for parameterisation of the FW BBNs.

Each species-specific FW BBN includes two sets of input nodes, namely the Wetland Features and the Management Levers, and a set of child nodes representing the Fish Responses, with the endpoint node Population Health. This is driven by three nodes representing the species' Population Characteristics, namely: Fish Condition, Total Abundance, and Population Structure. All other nodes describe the major influences on the three Population Characteristics nodes and are combined into six groups, namely: Threats, Wetland derived, Abundance, Loss and Gain, Spawning, and Movement. More details on the structure of the FW BBNs, including an individual description of all nodes, are given in Beesley et al. (2011).

3. Methodology

3.1. Computation of the belief index and its derivation

The belief index (BI) is defined as the sum of the products of the probabilities (P) of each state (k) in a node by the number of states in the same node (modified after Bubb et al., 2006):

$$\mathrm{BI} = \Sigma P(\mathrm{State}\, i) \times i \quad (i = 1, \ldots, k)$$

with values ranging from a minimum of 1 to a maximum of k. For example, the BI for the five-state endpoint node Population Health in the FW BBNs may assume all values in the interval [1, 5], so that 1 is the value obtained when the probability for the Very poor state equals 1 and that for all other states equals 0, and 5 is the value when the probability for the Excellent state equals 1 and that for all other states equals 0. As a caveat, except for two-state nodes, identical BI values may occur for nodes with three or more states (e.g. BI[0.2, 0.3, 0.5] = BI[0.1, 0.5, 0.4] = BI[0.0, 0.7, 0.3] = 2.3).

A derivative of the BI is the % improvement measure:

$$\%\ \mathrm{Improvement} = \left(1 - \left(\frac{\mathrm{BI_A}}{\mathrm{BI_B}}\right)\right) \times 100\%$$

where $\mathrm{BI_A}$ and $\mathrm{BI_B}$ are the belief indices for a target (such as an endpoint) node in the BBN under e.g. two different scenarios A and B. The % improvement can be either positive (scenario B results in a higher BI than scenario A), negative (scenario B results in a lower BI than scenario A) or zero (both scenarios have the same BI). Notably, in using both the BI and the % improvement measure the ordering of the states in the node is assumed to be from low to high and that this is consistent throughout the BBN.

3.2. Statistical analysis

Except for Spawning, which comprised only one node (Spawning Intensity) and was included only in the univariate analyses (see below), all other Fish Responses node groups were retained in the multivariate analyses. Groups were: Threats, Wetland derived, Abundance, Loss and Gain, Movement, and Structure. The latter group was modified to incorporate Population Health and the three nodes making up the Population Characteristics. A BI value was computed for each of the Fish Responses nodes and for all species-specific FW BBNs. A total of eight experts in fish ecology and limnology participated in the parameter estimation process for CPT generation, with each expert contributing knowledge to a different number of FW BBNs (Table 1). Experts acted individually following a set of common guidelines (cf. above). Netica® (version 4.16, Norsys System Corp., Vancouver, British Columbia) was chosen as the modelling shell for BBN implementation.

3.2.1. Overall variation

Variability between species and between experts was assessed by distance-based tests for homogeneity of multivariate

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Table 1
Experts involved in the parameter estimation stage of four species-specific fish in wetlands Bayesian networks (FW BBNs) for managing watering events for wetland fish.

Species	A	B	C	D	E	F	G	H
CARP	√	√		√	√	√	√	√
GOLDEN PERCH	√		√	√	√		√	
GUDGEON	√	√		√	√	√	√	
SMELT	√	√		√	√	√	√	

dispersions (Anderson, 2006). The species data matrix was 138 × 4 (observations × variables), and consisted of the BI values for the 138 nodes in total across the four species (39 nodes for CARP, 37 for GOLDEN PERCH, 31 for GUDGEON and 31 for SMELT) by the 4 experts assessing all species (i.e. A, D, E, G; Table 1). The experts data matrix was 22 × 29, and consisted of the BI values for the 22 species × expert combinations (except C and H, who assessed only one species each and therefore could not be included in the analysis, Table 1) by the 29 nodes in common to all species.

