



# Eliciting Expert Knowledge in Conservation Science

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**Abstract:** Expert knowledge is used widely in the science and practice of conservation because of the complexity of problems, relative lack of data, and the imminent nature of many conservation decisions. Expert knowledge is substantive information on a particular topic that is not widely known by others. An expert is someone who holds this knowledge and who is often deferred to in its interpretation. We refer to predictions by experts of what may happen in a particular context as expert judgments. In general, an expert-elicitation approach consists of five steps: deciding how information will be used, determining what to elicit, designing the elicitation process, performing the elicitation, and translating the elicited information into quantitative statements that can be used in a model or directly to make decisions. This last step is known as encoding. Some of the considerations in eliciting expert knowledge include determining how to work with multiple experts and how to combine multiple judgments, minimizing bias in the elicited information, and verifying the accuracy of expert information. We highlight structured elicitation techniques that, if adopted, will improve the accuracy and information content of expert judgment and ensure uncertainty is captured accurately. We suggest four aspects of an expert elicitation exercise be examined to determine its comprehensiveness and effectiveness: study design and context, elicitation design, elicitation method, and elicitation output. Just as the reliability of empirical data depends on the rigor with which it was acquired so too does that of expert knowledge.

**Keywords:** Bayesian priors, bias, decision making, elicitation, expert judgment, expert opinion, overconfidence

Obtención de Conocimiento de Expertos en Ciencia de la Conservación

**Resumen:** El conocimiento de expertos es utilizado ampliamente en la ciencia y práctica de la conservación por la complejidad de los problemas, la falta relativa de datos y la naturaleza inminente de muchas decisiones de conservación. El conocimiento de expertos es información sustancial sobre un tópico particular que no es conocido ampliamente por otros. Un experto es alguien que tiene ese conocimiento y a quien se recurre a menudo para su interpretación. Nos referimos a las predicciones de expertos de lo que puede suceder en un contexto particular como juicio de expertos. En general, un método de obtención de expertos consiste en cinco pasos: decidir como se utilizará la información, determinar que se va a obtener, diseñar el proceso de obtención, llevar a cabo la obtención y traducir la información obtenida en datos cuantitativos que puedan ser utilizados directamente o en un modelo para tomar decisiones. Este último paso es conocido como codificación. Algunas de las consideraciones en la obtención de conocimiento de expertos incluyen determinar como trabajar con múltiples expertos y como combinar múltiples juicios, minimizando el sesgo en la información obtenida, y verificando la precisión de la información de expertos. Resaltamos técnicas estructuradas de obtención que, de ser adoptadas, mejorarán la precisión y contenido de información del

*juicio de expertos y asegurarán que la incertidumbre sea capturada con precisión. Sugerimos que se examinen cuatro aspectos de un ejercicio de obtención de expertos para determinar su amplitud y efectividad: estudiar el diseño y el contexto, diseño de la obtención, método de obtención y resultado de la obtención. Tal como la confiabilidad de los datos empíricos depende del rigor con que fueron obtenidos, también lo es para el conocimiento de expertos.*

**Palabras Clave:** Bayesianos previos, exceso de confianza, juicio experto, obtención, opinión de expertos, sesgo, toma de decisiones

## Introduction

The growing use of expert knowledge in conservation science is driven by the need to characterize dynamic, complex systems, limited resources to collect new empirical data, and the urgency of conservation decisions (Sutherland 2006; Kuhnert et al. 2010). The utility of expert knowledge depends on the scientific rigor with which it is acquired and its accuracy. Just as observational data and the methods used to collect them are subject to scrutiny, so too should expert knowledge be scrutinized to ensure that uncertainty is quantified and bias in the elicited information is minimized (O'Hagan et al. 2006).

In this review, we define expert knowledge and consider who qualifies as an expert. We examined how expert knowledge is being used to inform conservation science and practice. We outlined an elicitation approach that consists of five steps: deciding how information will be used, determining what to elicit, designing the elicitation process, performing the elicitation, and encoding the elicited information to inform a decision directly or for use in a model. We focused on the elicitation of quantities, such as population sizes, the likelihood of extinction of a population, and the prevalence of a species. We examined ways to minimize bias, combine multiple judgments, address uncertainty, and increase the accuracy of elicited information. We also devised criteria that can be used to assess how comprehensive and informative an elicitation exercise has been.

