Chapter 12
Expert Knowledge as a Basis for Landscape Ecological Predictive Models

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12.1 Introduction

Defining an appropriate role for expert knowledge in science can lead to contentious debate. The professional experience of ecologists, elicited as expert judgment, plays an essential role in many aspects of landscape ecological science. Experts may be asked to judge the relevance of competing research or management questions, the quality and suitability of available data, the best balance of complexity and parsimony, and the appropriate application of model output. Even the initial decision to pursue modeling follows expert judgment regarding the cost and benefits of a model relative to data collection and the suitability of alternative modeling approaches for the specific application. Increasingly, however, professionals are asked to provide expertise to complement or even substitute for scarce data in landscape ecological models, by quantifying their personal experiences and anecdotal observations. In such cases, the professional is asked to reference their knowledge against geospatial data or landscape metrics derived from such data. We offer our chapter to raise awareness and promote discussion of this particular development within landscape ecological modeling. We draw examples from cases where expertise is provided as data in support of the predictive species-habitat models used to inform conservation planning objectives and strategies.

Most of the chapters in this book describe modeling approaches that are data intense. However, few taxa and few regions of the globe offer high-quality spatial data. Although protocols for sampling populations and habitat at landscape scales have advanced rapidly, few species or habitats have yet been systematically monitored over long temporal and broad spatial scales. Therefore, empirical data limitations are common both when setting broad-scale national population and habitat objectives, and when debating local management decisions to meet these objectives. The trend to substitute expertise for empirical data is most evident where models inform decisions

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C.A. Drew et al. (eds.), *Predictive Species and Habitat Modeling in Landscape Ecology: Concepts and Applications*, DOI 10.1007/978-1-4419-7390-0_12,

regarding the risk or utility of natural resource management alternatives, where ecological systems are complex and poorly defined, and where resource management questions are deemed too urgent to await the empirical information from rigorous experiments or field surveys. To some, turning to expert-based modeling opens a Pandora's Box of potential prejudice and error into what should be a carefully controlled, unbiased, repeatable, and transparent process. Others, however, are confident that careful attention to methodology and application can produce expert-based models of the same rigorous standards as their data-driven counterparts.

The growing popularity of expert-based models in applied landscape ecology reflects several trends in scientific knowledge, social values, and resource conflicts. Expert knowledge is viewed as subjective and sometimes associated with high uncertainty and bias. Yet, experts are often the most accessible and cost-effective source of immediate ecological information. Increasing urgency of conservation in the face of such threats as global climate change, habitat fragmentation and alteration by land use, and invasive species proliferation promotes the use of expert knowledge in conservation planning. Not only are such threats expected to intensify in the future (Balmford and Cowling 2006), but conservation managers are also challenged to consider potential impacts and trade-offs over broader spatial scales and longer temporal horizons than have been customary in the past. Expert-based landscape ecological models now regularly support natural resource management decisions by projecting how land cover is expected to change and where different types of habitat will be lost and gained, predicting the likely quality of present and future habitat patches, and evaluating the potential conservation value of future landscapes (Marcot et al. 2001; Pearce et al. 2001; Store and Kangas 2001; Petit et al. 2003; Yamada et al. 2003; Martin et al. 2005; MacMillan and Marshall 2006; Bashari et al. 2009; Murray et al. 2009; Doyon et al. 2010; Rothlisberger et al. 2010; Teck et al. 2010; Perera et al. in press). Unlike decision models designed to assess the quality or value of local resources in the present, predictive models define likely outcomes given complex and uncertain future conditions. The case is made that management decisions cannot await further data across such a broad range of species, habitats, and issues, so experts are called upon to fill ecological knowledge gaps. However, in contexts where management plans must meet "science-based" criteria, it is often implied that expert knowledge must gradually be tested and replaced by data gathered through monitoring in an adaptive management framework.

Given local and international attention to complex, landscape-relevant challenges such as climate change, alternative energy development, water resource conflicts, and population growth and migration, we expect expert knowledge to play an increasingly important role in landscape ecological applications. Therefore, for those landscape ecologists and land managers that find themselves data-limited and facing difficult decisions, we offer this introduction to expert-based modeling procedures for landscape-scale prediction of species and habitat distribution patterns. In this chapter, we discuss how expert knowledge is currently elicited and applied within predictive models, identify common traits that distinguish successful models from their unsuccessful counterparts, and review how expert judgment is typically quantified and compared prior to being incorporated into predictive models. We conclude with summary recommendations, drawn from the literature and our own experience in expert-based modeling, by which we hope to improve the rigor, appropriate use, and acceptance of expert-based modeling approaches.

