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LETTER

Integrating Expert Perceptions into Food Web Conservation and Management

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Abstract

Decision-makers often rely on expert knowledge, especially in complex and data-poor social-ecological systems (SESs). However, expert knowledge and perceptions of SES structure and function vary; therefore, understanding how these perceptions differ is critical to building knowledge and developing sustainability solutions. Here, we quantify how scientific, local, and traditional knowledge experts vary in their perceptions of food webs centered on Pacific herring—a valuable ecological, economic, and cultural resource in Haida Gwaii, BC, Canada. Expert perceptions of the herring food web varied markedly in structure, and a simulated herring recovery with each of these unique mental models demonstrated wide variability in the perceived importance of herring to the surrounding food web. Using this general approach to determine the logical consequences of expert perceptions of SES structure in the context of potential future management actions, decision-makers can work explicitly toward filling knowledge gaps while embracing a diversity of perspectives.

Introduction

Experts play a key role in decision-making in conservation. In the absence of certainty about the nature and behavior of complex social-ecological systems (SESs), expert opinions are often elicited in hopes of separating matters of fact from matters of value to complement existing data and inform conservation decisions (Dietz 2013). Typically, technical experts communicate their understanding of social-ecological processes to decision-makers, enabling them to rely upon best available science (Ryder *et al.* 2010). For example, assessments of oil spill impacts (e.g., major oil spills; Leschine *et al.* 2015), climate change mechanisms (e.g., IPCC 2014), and potential tradeoffs associated with scientific whaling (e.g., the case for scientific whaling; de la Mare *et al.* 2014) have all relied on expert judgment (reviewed in Redpath *et al.* 2013). However, experts can exhibit high levels of uncertainty because knowledge integration among individuals is inherently complex (Raymond *et al.* 2010; Drescher *et al.* 2013), and in some cases not possible (Gray *et al.* 2012).

Despite the potential for each expert's training, experience, and education to guide judgments (Burgman, Carr *et al.* 2011), many conservation decision-making processes focus on gathering input from select individuals with substantial, but not necessarily objective, information about a given topic (Burgman, Carr *et al.* 2011;

Martin *et al.* 2012; Drescher *et al.* 2013). Indeed, divergent views are common for two reasons. First, expert perceptions of SESs are typically based on what they have learned from experience or in the classroom (i.e., human cognition). Second, the terms employed to describe SESs (e.g., ecosystem structure) are human constructs, and the way in which perceived differences are discussed is typically qualitative, imprecise, and prone to biases in human reasoning (but see Doswald *et al.* 2007). For instance, differences in how the species concept is viewed by scientists (Levin 1979) have led to disputes (Hey *et al.* 2003), with important implications for conservation of imperiled species (e.g., Waples 1991; Beaudreau *et al.* 2011).

Here, we document varying expert perceptions of ecosystem interactions in the Northeast Pacific Ocean and explore their implications for conservation and management. In this region, Pacific herring (*Clupea pallasii*) are a key ecological, economic, and cultural resource. Numerous terrestrial and marine coastal organisms, including several commercially harvested fishes, prey on herring (Schweigert *et al.* 2010). Herring were a major focus of industrial seine and gillnet fisheries, but stock collapses in the 1960s and 1990s resulted in fisheries closures (DFO 2014) and conservation concern. Herring roe is also an important cultural and subsistence resource for a number of First Nations (Jones *et al.* 2010). Because of the central role of herring in Northeast Pacific SESs, fisheries closures and subsequent reopenings have led to tensions surrounding herring and herring fishing among First Nations groups, the Canadian government, and commercial fishery interests (DFO 2014).

Given the numerous social and ecological connections to herring, we explored how experts from a variety of backgrounds perceived Northeast Pacific ecosystem interactions. We asked each expert to describe the number, direction, and strength of food web interactions among functional groups connected directly or indirectly to herring. Based on these responses, we constructed Fuzzy Cognitive Maps (hereafter, cognitive maps) of the herring ecosystem, revealing each expert's unique perception of the number, strength, and direction of relationships among network nodes, and how perceptions of different experts related to one another. We also simulated responses of the cognitive maps to hypothetical scenarios, including an increase in herring, the continued recovery of humpback whales (a key herring predator), and changes in ocean productivity, asking if the logical consequences of differences in perception of ecosystem structure magnify or diminish variability in predictions about ecosystem responses to management actions.