## Definition of Expert Knowledge

Expert knowledge is substantive information on a particular topic that is not widely known by others. An expert is generally considered someone who holds information about a given topic and who should be deferred to in its interpretation (Barley & Kunda 2006). This knowledge may be the result of training, research, and skills, but could also be the result of personal experience (Burgman et al. 2011a). When experts use their knowledge to predict what may happen in a particular context, we refer to these predictions as expert judgments. Experts exist, are unequally distributed among the human population, and are not created only through formal education (Evans 2008). There are different types of expertise: substantive, which reflects knowledge of a domain; normative, which

is the ability to accurately and clearly communicate judgments in a particular format (e.g., probabilities); and adaptive, which describes the degree to which one is able to extrapolate or adapt to new circumstances (McBride & Burgman 2011). These types of expertise may be unrelated, but they are all integral to the effective use of expert information.

The quality of expert judgments is reflected in the calibration and informativeness of the judgments (Cooke 1991; O'Hagan et al. 2006). Calibration of a judgment indicates how closely a judgment corresponds to reality (e.g., the amount of agreement between an expert's judgment in the form of, for example, probabilities and what is observed in reality) (O'Hagan et al. 2006). The informativeness of an expert's judgment is reflected in the precision and confidence (e.g., uncertainty of an estimate). Calibration of judgments occurs through observation of the outcomes of predictions or through formal evaluation of an expert's knowledge (tests) or use of knowledge in scenario analyses (Cooke 1991; Burgman et al. 2011b).

## Value of Expert Knowledge

Data applicable to solving many conservation problems are typically scarce; nevertheless, management decisions must be made (Cook et al. 2009). Expert judgments can provide information about model parameters and help characterize uncertainty in models, the intent of which often is to confront these judgments with empirical data as they become available. When decisions are urgently required, the expert judgments may be the basis for the decision, without additional empirical evidence.

Expert judgment is commonly used to develop and evaluate projects at the stages of hypothesis generation, sample design, model development, and interpretation of results (Fazey et al. 2005; Runge et al. 2011; Sutherland et al. 2011). Expert judgments may be the only, or the most, credible source of information available for making management decisions (Martin et al. 2005; Joseph et al. 2009; Johnson et al. 2010b; Carwardine et al. 2011), for modeling species distributions (Langhammer et al. 2007), and for assessing the probability of colonization or expansion of non-native species (Kuhnert 2011). Nevertheless, there remains ongoing controversy about use of expert judgments (Ludwig et al. 2001; Kuhnert 2011). Reservations reflect concerns that expert judgments may

be biased, poorly calibrated, or self-serving (Tversky & Kahneman 1974; Krinitzsky 1993) and thus lead to poor inference and decision making. Substantial research has concentrated on methods to overcome these problems (Kynn 2008).

Conventional criteria of expertise that depend on qualifications and experience may not correspond to the reliability of an expert's judgments (Cooke & Goossens 2008). Provision of accurate judgments requires what psychologists call deliberate practice (Ericsson 1996), the structured repetition of tasks with immediate and unambiguous feedback about accuracy. In some domains, a minimum of 10,000 hours of deliberate practice, especially feedback, is required to reach expert performance (Ericsson 1996). Few experts reach highest levels of competence in less than a decade. We speculate that the conditions of many conservation projects rarely provide the opportunity for deliberate practice by individuals. In our view, the prominence of expert judgment in conservation and the potential for its misuse create an imperative to adopt explicit structured and robust procedures to gather expert judgments. These procedures include recording elicitation design and protocols, verifying expert accuracy independently, and training experts by providing them with feedback on their judgments.

## Use of Expert Knowledge in Conservation

Examples of the use of expert knowledge to inform decision making can be found in almost all areas of conservation science and practice, and we highlight only a few here. Expert knowledge has been used to inform different types of models of relations between species and abiotic or biotic covariates: generalized linear regression models (GLMs), classification trees, and Bayesian networks. For example, Smith et al. (2007) used expert judgments about habitat in a Bayesian network for the Julia Creek dunnart (*Sminthopsis douglasi*). For a model of the distribution of brush-tailed rock wallaby (*Petrogale penicillatus*), expert knowledge was used to fill information gaps associated with species occupancy in inaccessible sites (Murray et al. 2009; O'Leary et al. 2009).

