Observations from field trials with several elicitation techniques in an ecological domain

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Abstract

Quantitative ecologists use Bayesian networks (BNs) to scale up their collective understanding of system processes, and to adaptively investigate management alternatives. Consequently, subjective probability assessments are often critical data sources for ecological BNs. Several published probability elicitation techniques were trialled in development of a prototype ecological BN. The techniques used included verbal, numeric, text and matrix style formats. Observations of participants preferences for and performances under the different formats are described and discussed.

1 INTRODUCTION

We wanted to construct a BN collaboratively with the key end-user group for the domain, tropical seagrass managers and scientists in the Great Barrier Reef World Heritage Area (GBRWHA). Seagrasses are among the most productive ecosystems in the world (Duarte & Chiscano 1999); they are the rangelands of the coastal seas. The ecosystem services provided by seagrasses have been valued at US$3.8 trillion per year globally (Costanza et al. 1997). They provide connectivity between mangroves and reefs (Mumby et al. 2004), habitat and nursery areas for algae, invertebrates and fish (Heck Jr. et al. 2003), and are the primary food source of sea turtles and dugong (Marsh et al. 1999, Aragones et al. 2006). The dugong (*Dugong dugon*) is an herbivorous marine mammal vulnerable to extinction globally (IUCN 2000); its protection is a critical issue in the GBRWHA.

One way of protecting threatened species is to protect the ecosystems they use for food and shelter. Ecological risk analysis can help identify the biophysical factors and processes that maintain or threaten the health of these ecosystems (Hart et al. 2006). However, ecological knowledge is notoriously insufficient for most ecological risk analysis applications. This is particularly true in Australia, where landscapes are vast relative to the resources available to observe them. Subjective probability assessments are a critical data source to fill these gaps.

Given the data scarcity and complexity of most ecological systems, significant effort is required to maximise the information content of available data. Most data types can be adapted to BN analysis - this is one of the reasons why BNs are so appealing to ecological risk practitioners. However, rarely in an ecological application are all pertinent relationships represented adequately, if at all, by empirical data. In these instances machine learning and expert knowledge can be used to quantify these system relationships with probabilities. Many elicitation methods are available, but little guidance exists about how choose between them. We used our need for expert probabilities as an opportunity to informally trial several extant techniques. After introducing our domain, we describe the methods used, and our observations of our participants' responses to each.

2 THE ECOLOGICAL DOMAIN

The effect of land-based activities on marine ecosystems is a matter of global concern (GESAMP 2001). The most serious problems affecting the quality and uses of the marine and coastal environment are considered to be (GESAMP 2001):

- alteration and destruction of habitats and ecosystems;
- effects of sewage on human health;

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- eutrophication, or ‘over-fertilisation’ of waters;
- decline of fish stocks and other renewable resources; and
- changes in sediment flows.

Of these, all except fisheries problems are attributed to land-based activities. With the recognition of these persistent problems also comes acknowledgement that these problems cannot be properly managed without understanding the interdependencies that exist between marine and freshwater ecosystems (GESAMP 2001).

Australias north-east is primarily agricultural. Thirty-two catchments covering approximately 410,000 km^2 of land (Rayment 2005) drain directly into the Great Barrier Reef (GBR) lagoon, which extends 2,000 km along the north-east Queensland coast (Brodie et al. 2001a). The GBR contains approximately 3,000 reefs and large areas of seagrass beds and inshore mangrove forests (Brodie et al. 2001a). Agricultural runoff containing soil, nutrients and chemicals drains from catchments into rivers which discharge into the GBR. Eutrophication and changes in sediment flows are considered the most important land-based influences on adjacent coastal ecosystems (Brodie et al. 2007), although the issue is contentious (e.g. Starck 2005).

The Herbert River catchment was selected as the research case study (Figure 1). The Herbert River drains a catchment of about 10,000 km^2, which is the largest catchment in the humid tropics (Johnson et al. 2000; Figure 1). The catchment is dominated by beef cattle pasture and sugar cane with some mixed horticulture, and 19% of the catchment is in protected areas (Brodie et al. 2001b). Cane and grazing are locally important, both economically and socially (Rayment 2005). Pasture is typically limited to drier tablelands of the upper catchment (Johnson et al. 2001), which may be heavily grazed (Hateley 2005). Sugar cane cropping is restricted to the floodplains, but can be intensively fertilised and subject to herbicide use (Crossland et al. 1997).