In both cases, variables were first normalised and a Euclidean dissimilarity measure (because of simple count data) was applied to obtain the corresponding distance matrix. A multivariate dispersion index (MDI, Warwick and Clarke, 1993) was then computed for each species (across the nodes in the corresponding FW BBN) and for each expert (across the species assessed), and followed by a permutational test of multivariate dispersions (PERMDISP). Statistical analyses were implemented in PRIMER v6.1.11 with procedures MVDISP (for MDI computation) and PERMDISP (9999 permutations, level of significance $\alpha = 0.05$) (Clarke and Gorley, 2006).

3.2.2. Species-specific variation

For each FW BBN, variability between node groups also was assessed by a distance-based test for homogeneity of multivariate dispersions. The four species-specific data matrices consisted of the BI values for 39 nodes × 7 experts for CARP, 37 × 5 for GOLDEN PERCH, 31 × 6 for GUDGEON and 31 × 6 for SMELT. MDIs were computed for each node group across the four FW BBNs (all other multivariate analyses as per above).

For each FW BBN, differences between experts and node groups were tested by permutational (univariate) analysis of variance (PERANOVA, Anderson, 2001), based on a two-factor design with factors Expert and Group fixed, and with the BI values for each node in the expert × group combinations as replicates. Given that all groups (including Spawning) were included in the analyses, there were in total 280 BI values for CARP (40 nodes × 7 experts), 185 for GOLDEN PERCH (37 × 5), 192 for GUDGEON (32 × 6) and 192 for SMELT (32 × 6). Unrestricted permutation of the raw data (9999 permutations) was based on a Euclidean distance matrix following normalisation, with statistically significant effects ($\alpha = 0.05$) followed by a posteriori pair-wise comparisons. PERANOVA was implemented in PERMANOVA+ v1.0.1 for PRIMER v6.1.11 (Anderson et al., 2008).

4. Applications

4.1. Parameter estimation comparison

Between-species variation was similar, as indicated by MDI values (CARP: 0.978; GOLDEN PERCH: 0.970; GUDGEON: 0.985; and SMELT: 1.093) and statistically insignificant multivariate dispersions (MVDISP: $F_{3,134} = 0.34$, $P = 0.890$) (Fig. 1, top). Likewise, between-expert variation was similar (A: 0.903; B: 0.796; D: 1.226; E: 1.301; F: 0.774; and G: 0.785) and statistically insignificant (MVDISP: $F_{5,16} = 1.43$, $P = 0.610$) (Fig. 1, bottom).

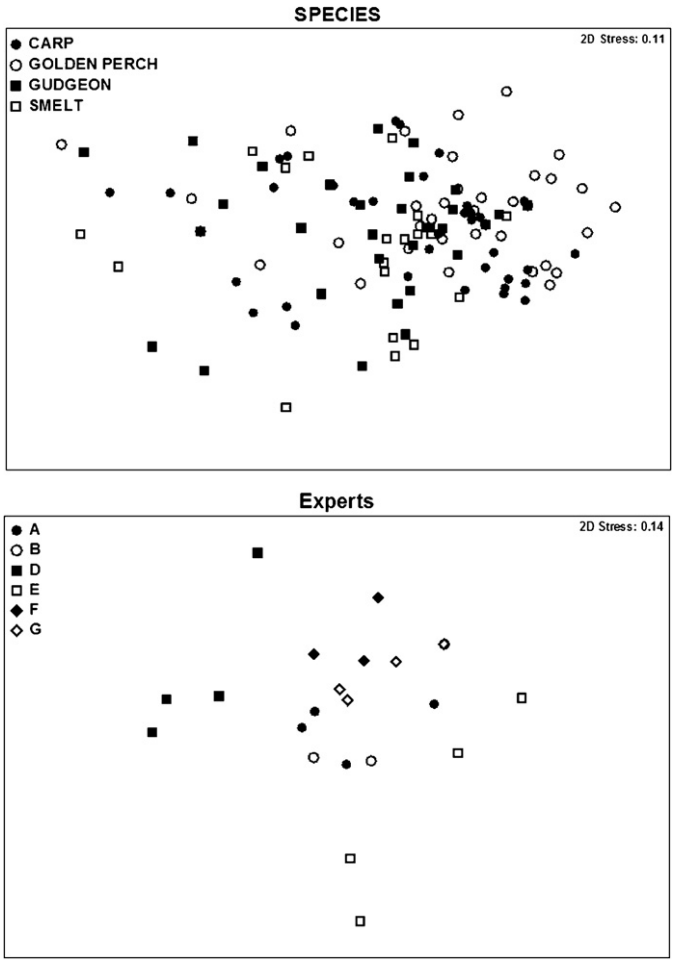

Fig. 1. MDS plots showing the level of dispersion in BI values amongst species (top) and experts (bottom).