Population management often depends on expert judgments of population sizes, life-history parameters, and responses of populations to management. Johnson et al. (2010b) used expert judgments to construct a Bayesian network to evaluate the viability of cheetahs (*Acinonyx jubatus*) in southern Africa following translocation. Runge et al. (2011) elicited expert judgments on the responses of endangered (U.S. Endangered Species Act) Whooping Cranes (*Grus americana*) to management to evaluate whether different decisions would be made if particular uncertainties were resolved. O'Neill et al. (2008) quantified the trends and variance of possible effects of climate change on polar bears (*Ursus maritimus*)

on the basis of judgments of 10 experts. Martin et al. (2005) and Kuhnert et al. (2005) investigated the effect of different intensities of livestock grazing on Australian woodland birds with a Bayesian GLM that was built with information from 20 ecologists. In many cases, the inclusion of expert information substantially improved the power to detect significant changes between treatments, whereas empirical data alone had insufficient power.

Sugiura and Murray (2011) noted that assessments of risk of colonization and expansion of non-native invasive species used data and expert knowledge from many disciplines. Quantitative approaches to invasive species management often rely on expert knowledge to quantify input parameters such as detection probability, prevalence, and risk of establishment (Kuhnert 2011; Low-Choy et al. 2011b) or to specify conditional probabilities in Bayesian networks (Johnson et al. 2010a; Smith et al. 2011). Hayes (2002a, 2002b) and Hayes et al. (2004) presented fault-tree analyses, infection models, and hierarchical holographic models (models that examine the arrangement of factors that influence a topic [hierarchy] from multiple perspectives [holographic]) to groups of experts to identify potential undesirable effects associated with the release of various organisms.

Expert knowledge also has been used in models of managed systems for which many relevant parameters (e.g., optimal harvesting levels, effects of harvest, future demand) cannot be assessed directly (Crome et al. 1996; Marcot 2006; Griffiths et al. 2007; Rothlisberger et al. 2010).

## Eliciting Expert Information

Typically, an expert elicitation team includes the problem owner (person who specifies the problem), facilitator, analyst, and one or more experts. One person, in theory, could have several roles. Generally, definition of the problem and selection of experts is the domain of the problem owner. The facilitator manages the interactions among experts and oversees the judgment-elicitation process, and the analyst handles calibration, elicitation procedures, processing of responses, and analysis of elicited information.

Again, a general elicitation approach includes five steps: deciding how information will be used, determining what to elicit, designing the process of eliciting judgments, performing the elicitation, and translating the elicited information for use in a model, otherwise known as encoding the elicited information. Examples of the elicitation approach used in conservation projects are provided in Supporting Information.

## Deciding How Information Will be Used

Before undertaking expert elicitation, the problem owner, facilitator, and analyst should have a clear

understanding of how the elicited judgments will be used. Will the expert judgments be incorporated into a model or form the basis of a decision directly? Bayesian models are particularly useful for incorporating expert judgments because prior probability distributions of model parameters can be based on existing information (Gelman et al. 2004; Kuhnert et al. 2010; Low-Choy 2011). These so-called subjective priors reflect the judgment held by an expert concerning a particular model parameter. Frequentist approaches have also been developed to incorporate expert judgments into GLMs (Lele & Allen 2006).

### Determining What to Elicit

To identify the variables about which to elicit information, we suggest considering which variables most strongly affect the decision or predictions to be made. That is, determine what lack of knowledge surrounding parameters impedes making inferences or decisions and focus judgment elicitation on these parameters and their uncertainty. Elicitation should reveal relevant information about these parameters and their uncertainty, and the format in which questions are posed to the experts should allow experts to express their knowledge easily. To resolve language-based misunderstandings and different interpretations of the decisions or predictions to be made, most elicitation exercises commence with discussion of the questions themselves. This discussion is aided by an awareness of the relevant types of uncertainty (Regan et al. 2002).

### Designing the Elicitation Process

There are several ways to elicit expert knowledge (e.g., Morgan & Henrion 1990; Cooke 1991). Recent publications in the conservation science and ecological literature detail the application of these methods (Burgman 2005; Low-Choy et al. 2009; Kuhnert et al. 2010; McBride & Burgman 2011). We synthesized the common details of the process described in these publications.