12.2 Who Is An Expert and What Is An Expert-Based Model?

In this chapter, we define an "expert" as anyone who has special knowledge, gained through a combination of formal training, direct personal experience, and reflection of the ecological pattern or process under investigation. Within the scope of this definition, the specific vocation of experts targeted for knowledge elicitation can be variable and goal-specific. It certainly includes professional ecologists and resource managers, but could, in some instances, also include non-professional members of the public. Hunters or wildlife photographers, for example, can provide valuable knowledge of certain species and habitats (Yamada et al. 2003; Gilchrist et al. 2005). Members of traditional cultures can also offer knowledge of historical and present day species-habitat associations and population dynamics (Huntington 2000).

Predictive landscape-scale species–habitat modeling approaches that incorporate expert knowledge include simple rule-based models (Petit et al. 2003; Drescher and Perera 2010), multi-attribute value functions (Store and Kangas 2001; Geneletti 2005), and Bayesian approaches. For this discussion, we focus on a subset of expert-based models: those that, in the absence or limited availability of empirical data to define statistical probability of a future event, call upon experts to substitute their own subjective estimates of probability via a formalized elicitation process. Much of the recent growth in this area of expert-based modeling for conservation applications builds upon the development of probabilistic modeling approaches that incorporate Bayesian statistics (Nyberg et al. 2006; Uusitalo 2007; O'Leary et al. 2008; Bashari et al. 2009; Low Choy et al. 2009; James et al. 2010). Most Bayesian procedures use Bayes rule to assimilate incomplete knowledge formalized as the subjective prior probability distribution updated with data and their corresponding likelihood function. The scaled product of the prior and likelihood result in a posterior probability distribution, which formalizes the updated uncertainty of a future event given the data and model. In the absence of prior information, expert elicitation can be used to generate the prior probability distributions. The opportunity to begin with a model based upon expert knowledge and then iteratively update both the model and the uncertainty through the addition of new information is an attractive feature of Bayesian approaches, because it fits well with the current paradigm of adaptive monitoring and management (Williams 2003; Williams et al. 2009). Bayesian models offer the opportunity to meet criteria of employing "best available science" in support of complex decisions, while also using the model to develop monitoring protocols that will gather the data necessary to test and improve the model for the next round of decisions.

Although we focus here on recent applications of expert knowledge in Bayesian models for landscape-scale species–habitat conservation, we do not wish to imply that the role of expert knowledge in natural resource planning is a novel development.

There exists a rich history of theoretical and methodological advances for eliciting and using expert knowledge within natural resource management research and planning (Coulson et al. 1987; Rykiel 1989; Starfield and Bleloch 1991; Giles 1998). Historically, when eliciting knowledge, the primary objective was to develop expert systems that could reliably reproduce expert judgments by codifying expert knowledge and reasoning (e.g., artificial intelligence). In contrast, the elicitation methods discussed here aim not to define and replace expert reasoning, but to provide the best possible representation of the existing knowledge base to support expert reasoning. However, while the fundamental objectives of eliciting knowledge may differ, many of the ideas presented within this chapter benefited from and build upon the earlier efforts to improve elicitation methods.

12.3 Evidence of Expert-Based Model Strengths and Weaknesses

Long-term success or failure in applying expert-based predictive models is not evident within landscape ecological literature. The absence of quantitative tests reflects both the relative short history of available techniques and the failure to implement monitoring programs to validate or update the original models. Most assessments of expert-based model performance have focused on the internal consistency of expert judgment either when an individual's knowledge is elicited by multiple methods (Yamada et al. 2003; Low Choy et al. 2009) or when multiple experts' knowledge is elicited by a single method (Yamada et al. 2003). Narrow credible intervals (the Bayesian approximation of confidence intervals) that result from expert agreement are interpreted as evidence that, in the absence of empirical data, using "expert information as prior in ecological models is a cost-effective way of making more confident predictions about the effect of management" (Martin et al. 2005). Studies have shown expert-based models to be highly sensitive to variation in expert opinion (Yamada et al. 2003; Drescher et al. 2008; Aspinall 2010). This suggests a need for caution when only one or few experts' knowledge can be gathered and supports a strong recommendation that all models be subjected to thorough uncertainty and sensitivity analyses, as well as stringent external review, prior to application in management decisions (Yamada et al. 2003; Johnson and Gillingham 2004). Unfortunately, while measures of expert consensus and consistency provide information on model precision, they provide no data on model accuracy.

Publications that compare results from expert-based versus data-based models typically do so for a single spatial and temporal extent. For example, distribution patterns of 93 faunal species in New South Wales Australia were predicted more accurately (based on comparison of model output with independent survey data) by logistic regression models fit to data than by expert-based models constructed from the elicited knowledge of three regional experts. (Pearce et al. 2001). Another multi-taxa study using expert-based rules to predict species occurrence concluded that poor model performance was possibly a result of low species prevalence, as models for insects performed much better than those for plants and birds (Petit et al. 2003). However, direct comparisons of expert-based with data-based models in data-rich settings may not address the correct questions to truly evaluate potential strengths and weaknesses of predictive models as applied in landscape conservation contexts. In such cases, when managers begin with little or no data, expert-based models are developed to summarize the only available relevant data – that held within the experts' personal experiences. If the applied alternative to an expert-based model is no model, a fairer test of the value of expert knowledge may be to compare expert predictions to random or null model predictions. When expert-based models are a starting point for an adaptive management process (Marcot et al. 2006; Nyberg et al. 2006), the implication is that new data will be added through time to gradually improve the model and move toward data-based prediction. It would therefore be useful to test whether expert-based models, through the gradual incremental addition of new data, do converge toward the same conclusions as data-based models. Furthermore, it would be insightful to test whether an expert-based model or a data-based model fitted to a very small dataset (e.g., simulating a delay in management action to conduct a one year baseline study) would more rapidly converge towards the conclusions of a data-based model fitted with a large dataset.

