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What is an expert?

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Abstract: Coral reefs are iconic, high-diversity, ecosystems that currently face an unprecedented set of hazards threatening their long-term existence. While widely recognized for being highly diverse, the extent of the diversity is still very poorly known. Much of it is yet to be discovered, and there is more than an order of magnitude uncertainty around the total number of multi-cellular species they host. As part of the Census of Marine Life CReefs Project, taxonomists' knowledge on the number of species on coral reefs within particular taxonomic groups was elicited (Fisher et al., 2011; O'Leary et al., 2011) in an attempt to provide a better estimate of global coral-reef species richness.

In ecology, expert opinion can provide valuable information for statistical modelling, particularly when data are limited or unreliable (e.g. Low Choy et al., 2009). However, unlike data-driven models, expert-driven models are not calibrated to empirical data. Instead, they rely entirely on the credibility and expertise of the experts. Therefore, it is important to be able to estimate how expert an expert is. In this case, how expert were the taxonomists elicited?

In this paper, we develop a conceptual model that describes criteria defining taxonomic expertise. This model was developed in group discussion with four taxonomists/ecologists about what constitutes an expert in the field of taxonomy. Criteria for evaluating what makes an expert were established first. Then a conceptual model was built, which identified relationships between these criteria. Together, these criteria and their interactions provide a conceptual model for defining taxonomic expertise, in the context of the data being elicited for the number of species on coral reefs. This conceptual model provides the basis for the next step of eliciting prior distributions of the parameters for these the relationships, to provide a full specification of a prior for a Bayesian hierarchical model (Donald et al., 2011).

Keywords: Bayesian statistics, expert elicitation, coral reefs, species richness.

1 INTRODUCTION

Corals reefs are hyperdiverse, but how many species are hosted by coral reefs worldwide remains very uncertain (Knowlton et al., 2010). Several estimates of global species richness on coral reefs exist, but these estimates are based on extrapolation from very sparse data, sometimes from quite different ecosystems. An alternative source of information on species richness can be obtained from taxonomic experts that specialise in coral reef ecosystems. Fisher et al. (2011) developed a protocol and software that aids elicitation of expert knowledge on species richness estimates for coral reefs. While this provides a sound framework for rigorous elicitation, such protocols do not help quantify the credibility of taxonomic experts, an essential facet of weighting information gained across multiple experts. This is particularly important when there is more than one expert available for a particular taxonomic group.

In ecology and conservation, experts can provide value to modelling, particularly when observed data are limited, or unreliable, or there are no alternative data available (e.g. Pearce et al., 2001; Yamada et al., 2003). In a Bayesian statistical context, this can be achieved through "expert elicitation", which is a formal and systematic approach to obtaining information from experts, translating this information into informative priors and can be combined with data in a Bayesian model (e.g. O'Hagan et al., 2006; Low Choy et al., 2009). Here, we focus on the credibility of taxonomic experts to provide estimates on the number of species on coral reefs, for their particular taxa of expertise.

An expert is a person who has specialist knowledge of a subject of interest, but does not necessarily know everything about it (e.g. Garthwaite et al., 2005). In the case of taxonomists, their expertise is gained through education, training, and field experience (Chi et al., 1988). In addition, experts are considered 'expert', or not, by their colleagues and peers in a particular field (Shanteau, 1988). There are also many types of experts (e.g. Hogarth, 1975; Shanteau, 1988). For example, Denham and Mengersen (2007) identified two types of experts for species distribution modelling. One has good knowledge of where the species is present or absent, although they may not necessarily be aware of the reasons why. The other has expertise in the physiological requirements of the species, but is less able to predict where the species is likely to be found. More generally, careful selection of experts with regard to the specifics of their expertise (together with testing and training them) and the use of structured elicitation with feedback, greatly increases the likelihood of obtaining credible (degree of belief), accurate (proximity of their assessment to what they believe), and reliable (repeatability under different conditions) information from experts (Low Choy et al., 2009; Kuhnert et al., 2010; Burgman et al., 2011).