Methods

Fuzzy cognitive maps

To quantify variation in experts' perceptions of the structure and function of the herring-centric food web in the Northeast Pacific Ocean, we collected cognitive maps from a range of scientific experts. Cognitive maps are basic mathematical and graphical representations of an individual's perception of the number and strength of relationships among nodes in a network. In this case study, the network is the Northeast Pacific Ocean food web, and the nodes in the network are the functional groups. Knowledge constructed in this manner can externally represent an individual's organized understanding of the workings of the world around them (Gray *et al.* 2014). These representations of understanding can then be manipulated mathematically to indicate the logical consequences of an individual's perceptions based on their understanding of the dynamics of the external world. For example, by increasing or decreasing key variables as continually high or low (referred to as "clamping"), future scenarios, such as the increased abundance of a predator, can be simulated given a specific set of perceived linkages and interaction strengths (Özesmi & Özesmi 2004). This clamping is conducted until the system reaches a new equilibrium that can be compared to the steady state—the equilibrium relative abundance in the absence of a perturbation (for additional detail, see Supplementary Material).

Expert elicitation

To build cognitive maps of the herring ecosystem in the Northeast Pacific Ocean, we identified 14 key functional groups in the herring food web (Table S2), based on published literature (Ainsworth *et al.* 2008; Schweigert *et al.* 2010; DFO 2014), the authors' natural history knowledge of important ecosystem interactions, and pilot testing with five experts inside and outside of our focal area in Haida Gwaii. While providing a particular set of functional groups can constrain cognitive maps of the system, it allows for quantitative comparisons among experts (Gray *et al.* 2014). Experts were defined as having scientific (e.g., agency or university scientists), local (e.g., long-term residents), or traditional (i.e., First Nations) ecological knowledge and/or practical experience in the Northeast Pacific Ocean herring ecosystem. Experts were identified through stratified chain referral sampling (Biernacki & Waldorf 1981), which yielded a complete sample of 27 experts. We then explored the potential role of training, experience, and cognition as key factors that may influence the diversity of expert perceptions (following Burgman, Carr *et al.* 2011; Morgan 2014).

We asked each expert their perception of the number and strength of interactions between all pairs of functional groups. Respondents were also given an opportunity to provide information on their uncertainty about interactions (Table S2). Interaction strength elicitations ranged from -2 (strongly negative) to +2 (strongly positive), and were scaled from -1 to +1 for analysis (for additional detail, see Supplementary Material). We also asked a series of demographic questions detailing information that could potentially influence responses (e.g., age, years of experience, professional affiliation, and place of residence; Table S1).

Network analysis of cognitive maps

We conducted a network analysis to describe the geometry and strength of interactions for each cognitive map and then subjected the resultant metrics to hierarchical cluster and nonhierarchical partitioning analyses. The network analysis metrics we used to represent herring ecosystem structure included number of connections in each food web, average of the absolute value of the interaction strengths, centrality of four key functional groups of conservation interest, a hierarchy index, and number of transmitters, receivers, and ordinary concepts suggested by Özesmi & Özesmi (2004; Table 1).

Analysis of expert perceptions of food web structure

Demographic characteristics were not effective predictors of variation in perceived ecosystem structure (Table S3). We therefore applied nonhierarchical partitioning analysis to ask whether evidence existed for ≥2 clusters of experts based on the similarity of cognitive maps, summarized in terms of the network metrics. To visualize the distances between experts, we calculated Euclidian distances between each pairwise combination of experts based on the network metrics described above, and used hierarchical cluster analysis to identify potential groupings of experts (using an agglomerative average linkage method; Venables & Ripley 2002). Hierarchical cluster analysis makes no assumptions about a priori relationships among experts (e.g., demographic characteristics) but rather searches for a posteriori groups based on the differences among individuals in cognitive map structural metrics, allowing comparison of expert knowledge by the nature of their understanding as opposed to membership in a demographic group (for additional detail, see Supplementary Material).