12.4 Strategies for Sampling Expertise

It is perhaps helpful to initially think of "sampling" expertise in the same sense as sampling any other landscape ecological phenomenon. For example, experts who observe species in the field generate informal, hypothesized species–habitat relationships. Elicitation seeks to acquire predictive value from these past observations. During elicitation, one or more experts may be asked to identify important ecological variables or processes, to categorize or rank variables, to define response curves with confidence intervals, and possibly even to classify their own level of expertise. Methods range from informal interviews to complex, customized graphical programs (Al-Awadhi and Garthwaite 2006; Drescher et al. in press), from mail-in survey questionnaires to large gatherings run by professional facilitators (Moody and Grand in press; Silbernagel et al. in press). Different methods provide different types of data, which in turn support different modeling objectives and applications. Therefore, as in any other ecological study, a clearly defined objective and study design (both for the study itself and the role of experts within the study) is essential to later interpret and apply the data within the predictive model. Basic questions that must be addressed at the onset include: (1) what is the purpose of the model? (2) where and when will the model be applied? And (3) how will the model be calibrated, evaluated, and validated? Only after these initial questions have been answered can individuals with the relevant expertise be identified and can a method be designed that will elicit the desired information. Furthermore, by defining the extent and resolution of the knowledge required, these questions clarify the bounds of the elicited knowledge and facilitate appropriate use and effective testing of the model products.

12.4.1 Identifying and Calibrating Experts

Developing a suitable method to identify individuals with the requisite expertise can be challenging, and is easily compromised as participation defaults to those willing to offer their time and knowledge. It is easy to visualize a scale of expertise – ranging from low to high – where expert utility varies from serving as a temporary substitute for point data to quantifying parameter rates or hypothesizing cause–effect relationships. However, in practice it can be quite difficult to assess an individual's level of expertise, especially when multiple experts with diverse experiences offer conflicting judgments. In general, the utility of knowledge from individuals attributed with "high" levels expertise will be of highest value to the scientific community. These are individuals that not only have direct experience relevant to the modeling objectives, but are also known for their ability to synthesize, extrapolate, and generalize from their experiences. They are also the same individuals whose professional judgment is frequently sought to review and validate data-driven models. There is greater dispute on the value and appropriate use of experts with very localized (in space or time) experience. Such experts may mistakenly be viewed as inexperienced and may simultaneously be more likely to undervalue their own knowledge. However, if the resolution of available data or high-level expert knowledge is more coarse than the scale of the proposed model and management application, local experts with low-level expertise may still be valuable to set global knowledge within the local context. (Drescher et al. 2008).

In reviewing the qualifications of an expert, it is not adequate to simply ask them to quantify their own expertise. Expert self-confidence can vary by gender, age, and personality type as much as by any ecologically relevant criteria. It is therefore important to consider multiple factors, including where, when, and how an expert gained their experience and how they have since filtered these experiences through conversation, reading, and reflection (Yamada et al. 2003; Battisti et al. 2008; Drew and Collazo in press). Most experts have built their knowledge base through a variety of sources, including academic course work, field research, primary literature, workshops or symposia, conversations with colleagues, and anecdotal/recreational observations.

12.4.2 Where Did Experts Acquire Knowledge?

Every expert has a "home range" from which they have gained their experience. Ideally (but unrealistically) the home-range of an expert would perfectly overlap the extent of the proposed species–habitat model and they would have visited all regions within their home range regularly. This would provide systematic knowledge of available habitats against which to reference their observations. However, expert observation, just like empirical data, never perfectly or describes a species' ecological niche. The knowledge of each expert reflects the perspective they have gained from a unique spatial and temporal setting. Careful consideration of the home range where an expert gained their knowledge and experience can suggest when differences in judgment reflect differences in landscape, rather than, or in addition to, different levels of observational skill and experience. For example, experts from coastal North Carolina and Virginia marshes work in conservation lands that vary greatly in their landscape and microhabitat characteristics. Some regions offer only narrow fringing marshes whereas others offer island and mainland marsh patches of varying size and isolation. In the absence of data to characterize the home range of the expert, their judgment regarding the relevance of patch size, shape, and isolation could look wildly discordant, as each tended to discount the relative importance of factors outside their experience (Drew and Collazo in press). Similarly, experts from different regions in Australia offered conflicting opinions regarding the influence of elevation and geology on brush-tailed wallabies (Murray et al. 2009). Their lack of consensus also reflected real geological differences influencing species–habitat associations. In boreal Canada, expert knowledge of forest succession is biased by the spatial configurations, as well as temporal periods, of the experts range of familiarity (Drescher et al. 2008). These examples suggest that although the ability of experts to extrapolate beyond their region of knowledge is highly variable and sometimes very poor (Murray et al. 2009), it may be possible to assess such ability through comparison of the experts' home ranges and the extent of the modeling landscape.