Even when all these criteria are met, however, the quality of the resulting data may still vary among experts of differing expertise. Where there is only a single expert, this information represents the best that is available. However, when information can be elicited from multiple experts, obtaining a single distribution that comprises several experts' beliefs is desirable. There are two options for acquiring this single distribution. First, information can be elicited through an expert panel using a "consensus" approach. This approach can be compromised by disagreement between experts or domination by one or more experts (e.g. O'Hagan, 1998; Clemen and Winkler, 1999). Alternately, information can be elicited individually from multiple experts and then combined into a single distribution. The most popular and simplest approach to obtaining a single distribution is calculating a consensus distribution as a weighted function of individual experts' distributions. The decision maker/statistician then decides the weights assigned to each expert, in which the most "democratic" assigns an equal weight for each expert or gives some experts more weight than others. Scoring methods (e.g. Cooke, 1991) allocate the weights based on the performance of each expert in a separate elicitation. However, the performance area needs to be chosen carefully, since extensive knowledge in a specialist area does not necessarily relate to an expert being able to provide accurate and coherent probability assessments in another (Clemen and Winkler, 1999). For example, a taxonomist should have substantive knowledge of their taxonomic group, but not necessarily of other taxonomic groups.

In this paper, we provide an alternative method of ranking experts and/or creating expert "weights". We apply expert elicitation methods to develop a conceptual model that identifies 'what is an expert". This idea is explored using the case study - ranking taxonomist's expertise in providing the number of species on coral reefs. Such a conceptual model provides the basis for further quantification to provide an expert-informed prior in a Bayesian graphical model. The resulting elicited conceptual model is described and some of the broader implications discussed.

2 METHODS

Our conceptual model was developed in two phases. In the pilot phase, modellers (including those with ecological and taxonomic specialisations) performed a "walk-through" of the elicitation (Low Choy et al., 2009) process. This exercise enabled us to identify key variables and their interaction. In addition, it provided a basis for probing and follow-up questioning during the elicitation.

The elicitation phase (development of the conceptual model) occurred during a half-day workshop involving four taxonomists/ecologists that are well regarded in their field. Here the target node (outcome of interest) is the category "expert", with five categories: "very good", "good", "ok", "bad" and "very bad". The focus of the conceptual model was to describe factors influencing how "good" an expert is (relative to others) in providing a well-accepted estimate of the global number of species on coral reefs, for a particular taxonomic group. This way of targeting elicitation (Low Choy et al., 2010) focuses on the reasons underlying expertise, and differs from a more direct elicitation that would request an evaluation of particular experts.

The first stage of this process was to identify, discuss, and potentially modify each of the variables that could be used to define, or may contribute to, the degree to which any expert may be considered "expert". This evaluation of the variables was achieved in group discussion with our four taxonomists/ecologists, where all relevant characteristics, qualifications, and traits of a taxonomist were listed that could be used to define the quality of an expert for the specific research question.

The next stage was to develop, from this list of characteristics, a conceptual model for how these characteristics influenced the level of expertise. This involved identifying the core factors (parent nodes) that most directly influence the level of expertise (target node), and how they themselves where influenced by other factors (child nodes of the parents), and so on (to define child nodes of these children). For example, what are the key factors that define the level of expertise? If it is hard to measure these factors, then what sub-factors can be used to define each factor in turn? Reputation is a major factor describing level of expertise. For a particular expert, this information could be elicited outright, however more consistency may be achieved by qualifying how the score of reputation is to be constructed from several other factors. It was important that at each stage, the underlying conditionality assumptions can be tested by confirming with the experts that this set of factors (the child nodes) predicts well the value of the parental node. This approach followed the general principles of eliciting the structure of conditional probability networks, as presented in the general BBN literature (e.g. Jensen and Nielsen, 2007; Uusitalo, 2007). Quantifying the conditional probabilities of the nodes can be achieved within the popular Bayesian belief network (BBN) framework (e.g. Uusitalo, 2007). However, this is a daunting task for experts (Pollino et al., 2007) and due to limited time was not conducted. It is also advisable to limit the number of states of a node to five or fewer (Marcot et al., 2006).