Reduced pasture cover on grazing has been linked to high erosion and river turbidity in Reef catchments (Brodie et al. 2001a, Bartley et al. 2003) and cane farms have been linked to high river nutrient and herbicide levels (Bartley et al. 2003). Elevated turbidity and nutrients levels have been measured in river plumes extending from many river mouths into the GBR lagoon (Devlin et al. 2001b, Brodie 2002, Furnas 2003), however direct linkages between river water quality and the health of GBR ecosystems are difficult to establish (Crossland et al. 1997). Rigorous quantitative analysis of catchment-coast linkages is difficult

Figure 1: Catchments of the Great Barrier Reef World Heritage Area, with the Wet Tropics boxed and the Herbert River catchment in dark brown.

because:

- the effect of management actions on ecosystem responses are uncertain and therefore difficult to formulate,
- terrestrial and marine tropical systems are complex and variable (uncertain), and therefore their responses to management interventions are difficult to predict
- the overall population density across the area are low and poorly resourced for the scale of research required,
- data are therefore likely to remain patchy and linkages poorly quantified, and
- each catchment-river-coastal system is unique, so generalisations across systems are difficult, and
- a user-friendly and robust methodology to handle the uncertainties of complex, data-poor ecosystem management applications has not been broadly accessible.

The difficulties of BN graph-building in the absence of substantial practical guidance has been acknowledged in the literature (Neil et al. 2000). Valuable contributions to the development and communication of a coherent ecological BN methodology are increasing (e.g. Cain 2001, Ticehurst et al. 2007). In particular, the Quantitative Knowledge Engineering of Bayesian Networks (Q-KEBN) methodology (Woodberry et al. 2004, Pollino et al. 2005), provides a broad framework for parameterising and evaluating BNs. Recent research has seen the development of a new framework for structural elicitation, and the extension of the parameter estimation and evaluation phases of Woodberry et al.'s Q-KEBN (Thomas et al. 2005, Thomas 2008).

The new framework was applied as follows. A tiered bottom-up approach was used to simplify a complex descriptive model to a smaller, more focused model of roughly half the size. The process worked through a rough hierarchy of system specificity (primary, secondary and tertiary factors controlling seagrass ecology) to create a graphical model of the system. Graphical modelling was followed by a phase of explicit simplification, then a phase of critical review and verification. The simplified model provided a starting point for parameterisation and refinement tasks. Automated methods were not used to learn the network structure. Once the qualitative structural characteristics were identified, relationships could be quantified and parameterised. The seagraph health and abundance submodel (Figure 2) was chosen for this field trial.

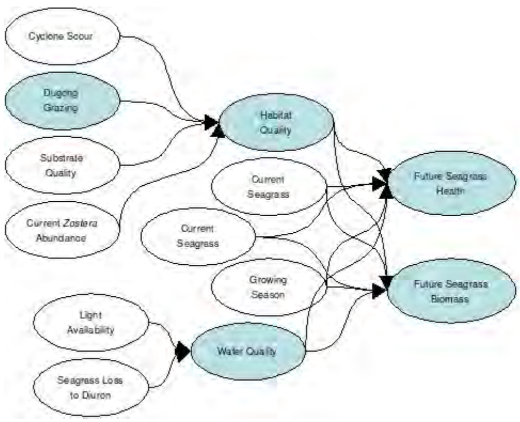

Figure 2: Seagrass health and abundance submodel

3 PREPARATION

Six seagrass experts were invited to provide subjective probabilities over nodes relating directly to their area of expertise (seagrass ecology). These experts had participated in earlier structural elicitations and were familiar with the BN domain. Details of the interviewing process and examples of the Verbal Elicitor software (Hope et al. 2002) and probability assessment worksheets supplemented the invitation to participate. Three experts accepted and participated in the interviews. Research shows that three to five good quality experts are often sufficient for forecasting tasks (Clemen & Winkler 1999).

Research also shows that if experts are made aware of potential biases, and are provided with training and feedback, the incidence of bias is likely to be reduced (Kahneman et al. 1982, Merkhofer 1987, List 2001). To help reduce bias, seagrass experts were provided with background material warning about the dangers of heuristics and biases on subjective judgments. Materials were also provided detailing node definitions and explaining concepts of causal interaction and independence relevant to later CPT partitioning tasks. Experts were allowed approximately two weeks to digest and if required, clarify the material before committing themselves to the elicitation process. Experts were interviewed once, individually, in a private meeting room. At the start of each interview they were trained in probability elicitation techniques. The efficacy of information and training measures in reducing bias could not be measured for practical reasons. Similarly cost and practicality issues prevented feedback being provided to experts about the accuracy of their subjective judgments. Each interview took up to eight hours, with breaks every two hours. All experts were interviewed by the same person.