Distinguishing when differences among experts reflect true ecological insight from unique landscapes, rather than simply differences in their respective levels of knowledge or ability, is especially important when deciding whether (and if so how) to aggregate elicited knowledge or force consensus. A common assumption has been that multi-expert elicitations are better than single-expert elicitations because they reduce effects of individual bias (Yamada et al. 2003; MacMillan and Marshall 2006). However, if individual experts provide locally precise and accurate information within a geographically large and environmentally diverse region, the value of using multiple experts is not to remove bias so much as to ensure the diversity of the region is fully sampled (Drescher et al. 2008; Murray et al. 2009). This implies a need to attend to expert selection to recognize potential problems of spatial bias, autocorrelation, and uneven sampling of environmental conditions, just as when designing sampling protocols of species or habitats.

12.4.3 When Did Experts Acquire Knowledge?

The time period over which experts gained their knowledge also provides an important context for eliciting and applying their judgment. This is especially true if elicitation methods will require experts to use mapped data or aerial photography, which offer temporal snapshots. Processes such as succession, erosion, and development can rapidly and significantly change landscapes and alter species geographic distribution. Locations that an expert visited in the past may have experienced significant change and may no longer reflect conditions recalled by the expert. Orienting experts to landscape conditions, as represented in the map or aerial imagery allows experts to identify regions that may have changed since their knowledge acquisition. Without this orientation, accurate knowledge of past species–habitat associations could easily be inaccurately applied to present landscapes, introducing an avoidable source of model error. The timing of knowledge acquisition is also important as it relates to extreme or episodic environmental conditions that affect species population dynamics (Stenseth et al. 2002; Battisti et al. 2008). For example, observations made during El Niño versus La Niña climate periods could lead to very different, but equally valid, conclusions about species–habitat associations and distribution patterns (Davis 2000; Kim et al. 2008). Exposure to extreme or rare events can also introduce bias in probability estimates through the heuristic termed "availability", if sensational or unusual events are recalled more easily or in greater detail than common events (Tversky and Kahneman 1974; Kynn 2008).

12.4.4 How Did Experts Acquire Knowledge?

As in any other landscape ecological study design, scale plays an important role in determining the relevance of available information. Elicitation of species–habitat associations will be confounded if experts do not clearly understand the relationship between the scale of their own knowledge relative to the scale of the proposed model (King and Perera 2006). For example, most field biologists or hunters do not consider species–habitat associations using the landscape metrics commonly used to define landscape patterns. Such metrics have simply not played a major role in their training (unless recently graduated) or experience, and so have not served as reference points for the synthesis of their knowledge. Furthermore, unless population surveys are conducted aerially, most empirical observations offer insights closer to the microhabitat perspective of an individual organism than to the coarser landscape perspective of geographic information systems (GIS) (Yamada et al. 2003; Drew and Collazo in press). While this would not present a challenge to the creation of site level habitat suitability indices or community level associations (e.g., matching species to forest types within a vegetation classification systems), it does confound efforts to construct accurate GIS-based landscape ecological models from expert knowledge. During elicitation and model development, it often becomes necessary to associate elicited fine-scale knowledge to coarse-scale mapped features through the use of indirect proxy variables. For example, if experts provide predictions based on forest structure, LIDAR data might provide a useful landscape-scale proxy for field measurements of forest structure (Lefsky et al. 2002). More subtle perhaps, and of unknown effect for expert-based models, are the potential consequences of translating their elicited knowledge to a GIS when proxy models seem unnecessary. For example, experience may lead an expert to predict a marsh species has a strong association with edges near open water. In a raster representation of marsh and water cover, locations classified as edge will be subject to the grain (e.g., pixel cell size) of the data. If the raster represents features using a 30-m grid, then any water feature within the marsh that is smaller than 30 m × 30 m would be mapped as marsh rather than water; edge habitat of small water features would not appear in the map data. If an expert assessment of a species' dependence on edge habitat stems from observations near water features smaller than this threshold, then predicted suitability or occupancy of any given marsh pixel and the landscape as a whole would potentially be underestimated. It is therefore essential to elicit the relevant scale of the expert's experience and observations, and ensure that participating experts understand the scale relationships between their knowledge and the proposed application of their knowledge.

