Chapter 2
What Is Expert Knowledge, How Is Such Knowledge Gathered, and How Do We Use It to Address Questions in Landscape Ecology?

Marissa F. McBride and Mark A. Burgman

Contents

2.1 Introduction: Why Use Expert Knowledge?

Expert knowledge plays an integral role in applied ecology and conservation (Burgman 2005). Environmental systems are characterized by complex dynamics, multiple drivers, and a paucity of data (Carpenter 2002). Action is often required before uncertainties can be resolved. Where empirical data are scarce or unavailable, expert knowledge is often regarded as the best or only source of information (Sutherland 2006; Kuhnert et al. 2010). Experts may be called upon to provide input for all stages of the modeling and management process, and specifically to inform

M.F. McBride (✉)
School of Botany, University of Melbourne, Parkville, VIC 3010, Australia
e-mail: mcbridem@pgrad.unimelb.edu.au

M.A. Burgman
Australian Centre of Excellence for Risk Analysis, School of Botany,
University of Melbourne, Parkville, VIC 3010, Australia

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the definition and structuring of the problem (Cowling and Pressey 2003; Sutherland et al. 2008), to inform the selection of data or variables, model structures, and assumptions about functional relationships between variables (Pearce et al. 2001; Czembor and Vesk 2009), and to inform the analysis of data, estimation of parameters, interpretation of results, and the characterization of uncertainty (Alho and Kangas 1997; Martin et al. 2005).

Expert judgment is susceptible to a range of cognitive and motivational biases, to an expert's particular context, and to their personal beliefs and experiences (Shrader-Frechette 1996; Camerer and Johnson 1997; Slovic 1999; Ludwig et al. 2001; Campbell 2002). Formal elicitation methods anticipate and account for the most serious and predictable frailties of expert opinions (Morgan and Henrion 1990; Cooke 1991). These methods improve the quality of elicited knowledge by treating elicitation as formal data acquisition, using systematic, well-defined protocols that reduce the impact of extraneous factors on the results and that make assumptions and reasoning explicit (van Steen 1992; Burgman et al. 2011).

Expert knowledge incorporates uncertainty derived from multiple sources. Uncertainty may arise from incertitude (sometimes termed "epistemic uncertainty"), natural variation (sometimes termed "aleatory uncertainty"), and linguistic uncertainty (Anderson and Hattis 1999; Regan et al. 2002). Incertitude arises from incomplete knowledge and can be reduced by additional research and data collection. Natural variation results from inherent natural randomness, such as fluctuations in rainfall and temperature. It can be better understood but not reduced by additional study or measurement improvements (Burgman 2005). Linguistic uncertainty arises from imprecision in language, and results from ambiguous, vague, underspecified, and context-dependent terms. This form of uncertainty can be reduced by resolving meanings and clarifying context, terms, and expressions (Regan et al. 2002). For example, Whitfield et al. (2008) used expert judgment to quantify the flight initiation distance (FID) of breeding birds in response to an approaching human. Epistemic uncertainty arose in, for example, the average FID, as a result of the expert's lack of knowledge, and could be reduced by additional study. Natural variation arose because different individual birds exhibit different FID responses, and the same individuals exhibit different responses in different circumstances.

Different types of uncertainty have different implications for decision-makers, and ideally, experts will be given the opportunity to address different sources of uncertainty separately (Ferson and Ginzburg 1996; Regan et al. 2002). Incertitude may prompt further research, whereas natural variation may lead to the development of management strategies, such as a maximum approach distance in the FID example. However, in practice, clear distinctions between the different types of uncertainty do not always exist (Hofer 1996; O'Hagan 1998).

In this chapter we explore the capacity of experts to contribute to better management and decision-making in environmental systems. We look at what expertise is and how it is acquired. We outline the process involved in the formal elicitation of expert knowledge, including the selection of appropriate experts, deciding the form of knowledge to elicit, and verification of expert responses. Finally, we discuss more broadly the role for experts and expert knowledge when addressing questions in landscape ecology, including examples of problems for which expert knowledge can usefully contribute, problems and pitfalls, and areas for possible improvement.

2.2 What Is Expert Knowledge?

"Expert knowledge" is what qualified individuals know as a result of their technical practices, training, and experience (Booker and McNamara 2004). It may include recalled facts or evidence, inferences made by the expert on the basis of "hard facts" in response to new or undocumented situations, and integration of disparate sources in conceptual models to address system-level issues (Kaplan 1992). For a more detailed discussion of expert knowledge, see Perera et al. (Chap. 1). Experts are usually identified on the basis of qualifications, training, experience, professional memberships, and peer recognition (Ayyub 2001), although broader definitions of expertise may include untrained people who possess direct, practical experience (Burgman et al. 2011; see Table 2.1). For example, a typical expert in landscape ecology might be a practitioner who has formal training, years of deliberate practice, and whose ability to solve professional problems has led to their recognition as an "expert" by their peers.

Expert knowledge is a product of unique reasoning systems (Ericsson and Lehmann 1996; Fazey et al. 2005; Chi 2006). Skilled experts have acquired extensive knowledge and experience that affects how they perceive systems and how they are able to organize and interpret information. The cognitive basis for expert performance is recognition: experts develop organizational structures that allow them to recognize a situation and efficiently recall the most appropriate knowledge to solve a specific problem (Ericsson and Charness 1994). As a result, experts are skilled in determining the most relevant information for a given context, structuring the problem definition, and finding an appropriate solution method (Chi 2006). Their reasoning typically is characterized as being automatic, abstract, intuitive, tacit, and reflexive. An expert operating in their area of direct expertise is often able to perform tasks without being aware of exactly how or what they do (Kidd and Welbank 1984).

Table 2.1 A proficiency scale for expertise under a traditional approach to expertise (modified from Collins and Evans 2007; see also R.R. Hoffman 1998).

Type	Characteristics
Contributory expertise	Fully developed and internalized skills and knowledge, including an ability to contribute new knowledge or to teach.
Interactional expertise	Knowledge gained from learning the language of specialist groups, without necessarily obtaining practical competence.
Primary source knowledge	Knowledge gained from the primary literature, including basic technical competence.
Popular understanding	Knowledge from the media, with little detail and less complexity.
Specific instruction	Formulaic, rule-based knowledge, typically simple, context-specific, and local.