During the design phase the steps in the elicitation process are delineated, how to manage bias is established, and the elicitation format (e.g., email survey, telephone interview, face-to-face interview, group meeting) is determined. In addition, experts are identified; background materials are compiled (e.g., reports, journal articles, data sets); questions are tested and finalized; scenarios to help the experts understand the questions are developed; logistics of acquisition of and interactions with experts are determined; methods of analysis of the expert data, including methods to address uncertainty, are determined; and roles of the elicitation team are identified (team members already described; McBride & Burgman 2011).

The design process includes training the experts. Training may involve having experts answer practice questions and develop familiarity with the elicitation style and pro-

cedure. For example, if probabilistic information is to be elicited, experts could be asked to estimate probabilities or frequencies through a variety of methods, including natural-frequency formats, cumulative-density functions, or probability wheels (Morgan & Henrion 1990; Caponecchia 2009; James et al. 2010; Kuhnert et al. 2010). This phase is particularly useful when detailed information is to be elicited in a format the expert may be unfamiliar with, such as probability distributions and their statistical summaries.

### Performing the Elicitation

Information may be elicited directly or indirectly (Low-Choy et al. 2009; Kuhnert et al. 2010). Direct elicitation requires the expert to express the knowledge in terms of the quantities required by the analyst. For example, the expert may be asked to provide statistical summaries (e.g., a lower and upper bound and a best estimate), quantiles or cumulative probabilities, or a full parametric probability distribution (see Jose et al. 2009; Kuhnert et al. 2010; Low-Choy et al. 2011a). Indirect elicitation requires experts to answer questions that relate to their experiences. Their responses are then encoded into the quantities required by the analyst. For example, the expert may be asked about expected site occupancy given different habitats, which the analyst then translates into an appropriate probability distribution for a model parameter.

If the elicitation process involves multiple experts, information can be elicited independently and then combined, or a group opinion can be sought. Common group approaches include expert panels and Delphi methods (e.g., Crance 1987; MacMillan & Marshall 2006). Although expert panels foster pooling of knowledge among experts and agreement on the problem and questions at hand, the full diversity of opinions are lost and responses are subject to biases, including dominance of one or more members of the group, polarization among subsets of members, and groupthink (a mode of thinking that occurs when the desire for harmony in a decision-making group overrides a realistic appraisal of alternatives; Janis 1972; Kerr & Tindale 2011). To overcome these limitations, structured interactions such as the Delphi method elicit individual estimates from experts and then allow each expert to adjust their estimates in light of the responses of others while maintaining anonymity (Linstone & Turoff 1975). In a variant of this method experts make initial individual estimates, discuss their responses, and then make a final, individual estimate. This procedure generates group estimates for ecological parameters that usually are more accurate than the estimates of the best-regarded expert in a group (Burgman et al. 2011b).

Another approach to expert elicitation that is gaining recognition is Cooke's method (Cooke 1991; Cooke & Goossens 2004; Cooke et al. 2008; Goossens et al. 2008;



Aspinall 2010). In this method the opinion of each expert is weighted on the basis of its accuracy. Experts are brought together to discuss a particular topic (e.g., arrival time of particular migratory species) under the guidance of a facilitator. Following group discussion, experts are asked individually to give their judgment (e.g., arrival time of particular migratory species over last 5 years). To weight each expert on the basis of accuracy, each expert is also asked a set of test questions for which the answers are known. Accuracy of answers to the test questions is used to weight their judgment, and the weighted judgment of all experts are pooled to provide a consensus judgment (Cooke 1991; Aspinall 2010). The challenge is to identify test questions with known responses that are closely related to the questions for which answers are unknown.

### Encoding the Elicited Information

Encoding is the process of translating information that has been elicited indirectly into quantitative statements that can be used in a model. For example, Martin et al. (2005) used indirect elicitation to assess the effects of livestock-grazing practices on native birds. For a given level of grazing, experts assessed whether a species' relative abundance would increase (score +1), decrease (-1), or exhibit no change (0). The mean and variance of all expert assessments, by bird species and grazing level, were encoded as priors in a Bayesian GLM. In another indirect approach, Low-Choy et al. (2010) asked experts to consider sites with different characteristics and estimate the probability a site would be occupied by an endangered mammal.