3 RESULTS

A wide range of characteristics were identified by our expert panel as being potentially useful for defining the level of "expertise" of taxonomists. Figure 1 depicts the conceptual model that was developed and Table 1 defines the nodes (characteristics), providing a description and the states/categories of each node. While considerable discussion was involved in deciding relevant factors to include and the interactions in the network, there was a high degree of agreement among the expert panel in the resulting consensus model.

The last column of Table 1 indicates whether we currently have this information on the taxonomic experts. For those characteristics listed as "yes", either this information was gathered directly during elicitation of species richness (see above), or could be relatively easily obtained from available data sources.

There are six groups of characteristics that can be used to define a "good" expert in the context of providing an estimate of the global number of species on coral reefs (Figure 1). They represent primary/parent nodes, feeding directly into the target node "Expert". The first four are relatively straightforward: Geographic Reach, Taxonomic Breadth, Habitat Breadth and Ecosystem Breadth. The level of expertise of taxonomists in accurately estimating the global number of species on coral reefs will be proportional

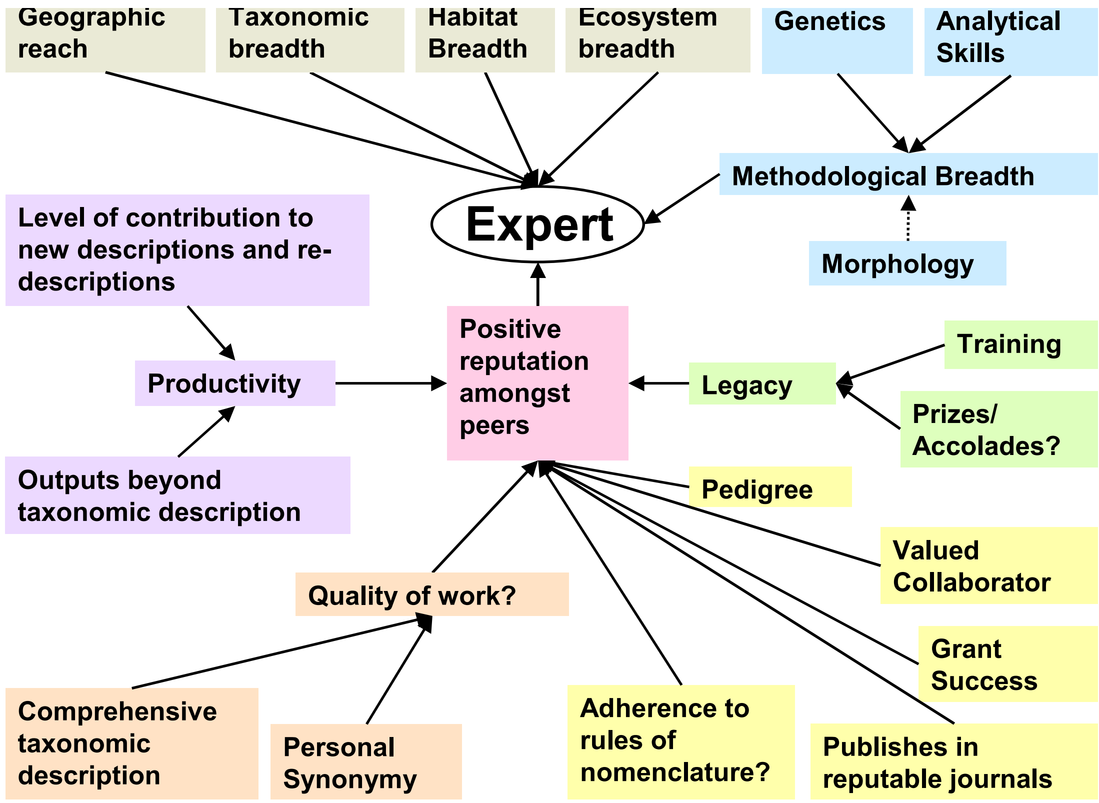

Figure 1. Conceptual model describing a taxonomic expert

to the extent of the geographic reach of their research, their taxonomic breath (which will give some indication of their general breadth of knowledge), as well as the habitat and ecosystem breadth of their research on their taxonomic group. If an expert has only collected and researched in one geographic region, ecosystem or habitat, then this expert will primarily have knowledge of that region and/or habitat. Therefore this expert will have limited to no knowledge of the number of species in other regions and/or habitats.