A domain (or substantive) expert is an individual familiar with the subject at hand and responsible for the analysis of the issue and providing judgments. The expert literature distinguishes between substantive expertise, which represents an expert's domain knowledge, and normative expertise, the expert's ability to accurately and clearly communicate beliefs in a particular format, such as probabilities (Ferrell 1994; Stern and Fineberg 1996). However, knowledge about a subject area does not translate into an ability to convey that knowledge. Similarly, experts are often required to convert incomplete knowledge into judgments for use in decision-making, or to extrapolate knowledge to new and unfamiliar circumstances. The degree to which they are able to extrapolate or adapt to new circumstances, referred to as "adaptive expertise" (Fazey et al. 2005), varies depending on the individual and not necessarily according to their substantive knowledge or training. As with substantive expertise, normative and adaptive expertise must be acquired through training and experience (Murphy and Winkler 1984; Ferrell 1994; Wilson 1994; Fazey et al. 2005).

2.2.1 Development of Expertise

Expert skill requires substantial domain knowledge and repeated experience with relevant tasks so that experts recognize the appropriate cues for future information demands (Ericsson and Kintsch 1995; Ericsson 2004). The traditional theory of expertise (Chase and Simon 1973; Richman et al. 1995) assumes that experts are trained appropriately, and then slowly accumulate knowledge over long periods through experience, and that this leads to a gradual improvement in their ability to estimate parameter values and make predictions (Ericsson and Towne 2010). However, experience and qualifications are often poor indicators of this kind of performance (Ericsson and Lehmann 1996; Camerer and Johnson 1997). Experience and training contribute to expertise, but their value depends on the characteristics of the task environment in which they are obtained (Shanteau 1992).

Where expertise is acquired in appropriate environments with adequate experience and feedback, it can be highly effective. In particular, when feedback quality is high (frequent, prompt, and diagnostic) and judgments are made in exacting environments (where mistakes are costly), expert knowledge is likely to be accurate. For example, chess players (Chase and Simon 1973), weather forecasters (Murphy and Winkler 1984), athletes (Ericsson et al. 2006), and physicists in textbook problem solving (Larkin et al. 1980) all display highly skilled expertise, developed through experience over an extended period in conjunction with consistent and diagnostic feedback.

When feedback quality is low, or when mistakes are not costly to those making the estimates, inaccurate beliefs are easily acquired. In such environments, experts are likely to have difficulty separating the influences of skill from those of chance and are likely to form superstitious beliefs (Kardes 2006). Delayed feedback, for example, makes it difficult for physicians to learn about the accuracy of their diagnoses (Christensen-Szalanski and Bushyhead 1981).

Sutherland et al. (2004) give several instances in which the failure to evaluate the outcomes of management actions resulted in the persistence of misperceptions about their effectiveness and suitability. For example, winter flooding of grasslands was considered by many experts to be beneficial for wading birds. However, an in-depth study by Ausden et al. (2001) revealed that although flooding of previously unflooded grasslands improved conditions for bird foraging, it also killed the invertebrates upon which the birds fed. Incorrect beliefs were propagated because appropriate diagnostic feedback about the effectiveness of grassland flooding was initially absent.

Adaptive expertise may be inhibited by knowledge within a narrow domain. Greater expert knowledge and more structured, automated reasoning processes can lead to more entrenched thinking that may be difficult to alter when circumstances change. For example, Chi (2006) noted that experts may perform worse than novices when adapting to new situations. This is particularly likely to arise when experts become complacent or do not recognize when a task lies outside their direct area of expertise.

2.2.2 Limitations of Expertise

The way in which expertise is acquired means that expert skill is limited to the tasks and domains in which it was acquired. Where experts deal with a known situation for which they have had repeated performance feedback, they give more accurate, better-calibrated information than nonexperts (Shanteau 1992; Hogarth 2001). Outside their specific sphere of expertise, experts fall back on the same reasoning processes as everyone else, and their judgments are subject to the same psychological and contextual frailties. The degree to which a person's unique set of experiences and training are relevant to a particular context is often difficult to determine (Bransford et al. 2000).

The seminal work by Tversky and Kahneman (Tversky and Kahneman 1974; Kahneman and Tversky 1982), and others (e.g., Fischhoff et al. 1982; Dawes and Kagan 1988; Gilovich et al. 2002; Slovic et al. 2004) has shown that experts rely on "heuristics" (shortcuts). Experts who make appropriate use of these shortcuts can make powerful inferences with limited time and data (Gigerenzer 1999, 2008). However, incorrect use of judgmental heuristics often leads to biases (Kahneman 1991; Shanteau and Stewart 1992; Wilson 1994).

Cognitive biases result from limitations on human processing ability and occur because of a failure to adequately process, aggregate, or integrate relevant information (Wilson 1994). For example, judgments from experts (and lay people) are undermined by overconfidence, with experts specifying narrower bounds than is warranted based on their knowledge or experience (Fischhoff et al. 1982; Speirs-Bridge et al. 2010). Overconfident experts fail to correctly process the full extent of uncertainty in their knowledge about a variable. For example, Baran (2000), as discussed by Burgman (2005), asked professional ecologists to estimate how many 0.1-ha quadrats would be necessary to sample 95% of the plant species within a 40-ha Australian dry temperate sclerophyll forest landscape. Field ecologists routinely perform this type of estimation task, and the respondents were familiar with the methodology and habitat. However, Baran (2000) found that only 2 of the 28 experts specified 90% credible bounds that included the true value.

Motivational biases arising from context, personal beliefs, and from what the expert stands to gain or lose personally from a decision may also color their judgments (Kunda 1990; Garthwaite et al. 2005). Motivational biases are “a conscious or subconscious adjustment in the subject’s responses motivated by his [sic] perceived system of personal rewards for various responses” (Spetzler and Stael Von Holstein 1975). Other biases common among scientists include a tendency to treat model or experimental results as more reliable than they really are (Hora 1992), predicting the future based on past events (”hindsight“ bias), overestimating their degree of control over an outcome, and underestimating the amount of variability in a system (Anderson 1998; Burgman 2000). Formal elicitation processes are motivated by the need to make experts aware of these potential biases, and to mitigate their effects (Morgan and Henrion 1990; Hokstad et al. 1998; Arnott 2006).