Selection of elicitation formats and techniques depends on the number and types of experts, accuracy required, and time and resources available to conduct the elicitation. In addition, there is a trade-off between the number of judgments that can be elicited with accuracy and the need to retain experts' attention throughout the process and complete the elicitation efficiently (Shephard & Kirkwood 1994).

Software can be used to automate and manage computational tasks, help experts express quantities, provide immediate feedback to experts about the elicited values, and encode elicited information. Packages designed to facilitate the elicitation of expert knowledge include SHELF (Oakley & O'Hagan 2010), Elicitor (James et al. 2010), Excalibur (Goossens et al. 2008), and ET (Speirs-Bridge et al. 2010).

### Additional Considerations

#### Interplay between Expert and Empirical Information

Expert knowledge is often portrayed as subjective and is contrasted with objective empirical data. However,

empirical data may reflect biases, inadequacies, and errors in study design, collection, and transcription. We believe expert knowledge and empirical data exist on a continuum of subjectivity and, depending on the particular case, one may be a better proxy for the truth. Both expert knowledge and empirical data require validation. Expert knowledge should be regarded only as a snapshot of the expert's judgments in time, and expert assumptions and reasoning should be documented in such a way that they can be updated as new empirical knowledge accrues.

In our experience, Bayesian methods best accommodate updating judgments in light of new empirical information because they broadly define subjective probability. Prior information from either empirical data or expert knowledge can be incorporated into Bayesian analyses by specifying appropriate prior probability distributions for parameters (McCarthy 2007). Bayesian methods are being used increasingly to augment empirical data with priors elicited from experts and vice versa (Kuhnert et al. 2005; Martin et al. 2005; Murray et al. 2009). Thus, the methods provide a natural platform for learning and managing adaptively (Keith et al. 2011; McDonald-Madden et al. 2011).

### Combining Expert Judgments

Multiple expert judgments can be combined mathematically with either opinion pooling (most common is equal-weighted linear opinion pool [i.e., group average]) or Bayesian approaches, which can incorporate dependencies between experts (expert judgments that vary as a function of others' judgments) (Clemen & Winkler 1999; O'Hagan et al. 2006). The equal-weighted group average is simple and delivers accurate judgments compared with more complex methods (Armstrong 2001). If there are considerable measurable differences in the accuracy of expert judgments, then use of unequal expert weights in opinion pooling or Bayesian approaches will improve estimation (Cooke 1991; Soll & Larrick 2009; Aspinall 2010).

Although generating an expert consensus may be important for modeling and decision-making, it is important that differences in judgment be retained and communicated to decision makers (Keith 1996; Morgan et al. 2001). In many cases, the considerable benefit of enlisting multiple experts lies in the additional questioning of reasoning and assumptions that arises when examining differences in expert judgments (Morgan & Henrion 1990).

#### Accounting for Bias

Humans are susceptible to a range of subjective and psychological biases (overview in Supporting Information),

often unknowingly (Slovic 1999; Kynn 2008; McBride & Burgman 2011). Motivational biases arise from the context of the expert, personal beliefs, and from the personal stake one might have in a decision. Accessibility biases arise when information that comes more easily to the mind of an expert exerts a disproportionate influence on an expert's judgments. Anchoring and adjustment biases occur when an expert anchors an estimate on a benchmark and then is unable to adjust this estimate much above or below the benchmark. Overconfidence bias arises when the confidence of experts in their judgments is higher than is warranted by the accuracy of their estimates (McKenzie et al. 2008). This bias sometimes results in systematic underestimation, in which experts fail to express the extent of uncertainty (O'Hagan et al. 2006).

Although it is important to be aware of the potential for bias, not all experts in all elicitation processes will be biased. Forty years after Tversky and Kahneman's (1974) seminal work, much more is known about the conditions that exacerbate or minimize cognitive biases. In particular, bias may be mitigated by setting tasks that allow for deliberate practice, including unambiguous feedback, and phrasing questions for experts in such a way that they are aligned with an expert's knowledge. Several authors provide more extensive advice on managing elicitation bias (Meyer & Booker 1991; O'Hagan et al. 2006; Kynn 2008; Low-Choy et al. 2009).