The fifth primary characteristic that was identified was Methodological Breadth, which is fed by three child nodes: Genetics, Analytical Skills and Morphology. The quality of an expert's estimate in our context should be ranked higher if they use, and have been exposed to, genetic techniques (e.g. genetic bar coding), have analytical skills, and broad methodological breadth of taxonomic sampling methods.

The sixth primary characteristic for ranking experts was a broad concept of Positive Reputation Amongst Peers. This node has eight child nodes, likely reflecting the complexity required to define this. Three of these child nodes were also supported by more than a single child, including: Productivity, Quality of Work, and Legacy. Productivity was characterised by two child nodes: Level of Contribution to New Descriptions and Re-descriptions, and Outputs Beyond Taxonomic Description. The quality of the taxonomic work of the expert, was charactersed by two child nodes: does the expert always provide comprehensive taxonomic descriptions of new species, and level of the expert's personal synonymy (two or more named species later found to be the same). The final primary characteristic was Legacy, defined by two child nodes: Training, and Prizes/Accolades.

Lastly, there were five direct child nodes that were thought to contribute to the parent node: Positive Reputation Amongst Peers. These nodes include Pedigree (quality of training), Valued Collaborator, Grant success, Publication in Reputable Peer-Reviewed Journals, and Adheres to Rules of Nomenclature. Details of these child nodes are given in Table 1.

Table 1. Nodes, description and states defining an expert (Figure 1).

Nodes – Description	States (Information available)
Geographic reach – Geographic reach of their research including places they have worked or places where they have processed samples from	Local,Regional,Global (Yes)
Taxonomic breadth – How many different types of taxa they work on (will give some indication of breadth of knowledge)	Low,Medium,Broad (No)
Habitat breadth – Within the broader coral reef ecosystem from what range of habitats have they sampled?	Narrow,Broad (Yes)
Ecosystem breadth – Have they worked beyond coral reefs?	Yes,No (Yes)
Methodological breadth – Based on the three child nodes: Genetics, Analytical skills and Morphology	Low,Medium,High (Yes)
Genetics – They use genetics and/or are receptive to genetic based inference	Yes,No (Yes)
Analytical skills – They use sophisticated/modern analytical methods (cladistics,complex multivariate morphometrics, meristics, phylogenetics)	Yes,No (Yes)
Morphology – They perform morphological based analysis (likely true for all Taxonomists)	Yes,No (Yes)
Positive reputation amongst peers – Based on the various child nodes: Productivity, Quality of work, Legacy and various others (see Fig 1)	Yes,No
Productivity – Based on the two child nodes: Outputs beyond taxonomic description and Level of contribution to new descriptions and re-descriptions	High,Medium,Low (Yes)
Outputs beyond taxonomic description – Publications other than species descriptions (e.g. interactive keys, checklists, field guides)	Broad,Medium,Narrow (Yes)
Level of contribution to new descriptions to new taxonomic descriptions and re-descriptions – Level of contribution to new taxonomic descriptions, revisions and re-descriptions relative to the diversity of their group	High,Medium,Low (No)
Quality of work – Based on the two existing child nodes: Comprehensiveness of taxonomic description and Personal Synonymy	Low,Medium,High (No)
Comprehensiveness of taxonomic description – Does the person publish comprehensive descriptions?	Always,Mostly,Seldom (No)
Personal synonomy – Do other taxonomists tend to synonimize species names they have erected? (indicative of being a “splitter”)	Yes,No (yes = negative impact on expertise) (Yes)
Legacy – Based on the two child nodes: Legacy and Prizes, accolades	High,Medium,Low (No)
Training – Number of students/post docs (spawning the next generation)	Many,Few (No)
Prizes/accolades – Prizes, Awards, Invitations (workshops,seminars, chair, sessions, editorships, grant committees, invited committee work)	Many,Few (No)
Pedigree – Quality of training environment	Good,Poor (Yes)
Valued collaborator – Do the skills of this person lead to a high demand for them to participate in collaborations?	Yes,No (No)
Grant success – Success in attracting competitive grants	High,Low (No)
Publishes in reputable journals – Publishes in reputable journals (peer review)	Always,Mostly,Seldom(Yes)
Adheres to the rules of nomenclature – They follow established rules and protocols for taxonomic naming	Always,Mostly,Seldom (Yes)