2.3 Gathering Expert Knowledge

Experts provide knowledge informally when they specify information “off the top of their heads”. Informal, subjective judgments are often incorporated into scientific decisions through the selection of which problem needs to be analyzed, how the problem is to be structured, what data sources to draw upon, how results are interpreted, and what actions are recommended. Formal procedures have been developed to counter the cognitive and motivational biases prevalent in informal expert judgments (Morgan and Henrion 1990; Hokstad et al. 1998). They are employed with the aim of increasing the credibility, repeatability, and transparency of expert knowledge. Generally, they involve a protocol for elicitation; that is, a set of defined, repeatable steps that control the way in which information is elicited to reduce the effects of extraneous factors.

A successful elicitation is one that provides an accurate representation of an expert’s true beliefs (Garthwaite et al. 2005). There is a particular emphasis on establishing a complete understanding of the reasoning and assumptions behind an expert’s judgments, and ensuring that experts make judgments on the basis of all relevant information. Questions are formulated to help experts draw on appropriate data and relevant background information (Spetzler and Stael Von Holstein 1975). Feedback and verification stages are included to ensure that experts give fully reasoned responses and that the responses are internally (for the expert) and externally (with existing knowledge) consistent (Keeney and von Winterfeldt 1991). Although the specifics vary between protocols, there is general agreement on the key stages (Spetzler and Stael Von Holstein 1975; von Winterfeldt and Edwards 1986; Morgan and Henrion 1990; Cooke 1991; Keeney and von Winterfeldt 1991):

1. Preparation:
   - Problem definition and development of questions.
   - Definition and selection of experts.
2. Elicitation:
   - Training of experts before conducting the actual elicitation.
   - The actual elicitation.
3. Analysis:
   - Verification of responses.
   - Aggregation of expert responses.

Within this broad framework, there is scope for considerable variation at each of the stages. Key variables include the format for the elicitation, number of experts selected, kind and degree of interaction among the experts and between the elicitors and experts, format of the elicitation, and the way in which the elicited knowledge is combined. Often, details depend on the preferences of the researcher and the characteristics of the problem at hand. Key factors include the number and type of experts available, and the time and other resources available to the researcher (Kuhnert et al. 2010). The development of a tailored elicitation protocol for the requirements of a particular problem is referred to as elicitation design (Low-Choy et al. 2009).

Readers interested in eliciting expert knowledge must understand the distinct roles that are involved in a formal elicitation process (Rosqvist and Tuominen 2004; O'Hagan et al. 2006):

1. The *client* is the decision-maker or body that will use the results of the elicitation.
2. *Substantive experts* have the relevant domain knowledge about the parameters that will be elicited; most of these experts contribute judgments, but ideally one or two should inform the initial structuring of the problem and design of the questions.
3. *Analytical experts* have relevant quantitative knowledge and are responsible for analyzing the expert responses.
4. The *facilitator* manages the dialogue with or among the experts.

We refer to the individual who undertakes the elicitation as the researcher; there may be more than one. The researcher may also function as the analytical expert, facilitator, and even as the client. However, generally the steps in the elicitation are best performed by separate individuals with experience performing the necessary tasks (Hoffman and Kaplan 1999; Garthwaite et al. 2005; O'Hagan et al. 2006).

2.3.1 Preparation

The preparation stage is where the researcher decides the structure of the elicitation. Key tasks include definition of the problem, development of questions, and selection of experts. Adequate preparation is a key part of successful elicitation, since it will ensure a smoother process and maximize opportunities for identifying and countering possible biases. Experts respect and appreciate the effort a researcher has put into developing the elicitation documentation and the questions, and are generally inclined to reciprocate by devoting similar time and effort when making their judgments (van der Gaag et al. 1999).

2.3.1.1 Problem Definition and Question Development

The first step is to determine the purpose of the elicitation and define the objectives precisely. The elicitation designer must determine what information is required, the level of precision, and the appropriate selection of experts. For example, is the purpose to inform policy, support decision-making, determine research priorities, or characterize uncertainty about a particular model, analysis, or parameter? The researcher may need to work with decision-makers and stakeholders to develop goals if the objectives of the process are not already specified.

The scientific literature should be reviewed to determine the extent of relevant scientific knowledge and to identify information gaps. It is usually helpful to provide experts with documentation outlining the relevant evidence that has been compiled into an appropriate, accessible form (Cooke and Goossens 2000). Background materials usually provide information about the objectives of the elicitation, explain the motivations for the formal methodology, outline what the elicitation will involve, explain relevant statistical concepts, and document the questions (e.g., Hogarth 1987; Morgan and Henrion 1990; Rothlisberger et al. 2010). Experts should have time to review the materials, raise any potential concerns, and volunteer relevant information prior to the elicitation proper.

Having identified the requirements for the elicitation, the researcher then defines and structures the problem and identifies the variables for which knowledge is to be elicited. Problem structuring refers to the process of breaking down the problem into a set of variables or relationships for which knowledge will be elicited. Planning, often in conjunction with substantive experts, aims to ensure that the structure is straightforward and intuitive for experts (Keeney and von Winterfeldt 1991). The level of problem disaggregation is an important consideration. In general, researchers disaggregate complex questions into more manageable sub-problems, aiming to create knowledge environments that are more comfortable and familiar to experts. This strategy aims to create a set of variables that best allow experts to incorporate their knowledge, for example, about quantities that are observable or that the experts have experienced directly (Cooke and Goossens 2000). The variables should be sufficiently well defined that experts can answer questions without further specification (Morgan and Henrion 1990).