There were no differences in multivariate dispersion between node groups for all FW BBNs except for GUDGEON, for which higher MDI values were recorded for the Movement and Wetland derived node groups, and lower MDI values for Abundance and Threats (Table 2, Fig. 2).

Finally, there were differences between experts for CARP, due to expert H differing from all others except A; and between groups

Table 2
Multivariate dispersion indices for the belief index (BI) of the nodes in the groups (except for Spawning, and with the Population Health node incorporated into a Structure group including the Population Characteristics nodes) identifying the ecological sub-model of the four species-specific FW BBNs.

	CARP	GOLDEN PERCH	GUDGEON	SMELT
Threats	0.600	0.648	0.500	0.405
Wetland derived	1.233	1.399	1.278	1.282
Abundance	0.922	0.866	0.409	0.385
Loss and Gain	0.935	1.033	0.814	0.998
Movement	1.058	1.006	1.329	1.116
Structure	0.820	0.721	0.976	0.901
F	1.65	3.07	4.55	2.90
df1	5	5	5	5
df2	33	31	25	25
$P^{\#}$	0.521	0.141	**0.034**	0.186

Statistically significant effects (in bold) at $\alpha = 0.05$.
Permutational *P* value.

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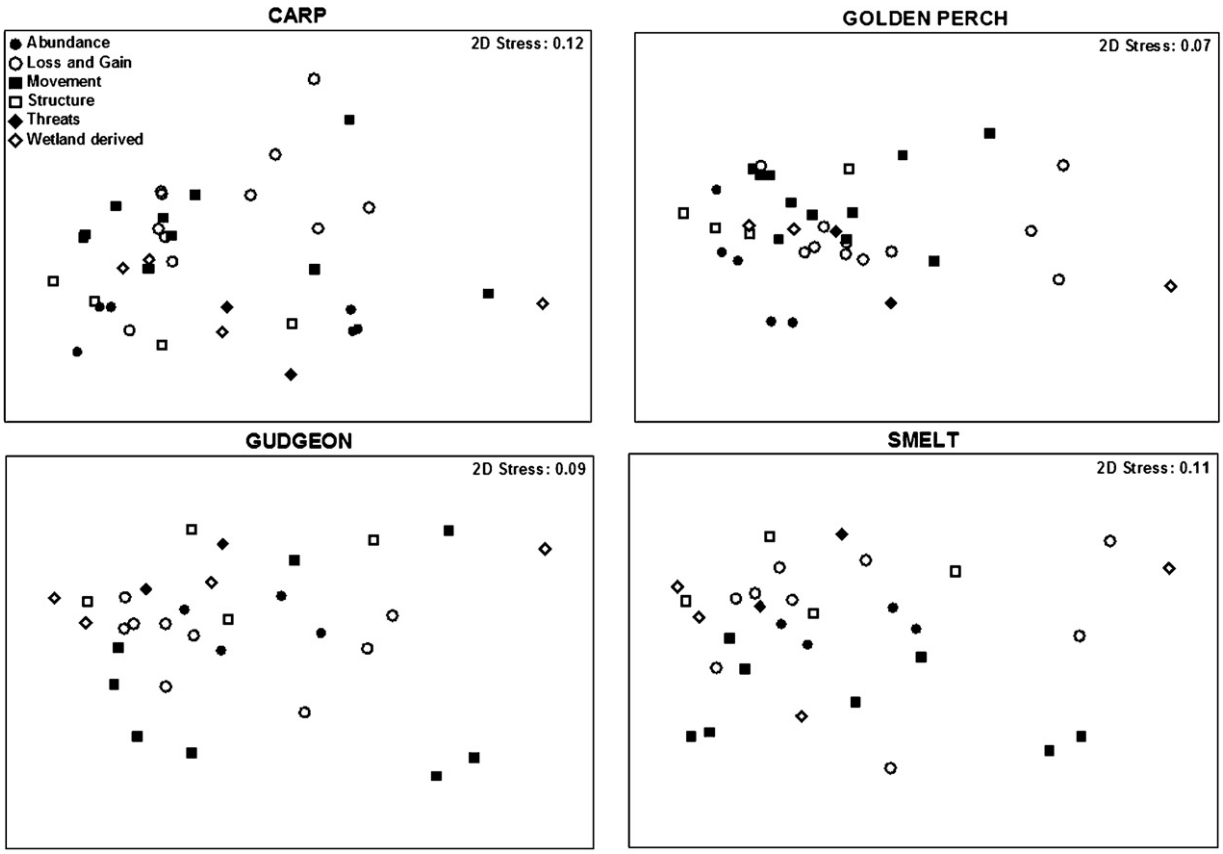