4 DISCUSSION AND CONCLUSIONS

Here we propose a conceptual model of what defines taxonomic expertise. Our goal was to provide a way of evaluating the level of expertise for an individual taxonomic expert, providing an estimate(s) of the global number of species on coral reefs for particular taxonomic groups. Our “supra-Bayesian” approach represents a novel method for ranking experts and/or creating expert “weights” that will be useful for combining multiple expert opinions.

When adopting this approach for evaluating expertise, it is important to note that the exercise must be carried out such that the resultant conceptual model will rank expertise relative to the specific research question for which information was elicited from expert/s. Characteristics important in defining “expertise” more broadly may be irrelevant to the capacity of an expert to provide a good estimate on the narrower topic of interest. Here the topic involved estimating the number of species on coral reefs globally. Because of this, factors such as "geographic reach" are important, because experts that have more knowledge about the global number of species should be able to provide a better estimate for this than experts that research in a single region (e.g. Great Barrier Reef).

It was also evident from our workshop discussions was that some characteristics may initially appear critical for evaluating expertise (and be potentially quite easy to quantify), but ultimately what they would capture may be better represented by other criteria. Careful consideration, therefore, needs to go into the selection of characteristics and variables defining each node. The best example of this in our case study was "length of career". This criterion was identified as important very early on by our panel, discussed extensively, and ultimately discarded because some taxonomists that are relatively young have been highly productive in describing and re-describing species. Conversely, there are more senior taxonomists that have made smaller contributions for a variety of reasons. Therefore, it was decided that an index of "productivity" would be a better criterion for evaluating taxonomic expertise than length of career.

Here we explored the idea of applying elicitation to the structure of a conceptual model for a Bayesian graphical model, using a "supra-Bayesian" approach to ranking expertise and describing the underlying factors. Future work will attempt to quantify the parameters within this conceptual model, by asking several taxonomists to rank colleagues/peers, and then compare the outcome predicted by the conceptual model with their initial expectation. Such testing, however, was beyond the scope of this paper. In the future, we aim to use the resulting expert ranking model to weight experts who provided input to an assessment of species richness on coral reefs (Fisher et al., 2011). Our graphical model can be estimated in stages with each stage focused on a particular sub-model, for example, how analytical skills and attitudes to genetics contribute to an expert's methodological breadth. This staged approach can be flexibly adapted to the time and supporting information available. For many of the sub-models, some empirical information is available, or can be elicited using super-expert opinion (however this can be a very difficult task for experts, see Pollino et al. (2007)). When these sub-models are assembled into the complete model (Figure 1), it will be useful for determining the quality of a particular taxonomic expert, and calculating rankings or generating set of weights. Alternatively, the conceptual model could be collapsed to three nodes (reputation, methodological breath, and global knowledge), with the child nodes used as prompts to elicit information about the parent node directly. Both approaches provide a more robust means of ranking experts than merely eliciting ranks outright.

Overall, we have developed a rigorous, model-based approach to defining taxonomic expertise in the context of estimating the number of species on coral reefs. The elicitation of a conceptual model provides a useful framework for using core factors to rank experts used in studies involving the elicitation of expert knowledge.

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