Habitat suitability indices are good example of disaggregation techniques in ecology. These indices provide a quantitative representation of the relative suitability of some part of a landscape for the survival and reproduction of a species (Reading et al. 1996; Cohen et al. 2004). Rather than asking experts to estimate the suitability outright for every point in the landscape, elicitation of these indices instead requires experts to nominate which variables are most important in determining suitable habitat for a species, and how measures of these variables should be combined into an overall measure of suitability. Thus, they represent a disaggregated model that links environmental data to the persistence of a species.

The draft protocol and background information should be carefully piloted (tested and revised before it is used to collect actual data) to ensure that the questions have been framed appropriately, to identify possible problems with biases or question phrasing, and to receive feedback about any potential ways to improve the quality of the process and of the knowledge that is being elicited. To some degree, all questions are biased, but careful development combined with testing and refinement of the protocol by substantive experts can minimize adverse effects considerably (Payne 1951). It should also be noted that experts used in testing the protocol should not be used to answer the questions; this is a formal technical requirement in Bayesian analysis.

2.3.1.2 Selection of Experts

The selection process involves identification of the expertise that will be relevant to the elicitation process, and selection of the subset of experts who best fulfill the requirements for expertise within the existing time and resource constraints. In some cases, the selection of appropriate experts is straightforward, but in other cases, an appropriate expert group will need to be defined by the researcher according to the experts' availability and the requirements of the elicitation. Experts should be selected using explicit criteria to ensure transparency, and to establish that the results represent the full range of views in the expert community. Common metrics for identifying experts include qualifications, employment, memberships in professional bodies, publication records, years of experience, peer nomination, and perceived standing in the expert community (e.g., Chuenpagdee et al. 2003; Drescher et al. 2008; Whitfield et al. 2008; Czembor and Vesk 2009). Additional considerations include the availability and willingness of the experts to participate, and the possibility of conflicts of interest.

The appropriate number of experts depends on the scope of the problem, the available time and other resources, and the level of independence between experts. Experts often share beliefs because of shared information sources and training. In such cases, the marginal benefits of including more than about five to eight experts decrease quickly (Winkler and Makridakis 1983; Clemen and Winkler 1985). As a result, researchers are encouraged to include as diverse a range of experts as possible. The literature on expert elicitation strongly recommends the use of multiple experts to buffer against individual mistakes and biases, and to allow for assessments that are representative of the whole expert community (Hokstad et al. 1998; Clemen and Winkler 1999; Armstrong 2006). Even in cases where one expert is considered substantially more knowledgeable than the others, a diversity of opinions from a group of "lesser" experts may outperform the opinion of a single "best" expert (Bates and Granger 1969; Dickinson 1973; 1975; Otway and von Winterfeldt 1992;

Clemen and Winkler 1999; Armstrong 2001; Fisher 2009). The combined judgment also tends to be more reliable, since *a priori* identification of a single best expert is not always straightforward.

In most ecological settings, the breadth of concerns means that no one individual will be expert for all aspects of the problem (e.g., Ludwig et al. 2001; Martin et al. 2005). For example, in the elicitation described by Martin et al. (2005), no single expert had the required expertise for all 20 bird species that were considered. Using multiple experts was an important strategy to obtain the required expert coverage. The use of larger expert groups may also be beneficial if it will increase the acceptance or perceived validity of the elicitation outcomes. This is particularly true in contexts such as a public consultation process, in which the stakeholders may include many groups of individuals who are not traditionally considered to be experts, but who nonetheless possess expertise in certain relevant domains.

2.3.2 Elicitation

2.3.2.1 Expert Pretraining

Substantive experts may be unfamiliar with expressing their beliefs numerically or in the format required by the elicitation protocol. Pretraining provides participants with appropriate experience, and where relevant, improves their understanding of the concepts involved in the elicitation. Given sufficient practice combined with adequate feedback, experts can substantially improve their performance, thereby becoming more reliable and accurate (Ferrell 1994; Renooij 2001). Inclusion of pretraining may be particularly important where elicitations involve the assessment of complex, unintuitive statistical formats such as quantiles or the moments of a probability distribution (see Hogarth 1987; Morgan and Henrion 1990; Cooke and Goossens 2000; Renooij 2001).

2.3.2.2 Elicitation

During this step, the experts respond to questions to assess the required variables, usually under the guidance of a facilitator. The expert performs four tasks during the elicitation (Meyer and Booker 1991):

1. Understands the question.
2. Searches for and recalls the relevant information.
3. Makes judgments.
4. Constructs and reports an answer.

Errors may enter the elicitation process at any of these stages. The process should, therefore, be viewed as one that helps an expert construct a set of carefully reasoned and considered judgments.

Five steps can help to counteract the psychological biases associated with elicitation: motivating, structuring, conditioning (i.e., defining any conditions that affect the problem definition), encoding, and verifying (Spetzler and Stael Von Holstein 1975; von Winterfeldt and Edwards 1986; Morgan and Henrion 1990; Shephard and Kirkwood 1994). We outline these steps in the remainder of this section. They involve ensuring that the expert has a complete understanding of each variable for which knowledge will be elicited and of any assumptions or conditioning factors, that they have had a chance to discuss and develop their reasoning and reflect on the relevant evidence, and having responded, that they have a chance to review and verify their responses.

2.3.2.3 Motivating

The facilitator works to develop an initial rapport or understanding with the experts and to establish their approval of the objectives of the elicitation. Facilitators explain the context and reasons for the elicitation and how the results will be used, the motivation for the experts' involvement, and how the expert's judgments will contribute (Walls and Quigley 2001). An introduction to the psychology of human judgment and bias in the elicitation will help the expert to understand the need for the formal elicitation process.

Experts are often wary of giving estimates that are not based on direct evidence. It is usually important to stress that there is no single correct response and that the aim of the process is only to elicit an accurate representation of the expert's true beliefs (Cooke 1991). The facilitator also identifies issues that may bias an expert's assessments, such as personal beliefs or conflicts of interest.

2.3.2.4 Structuring

At this stage, the facilitator goes through the details of each of the independent variables for which knowledge is to be elicited, including the model structure and conditions that constrain the expert's responses, and resolves any ambiguities. The aim is to ensure that each expert has a complete, unambiguous understanding of what information they are being asked to provide and what assumptions they are based on.