4 TOOLS

Five nodes required subjective probabilities to be provided by each expert. Three nodes (Future Seagrass Biomass, Future Seagrass Health, Dugong Grazing) had a parent node that also required subjective assessment. Probabilities for these three nodes were elicited last, ensuring that experts thoroughly understood the parent variables prior to specifying associated child node probabilities.

Experts were encouraged to complete as many probability assessments as possible. To facilitate this, the coding effort required from experts was reduced using four strategies, presented below.

1. Start with simpler nodes and work up to more complex assessments. Effort was made to simplify the range of state combinations (i.e. the size of the CPT) of the first nodes that were elicited, so experts did not become overwhelmed by the time they came to assess the two critical, and complex, endpoint nodes late in the day. To further insure that endpoint nodes received sufficient assessment, a rough guide to the amount of time that could be spent on each node was provided.

2. Reduce the number of assessments to those lying in critical areas of the distribution; either by eliciting the best, the worst and the most moderate cases or the 10th, 50th and 90th percentile regions of the distribution before gathering everything else in between, or by directing the experts to complete the assessments for cases they felt most confident about before contemplating the more difficult assessments.

3. If it became clear that an expert could not complete the node within the session, the most difficult parent state combinations were set aside entirely and one child state was omitted from the remaining assessments. Omitted child states were later completed using a simple default rule requiring the child state values summed to one.

4. To provide flexibility in probability coding and response tasks, five different response formats were provided. Each format was explained prior to training the expert on each technique. This training began with small and conceptually simple nodes. Experts could use any of the five response formats provided. The formats used were:

   - graph paper for sketching probability distributions and associated parameters. Domain experts draw the distribution they believe best represents the parent-child relationship, indicating pertinent parameter values where appropriate (e.g. mean, maxima).
   - the Verbal Elicitor software (Hope et al. 2002; Figure 3). This software, based on work in van der Gaag et al. (1999), allows entry of probability values in ordinary English. The domain expert makes qualitative assessments using a scale with numerical and verbal anchors, by selecting a verbal cue such as 'unlikely' or 'almost certain'. The associated numerical probabilities are either set manually or optimised to minimise probabilistic incoherency.
   - text-scale worksheets (Figure 4). This method is also adapted from van der Gaag et al. (1999). The knowledge engineer reads aloud the description of the parent-child state combination. They circle their preferred verbal or numeric anchor, or slash the scale axis at a preferred point along it.
   - matrix worksheets. This method is adapted from Laskey & Mahoney (2000). Domain experts complete the full series of dependant variable state responses, given information provided on the conditioning variables. A copy of the same verbal-numeric scale used in the above format was provided to enable both verbal and numeric responses.
   - partitioned conditional probability table matrices (Figure 5). Domain experts identified conditioning variable states that would not change the value of the dependent variable response. A copy of the same verbal-numeric scale used in the above format was provided to enable both verbal and numeric responses.

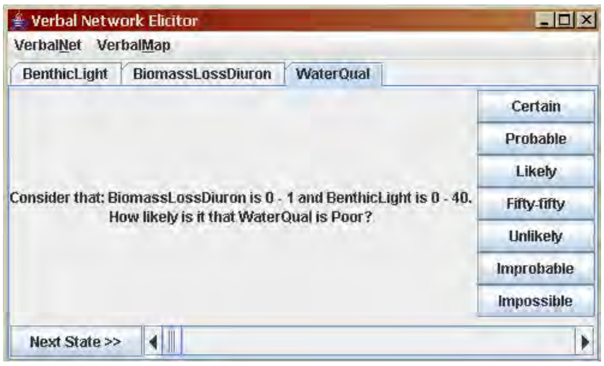

Figure 3: Screenshot from the Verbal Elicitor software (Hope et al. 2000)

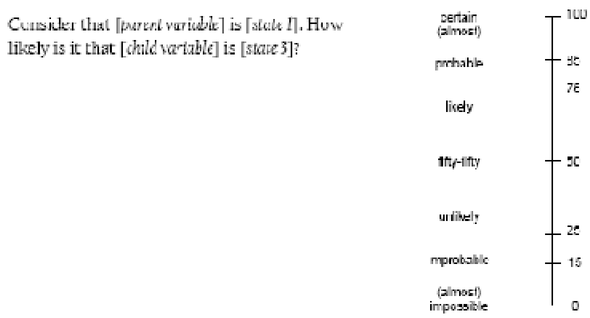

Figure 4: Extract from the text-scale worksheet (adapted from van der Gaag et al. 1999).

