Quantitative Analyses in Wildlife Science

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QUANTITATIVE ANALYSES
in Wildlife Science

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16 Causal Modeling and the Role of Expert Knowledge

Bruce G. Marcot

Nature possesses stable causal mechanisms that, on a detailed level of descriptions, are deterministic functional relationships between variables, some of which are unobservable. —Pearl (2000:43)

Time, space, and causality are only metaphors of knowledge, with which we explain things to ourselves. —Friedrich Nietzsche (quoted in Braezeale 1990)

This chapter addresses the role of expert knowledge in constructing models of wildlife-habitat and stressor relationships and compares objectives and results of guided model creation with machine-learning and statistical model construction for various modeling objectives. A critical look is given to defining expertise and how expert knowledge and experience can be codified and verified. I then discuss how models can be structured from machine learning, from expert knowledge, and from a synthesis of both approaches to ensure credibility and validity of expert knowledge–based models. Next, I address pitfalls and uncertainties in the use of expert knowledge, and the kinds of constructs best used to represent knowledge and expert understanding, including mind mapping, influence diagrams, and Bayesian networks.

Causality as a Concept and a Modeling Construct

What Is Causality in an Ecological Model?

What constitutes causality in an ecological model, and how do we know it when we see it? This seems a trivial question, but trivial it is not. Ecological models are generally constructed from three major sources: directly from empirical data, represented by mathematical or theoretical constructs, or interpreted from expert knowledge and experience. Empirical-based models are typically constructed from a variety of statistical frameworks. Mathematical or theoretical-based models are borne of known or hypothesized analytic relationships. Expert-based models are derived from practical experience and personal expertise.

In all three cases, demonstrating and verifying causality is more challenging than it may appear. For one, empirical-based statistical models do not, and cannot, identify causal relationships between some ecological outcome and affector covariates; statistical models are based essentially on correlations, including even some statistical approaches purported to reveal causality, such as structural equation modeling. Mathematical and theoretical models, like expert-based models, are generally constructed with the assumption of causality, but, again, the definitive evidence of cause still hides in the shadows.

So what is causality in ecological modeling, and how can it be identified, demonstrated, constructed, and verified? When some condition *C* can be seen to induce or affect some effect *E*, from a statistical perspective a true causal relationship can be asserted only when all other alternative explanations can be ruled out. This is the intent of clinical trials in medical experimentation, where condition *C* and its absence *not-C* are assigned randomly, with all other conditions held constant and accounted for, and with such a trial replicated many times over. Such experimental designs are, at best, very difficult to achieve in environmental laboratory conditions, and essentially impossible in natural field conditions with mixes of direct and indirect effects, time-lag effects, variable site histories, and other knots in the causal tapestry.

Take, for example, landscape ecology, where each landscape study area is a sample size of one; we assume away many complicating variables and focus on the assumed proximate causes, that is, the most immediate influence, while the ultimate influences can muddle analysis and result in misinterpretation of true causes. At the very least, we can ponder the nature of hidden and unstudied causes, represented in models as *latent variables*, which are those inferred from the mathematical relation among other observed variables (Rohr et al. 2010; Fig. 16.1). More confusing are *confounding variables* that are simply not measured, or in some cases are unmeasurable, but that nonetheless influence outcomes. Ignoring latent and confounding variables could result in assigning causality to the wrong factors, such as to some variable that correlates both with some outcome of interest and to some other, unobserved variable that is the true cause of the outcome.

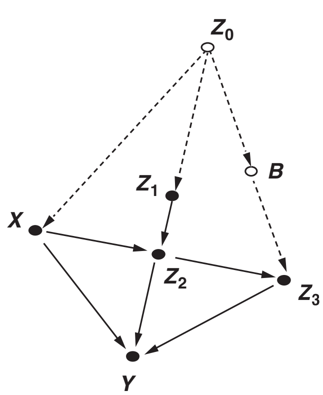

Fig. 16.1. Causal diagram of factors controlling a population of eelworms (Nematoda). Shown are direct effects among measured quantities (solid circles linked by solid arrows) and unmeasured quantities (open circles linked by dotted arrows). The unmeasured quantities represent latent variables. *Source: Pearl (1995).*