2.3.2.5 Conditioning

The facilitator and experts review the information and any assumptions on which the experts will base their assessments. The facilitator then questions the experts about their reasoning to ensure they have fully considered all possibilities, for example, by considering scenarios that may lead to unexpected outcomes.

2.3.2.6 Encoding

At this stage, the expert is asked to state their beliefs for each variable, for example, as probabilities or relative weights. Different techniques can be employed to encode the expert's beliefs, and we outline a number of the approaches commonly applied within landscape ecology in Sect. 3.2.8. In-depth coverage of different encoding techniques can be found in Spetzler and Stael Von Holstein (1975), von Winterfeldt and Edwards (1986), Morgan and Henrion (1990), Cooke (1991), Renooij (2001), Garthwaite et al. (2005), and the references therein.

2.3.2.7 Verifying

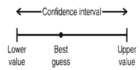
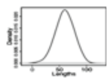
Following the assessment, the facilitator reviews the responses for signs of bias (e.g., experts who gave consistently high or low probabilities), and confirms that the responses are logical and consistent. Experts are asked to review their judgments, consider alternatives, and verify or change their judgments if they wish. Experts are rarely aware of the full implications of a set of judgments, and viewing their assessments in multiple formats (e.g., computer visualizations, statistical graphs, data tables) prompts a more rigorous reassessment of their beliefs. Experts should also be given an opportunity to review the outputs of any model or final representation, such as a graphical representation of the probability distribution constructed from their responses, to ensure that this result represents a reasonable reflection of their beliefs. The facilitator should actively question the expert, and should provide examples of their responses in multiple formats to prompt the expert to reconsider their statements in a new light.

2.3.2.8 Encoding Techniques

At the encoding stage, the expert is asked to state their knowledge using a particular response format. Experts can be asked to state their knowledge directly, for example, using questions such as "What is the probability of the event?" or "What is the value of variable x?". However, methods such as these do not help the expert to construct their beliefs. Experts are sensitive to the effects of the question framing and the response format in constructing their beliefs, and may benefit from assistance that reduces the cognitive strain in translating their beliefs into the required response format. Encoding techniques in the form of particular question formats have been developed to assist in estimating quantities and probability distributions that align with the expert's beliefs. We discuss these techniques in the remainder of this section.

Different encoding approaches can be used, depending on the type of information being elicited (e.g., probabilities, means, probability distributions; see Table 2.2). A complete enumeration of the full set of approaches is beyond the scope of this chapter. Below, we outline a few techniques that have been applied in landscape ecology.

Table 2.2 Summary of some approaches that have been commonly used for elicitation in landscape ecology (after Kuhnert et al. 2010, reproduced with permission from Wiley)

	Quantitative measures						Qualitative measures	
Criteria/methods	(1) Probability	(2) Frequency	(3) Quantity (e.g., means)	(4) Weighting	(5) Quantitative interval	(6) Probability distribution	(7) Categorical measure	(8) Relative measure
Type of elicitation	Direct	Indirect	Direct	Indirect	Direct/indirect	Direct	Indirect	Indirect
Benefits from multiple experts	✓	✓	✓	✓			✓	✓
Language easily interpreted		✓	✓	✓			✓	✓
High level of expertise required	✓	✓	✓		✓	✓		
Knowledge of probability theory required						✓		
Can be performed remotely	✓	✓	✓	✓	✓		✓	✓
Fast and easy	✓	✓	✓	✓			✓	✓
Uncertainty explicitly specified					✓	✓		
Example	$p = 0.3$	x out of n trials	n	rank			low/medium/high	↑ ↓
Key references	Griffiths et al. (2007)	Gigerenzer (2002)	Christen and Nakamura (2000)	MacNally (2007)	O'Neill et al. (2008)	Kynn (2004)	Yamada et al. (2003)	Martin et al. (2005)

Ranking methods can be used to elicit information indirectly. In the analytical hierarchy process (Saati 1980; Tavana et al. 1997), the expert is presented with pairs of events or criteria and asked to rank the relative importance of each pair. Rankings use a scale ranging from 1, which represents equal importance, to 9, which represents a situation in which one alternative is "absolutely" more important. The analytical hierarchy process can also be adapted to elicit information about relative likelihoods. Weights or probabilities are then fitted using matrix algebra. Experts find this process easy and intuitive. However, it is best suited to small numbers of discrete events because the number of assessments becomes impractically large for large numbers of events. Assessed probabilities may be anchored by including events for which the "true" probability is known.

Verbal qualifiers of uncertainty, which include words or phrases such as "highly likely" or "uncertain", can be used to qualify a probability or a degree of confidence, or to specify the incertitude associated with a concept. They are intuitive and are used as an alternative to numerical probabilities in eliciting information from experts (Wallsten et al. 1997). People often prefer to express their uncertainty with verbal phrases rather than numbers, though as experts gain experience with numerical techniques, this preference often lessens (Spetzler and Stael Von Holstein 1975; Cooke 1991; Walls and Quigley 2001).

Verbal qualifiers have the potential to introduce substantial linguistic uncertainty. Phrases do not correspond to a single numerical value, and individuals interpret them differently depending on the context (Beyth-Marom 1982; Budescu and Wallsten 1985; Wallsten et al. 1986; Wallsten and Budescu 1995; Windschitl and Wells 1996). For example, the phrase "very unlikely" may mean different things when referring to the possibility of a disease outbreak and the chance of rain tomorrow. Variance in the interpretation of such phrases between individuals can span almost the entire probability scale. People are usually unaware of the extent of these differences (Brun and Teigen 1988). Phrases such as "insignificant", "negligible", or "moderate" may also carry implied value judgments.