Some biases, such as overconfidence, are more resistant to mitigation (Moore & Healy 2008). Overconfidence may increase as availability of information increases (Oskamp 1965; Tsai et al. 2008) and in the absence of regular systematic feedback (Lichtenstein et al. 1982; Dawes 1994). Overconfidence can also be high when the predictability of the future is low (Lichtenstein & Fischhoff 1977; Griffin & Tversky 1992). Unfortunately, this is when expert judgment is likely to be needed the most. Overconfidence may also be influenced by the expert's "cognitive style" (Tetlock 2005). Suggested remedies for overconfidence come from information-sampling theory (e.g., Klayman et al. 2006) and include asking the same question more than once or with alternative wording.

Building on the work of Soll and Klayman (2004), Speirs-Bridge et al. (2010) developed a four-step procedure to mitigate overconfidence that elicits a lower bound, upper bound, best estimate, and a level of confidence that the true estimate lies within the nominated lower and upper bounds. For example, to estimate the mean number of native bird species in a particular land-management scenario, one would ask the following: Realistically, what do you think could be the lowest mean number of species? Realistically, what do you think could be the highest mean number of species? What is your best estimate of the mean number of species? For the interval created (lower and upper bound), what is the probability between 0% and 100% that the mean number of species

observed in the study will fall within this interval? The first three steps require the expert to produce an interval, whereas the last step requires the expert to evaluate an interval. The addition of this last step takes advantage of the fact that experts are much better at evaluating intervals than producing intervals (Teigen & Jorgensen 2005; Speirs-Bridge et al. 2010).

## Dealing with Uncertainty

Expert elicitation is used to capture an expert's best estimate and the uncertainty around this estimate. Eliciting the uncertainty around an estimate may lead to different responses depending on the way in which the question is asked. For this reason, it is useful to distinguish between epistemic (knowledge) uncertainty and natural (aleatory) uncertainty (Regan et al. 2002). The former can be reduced by studying the system and acquiring additional knowledge. The latter can be better understood, but not reduced, by collecting additional data. For example, consider a question about the juvenile dispersal rate of a small mammal: What is the average proportion of juvenile males that disperse from a particular patch each year, and what are the 5th and 95th quantiles for the proportion? **An expert may estimate the range of variation expected from year to year, may estimate her or his personal uncertainty about the average proportion that disperse over all years, or may include both elements in the estimate.** The question should be posed so as to clarify which elements of uncertainty are sought and to partition them into separate questions.

The question, revised to control epistemic uncertainty, could be broken into two parts: What is the average proportion of juvenile males that disperse from this patch? and What are the bounds on the estimate such that you are 90% certain the interval includes the true mean dispersal proportion, averaged over all years? For aleatory (natural variation) uncertainty, questions should allow encoding of variation and skew of the distribution of dispersal proportions from year to year. For example, the question might be, Given a true mean dispersal rate equal to the rate you have just estimated, by how much do you expect the proportion to deviate from the underlying true mean, from year to year?

It is not always possible to separate epistemic and aleatory uncertainty in an elicitation. However, the risk of failing to consider these sources of uncertainty is that experts may confound them, and it is not generally possible for an analyst to partition them in retrospect. Questions almost always involve language-based misunderstandings. Pilot elicitations, particularly discussion among expert participants, can often resolve most instances of vagueness, ambiguity, context dependence, and underspecificity (Regan et al. 2002; Burgman 2005) that emerge when questions are first tested.

## Accuracy of Elicited Information

A fundamental question in expert elicitation is how to evaluate the accuracy of the elicited information. The judgments elicited from experts can be viewed as accurate if the expert judgments correspond with the truth.

But accuracy can also reflect how well the elicited information corresponds to the experts' true belief (O'Hagan et al. 2006). Poor accuracy of an expert's judgments could have very different causes. For example, an expert may hold judgments that are well calibrated to the truth, but may fail to express these judgments accurately. In this case the poor accuracy is a result of poor elicitation. Conversely, an expert may express his or her judgments accurately, but those judgments correspond poorly with the truth. In this case, poor accuracy is due to inaccurate knowledge (O'Hagan et al. 2006). Only through the use of calibration and feedback can these sources of inaccuracy be separated. In general, consistent bias across a range of experts and knowledge areas indicates poor elicitation (O'Hagan et al. 2006).