It is also valuable to know the observation methods used by experts in the field. In field research, gear selection and survey method can have a strong impact on estimates of population size, vital rates, and habitat associations. Therefore, knowing how their knowledge was acquired would provide insight into differences in judgments. If the relative efficiency of two observation methods is known, it may be possible (and desirable) to correct for differences attributed to method prior to contrasting or aggregating elicited judgments.

12.4.5 Challenges Unique to Sampling Expertise

12.4.5.1 Miscommunication During Elicitation

Sampling expertise differs from sampling other ecological phenomenon in that communication between the elicitor and experts presents a unique source of potential confusion, uncertainty, and error (Ray and Burgman 2006). Effective communication requires early and frequent interaction among all participants to ensure transparency and to establish a common lexicon. This includes not only those involved in the elicitation and synthesis of expert knowledge, but also those who will have responsibility for model development, delivery, and application. Due to confusion in terminology, especially across fields, it is essential to ensure that the language of the elicitation matches that of the expert being queried (Johnson and Gillingham 2004). Many problems relative to eliciting and comparing expert knowledge arise through the use of vague terms and concepts (Elith et al. 2002). If knowledge is elicited without direct interaction (e.g., only through mail-in survey), it can be very difficult to assess how the questions were interpreted. Imprecise language, the use of different terms in parallel disciplines, and vague concepts and terminology compound knowledge uncertainties (Elith et al. 2002). For example, categorical descriptors of gradients such as wet/dry, large/small, steep/dry have specific local meanings and will confound an elicitation and misinform models unless defined and expressed in unequivocal terms. Without an effective communication plan, individual experts may also hold different assumptions about what information is desired.

The elicitation questions provide the sampling "quadrat" applied to expert knowledge. While few ecologists would haphazardly use different quadrat sizes during a single vegetation survey, elicitations are sometimes conducted without clearly defining and consistently using terminology that matches the objectives. For example, suppose expert knowledge is sought to generate a model of predicted species distribution. Then, throughout the elicitation, experts are asked questions about where species have been detected, with little thought to the fact that detections often under-represent true occupancy and the two quantities can vary independently in relation to habitat characteristics (MacKenzie et al. 2003). The risk of miscommunication may be greatest in informal elicitations where the modelers more easily interchange terms that are synonymous in casual conversation, but which have strictly different meaning in the context of predicting species-habitat associations (e.g., Where have you seen the species? Where have you detected the species? Where does the species live? What habitats are suitable for the species?). Similar semantic confusion has been documented for the terms use, selection, and preference in reference to species–habitat associations (Jones 2001).

12.4.5.2 Cognitive Limitations and Group Dynamics

Several choices are made during the selection and development of an elicitation approach. Foremost among these decisions are: (1) whether to conduct group or individual elicitation, and (2) if using multiple experts, whether to seek consensus. The social science and psychology literature provide valuable insight regarding how individual biases and group dynamics influence the interpretation and summary of experience during elicitation procedures (Tversky and Kahneman 1974; Kynn 2008). Work assessing the influence of such factors on expert-based ecological models used to support conservation management decisions is just beginning (Anderson 1998; Perera et al. in press). However, these same authors illustrate that human cognitive limitations and social dynamics, which can generate bias in elicited data, remain even after the elicitation terminology and questions are clearly defined.

The knowledge of any one individual will reflect the sum of their experience gained through direct observation, peer interaction, literature review, and personal reflection and synthesis of these combined inputs. In an elicitation to support Bayesian models, individuals are asked to summarize past experience to generate probability estimates to define Bayesian priors or conditional probability tables. People make predictable cognitive errors during probabilistic reasoning and commonly provide answers that defy the laws of probability (Anderson 1998; Baddeley et al. 2004; Kynn 2008) due to over-dependence upon heuristic rules-of-thumb. The use of heuristics to process information has been linked to predictable errors (Tversky and Kahneman 1974; but see Kynn 2008), such as over-estimating the probability of a rare event, if such an event has been recently experienced or is easily recalled (i.e., the bias of availability). Also, although direct observations are personal experiences, this information can quickly disperse through the expert community either formally through published literature or informally through conversation. Knowledge sharing reduces the independence of expert knowledge as data, as individual experts qualify their personal experiences in light of group knowledge and opinion (i.e., the bias of anchoring and adjustment). Fortunately, good elicitation design can reduce the potentially significant impact of these biases and other cognitive errors (Meyer and Booker 2001). For example, experts tend to more accurately estimate the frequency of events, than the probability of a single event (Anderson 1998).

Common cognitive and motivational biases of individuals can be magnified or unduly suppressed through group dynamics. Baddeley et al. (2004) identified a herding trend among experts asked to provide judgments in contexts offering little data, but the opportunity to apply heuristics. Without skillful mediation of the elicitation process, such group dynamics can lead to strong consensus without any foundation in objective reality and lead to over-confidence in the group's conclusions (Baddeley et al. 2004).