Experts could change response formats between nodes but were discouraged from changing from one format to another in the middle of a node assessment. Experts were given the choice of response format only for nodes with less than three parents. For nodes with more than three parents CPT partitioning was used. Experts were encouraged to use verbal-numeric responses across all formats but were never constrained to do so.

Training sessions were used at the beginning of each experts interview to familiarise experts with BN concepts and allow them to experiment with each response format. Training sessions used the Animals

Cyclone Scour?	Substrate Quality	Zostera Biomass	% Lost to Dugong	Habitat Quality Poor	Moderate	Good
yes	low	0 to 5	0 to 10	probable	improbable	impossible
yes	low	0 to 5	10 to 90	probable	improbable	impossible
yes	low	0 to 5	90 to 100	probable	improbable	impossible
yes	low	5 to 15	0 to 10	probable	improbable	impossible
yes	low	5 to 15	10 to 90	probable	improbable	impossible
yes	low	5 to 15	90 to 100	probable	improbable	impossible
yes	low	15 to 100	0 to 10	probable	improbable	impossible
yes	low	15 to 100	10 to 90	probable	improbable	impossible
yes	low	15 to 100	90 to 100	probable	improbable	impossible
yes	high	0 to 5	0 to 10	probable	improbable	impossible
yes	high	0 to 5	10 to 90	probable	improbable	impossible
yes	high	0 to 5	90 to 100	probable	improbable	impossible
yes	high	5 to 15	0 to 10	probable	improbable	impossible
yes	high	5 to 15	10 to 90	probable	improbable	impossible
yes	high	5 to 15	90 to 100	probable	improbable	impossible
yes	high	15 to 100	0 to 10	probable	improbable	impossible
yes	high	15 to 100	10 to 90	probable	improbable	impossible
yes	high	15 to 100	90 to 100	probable	improbable	impossible
no	low	0 to 5	0 to 10			
no	low	0 to 5	10 to 90			
no	low	0 to 5	90 to 100			
no	low	5 to 15	0 to 10			
no	low	5 to 15	10 to 90			
no	low	5 to 15	90 to 100			
no	low	15 to 100	0 to 10			
no	low	15 to 100	10 to 90			
no	low	15 to 100	90 to 100			
no	high	0 to 5	0 to 10			
no	high	0 to 5	10 to 90			
no	high	0 to 5	90 to 100			
no	high	5 to 15	0 to 10			
no	high	5 to 15	10 to 90			
no	high	5 to 15	90 to 100			
no	high	15 to 100	0 to 10			
no	high	15 to 100	10 to 90			
no	high	15 to 100	90 to 100			

Figure 5: The CPT for the Habitat Quality node. A partition over the Cyclone Scour node is indicated with double lines

BN (Norsys 2007), which is a qualitative school-level animal classification network, and a domain-relevant BN called Simple Eutrophication (Webb unpubl.). All formats except the freehand sketch were demonstrated during training sessions.

5 OBSERVATIONS ON ELICITATION PROCESSES

The response format appeared to play a role in probability elicitation results. No single format was collectively favoured by the experts over the others. Interestingly, the option to sketch the node's probability distribution was never taken up by experts during elicitation. This might indicate that familiarising experts with training materials before elicitations begin has some benefit. However, the effect of training on format preference was not tested in this study so we cannot be sure.

Text-scale worksheets and the VE software were generally preferred in both the training sessions and during elicitations of simple BN nodes. As node relationships became more complex, experts tended to prefer matrix-style formats and were eventually constrained to CPT partitioning formats for the final two, complex, nodes (Future Seagrass Biomass and Future Seagrass Health). Overall, one expert preferred the VE format and one preferred the text-scale format using verbal responses. The third expert preferred the matrix worksheet using numeric responses, stating that scientists were more accustomed to receiving information in numeric/matrix rather than verbal/text formats.

During training assessments with non-matrix formats (using VE and the text-scale worksheet) some experts showed a tendency to prefer positive cues. Answers were often bunched at the upper end of the vertical verbal scale, with experts showing preferences for cues such as 'likely' and 'probable', and avoiding cues such as 'unlikely' or 'improbable', even though they were attempting to represent small probabilities.

The pattern was not clearly observed during assessments using probability matrix formats, indicating that the assessment format may influence experts' probability allocations. However, when reminded that parent state combinations presented to them were just scenarios, experts were able to refocus their assessment on the child state again, usually resulting in a different assessment value.