Some approaches (e.g., Shipley 2013) purport to utilize statistical techniques to test causal relationships without latent variables and without prior knowledge of how a system might work. Such approaches might be useful for formulating initial hypotheses about causality, but again they cannot definitively determine causal structures in the absence of repeated randomized trials or time-series explorations of relationships in before-after conditions. In attempting to account for effects of latent variables, Guillemette and Larsen (2002) studied factors influencing the abundance, distribution, and behavior of wintering common eiders (*Somateria mollissima*) and removed the confounding variable of prey abundance from their model by randomizing its effect over the study area. Similarly, King et al. (2005) factored out their spatially autocorrelated confounding variables when modeling ecological indicators of watershed land cover. But such approaches serve more to hide away those hidden influences rather than explicitly incorporate them into the modeling structures.

Why Determine Causality?

So what is the importance of determining causality in ecological modeling? In some cases, it may not be a study objective if correlations suffice to provide some degree of descriptive power. However, if explanation is the objective, then causal modeling provides a trustworthy basis for forecasting, projecting, and predicting outcomes. Moreover, identifying causal relations can provide key information on management controllability of a system, such as the degree to which prohibitions on poaching might serve to conserve or restore an at-risk species that is also subject to other environmental stressors. However, Perdicoulis and Glasson (2012) found that environmental impact assessments, at least in the United Kingdom, typically do not explicitly identify causal relations.

Depicting Causality in Ecological Models

Causality can be depicted in ecological models with a variety of constructs. One approach is to model a chain of influences—for example, as Markov processes, where a condition is influenced by other, or prior, conditions just one step away in the sequence. It is then the joint conditional influence of all steps that produce the result. Such a construct is useful if each step depicts a proximate causal relationship.

When conditions are influenced by unknown continuous functions of other factors or with error distributions, they can be depicted with interaction terms as is done in generalized additive models (GAMs) and generalized linear models (GLMs). For example, Hofmeister et al. (2017) used GAMs to explain the causal effects of the size and conditions of vegetation fragments on bird communities in central Europe. From those relationships, the authors surmised the types of timber harvesting that could be more or less detrimental to the birds. But still, their GAMs were based on correlations interpreted as direct causal influences, such as common bird species being most influenced by distance to the forest edge and size and vegetation of the forest fragments. Ando et al. (2017) used GLMs to determine that density of Jezo spruce (*Picea jezoensis* var. *hondoensis*) in Japan was adversely influenced by basal area of nearby mature Jezo spruce trees and by the amount of cover of the moss *Pleurozium schreberi*. However, as with the previously mentioned study, the GLMs were based on correlations of conditions; the authors inferred causality from the study results.

When conditions are influenced by more than one factor or when multiple factors combine in their causal influence, then some forms of network models can be useful. They can take the form of path regression models (e.g., Fig. 16.2), which denote partial correlations among variables (e.g., Chbouki et al. 2005), network theory models (Upadhyay et al. 2017), and Bayesian probability network models (Borsuk et al. 2006).

Ultimately, ecological modeling is the art of correctly interpreting correlations and simplifying multiple causal influences as cumulative effects. Time-dynamic simulations, as with agent-based simulations or individual movement models, can be useful to represent influences of potential causal factors in ecological systems.

Expert Knowledge as a Basis for Causal Modeling

Finally, expert-based models can be useful constructs for depicting and exploring potential causal structures in ecological systems. Developing models