Probabilities are often difficult to elicit directly. Tools such as probability scales and probability wheels provide a straightforward visual representation for experts, though responses may be subject to scaling biases such as centering and spacing. Renooij (2001) recommended the use of such tools when experts are inexperienced with assessing probabilities. Presenting and eliciting information using natural frequencies (e.g., 13 out of 100), rather than percentages or probabilities (e.g., 13% or 0.13), can improve the accuracy of elicitation, particularly when experts are unfamiliar with probabilistic terms (Gigerenzer and Hoffrage 1995; Cosmides and Tooby 1996). For example, rather than assessing the probability that Hawaiian birds will become extinct in the next 10 years, we can ask experts to predict the number of bird species that will become extinct out of the number of original bird species. Frequency formats are easier to understand and may be less susceptible to mistakes such as overconfidence and base-rate neglect, in which an expert tends to ignore background frequencies when estimating probabilities (Tversky and Kahneman 1983; Tversky and Koehler 1994; Gigerenzer and Hoffrage 1995; Price 1998; Hertwig and Gigerenzer 1999). However, they may be less useful when experts find it difficult to imagine occurrences of a very rare event (e.g., Slovic et al. 2000; van der Gaag et al. 2002).

There are two main ways to elicit intervals: using a fixed probability (a quantile) or using a fixed value (Tallman et al. 1993). In the fixed-probability method, experts are asked to specify the value of a quantity within a specified quantile. It is common to elicit the 5, 50, 80, and 95% quantiles and to elicit quartiles (25, 50, and 75%). In the fixed-value method, the expert is asked to assign a probability that a quantity lies within a specific range of values, normally centered at the median. With both methods, experts typically display overconfidence, generating too-narrow intervals or assigning too-high levels of confidence.

O'Neill et al. (2008) were interested in estimating polar bear populations in the Arctic in the future. To elicit opinions about the relative changes in these populations, they asked experts to estimate the population in 2050 under current management regimes (based on the change in sea-ice distribution, which was shown using maps), expressed as percentage of today's population. The experts were asked to give their opinion and associated uncertainty using questions such as the following (adapted from O'Neill et al. 2008):

1. Please estimate the lower confidence bound for the total polar bear population in 2050.
2. Please estimate the upper confidence bound for the total polar bear population in 2050.
3. Please give your best estimate for total polar bear population in 2050.

Speirs-Bridge et al. (2010) reduced the level of overconfidence with a four-step question format. They recommended asking:

1. Realistically, what is the smallest the value could be?
2. Realistically, what is the largest the value could be?
3. What is your best guess for the true value?
4. How confident are you that the interval from lowest to highest contains the true value?

The most comprehensive form of elicitation is to elicit full probability distributions for each quantity. Parametric methods for eliciting distributions involve fitting expert assessments to a particular distribution or family of distributions (Garthwaite et al. 2005). Non-parametric distributions are usually constructed from a series of points or intervals elicited using graphical and numerical techniques, such as those described above. Points or intervals are elicited because the ability of experts to specify parameters such as the sample variance is poor (Peterson and Beach 1967). Eliciting four to five (well chosen) points allows a curve to be fitted that provides a reasonable approximation of the expert's beliefs (e.g., O'Hagan 1998; O'Hagan et al. 2006).

Methods have been developed for eliciting many of the commonly used parametric distributions, such as the normal and multivariate normal. We do not review these parametric methods here, but excellent overviews are given in, among others, Kadane et al. (1980), Al-Awadhi and Garthwaite (1998), Kadane and Wolfson (1998), Garthwaite et al. (2005), and O'Hagan et al. (2006).

2.3.3 Analysis

2.3.3.1 Verification

Following the elicitation, the researcher should perform a second, more rigorous verification process. In addition to checking for obvious errors or inconsistencies, the researcher compares the expert's responses to those of others in the group and against available information to establish the external validity of the expert responses. External validation is important, but is often limited by a lack of appropriate alternative sources of information with which to corroborate expert responses. In comparing an individual expert's responses with those of the rest of the group, the researcher looks for biases, anomalies, or strongly discordant opinions, as well as for varying interpretations of the information. The researcher should follow up on any interesting or problematic responses through further discussion with the expert. In some procedures, the verification stage includes a step in which experts see and may even question the responses of other experts before making their final judgment (Cooke 1991). If any calculations are performed using the expert's responses, the results should be provided for the expert to review and confirm. The aim of this stage is to arrive at a final set of judgments that the experts have approved. The responsibility rests with the researcher to ensure that the documented responses are consistent and that they faithfully reflect each expert's true beliefs.

2.3.3.2 Aggregation

Where judgments are elicited from two or more experts, it will usually be necessary to aggregate their opinions. Expert opinions often vary considerably and can often be contradictory or inconsistent. For example, it is not uncommon for experts to specify estimates that don't overlap.

Deciding how to aggregate the responses depends on why the expert judgments differ. Differences may arise as a result of (1) differing levels of knowledge or expertise, (2) different interpretations or weights assigned to pieces of evidence, (3) different theoretical models, and (4) differences in personal values or motivational biases (Morgan and Henrion 1990). In some cases, combining expert judgments may not be theoretically defensible or practical, or might lead to misrepresentations of the data (Keith 1996; Hora 2004; O'Hagan et al. 2006).

In some cases, differences in responses may lead the analyst to revisit earlier stages of the elicitation, or to consult experts further to understand the source of their beliefs. For example, it is possible that some of the experts failed to use information that others found to be influential, or weighed evidence differently. Alternatively, it may be clear from the responses that one of the experts misunderstood the question (or understood it differently). In these cases, it may be possible to ask the expert to revisit their response.

If there are wide differences in opinion, especially relative to intraexpert variability (i.e., the epistemic uncertainty in an expert's judgments), this is an important insight and should be communicated to decision-makers. Similarly, it may be important to know whether disagreements will have a significant impact on a decision. If differences of opinion persist and they could affect a decision, the analyst may elect to present a range of scenarios, each based on a different set of expert judgments (e.g., Crome et al. 1996).

If aggregation is appropriate, judgments may be combined using either behavioral or mathematical approaches (Clemen and Winkler 1999). Behavioral approaches involve interactions among experts, typically in a group setting, with opinions aggregated by the experts. Behavioral methods for resolving opinions may be structured, such as following a protocol for reaching agreement, or unstructured, by means of informal seeking of consensus (see Hogarth 1977; Crance 1987; Lock 1987; Burgman 2005; Macmillan and Marshall 2006).