Teigen & Brun (2003) have shown that verbal probability phrases are chosen to correspond to the linguistic rather than the numeric content of questions or statements. Their experiments show that sentences containing positive quantifiers will tend to receive positively framed responses, indicating that probability estimates are influenced by the way the conditioning information is presented.

Participants choose verbal phrases as a function of their frame; if they want to affirm that a particular outcome could in fact occur then they will use a term with positive directionality (e.g. 'possible', at the upper end of the vertical verbal scale) but if the purpose is to draw attention to an events non-occurrence then the negative phrase (e.g. 'improbable', at the lower of the scale) will be chosen (Teigen & Brun 2003). This may be because the phrases used in the text-scale worksheets and the VE software both request participants to determine "how likely" a certain response is given certain conditions. The word 'likely' creates a positive frame for the parent-child state combination requiring assessment. Positive frames may encourage positivity bias; a general readiness of participants to prefer positive over negative descriptive terms, as if positivity is the rule and negativity must be treated as an exception (Teigen & Brun 1995).

Positive framing could be reduced by omitting the word 'likely' and presenting the parent-child state combination as a factual statement against which the expert applies a probability;

> "When [parent variable 1] is in [state 1] and [parent variable 2] is in [state 1], [child variable] is [state 3]. What is the chance that this is true?"

To our knowledge the presence of positivity bias in probability elicitation for BNs has not been tested directly, and may not be adequately controlled for in extant BN elicitation techniques or formats. However our observations may provide some evidence that these biases can be reduced.

For example, matrix formats (e.g. Figure 5) present experts with the entire set of parent-child state combinations all at once. So instead of considering each parent-child state combinations in isolation, experts can choose to view sets of conditioning (parent) states, including the full range of possible responses (child) states across which the entirety of the probability budget must be allocated. This has the advantage of making the assessment context explicit. Matrix formats may therefore provide a mechanism for participants to frame assessment requests more broadly.

We tried describing the concept of a probability allocation using the idea of a probability 'budget' as a metaphor. The budget metaphor is similar to whereby each participant had to 'spend' all of the 100 'probabilities' on each child node, with the goal of using more values to indicate which outcome was considered more likely. This appeared to make clear the problems that ensue if that budget is not balanced appropriately.

We observed that subsequent to these discussions, experts preferred to rank probability responses preferentially across states for each parent-child state combination rather than continuing to tackle them individually and isolation. This change of approach resulted in substantially fewer instances of what we suspect to be a positivity bias. These reductions were observed in both verbal and numeric response types. It is interesting to note that although one expert initially preferred to use verbal responses for matrix formats, once she started ranking responses as relative probabilities across the child node, she eventually switched to numeric responses for the remainder of the interview (and was faster at it). These observations indicate that provision of greater context improves probability estimation. This concept has not been tested here.

Although the apparent positivity bias was fairly easily observed, we believe a different bias was also observed during elicitations. Some experts expressed aversion to the absoluteness of the words 'certain' and 'impossible' because, in the words of one expert, "nothing is certain in ecology". However, when allowed to use numeric probabilities, the same expert still responded with 1.0 (certain) and 0 (impossible) values. Expressions of absolute certainty were also common in verbal responses. The result suggests that these experts may also be displaying overconfidence. There were many probabilities at the very high or very low end of the spectrum (near 1.0 or 0), and instances of complete disagreement were observed, where one expert assessed a parent-child state combination as 'certain' and a different expert rated it as 'impossible'. This observation is similar to that described by Keren & Teigen (2001) as 'the principle of definitive predictions', or 'uncertainty avoidance', where only extreme probabilities are used in responses because participants wish to appear quite clear about what will happen next.

Subsequent to the elicitation processes described in this paper, we aggregated (averaged) subjective probabilities and evaluated the responses in two ways. Divergence between experts' probability assessments were analysed using the relative standard deviation of the average value and the Bhattacharrya distance measure (Bhattcharrya 1943). These techniques allowed the experts, nodes and node elements for which disagreement occurred most strongly be identified. Further, the techniques showed that although experts provided differing distributions, differences across experts occured in equal measure therefore averaging was an appropriate aggregation technique. Details of this research are reported in Thomas (2008).

6 CONCLUDING REMARKS

There is currently little guidance about how to choose between subjective elicitation methods. Preferences and responses of ecological managers and scientists were informally field-trialled using a selection of probability elicitation formats. Experts' format preferences appeared to be influenced by their familiarity with the format and node complexity.

Our observations indicate that none of the trialled techniques are likely to be completely impervious to positivity bias and overconfidence. Positively framed text-based descriptions of parent-child state combinations may have contributed to the observed bias.

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