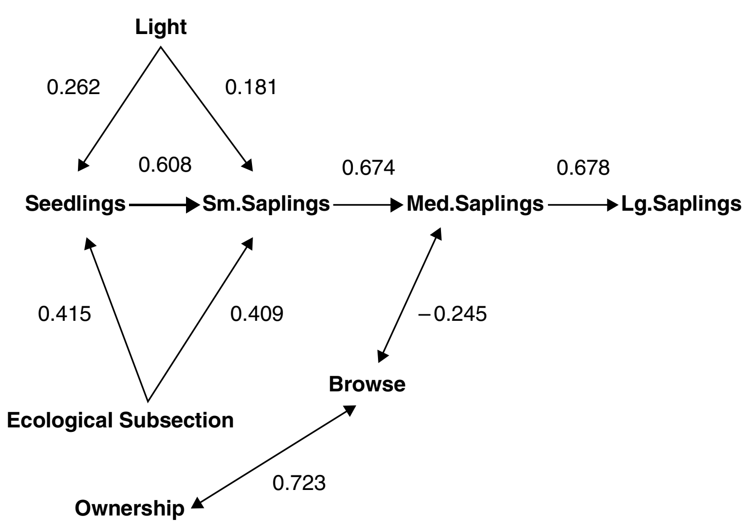

Figure 16.2. Example of a path regression model depicting the strength of causal relationships inferred from the partial correlations (path coefficients). Correlations are depicted on arrows pointing from affectors to response variables of the density of seedling and sapling eastern hemlocks (*Tsuga canadensis*) in conifer-hardwood forests of upper Midwestern United States. *Source: Rooney et al. (2000).*

from personal experience can be an enticing enterprise, but can also be fraught with many biases, as discussed further below.

Most fundamental to using expert knowledge as a basis for causal modeling is the need to identify what, or who, is an expert? The noun *expert* dates to the early fifteenth century and refers to "a person wise through experience"; the adjective *expert*, which dates to the late fourteenth century and "having had experience; skillful," comes from the Old French *espert*, meaning "experienced, practices, skilled" and from the Latin *expertus*, "tried, proved, known by experience."

Such denotations avoid reference to superficial or pedestrian understanding. Steels (1990) defined "expert knowledge" and "expertise" in terms of the degree to which inference can be made from one's understanding, the depth of that knowledge, and the degree to which such knowledge can be useful for problem-solving methods. Caley et al. (2014) developed a scoring system to rate the degree of expertise in taxonomy based on some 18 factors distilled into descriptions of the person's quality of work and total productivity. Other similar definitions of expertise and expert knowledge exist in the literature.

Here, the focus is on building credible and reliable ecological causal models from expert knowledge, and not from inexpert value judgment or personal opinion. Approaches to collecting and representing expert knowledge can range from single-expert interviews to highly structured expert panels (Ayyub 2001; Ayyub and Klir 2006; Cooke 1991). A rigorous approach to expert paneling is presented farther below.

Determining Causality in Ecological Systems

Causality and Study Designs

No model can tell causality; that is inferred by the researcher from the context of the system being modeled. One must proceed cautiously when interpreting correlation, especially spatial or temporal autocorrelation, as causation. Well-designed experimental studies that implement management guidelines can go a long way to helping researchers infer—or at least hypothesize—causality and determining the degree to which management affects ecological systems in desired, or undesired, ways; this is the heart of active adaptive management (Gunderson 1999; Williams 2011). Study designs and approaches to adaptive management can run the gamut of some seven types (Marcot 1998)—literature review, expert judgment, demonstration, anecdote, retrospective study, nonexperimental study, and experimental study; the last of these provides the most definitive evidence from which to infer causality, although it is the most difficult to perform in situ.

Analytical Approaches to Determine Causality

In evaluating study results, a variety of analytical approaches can be useful for inferring causality. One such construct is structural equation modeling (SEM) with path analysis (Pearl 2011) and graph-theoretic representation (Grace et al. 2012), which can account for latent variables (Bollen 1989) and indirect effects (Clough 2012). SEM is more of a method for building causal relationships among variables, such as with construction of influence diagrams, than it is a specific analytic structure per se. An approach analogous to SEM is that of Bayesian networks. SEM and Bayesian network modeling share some traits but take different approaches (Table 16.1; Pearl 2000).

Another means of inferring causality is with *d*-separation (*d* is for *dependence* or *directional*), which is a procedure to help determine if two variables are independently conditional on a third variable (Clough 2012). Typically, *d*-separation is used in causal webs, influence diagrams, and probability networks. Also used are hidden Markov models (e.g., Etterson 2013) that can help reveal correlates and potential causal factors in state-path animal movement data. Sugihara et al. (2012) suggested using

Table 16.1. Congruence and isomorphisms between structural equation modeling (SEM) and Bayesian network (BN) modeling.