12.5 Methods and Tools for Eliciting Knowledge

12.5.1 Elicitation Framework

An elicitation framework is the step-by-step process by which expert knowledge is obtained, summarized, and documented. Framework details will be specific to each project, given different objectives and available resources (experts, time, and money). However, guidelines for a successful elicitation framework share a number of recommendations. These include bringing the experts together at least once; clearly defining the issues, objectives, and terms; explaining the methods and application; providing some training in probability assessment and common biases; eliciting and documenting disagreement as well as consensus; and performing a dry run to test communication strategies (Cooke 1991). Meyer and Booker (2001, Chap. 7) outline six components of an elicitation framework: elicitation techniques (verbal or ethnographic), modes of communication (mail, telephone, or in person), elicitation situations (individual, interactive group, or Delphi), response modes (e.g., quantities, probabilities, ranks), aggregation schemes (mathematical or behavioral), and documentation. Their guidelines clarify when each component is necessary and highlight critical methodological choices made within each component. We refer readers to their work, but also here outline and expand upon their discussion of situation and response mode choices.

When the judgments of multiple experts are sought, these may be elicited independently and compared, elicited independently and combined, or elicited together for group consensus. Individual face-to-face interviews eliminate bias due to group dynamics, but also eliminate the possibility of synergistic effects from inter-expert discussion (Meyer and Booker 2001). Two common and versatile approaches for multi-expert elicitation in the natural resource and environmental assessment literature are Delphi or modified-Delphi surveys (Marcot et al. 2001; Meyer and Booker 2001; Hess and King 2002; MacMillan and Marshall 2006) and structured decision-making workshops (Ralls and Starfield 1995). The traditional Delphi process uses an iterative series of questionnaires to build consensus among survey participants who remain anonymous to one another. After each survey round, experts are returned their own answers along with summary statistics defining the mean and variance of all participants' responses. Experts then have the opportunity to revise their own response or, if choosing not to alter an outlier response, to provide a written justification of their unusual observation or prediction. Modified Delphi surveys typically place less emphasis on anonymity and, in bringing experts together for group elicitation, allow more opportunity to explore differences among expert judgment. Structured decision-making (Lyons et al. 2008) is typically performed in a workshop setting (Moody and Grand in press). The method requires participants to define three aspects of a management scenario: (1) the objective, (2) a set of alternative potential actions, and (3) the expected consequences of each action, stated in terms of the objective (Lyons et al. 2008). The elicitation of expert knowledge as data occurs in step three, when experts can define the probability of how each alternative action will impact the modeled system.

Within the structure of the elicitation framework, the modeler must pose clearly stated questions to obtain the necessary knowledge in the necessary format to support the modeling objective (Cooke 1991; Meyer and Booker 2001). Questions may be posed to elicit knowledge as physical quantities, such as, "What is the minimum patch size that would support this animal's home range?" Alternatively, they may be posed to elicit knowledge as probabilities or frequencies: "What is the probability that this animal would establish a territory in a 20 hectare patch?" or "In surveys of 100, 20-hectare patches, how many would contain an active territory of this animal?" Questions of physical quantity are direct and easily interpreted, so experts are often most comfortable with this approach. Eliciting probabilities also provides a direct means of expressing each individuals' uncertainty within the model, although combining elicited quantities from multiple experts could provide a measure of group uncertainty (Aspinall 2010). As estimates of probabilities are prone to various cognitive and motivational biases (Tversky and Kahneman 1974; Kynn 2008), it is essential that the framework include some means to assess or calibrate experts.

It is helpful if the elicitation includes opportunities for experts to visualize their responses in multiple formats so they can seek internal consistency (Cooke 1991; Meyer and Booker 2001; Yamada et al. 2003; Denham and Mengersen 2007; James et al. 2010). In landscape ecological applications, complementary visualizations usually include GIS maps and graphs (e.g., response curves). These graphs typically illustrate the relationship between a univariate predictor variable and the response variable (e.g., suitability, probability of occupancy) with some depiction of variation or uncertainty. In a GIS, the expert can interactively view species point or range data, or simply locate familiar sites, in relation to the available spatial data layers. In the past, maps or graphs of expert knowledge would be produced after the elicitation and then returned to the experts for their review and feedback. However, an increasing number of tools are available to supply these graphics interactively throughout the elicitation process (Yamada et al. 2003; Al-Awadhi and Garthwaite 2006; James et al. 2010). Where data are elicited and presented within graphs and maps simultaneously, both the participating experts and the modelers conducting the research claim that the final quantified judgments better reflect true beliefs (Yamada et al. 2003).

12.5.2 *Combining Knowledge of Multiple Experts*

The issue of how many experts to interview and how (or whether) to combine their elicited data deserves careful consideration. The knowledge of multiple experts may be combined by requiring all experts to reach consensus together or by combining results of individual elicitations (Morris 1977; Cooke 1991). Where a single consensus or merged result is the objective, there is an implicit assumption that combining the knowledge of multiple experts will produce more reliable results than any one individual (MacMillan and Marshall 2006). Tests of this assumption have received mixed reviews (Cooke 1991, Aspinall 2010). Ultimately, the value of a group versus individual judgment depends on the time and space scale of each individual's experience in relation to the proposed application of the elicited knowledge (Drescher et al. 2006).