Mathematical approaches involve combining the expert opinions using rules and do not involve any interactions between experts. Mathematical aggregation can be accomplished with Bayesian methods or opinion pools. Bayesian methods treat the resolution of differences among experts as a Bayesian inference problem (Morris 1974, 1977). A practical impediment is that the Bayesian approach requires the estimation of complex dependencies between experts (Jacobs 1995). Instead, in practice, opinion pools (typically the average or median for the group) are commonly implemented (Clemen 1989; Genest and McConway 1990; Armstrong 2001). Averaging is easy to implement, and more complicated methods may not provide better results (Clemen 1989). Methods may also combine elements from both behavioral and mathematical approaches (Cooke 1991). The theory and application of expert aggregation methods is reviewed in detail in Seaver (1978), Genest and Zidek (1986), and more recently by Clemen and Winkler (1999).

2.3.4 Trade-offs Between Cost and Accuracy

The use of a full formal elicitation protocol is neither necessary nor desirable for every analysis or decision (Pate-Cornell 1996). A tradeoff exists between time and precision, since methods that provide precise estimates by mitigating cognitive biases are also the most time-consuming. Interviews, for instance, are likely to result in better-quality responses than questionnaires, but make onerous time and resource demands. A full-scale elicitation process can involve dozens of people and last from 1 to 2 years, with estimated costs ranging from $100,000 to in excess of $1 million (e.g., Moss and Schneider 2000; Slottje et al. 2008). It is reasonable to assume that in many cases, decision analysts will not have access to, or wish to commit, this level of time and resources to elicitation.

Different formats and techniques will be appropriate, depending on the available time and resources and on the requirements of the problem. Particular considerations will include the number and types of experts who are available, the precision required, and the time and resources available to conduct the elicitation (Kuhnert et al. 2010). For example, Shephard and Kirkwood (1994) noted that the analyst must balance the desire for a probability distribution that more accurately represent the expert's knowledge against the need to retain their interest and attention throughout the elicitation process and to complete the elicitation efficiently. This tradeoff can require compromises, leading the analyst to forgo opportunities to iterate the estimation–validation–discussion process, or to use simpler question formats.

Less-intensive elicitations should still be guided by the principles outlined above. Researchers should always construct questions carefully, for example, and provide experts with the opportunity to revise their responses. In some cases, an expert may be reluctant to make estimates if they feel it is not scientifically appropriate. Morgan and Henrion (1990) suggest that there is a big difference between taking a position on what the answer might be and identifying what range of values might be correct. Indeed, scientists frequently advance their research using this type of reasoning.

2.4 Expert Knowledge in Landscape Ecology

In the previous sections, we examined expertise and techniques for the formal elicitation of expert knowledge. A core theme has been that both expert characteristics and appropriate elicitation practices vary with the task setting and requirements. In this section, we use this framework to critically examine current practices for employing expert knowledge in ecology, and make recommendations for future use of this knowledge.

The use of expert knowledge in landscape ecology is widespread. It is used regularly in problem characterization, model conceptualization, parameterization, and processing of data (Burgman 2005). Expert knowledge is frequently used as an alternative source of information when empirical data are not available (Burgman 2005; Sutherland 2006). The recourse to expert knowledge is particularly common for decision-makers operating in new, changing, or understudied systems. It is also valuable as a tool to supplement empirical information when the empirical information available is biased or incomplete, to corroborate model findings, to synthesize existing knowledge, and to correctly extrapolate, interpret, and apply knowledge to new situations (Pellikka et al. 2005; Teck et al. 2010).

Structured techniques and expert judgments have been used in scenario planning, species distribution modeling (Pearce et al. 2001; Johnson and Gillingham 2004), forest planning (Crome et al. 1996; Alho and Kangas 1997; Kangas and Kangas 2004), and the evaluation of conservation priorities (Sanderson et al. 2002; Marsh et al. 2007; Teck et al. 2010). The increasing use of Bayesian techniques, which provide a framework for the explicit inclusion of expert knowledge through the creation of a "prior" distribution for the problem parameters and subsequent improvement of the distribution using empirical knowledge, has contributed to a wider awareness of structured elicitation protocols (Kuhnert et al. 2010).

Despite the advances in and the advantages of structured elicitation methods, informal expert knowledge is more commonly deployed. For example, distances between bird nests and human habitations and analyses of breeding success in relation to distance to human habitations have been used to designate buffer zones for some species (e.g., Helander and Stjernberg 2003; Helander et al. 2003). It has become apparent that in many cases expert opinion had been used to recommend and designate buffer zones. Although such approaches are valid, this reliance on expert rather than empirical knowledge was rarely acknowledged explicitly (e.g., Grier et al. 1993; Currie and Elliott 1997). The problem this creates for decision-makers and subsequent researchers is that without knowing the sources of the knowledge or how it was elicited, it becomes difficult to know how much to rely on the knowledge. In addition, it becomes difficult to update the knowledge, since the assumptions and reasoning on which the previous knowledge was based are unknown.

Formal applications of expert knowledge in ecology and conservation typically omit many of the principles for structured elicitation outlined in Sect. 3. Only a handful of examples of elicitations have employed the principles of elicitation design (Low-Choy et al. 2009). Selection or development of an elicitation approach appears to have been primarily *ad hoc*, and documentation of the methodology was usually incomplete or absent. Experts are rarely trained before the elicitation. It is rare that clear explanations of the elicitation process and goals, or opportunities to verify or evaluate the elicited knowledge are provided (Roloff and Kernohan 1999).

2.5 Conclusions and Future Directions

Expert knowledge should be incorporated formally within a framework that is explicit and transparent, and both the experts and the researchers must be accountable to those who will use the elicited knowledge. Formal methods help to make knowledge available that otherwise might not have been accessible. As a result of a structured elicitation process, experts consider more facets of the problem, are interrogated more fully about their beliefs, and have opportunities to correct ambiguities and errors of understanding (Burgman et al. 2011).

The move in ecology toward more formal, structured processes for incorporating expert knowledge is promising (Martin et al. 2005; Low-Choy et al. 2009; Kuhnert et al. 2010; Burgman et al. 2011). The development of elicitation procedures should be informed by the characteristics of the task at hand and of the environment in which the experts have acquired their knowledge. Lessons from the formal paradigm include the importance of adequate preplanning and preparation (including pretesting of the protocol), of an opportunity to train experts, of appropriate tailoring of questions and elicitation formats to the expert's knowledge and experience, and of including a verification stage.