Structural equation modeling	Bayesian network modeling
EFA (exploratory factor analysis; Ullman 2006)	Induction of naive Bayes networks from data sets
CFA (confirmatory factor analysis) and network induction and updating (Ullman 2006)	Incorporation of case files to update probability tables (e.g., by use of the expectation maximization algorithm)
SEM diagramming	Influence diagramming to denote logical and causal relations among variables based on expert knowledge
Path regression modeling to identify degree of correlation and influence of covariates	Structure-induction algorithms to denote variable relations based on case data sets
Latent variables (unobserved, not directly observed; Ullman 2006)	Latent (hidden, summary) nodes
Counterfactual analysis	Influence analysis (sensu Marcot 2012)
Depiction of uncertainty: error terms	Depiction of uncertainty: posterior probability distributions
Confidence intervals	Credible intervals
Explanatory power of covariates: standardized regression coefficients or partial correlation coefficients in a path regression model	Explanatory power of covariates: sensitivity values of node

hindcasting to measure the degree to which historical records of some presumed causal precondition can reliably estimate some outcome effects, calling this approach "convergent cross mapping".

Still another approach is what is called power probabilistic contrast (PC) theory, which is used more in psychology (Buehner et al. 2003; Cheng 1997) but is generally applicable to inferring causality in any system. This method determines the power of a potential cause *c* normalized by the influence on the effect *e* (Collins and Shanks 2006). In general, a main contrast effect is calculated as $\Delta P(e|c) = P(e|c) - P(e|{\sim}c)$, or the difference between the probability of the effect, given the cause, minus the probability of the effect, not given the cause (the "not-cause"). High main-contrast values suggest a greater degree of causal linkage between *c* and *e*.

Using Expert Knowledge in Causal Modeling

Given how tricky—and misleading—it can be to definitively determine proximate, ultimate, and indirect causality in ecological systems, it is no surprise that many models are constructed from expert knowledge. This is no new approach, having been used in modeling and analysis of environmental systems for many years (e.g., O'Keefe et al. 1987). There is a potential dark side, however, to relying on expert knowledge in structuring ecological models, and it is related to numerous pitfalls and uncertainties.

Pitfalls and Uncertainties in Using Expert Knowledge

For one, expertise can be biased in various ways. One set of biases can be characterized in terms of a "psychology of uncertainty," which reflects the ways that people estimate probabilities, frequencies, or implications of events or situations. For example, Balph and Romesburg 1986 addressed the role of observer-expectancy bias as one aspect of systematic error in avian studies. In another example, people tend to more heavily weight more immediate events and costs over future events and costs, even if future events and costs might be far more dire. This is the "immediacy effect" (Gideon and Roelofsma 1995) and explains why we are less concerned with asteroid strikes than with potholes in our streets. It may also play out in emphasizing more proximate causes, such as current weather, over less immediate ultimate or more indirect causes, such as climate change, even if the latter tend to have greater control over the system in question.

Another potential bias in using expert knowledge to structure ecological models pertains to having incomplete experience or, worse, being unaware of having incomplete experience. This is "ignorance of ignorance," sometimes referred to as the "unknown unknowns." In a sense, then, what you don't know *can* hurt you, or at least bias the model. A variant of this bias is the Dunning-Kruger effect that states that people who lack the expertise to perform well are often unaware of this fact (Kruger and Dunning 1999).

A host of other potential biases can arise in group activities such as in expert paneling to derive collective knowledge for structuring ecological models; even group facilitators can hold bias and adversely influence outcomes (Table 16.2). For instance, the emotional state of an expert can taint how he or she recollects experience (Tambini et al. 2017). A rigorous approach to holding expert panels is suggested below.

In summary, expertise can be biased, and expertise can be partial. And expertise is based on personal experience, meaning past or current conditions, not novel future conditions.