Fig. 2. MDS plots showing the level of dispersion in BI values between node groups for the four species-specific FW BBNs.

for GOLDEN PERCH mainly attributable to the Abundance and Structure node groups. For GUDGEON and SMELT there were no differences either between experts or between groups (Table 3).

4.2. Scenario comparison

4.2.1. Example 1 – which wetland to water?

Scenario – Management of the ecological values of several small wetlands is required. To this end, 150 ML of environmental water are available for delivery via a regulator (with no carp screen installed) from the river. It is estimated that it will take a total of 13 days for the water to be delivered. There are two wetlands to choose between:

1. Wetland A is a billabong (i.e., oxbow lake) with an area of approximately 20 ha prior to watering and a depth >60 cm. The wetland has no known history of acid sulphate soils (ASS), approximately 10–25% vegetation cover when inundated, and little decomposable vegetation. Once watered, hydrological modelling shows that an additional 9 ha should be inundated. Once inundated, the depth in summer is likely to be >1 m.
2. Wetland B is a deflation basin lake that is currently dry. It has no known history of ASS, approximately 25–50% vegetation cover when inundated and is covered in leaves and weeds; it has a large amount of decomposable vegetation (>75%). Once watered, hydrological modelling shows that 25 ha should be inundated and maximum depth in summer should be 30–60 cm.

Neither wetland is likely to be colonised by a large number of piscivorous birds. Likely nutrient status of the wetland or predatory fish abundances are unknown, but it is predicted that vegetation cover in the wetlands is 10–25%. The FW BBNs are run to assess the population health response for native fish (i.e. golden perch, carp gudgeon and Australian smelt) and for invasive common carp in wetland A compared to wetland B (Table 4).

Prediction – The FW BBNs predict an improvement in Population Health for all species as a result of watering in wetland A compared to wetland B (Table 5). However, the output for wetland A still does not appear ideal in absolute terms due to low probabilities for the Good and Excellent states, and is limited by its small area. Using the % improvement measure, the improvement in Population Health in wetland A is predicted to be 59.3% for CARP, 27.5% for GOLDEN PERCH, 66.6% for GUDGEON, and 80.7% for SMELT.

4.2.2. Example 2 – improving native fish health

Scenario – A large wetland in the lower River Murray is being managed. Watering has occurred at the end of the irrigation season (May) and pumping into the wetland is required. Pumping water in May is suitable for watering lignum (*Muehlenbeckia florulenta*), but few fish are expected to survive passage through the pump. Therefore, construction of a regulated channel as well as watering during the fish breeding season is under consideration.

Prior to watering, the wetland is 150 ha in size and 30–60 cm deep. One GL of water is available, which will take over a month to deliver and will inundate an additional 110 ha. After watering, the wetland is likely to be 60–100 cm deep and have high levels of inundated vegetation cover (50–75%). The wetland

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Table 3
PERANOVA results for the BI computed for each node in all Expert × Group combinations of the four species-specific FW BBNs.

Source	df	MS	$F^{\#}/t$	$P^{\#}$
CARP				
Expert	6	2.681	2.96	**0.008**
H v A	1		0.01	**0.001**
H v D	1		0.03	**0.027**
H v E	1		0.01	**0.007**
H v F	1		0.01	**0.004**
H v G	1		0.01	**<0.001**
Group	6	1.365	1.51	0.175
Expert × Group	36	1.328	1.47	0.052
Residual	231	0.906		
GOLDEN PERCH				
Expert	4	0.754	0.88	0.476
Group	5	6.867	8.01	**<0.001**
Abundance v Loss and Gain	1		5.19	**<0.001**
Abundance v Movement	1		3.95	**<0.001**
Abundance v Threats	1		3.92	**<0.001**
Abundance v Wetland derived	1		3.06	**0.005**
Loss and Gain v Structure	1		4.75	**<0.001**
Movement v Structure	1		3.65	**0.001**
Structure v Threats	1		3.75	**0.001**
Structure v Wetland derived	1		2.77	**0.011**
Expert × Group	20	0.803	0.94	0.539
Residual	155	0.857		
GUDGEON				
Expert	5	0.649	0.65	0.646
Group	6	1.836	1.85	0.096
Expert × Group	30	0.752	0.76	0.808
Residual	150	0.992		
SMELT				
Expert	5	0.945	1.028	0.403
Group	6	1.659	1.806	0.103
Expert × Group	30	0.872	0.949	0.542
Residual	150	0.919		