Scenario analysis: perturbing the herring food web

There is a fair amount of uncertainty surrounding the future of Pacific herring in the Northeast Pacific. This uncertainty is rooted in the complex social and ecological influences on the species, all of which occur at a range of spatial scales. We evaluated the functional consequences of each expert's perceived ecosystem structure by simulating three perturbations, each of which caused a consistent increase (press perturbation) in a single node in the food web until all nodes in the food web reached a new equilibrium. Specifically, we Specifically, we simulated the following: (1) an increase in humpback whales concordant with projected humpback population growth (Ford 2009), (2) an increase in herring—a simulation in accordance with the desired trajectory of the depleted stock (DFO 2014), and (3) an increase in zooplankton—analogous to a regime of cold, nutrient-rich water years that support productive zooplankton populations (Mantua & Hare 2002; Figure 1). We conducted scenario analyses on each cognitive map ($n = 27$) and measured the change in relative abundance of each of the 14 functional groups compared to its relative abundance at equilibrium in the absence of a perturbation. Such an approach is expected to represent predicted outcomes under different ecological change scenarios across different types of experts.

Statistical analysis of expert perceptions of ecosystem function

As with the analysis of expert perceptions of herring ecosystem structure, we used hierarchical cluster and nonhierarchical partitioning analyses to ask whether subsets of experts perceived ecosystem responses similarly. Importantly, these predictions represent the logical consequences of information elicited from experts, rather than direct elicitations from scenario-based questions. Though we tested whether expert demographics were effective predictors of variation in responses to perturbations from the three scenarios, we found none (Table S2). Thus, in this application, we sought clusters of experts based on the expected percent change in relative abundance of each of the 14 functional groups under each scenario. We also estimated two ecosystem responses for each of the three scenarios: (1) average percent change in abundance of all 14 functional groups and (2) ecosystem reorganization index, which estimates discordance among functional groups in their response to a scenario, relative to the aggregate response of all functional groups (sensu Samhouri *et al.* 2010).

Table 1 Structural metrics that applied to matrix forms of fuzzy cognitive maps to quantify structural properties of each expert's perceived food web

Mental model, structural measurement	Description of measure and cognitive inference
N (connections)	Number of connections included between variables; higher number of connections indicates higher degree of interaction between components in a mental model
N (transmitter)	Components which only have "forcing" functions; indicates number of components that affect other system components but are not affected by others
N (receiver)	Components which have only receiving functions; indicates the number of components that are affected by other system components but have no effect
N (ordinary)	Components with both transmitting and receiving functions; indicates the number of concepts that influence and are influenced by other concepts
Centrality	Absolute value of either (a) overall influence in the model (all + and − relationships indicated, for entire model) or (b) influence of individual concepts as indicated by positive (+) or negative (−) values placed on connections between components; indicates (a) the total influence (positive and negative) in the system or (b) the conceptual weight/importance of individual concepts (Kosko 1986a). The higher the value, the greater the importance of all concepts or the individual weight of a concept in the overall model
Hierarchy Index	Index developed to indicate hierarchical to democratic view of the system. On a scale of 0–1, indicates the degree of top-down (score 1) or democratic perception (score 0) of the mental model