Again, it is helpful to consider elicitation in light of traditional research study design. Certainly, as in experimental studies, more sample points offer potentially greater analytical power to discern pattern and infer process. However, to offer this benefit, sample locations must be carefully selected to fully represent variability in the factors of interest while controlling for variability that would confound interpretation of results. Similarly, it is critical to consider and control for consistency and representativeness in the pool of expertise that is sampled. Divergent personal experience (e.g., where, when, and how experience was gained) can lead equally qualified experts to provide widely divergent species-habitat predictions (e.g., Yamada et al. 2003; Murray et al. 2009). If the purpose is to construct a broadly applicable model predicting habitat associations or climate change effects over a large area, then a sample of experts from across the country may contribute useful information and consensus may provide a balanced view of how species respond to different environmental gradients. If instead the purpose is to construct a model for a very localized system, it would be wise to carefully consider the potential value of an expert familiar with the system generally, but not familiar with the local landscape. As a separate example, if experts are asked to characterize species response to a given gradient, then consensus may avoid problems of poor calibration (see below). However, if experts are asked to develop a single importance ranking for each environmental gradient to be applied over a broad spatial scale, then this may be at odds with ecological theory stating that limiting factors for species can vary within their range (Root 1988; Brown et al. 1996). In this case, there may sometimes be more information in the conflicting judgment of experts rather than in a single final consensus estimate.

If the knowledge of multiple experts is elicited on an individual basis, these data must somehow be combined to provide the required probability and uncertainty estimates for modeling (unless specifically intended to serve as alternative hypotheses). The simplest approach is by averaging the elicited values. An unweighted average assigns all experts equal weight and generally assumes that each expert represents an independent and unbiased sample. However, there are a variety of reasons that an expert's knowledge might be highly correlated, poorly calibrated, or strongly biased. Therefore it is generally more common to calculate a weighted average. An expert's weight maybe based on their rank as determined either through a self-assessment of their own degree of confidence, or a metric of expertness (e.g., years experience). Alternatively, experts may be weighted by their ability to accurately estimate known values and judge uncertainty (Cooke 1991; Aspinall 2010; Rothlisberger et al. 2010; Teck et al. 2010). If a suitable test can be developed, such a performance-weighted approach offers the most quantitative and defensible method of weighting experts (Aspinall 2010).

12.6 Landscape Ecological Theory in Expert-Based Models of Conservation

Landscape ecologists have clearly demonstrated that landscape context, extent, resolution, hierarchy, and spatial geometry matter in conservation planning. It is also now a firmly established working hypothesis that landscape structural heterogeneity is important to maintain healthy populations and functioning ecosystems. However, variability in space and time limits our ability to transfer lessons from data and models describing one place and time to applications set in another, new place or time. Furthermore, ecological theory continues to move away from an equilibrium, steady-state worldview toward one that embraces complexity (Holling 2001) and acknowledges the emergent properties of ecological systems. Landscape ecological principles of hierarchical structure and function provide a framework for scaling ecological investigations and mediating resource conflicts, but novel methods and tools take time to permeate into conservation and management practice.

An expert's exposure to landscape ecological theory influences their knowledge of ecological pattern and processes relevant to species distribution patterns. Experts who regularly peruse and discuss the primary literature may have very different perspectives on species distribution dynamics than those that primarily interact with agency technical reports and empirical data. There is, not surprisingly, a substantial delay between the first proposal of ecological theory and the establishment of management guidelines based on that theory, as ideas are tested and debated in diverse contexts. Furthermore, nuances in the theoretical literature are often lost in translation to the heuristics used to guide management decisions. Thus, the theoretical assumptions and understanding that shape expert judgment may differ greatly depending on their exposure to recent advancements in the field of ecology. It is not uncommon for applied ecology literature to generate guidelines that, unintentionally, become established as conservation gospel. One example would be the idea that habitat patches connected by corridors offer higher conservation value than isolated patches (Beier and Noss 1998). Although experts rarely hold absolutely to such simplistic assumptions, bias is introduced when these heuristics serve as anchors or reference points in their interpretation and synthesis of personal experiences.

Although most landscape ecology textbooks highlight the link between research and applied landscape management for conservation (e.g., Gutzwiller 2002; Liu and Taylor 2002; Bissonette and Storch 2003; Millspaugh and Thompson 2009), significant gaps remain between theory and practice (Perera et al. 2006). Interviews of individuals active in the management of conservation lands revealed a scale mismatch between the individuals' expertise derived from experience and expertise derived from literature (Drew and Collazo in press). Despite broad acceptance of the proposition that landscape structure likely influences species occurrence in a landscape, experts were more confident and consistent when defining a species association with either a very fine-scale microhabitat feature or a vegetation community class, than with various metrics of landscape structure. This discrepancy appears to arise because whereas microhabitat and vegetative community observations are easily noted in the field even for informal species observations, landscape structure associations can only be made through purposeful sampling design or after-the-fact plotting of the observation coordinates onto a map.