Statistically significant effects (in bold) at $\alpha = 0.05$ for the fixed effects Expert and Group. Only significant a posteriori pair-wise comparisons are shown. MS = mean sum of squares.

Permutational *F* and *P* values, respectively.

has 10–25% decomposable vegetation cover and wetlands in the area are at low risk from ASS. Predatory fish abundance is unknown, but piscivorous bird abundances are likely to be medium. No information is available about the wetland's nutrient status. The FW BBNs are run to evaluate watering in May using a medium pump and then watering in November using a regulator (Table 4).

Prediction – The FW BBNs predict that watering in November through a regulator will result in improved Population Health for all three native species (Table 5). Using the % Improvement measure, if the wetland is watered via a regulator compared to a pump in May this improvement is predicted to be 39.3% for GOLDEN PERCH and 15.0% and 18.4% for GUDGEON and SMELT, respectively.

5. Discussion

This study has demonstrated how a simple, empirical summary measure of the probabilities of the states (or beliefs) of any one node in a BBN can be used in a range of modelling applications. By providing a general indication of the overall location of the probability mass of a node, the BI has been used effectively in this study to assess variation in parameter estimation and in the comparison of alternative management scenarios. Also, due to the computational ease of both the BI and the % improvement measure, large amounts of data could be processed in a minimal amount of time.

Clearly, as with any other index or statistic a limitation remains intrinsic to the BI, namely the possibility of identical values resulting from different probability states in a node with three or more states. Even though this issue was not encountered in this study, identical BI values arising from different node state probabilities will have to be carefully evaluated for proper interpretation and comparisons of BI scores. For this reason, the measures proposed in this study should become part of a larger set of tools in BBN modelling.

Elicitation of parameter estimates from multiple experts is common practice in BBN-based modelling, and this can be achieved through either behavioural (Nyberg et al., 2006) or mathematical aggregation methods such as simple averaging (Chan et al., 2011; Shenton et al., 2011). However, applications of the latter method did not evaluate the degree of variability in parameter estimates amongst experts. Whereas, Borsuk et al. (2006) used the average of the values stated by three experts as the mode of triangular distributions, and maximum and minimum values of the distributions given by the average of the corresponding values across the three experts. By contrast, in the present study computation of BIs for all nodes in the BBNs supported by statistical analysis has allowed for a convenient assessment of variation in parameter estimation.

The similar level of variation recorded both between species and between experts is an indication of the homogeneity in the knowledge available for the four fish species under investigation as well as in the degree of confidence in the experts' estimates. On the other hand, the higher variation measured for GUDGEON could be explained, at least in part, by the taxonomic 'noise' surrounding what is currently recognised as a 'species group' (Bertozzi et al., 2000), with the different taxa showing different ecological responses.

The finding that parameter estimates for only one expert differed from those of the others is overall an indication of the high level of concordance achieved amongst experts, especially given that the outlier was the only expert that, for logistic reasons, was unable to revise their parameter estimates during the quantitative evaluation stage of the knowledge engineering process (Beesley et al., 2011). Whereas, the differences recorded for the Abundance and Structure node groups for GOLDEN PERCH are not surprising, given current debate on whether recruitment in this species should be regarded as more flexible than previously thought (Mallen-Cooper and Stuart, 2003; King et al., 2005, 2009; Balcombe et al., 2006; Roberts et al., 2008; Ebner et al., 2009).

Comparison of the probability state(s) of one or more (endpoint) nodes across different scenarios is common in BBN-based modelling. Such comparisons have been so far either qualitative by visual assessments or quantitative by ad hoc methods. Examples of qualitative comparisons are: visual comparisons of BBN outcomes (Borsuk et al., 2004), graphical evaluation (McNay et al., 2006), and plotting of outcomes of several management scenarios (Chan et al., 2011). Examples of quantitative comparisons are: computation of percentage ranges (Shenton et al., 2011) and implementation of a quantitative measure of causal strength (Borsuk et al., 2006). However, in none of those studies was a consistent measure like the % improvement formally defined. As shown in the present study, the % improvement measure facilitated the comparison of management scenarios in the two sample applications provided.