Modeling Frameworks for Structuring Expert Knowledge

So what are some useful tools for depicting and structuring expert knowledge? Some modeling frameworks that can help organize thinking are mind maps and cognitive maps, which, at their simplest, are diagrams of variables and their causal, correlational, or logical connections (Lee and Danileiko 2014). Think of a diagram of a food web, which is, in essence, a cognitive map of the trophic structure of an ecosystem (e.g., Fig. 16.3). When parameterized with bioenergetic flow rates, food webs can be useful cognitive maps for exploring the implications of species loss (Zhao et al. 2017) and associated trophic cascades of ecosystems (Canning and Death 2017).

Table 16.2. Potential biases when using expert knowledge to structure an ecological model. These biases pertain to eliciting knowledge from an expert or from expert panels.

Bias	Description
Expert bias: emotional	Unconsciously representing some causal effect to be more or less effective than it actually is, because of expert's mood or attitude toward the subject.
Expert bias: expectation, motivational	Providing an answer expecting that the recipient or user of the answer will misuse the information or will behave in a manner with which the expert does not agree.
Expert bias: lexicon uncertainty	Differing on definitions of key terms.
Expert bias: lack of knowledge parity	Differing in levels of understanding and knowledge of a key topic.
Group bias: anchoring	Adhering to information either recently encountered even if irrelevant.
Group bias: bandwagoning	Everyone on a panel going along with one answer or idea.
Group bias: domineering	Dominating the discussion by a single voice or personality or intimidating others to concede to his or her view.
Cognitive bias: plausibility	Giving a line of thought undue weight because it seems plausible and is thus deemed to be probable.
Facilitator bias: herding	Guiding the group to one idea and downplaying others.
Facilitator bias: charisma	Favoring views of the more charismatic or "big name" experts.
Facilitator bias: last opinion	Favoring the last expressed opinion; also called the "last speaker effect."

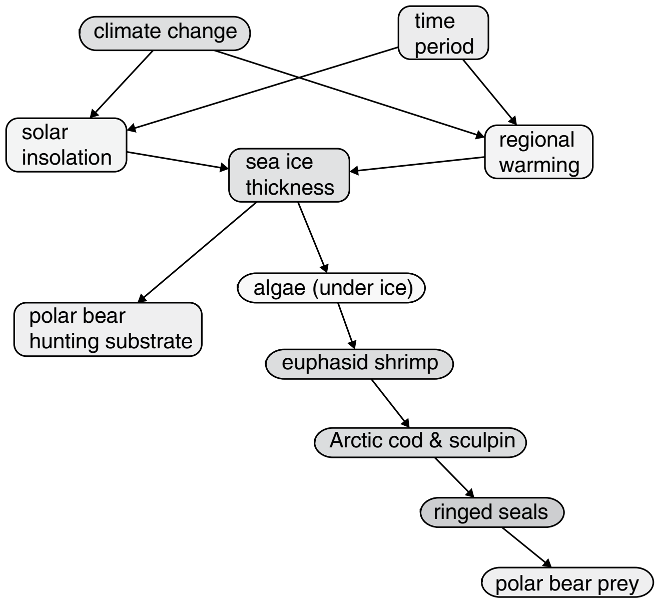

Figure 16.3. Example of a cognitive map of a polar bear (*Ursus maritimus*) food web in the Arctic.

Vasslides and Jensen (2016) used fuzzy cognitive maps (depicting degrees or probabilities of connections among variables) to model an estuarine system and to compare four stakeholder groups' perceptions of social and ecological factors affecting the system. Similarly, Elsawah et al. (2015) used cognitive maps to help depict mental models of factors affecting viticulture irrigation in South Australia, and as a construct from which to build more quantitative agent-based models (see Chapter 10 of this volume). When parameterized with probabilities of states and interactions, cognitive maps become influence diagrams and the basis of probability-based models such as Bayesian networks.

How Reliable Is Expert Knowledge?

But how reliable is expert knowledge as a basis for constructing and using ecological models? Reliability and credibility are related to the degree to which any such model can be subjected to strict peer review, calibration, updating, and validation.