## The Future of Expert Elicitation

The benefits of incorporating expert knowledge in decision making are real and established. Despite the potential of expert knowledge to contribute to decision making, however, formal methods for eliciting and combining judgments only recently have been adopted and tested for application to conservation science and practice. In our experience, it is often not possible to elicit the required quantities directly; hence, we focus our own research on indirect elicitation techniques (Martin et al. 2005; Kuhnert et al. 2010; Low-Choy et al. 2010). Indirect elicitation reduces the cognitive burden on the expert because questions target what the expert knows. With this approach, the amount of work required from the analyst is greater because sophisticated statistical modeling is required.

Development of methods of expert elicitation is a growing domain in conservation biology and many issues remain open for debate and research. Some of these are the number of experts that are sufficient, identification of experts, aggregation methods for combining judgments, assessment of reliability of experts, techniques for training and feedback, and independent verification of the accuracy of expert judgments with test questions.

We have identified some commonalities in expert-elicitation procedures and provided general suggestions that will improve elicitation methods, including developing a structured procedure that matches the questions to be posed to the expert, encoding the elicited information to fit the modeling framework, mitigating the most pervasive and predictable cognitive biases, encouraging experts to make independent assessments, and eliciting

uncertainties together with best estimates. We suggest the problem owner and analyst anticipate and work to minimize overconfidence and frame questions to suit the experts' experience, skills, and limitations. The potential that questions will be understood should be tested and questions revised accordingly to clarify meaning. When possible, it is beneficial to clearly distinguish between different types of uncertainty when eliciting bounds on estimates. When eliciting information from multiple experts, identify a method of weighting and combining different judgments.

It is crucial to provide feedback to experts throughout the elicitation process to ensure expert knowledge is captured accurately. One can ensure expert knowledge is calibrated by providing feedback on the basis of responses to questions for which empirical answers exist. The accuracy of expert knowledge can be addressed by managing over- and underconfidence (and other biases) and by designing elicitation and encoding to target expert knowledge more effectively.

Low-Choy et al. (2011b) devised a checklist of attributes for assessing how comprehensive and effective an elicitation process has been. They based the checklist on four criteria: (1) study context and justification (including study location and topic) and singularity of expert knowledge (expert knowledge supplemented, complemented, or sole source of information); (2) elicitation design (number of experts invited and that participated; expert category [sage, holder of highest level of expertise], practitioner, scientist, or stakeholder; elicitation process piloted with test subjects or reviewed by an elicitation specialist; training provided to standardize terms and mitigate biases); (3) elicitation method (knowledge elicited individually, in groups, or both; knowledge elicited in person, remotely, or both; expert metadata collected; and elicited information was qualitative, quantitative, or both); and (4) elicitation output (expert metadata used to weight or interpret results; representation of uncertainty in final output; validation of the experts' knowledge and validation with independent data or expert review). These criteria may motivate ongoing scientific investigation, validation, and use of expert knowledge in conservation science and practice.

Given limited resources, complexity of conservation problems, and imminent nature of conservation decisions, expert knowledge will continue to play a pivotal role in informing models and decisions. We take the position that independent validation of expert judgments is essential because there is a potential for motivational biases and the propensity for highly divisive conservation issues to influence judgments. We hope that the rigor applied to the elicitation and use of expert knowledge will be the same as is applied to the collection and use of empirical data to ensure the validity of expert knowledge in informing future conservation science and decisions.

## Acknowledgments

We are grateful to E. Fleishman for her encouragement to write this paper and for her and E. Main's insightful and skillful editing. We are also grateful to W. Aspinall, M. Runge, K. Hayes, C. Cook, and an anonymous reviewer for their thoughtful and thorough reviews. T.G.M. and P.M.K. acknowledge the support of a CSIRO (Commonwealth Scientific and Industry Research Organisation) Julius Career Award, and M.B. was supported by AC-ERA (Australian Centre of Excellence for Risk Analysis) Project 0611 and a National Science Foundation Award (SES 0725025). T.G.M. and M.A.B. acknowledge the support of the National Environmental Research Program, Research Hub for Environmental Decisions. S.L.C. and K.M. gratefully acknowledge Commonwealth of Australia funding for the CRC (Cooperative Research Centre) program.

## Supporting Information

Steps in the expert-elicitation process illustrated with examples from conservation science (Appendix S1) and a summary of subjective biases encountered in expert elicitation (Appendix S2) are available online. The authors are solely responsible for the content and functionality of these materials. Queries (other than absence of the material) should be directed to the corresponding author.

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