Table 2.3 summarizes what we view as the key decisions that characterize the development of an elicitation procedure. Design of an elicitation procedure may be viewed as a resource-allocation problem in which the analyst allocates limited

Table 2.3 Eight key decisions in the design of a formal elicitation procedure

Decision	Characterization	Guidelines
1. The format for the elicitation	Setting in which the elicitation will take place. For example, via e-mail survey, phone interview, or in person.	Interviews are preferable unless the expense or number of experts makes it infeasible. In person, it is easier to correct any misunderstandings, maintain expert motivation, provide training and feedback, and incorporate interactions between experts and between the expert and the facilitator.
2. The information that will be elicited	Involves decisions about how many variables will be elicited, in what form, and under what conditioning assumptions. Usually determined as a part of structuring the problem description and the conceptual models for the decision or processes of interest.	Ideally, experts should be able to state their knowledge directly, in a format that is as close as possible to the conditions under which the knowledge was acquired. This helps to remove any additional, unnecessary cognitive burdens. Research suggests that for complex problems, expert knowledge is best incorporated within a model or a broader conceptual framework (Armstrong 2001).
3. The experts who will be involved	How the experts will be identified and the number that will be included.	Multiple experts should be involved to provide corroboration and avoid simple errors. Diversity of experts may be more important than their number or years of experience because this helps to ensure that all aspects of the problem are considered, from multiple perspectives.
4. The level of pretraining to be provided	The number and type of practice questions that will be provided, and the level of feedback. Additional options include an introduction to cognitive and motivational biases, and to probability concepts if probabilities are to be elicited.	Practice accompanied by feedback on the expert's performance has been shown to improve performance for questions that are sufficiently similar to those used in the actual elicitation. This is particularly beneficial where experts are inexperienced with the question format. There is no evidence yet that providing information about cognitive and motivational biases help experts to avoid reasoning fallacies.
5. How uncertainty will be elicited	How uncertainty is to be incorporated and propagated through the analysis. For example, elicitation of a complete probability distribution versus definition of the upper and lower bounds around an estimate.	The choice of method with which to elicit uncertainty will depend on the level of precision required, the time available for elicitation, and the expert's knowledge. If uncertainty is not elicited, decision-makers will need to infer the precision of the responses.

(continued)

Table 2.3 (continued)

Decision	Characterization	Guidelines
6. The question format	Whether qualitative or quantitative information will be elicited and in what format, for instance as probabilities, probability distributions, ranks, or categorical measures.	Knowledge is available to inform the selection of appropriate response formats (see O'Hagan et al. 2006 and the references therein). Ranks and category formats are often preferred by experts over numerical responses, but are susceptible to linguistic uncertainty and confounding of knowledge with value judgments.
7. The degree to which experts will verify their responses	Whether and how experts will verify their responses, for example, in conjunction with graphical feedback, analysis of the output, or assisted by responses and reasoning from other experts.	Some minimum level of verification is important to catch errors and misunderstandings, particularly for less intensive protocols. Provision of feedback in multiple formats helps experts to check the coherence and accuracy of their responses more thoroughly.
8. How judgments from experts will be combined	Via mathematical or behavioral means, and the degree to which the experts will be given the opportunity to interact.	Empirical results suggest that mathematical methods outperform behavioral techniques. Use of measures such as the group average is a standard approach. Group discussions should be facilitated by a skilled facilitator, and may be most fruitful when combined with a final mathematical step to summarize the data that results from the discussions (Clemen and Winkler 1999).

available resources to achieve the greatest expected gains in response quality. Elicitation procedures should be developed with a view to how each feature will contribute to the elicitation as a whole. Improvement of existing practices within landscape ecology will require a greater awareness of the tools available to improve elicitation quality, and an understanding of how to select and tailor these techniques to best suit the decision problem at hand.

Ecological systems are complex and non-linear, with processes that unfold over long timescales and large spatial scales. In making predictions about future dynamics, experts are likely to be operating outside their direct area of expertise. Our guidelines (Table 2.3) suggest that expert knowledge may be most appropriately incorporated within a conceptual framework that avoids the need for experts to make predictions for complex, compound events. Use of multiple experts introduces more knowledge about a system and its dynamics, thereby creating a more detailed and comprehensive picture of the problem, and if the knowledge is deployed appropriately, it may lead ultimately to better decisions.

The primary focus of the methods presented in this chapter is on eliciting numerical information, which is a useful way of making tacit (implicit) knowledge more transparent, explicit, and useful to the decision-maker. The translation of expert knowledge into numbers is often difficult and requires care, but it is worthwhile making the effort to rigorously obtain these numbers, as they have considerable benefit for the decision-maker. In this chapter, we focus less on eliciting conceptual models or qualitative information, though many of the principles remain the same. The details of such elicitations are beyond the scope of the chapter, but they are nonetheless important in some contexts. For example, qualitative information may provide useful insight into the understanding of a system (e.g., McCoy et al. 1999), Yamada et al. 2003).

Expert knowledge is a necessary component in the analysis of any complex decision problem (Keeney and von Winterfeldt 1991). This knowledge represents a valuable resource for decision-makers, but as with any tool or resource, its value may be lessened by inappropriate or ill-informed application. Expert status alone is not enough to guarantee accurate responses, and traditional metrics of expertise such as the expert's age, rank, or experience, do not necessarily predict an expert's performance (Burgman et al. 2011). Structured elicitation techniques can be used to increase the reliability of expert opinions and counter some of the limitations associated with expert knowledge.

The use of formal practices within landscape ecology is increasing, but these uses would benefit from a greater emphasis on structured design. Steps such as the use of multiple, diverse experts and the inclusion of pretesting, training, and validation stages will contribute significantly to the elicitation of better-quality results. A move toward greater evaluation of both expert knowledge and the elicitation practices used to elicit that knowledge will improve the quality of knowledge available to inform future decisions, and improve expert and decision-maker accountability.

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