Ensuring Credibility and Validity of Expert-Based Causal Models

Insofar as possible, cross-validation using portions of independent data sets is the best measure, although with some expert-based models, as with testing stakeholder perceptions (Ozesmi and Ozesmi 2003), empirical case data are not really available or feasible. In such situations, one could compile a case database of the judgments of experts not used to construct the original model, and then test and adjust the model against that database, although this really amounts to calibrating a model against other experts, and not validating the model per se.

Crowd-Sourcing Expert Knowledge

One approach to developing models is using the "wisdom of the crowd" (Lyon and Pacuit 2013), as Eikelboom and Janssen (2017) did in involving stakeholders to address climate-change adaptation planning by using geodesign tools. Much due caution, however, is indicated when accepting opinions or judgments (Koriat 2012), even from multiple experts, without careful vetting and review.

This extends to use of, and cautions for, information derived from "citizen science" projects (Villaseñor et al. 2016). Kosmala et al. (2016) offered a set of criteria for helping ensure the veracity of citizen science monitoring data: iterative project development, volunteer training and testing, expert validation, replication across volunteers, and statistical modeling of systematic error.

Use of Expert Panels

Can the collective wisdom of multiple experts be wrong? (Spoiler alert: yes, but this can be corrected.) An approach to securing reliable input from multiple experts for developing causal ecological models is a rigorous use of expert panels. Following are steps for gathering knowledge from multiple experts in an organized process (after Marcot et al. 2012; also see Ayyub 2001; Burgman 2016; Krueger et al. 2017; and others).

STEP 1. CLEARLY STATE OBJECTIVES

This is self-evident, but it is surprising how often experts are consulted and models are constructed with vaguely stated goals and purposes. Remember, building a causal model for the aim of understanding and managing some ecological system is a method, not an objective. Objectives should be stated in terms of the specific condition to be evaluated and/or managed. For example, an objective could be to determine the viability outcome for some listed species under a suite of possible management activities.

The objectives should also clearly state if the purpose of securing expertise is to develop a single depiction representing all experts' collective knowledge, as with reaching consensus under the traditional Delphi paneling process (MacMillan and Marshall 2006), or if the objective is to depict the variation of knowledge among experts.

STEP 2. IDENTIFY PANELISTS AND PROVIDE PRE-MEETING MATERIALS

A key to holding a successful expert panel is to engage individuals who can work well with others in a panel setting, not try to dominate the panel, and who can "think beyond the data"—that is, who are comfortable extrapolating their experience beyond the boundaries of strict empirical studies. Depending on the project objectives, it may be useful to invite panelists who represent a spectrum of expertise and knowledge, such as from different geographic locations or ecosystems or ecological conditions. Also, it is useful to aim for an uneven number of panelists so that equally-numbered "teams" do not form on some issue. Panels of five or, at most, seven members seem to work best and still allow for independent contributions.

Pre-meeting materials are quite helpful for alerting invited panelists as to the specific objectives for the panel, the type and subject of their knowledge that is sought, how the panel will be held, and what will be done with their knowledge. Materials can include a few background papers or readings. For example, materials may include a status summary of the species of interest, including its biology and ecology, and threats to its viability, and also the set of management activities to be considered when evaluating the species' viability response.

The materials would also include a brief glossary of key terms—for instance, in our example here, definitions of "recovery," "viability," "extirpation," "threat," "stressor," and other terms related to the management alternatives to be considered. The materials should also define the terms used in an information or scoring sheet, such as levels of potential response in a viability rating scale, if the panelists will be asked to score outcomes. The overall aim here is to avoid "lexicon uncertainty," so that everyone uses the same definitions of the terms, and to reach "knowledge parity," so that everyone arriving at the panel has the same background understanding of concepts.

STEP 3. BEGIN PANEL REVIEW OF THE WORKSHEET AND TERMS

Here starts the actual panel meeting, best done in person with a panel facilitator. Typically, expert panels are convened to provide specific information or to rate or rank some alternative conditions, using a text worksheet or some scoring table. The facilitator would begin by reviewing the overall objectives for the panel, the background pre-meeting materials, the worksheet, and key terms. Again, the objective is to ensure that all panelists understand the purpose, context, and terminology the same way and the same degree.