The expectation that wildlife professionals gain increased familiarity with their landscapes requires that relevant ecological knowledge be actively managed and reviewed in a spatially-explicit format. As GIS and their associated map products become more commonplace, landscape ecological theory should become increasingly accessible and applicable to wildlife conservation practitioners. Just as the term landscape ecology arose from exposure to early aerial imagery and contemplation of the potential ecological significance of this newly revealed perspective (Troll 1939) – so too the illustration of species data on land cover maps can prompt experts to more easily consider their observations within a framework of landscape context, connectivity, and patchiness.

12.7 Conclusions and Recommendations

As expert-based models become more prevalent in landscape ecology applications, more attention must be focused on developing methods to utilize expert knowledge in a manner that is rigorous, transparent, repeatable, and unbiased. These criteria concern every aspect of expert modeling, but especially the stages of: (1) designing and implementing the elicitation procedure, (2) conveying multiple possibly discordant responses, and (3) quantifying uncertainty. Collaboration among ecologists, statisticians, and social scientists to define best practices for expert-based ecological modeling is an active area of research (e.g., Cleaves 1994; Ralls and Starfield 1995; O'Leary et al. 2008). Awareness of potential individual and group biases has led to improved elicitation and weighting techniques (Aspinall 2010). Bayesian statistical methods have provided a foundation for integrating expert knowledge and other data sources within complex ecological models, by providing a means to formalize expert knowledge within a statistical framework (e.g., Garthwaite et al. 2005; McCarthy 2007; Low Choy et al. 2009). New software packages developed or customized for wildlife and natural resource applications to seamlessly integrate elicitation and modeling processes are increasingly accessible to the research and practitioner community (James et al. 2010). Much of the work to improve elicitation of landscape ecological expertise draws upon the well-developed literature on decision risk analysis and uncertainty assessment (Cooke 1991; O'Hagan 1998; Ayyub 2001; Meyer and Booker 2001; O'Hagan 2006).

The process of eliciting expert knowledge requires the same level of planning and attention to detail as does the collection of empirical data. In the field, experience and training ensure that ecologists are alert to potential sources of error and uncertainty in their data. The skills and knowledge necessary to recognize and either avoid or account for error and uncertainty in expert knowledge, however, are more typically taught to social scientists than to ecologists. Therefore, we conclude with several practical recommendations to landscape ecologists considering an expert-based modeling approach.

1. Spend some time reviewing expert elicitation literature, focusing particularly on the methods used to identify and correct expert bias, develop and apply good survey design and interview technique strategies, and compare or combine knowledge from multiple experts.
2. Seek advice from social scientist colleagues, possibly even asking such a colleague to observe and review a practice elicitation session. Training in interview or group facilitation techniques could also be helpful.
3. Allow time initially in every elicitation to define or clarify project objectives, to review key terminology, and orient experts to common heuristics of probabilistic reasoning and their associated biases. This will help to ensure clear communication and facilitate translation of elicitation responses to the model. Be aware that individuals' understanding and use of terminology will vary greatly, as will their ability to translate their personal experiences to probabilistic estimates.
4. Clearly communicate to experts the scale (grain and extent) at which their knowledge will be applied and explicitly define the scale of each expert's knowledge. Both spatial and temporal scale mismatches can introduce unnecessary model error and bias. Where scale mismatches cannot be directly reconciled (e.g., microhabitats not captured in remote imagery), proxy variables could be proposed for expert consideration.
5. Quantify the expertise of participating experts, preferably by testing their ability to accurately assess probability and uncertainty using independent data.
6. Critically explore disagreements among experts rather than simply forcing consensus. If different experts respond based upon different scale or contextual perspectives, their divergent responses may reflect important variation within the focal landscape or alternate hypotheses regarding ecological processes.
7. Provide clear documentation of the entire elicitation process. "Recording the reasoning underlying the experts' professional judgment, and their beliefs in the best or most feasible outcome is essential to keep track of how the evaluation was made and to promote clarity and trust in the model." (Kontic 2000) As expert subjectivity and bias can never be fully eliminated, the interviews or survey materials themselves must be accessible to those that review or use the models. Along these same lines, experts should never be anonymous in cases where their knowledge will be used as data, to ensure maximum accountability and credibility.
8. Always provide an assessment of model quality. At minimum, define a scale of expertness and quantify uncertainty of both expert knowledge and model output. Sensitivity analysis can provide valuable insight through identifying which elicited model parameters most contribute to model uncertainty.

Acknowledgments We thank J. Collazo and two anonymous reviewers for helpful comments provided on an earlier draft of this chapter.

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