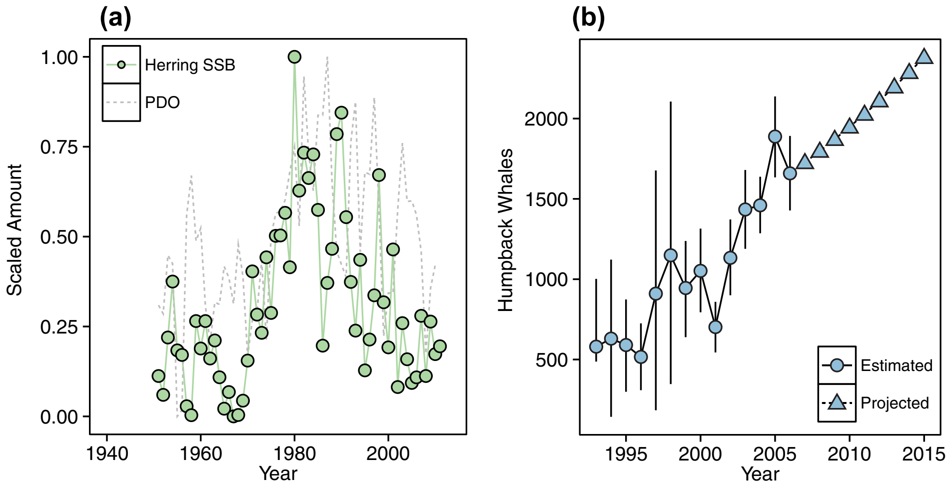


Figure 1 Time series motivating three scenarios simulating future increases in herring, zooplankton, and humpback whales. Panel A shows estimated herring spawning stock biomass (green) in Haida Gwaii, British Columbia, Canada, and scaled Pacific Decadal Oscillation (PDO) estimates (gray) in the Northeast Pacific Ocean—a known correlate of zooplankton productivity. Panel B shows the estimated (circle) and projected (triangle) abundance of humpback whale populations (blue) assuming the median 4.1% annual growth rate from the most recent stock assessment from British Columbia, Canada. Time series extracted from three published resources. Herring: 2014 Department of Fisheries and Oceans stock assessment for pacific herring (DFO 2014). PDO: JSIAO database (http://research.jisao.washington.edu/pdo). Humpback whales: Department of Fisheries and Oceans stock assessment for Humpback Whales (Ford 2009).

Contextualizing our approach within existing mental model approaches

Our approach advances existing methods focused on building cognitive maps to improve conservation and management (Biggs *et al.* 2011). Researchers use several methods to collect and evaluate mental models and shared beliefs in natural resource management (Lynam & Brown 2011). For example, some methods assume homogeneity in knowledge within demographic groups, despite examples of ample heterogeneity within knowledge groups (e.g., Gray *et al.* 2012) and at various scales (e.g., Iniesta-Arandia *et al.* 2015). While some mixed oral and graphic concept mapping methods have been used to compare and scale up individual cognitions (Jones *et al.* 2011), these methods are often static and do not provide a way to explore how individuals reason dynamically. Our use of cognitive maps in combination with scenarios allows us to explore the consequences of individual perceptions. Furthermore, typical analysis