STEP 4. PERFORM INITIAL (ROUND 1) SCORING

If the purpose of the panel is to provide scores of outcomes, such as levels of viability of an at-risk species under a suite of potential management actions, this step entails having the panelists independently and silently write down their scores, encouraged by the facilitator to do independent thinking. As an example, panelists might be asked to allocate 100 points among one or more of possible levels on a viability outcome scale, for each of a set of potential management actions, whereby spreading their points (to sum to 100) among >1 outcome level would represent their degree of uncertainty of outcomes. Panelists may also be asked to write down brief explanations of the type and strength of evidence that led them to denote which outcome would be most likely, and the key uncertainties that may have led them to spread their points among >1 outcome level.

STEP 5. ENGAGE IN STRUCTURED DISCLOSURE AND DISCUSSION

Next, the facilitator would have each panelist in turn reveal his or her scores and explain the evidence and uncertainties he or she considered. Each panelist would have equal time and opportunity for this explanation, uninterrupted. At the end of the disclosures, the panelists would then have an opportunity to ask questions of each other and offer their perspectives. The purpose of the discussion phase is for panelists to learn from each other, not for attempting to convince other panelists of the merits of one's scores and ideas. If the panelists were selected to represent a diversity of experience and knowledge, then the contribution of every panelist has equal value.

Some expert panels may be held with an audience of others with specific subject knowledge that may be pertinent to the issue at hand, such as with managers or biologists who do not specifically serve on the panel. The facilitator would have had the audience remain silent to this point, but now could open the floor for any brief contributions or clarification questions that the audience members may wish to provide. Again, the aim here is not for audience members to convert panelists' thinking, but to inform for the purpose of mutual learning.

STEP 6. PERFORM SECOND (ROUND 2) SCORING

At this time, the facilitator has the panelists do another round of scoring in which they are free to retain their round 1 scores or update any scores based on what they may have learned from the structured disclosure and discussion from step 5. Again, scoring is to be done silently and independently, if the aim is to collect individual knowledge from each panelist.

STEP 7. ENGAGE IN STRUCTURED DISCLOSURE AND DISCUSSION

The facilitator then engages the panelists in another round of structured disclosure and discussion. As may be necessary, there may then be further rounds of scoring, disclosure, and discussion, but typically two rounds suffice to satisfy panelists' contributions.

STEP 8. REVIEW RESULTS

The facilitator can then quickly compile and review the final scores, and panelists may be given a last opportunity to clarify or explain their contributions. At this point the expert panel procedures are completed.

The overall roles of the panel facilitator are to ensure that panel discussions remain focused on the science; that the panelists adhere to the procedures of scoring, disclosure, and discussion; that the panel is held to the prescribed schedule for completion; that audience members follow such procedures; and that the panelists' information is duly recorded and presented. It may be useful to have a scribe present at an expert panel to record discussions and information not captured in the panelists' worksheets. It is also useful, in the final report of the panel outcome, to acknowledge the panelists' participation but to keep their individual contributions anonymous; this encourages the panelists to speak freely without worry of specific attribution for any statements or contributions that could be misinterpreted or taken out of context.

Following such a rigorous paneling procedure can help ensure, in an efficient and credible manner, that expert knowledge can be garnered to suggest outcomes, reduce areas of uncertainty, identify topics requiring further exploration or study, and to best represent collective knowledge and experience.

Using Expert Knowledge in Causal Modeling

In the end, expert knowledge, such as that gathered through an expert panel or another expert knowledge elicitation approach, can provide the basis for developing cognitive maps, mind maps, influence diagrams, and models representing causal influences in some ecological system. Beyond the initial mining of expert knowledge, it is then the use of peer review that can help ensure reliability, the use of validation to ensure robustness, and the updating of the knowledge base to ensure longevity and utility of the resulting models. The target is to use uncertainty as information to guide and temper management decisions in a risk analysis, risk management, and overall structured decision-making framework (Sloman 2009).

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