An important input in the development of the % improvement measure in this study was the direct engagement of managers who explicitly enquired about the possibility of developing a more effective way to facilitate comparisons between scenarios, other than reading probability states off the endpoint node (i.e. Population Health) in the FW BBNs or visually assessing probability distributions charts. Importantly, this engagement process was in line with the knowledge engineering of BBNs paradigm advocated by Pollino et al. (2007b), and represented a key component of the quantitative evaluation stage (Beesley et al., 2011).

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Table 4
Model input parameters for two sample applications of the four species-specific FW BBNs. In Example 1, *Which wetland to water?*: A is a billabong (i.e., oxbow lake); B is a deflation basin. In Example 2, *Improving native fish responses*: A is a medium pump (in May); B is a Regulator (in November).

Node	A	B
Example 1		
Wetland Features		
Max Newly Inundated Shallow (<50 cm) Area (Spring/Autumn)	<10 ha	10–50 ha
Max% Inundated Veg Cover during Spring/Autumn	10–25%	25–50%
Likely Nutrient Status of Wetland	–	–
Wetland depth (Minimum Thalweg) in Summer	>100 cm	30–60 cm
Piscivorous Bird Abundance	Low	Low
Predatory Fish Abundance	–	–
% Decomposable Veg Cover in Newly Wetted Area	1–10%	>25%
% Newly Inundated Area with ASS	0%	0%
Current Area of Wetland	10–50 ha	0 ha (dry)
Current (Pre-Wetting) Max Wetland Depth	>60 cm	<30 cm
Management Levers		
Source Water	River channel	River channel
Time Inundation Commenced	November–December	November–December
Method of Wetland Filling	Regulator controlled channel	Regulator controlled channel
Duration of Connection	3 days to 2 weeks	3 days to 2 weeks
Do All Inflows Come through Carp Screens?	No	No
Example 2		
Wetland Features		
Max Newly Inundated Shallow (<50 cm) Area (Spring/Autumn)	100–500 ha	100–500 ha
Max% Inundated Veg Cover during Spring/Autumn	50–75%	50–75%
Likely Nutrient Status of Wetland	–	–
Wetland depth (Minimum Thalweg) in Summer	60–100 cm	60–100 cm
Piscivorous Bird Abundance	Medium	Medium
Predatory Fish Abundance	–	–
% Decomposable Veg Cover in Newly Wetted Area	10–25%	10–25%
% Newly Inundated Area with ASS	1–10%	1–10%
Current Area of Wetland	100–500 ha	100–500 ha
Current (Pre-Wetting) Max Wetland Depth	30–60 cm	30–60 cm
Management Levers		
Source Water	River channel	River channel
Time Inundation Commenced	May–June	November–December
Method of Wetland Filling	Pumping–Medium	Regulator controlled channel
Duration of Connection	>1 month	>1 month
Do All Inflows Come through Carp Screens?	No	No

Table 5
Model output probability values (%) for two sample applications of the four species-specific FW BBNs with corresponding BI values. Cf. Table 4.

Population Health	CARP		GOLDEN PERCH		GUDGEON		SMELT	
	A	B	A	B	A	B	A	B
Example 1								
Very poor	6.0	50.7	41.5	69.8	17.4	75.7	11.2	76.9
Poor	40.9	40.0	49.5	28.8	56.6	22.6	55.8	21.9
Moderate	46.9	9.0	8.6	1.4	24.7	1.7	30.4	1.2
Good	6.0	0.4	0.4	0.5	1.3	0.1	2.6	0.0
Excellent	0.2	0.0	0.0	0.0	0.1	0.0	0.0	0.0
BI	2.52	1.59	1.68	1.34	2.10	1.26	2.24	1.24
Example 2								
Very poor	–	–	85.5	29.6	9.9	2.6	14.9	3.6
Poor	–	–	13.7	52.1	56.7	38.3	62.5	43.7
Moderate	–	–	0.7	16.9	30.4	49.6	21.2	45.7
Good	–	–	0.3	1.4	3.0	9.1	1.4	6.7
Excellent	–	–	0.0	0.0	0	0.4	0.0	0.2
BI			1.16	1.90	2.26	2.66	2.09	2.56

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