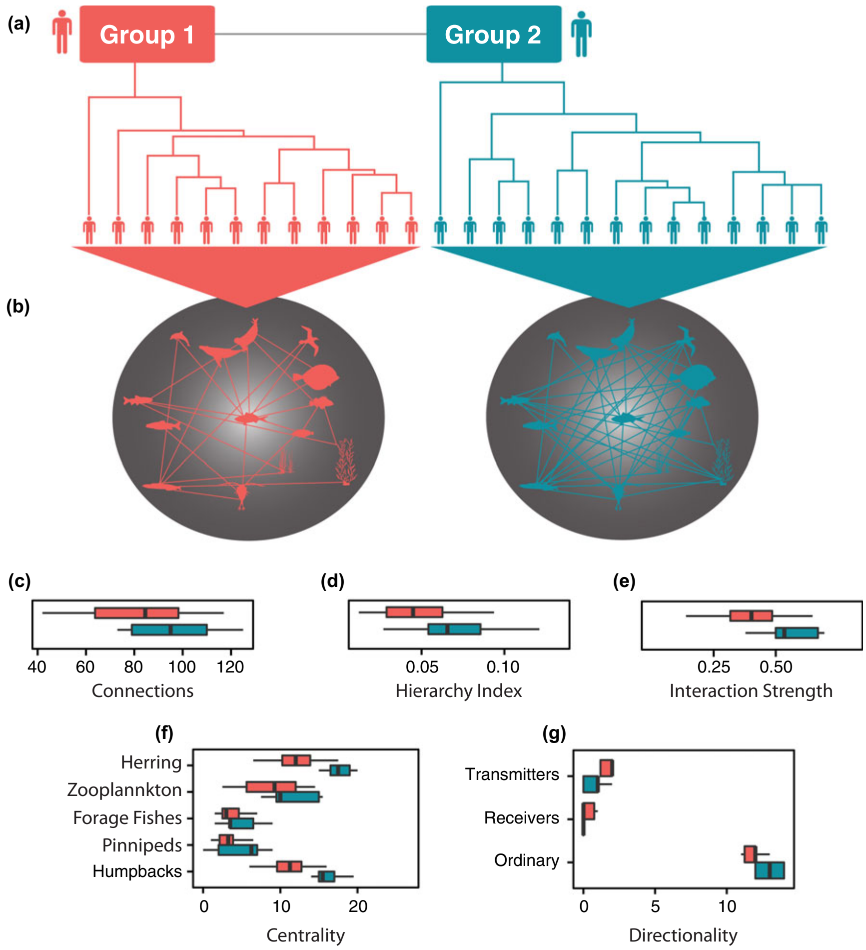


Figure 2 Hierarchical cluster analysis of mental model structural characteristics revealed two significant clusters (1: pink and 2: turquoise). Silhouettes at tip of dendrogram represent each expert, and branch distance is proportional to similarity of experts in their perceived network structure (a). Food web drawings represent the median cognitive maps of experts from each group (b). Clusters of experts based on perceptions of food web structure are based on multivariate analysis of 11 different network metrics (Table 2), which are plotted univariately for each expert group in boxplots (c–g). In box and whisker plots, the upper and lower "hinges" correspond to the first and third quartiles (the 25th and 75th percentiles) and whiskers represent 1.5 times the interquartile range.

exploring variation in individual cognitions assumes perceptions are linked to demographic backgrounds a priori, whereas here we test for links between demographic backgrounds and perceptions, but also use multivariate clustering analysis to define cluster of similar experts based on perceptions of food web structure and function. Overall, our approach highlights the utility of building individual cognitive maps, which can increase stakeholder communication and facilitate the integration of multiple knowledge sources (Biggs *et al.* 2011), while also avoiding assumptions about links between demographic characteristics and expert perceptions.

Results

Expert experience with the herring ecosystem in the Northeast Pacific Ocean averaged 19 years (range 5–61years), yet this depth of experience did not translate into cognitive maps with highly similar network properties (Table S4). For example, networks varied widely in number of connections (range 42 to 125). Multivariate analysis suggested expert demographics did not explain variation in perceptions of herring ecosystem structure (Table S3). Instead, cluster analysis revealed two prevailing views that were unrelated to amount of experience (Figures 2a, b). An OLS regression testing for univariate relationships between years of experience and food web structural properties revealed no correlation ($P > 0.15$ for all structural properties). Experts with different demographic characteristics were well represented in both groups. For example, Group 1 was 50% academics, 66% NGO, 66% island residents, and 64% individuals who identified as female. Group 2 was 50% academics, 33% NGO, and 33% on island, and 64% individuals who identified as male. This high within-group variability in demographic characteristics was a major contributor to statistically nonsignificant differences based on demographic background. An additional explanation for our inability to detect statistical differences among groups is the number of experts sampled, which is somewhat low despite

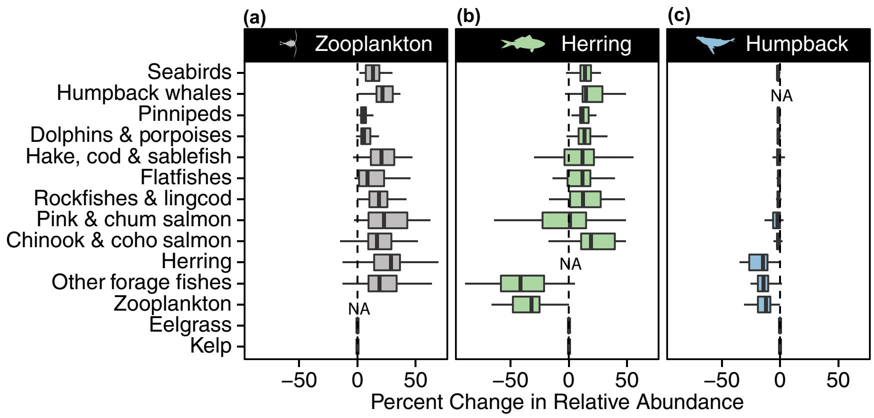
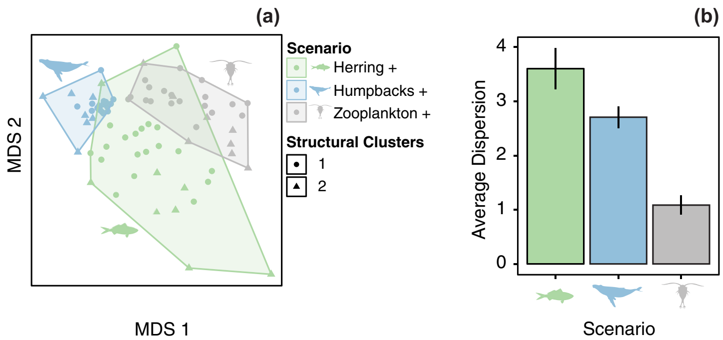


Figure 3 Ecosystem response (i.e., percent change in relative abundance of functional groups) to three different scenarios simulating increases in zooplankton (a), herring (b), and humpback whales (c) averaged across all cognitive maps. Upper and lower "hinges" on box and whisker plots represent the first and third quartiles (the 25th and 75th percentiles) and whiskers represent 1.5 times the interquartile range.

Figure 4 Among-scenario comparison of ecosystem response to simulated food web perturbations. Nonmetric multidimensional scaling plot generated from change in relative abundance of functional groups in each scenario relative to a steady state (a). Each point represents an expert, with each expert represented for each of the three scenarios. Experts perceiving a similar ecosystem shift in response to each of the three scenarios are closer together. Point color represents the three different scenarios (Blue: humpback +, Green: Herring +, Gray: Zooplankton +), and point type (circle or triangle) represents the two clusters that emerged from the expert's perceptions of ecosystem structure. Univariate plot of average (±1 SE) multivariate dispersion demonstrates among expert variability in response to scenarios (b).



exhaustively sampling the expert pool through stratified referral sampling. Expert perspectives of the ecosystem diverged based on several characteristics of the cognitive maps, including a 35% difference in overall influence of focal functional groups (i.e., centrality), 25% difference in interaction strengths, 15% difference in connections, and a 28% difference in whether connections were democratic (i.e., hierarchy index; Figures 2c–g).

Variable perceptions of herring ecosystem structure did not necessarily correspond to differences in expected outcomes of hypothetical scenarios, despite unique responses of each cognitive map to simulated perturbations (Figure 3). Furthermore, backgrounds and demographic characteristics of experts did not readily explain variability in expected changes in species relative abundance (Table S4). In fact, we found cryptic agreement surrounding scenarios despite divergent perceptions of herring ecosystem structure. For example, simulated increases in herring predators led to a predicted decrease in herring, zooplankton, and other forage fishes, whereas simulated increases in zooplankton predicted increases in relative abundance of all species (Figure 4a).

The two clusters that emerged from analysis of structural metrics describing cognitive maps effectively predicted responses to hypothetical scenarios (Figure S1). For example, food webs with more connections and higher estimated interaction strengths exhibited a greater level of ecosystem reorganization (Figure S2). However, each of the three simulated scenarios differed in the level of among-expert disagreement, with the widest variation emerging from the simulated increase in herring (Figure 4b). Hypothetical scenarios representing expected ecosystem state related to increases in herring predator (whales) and prey (zooplankton) abundance produced variable responses among cognitive maps, but these responses did not diverge into distinct groups. In contrast, the hypothetical scenario related to an increase in herring produced two significantly divergent perspectives (Figure 5a). One expert group predicted a 182% greater reorganization of the ecosystem and a 78% higher average percent change in relative abundance relative to

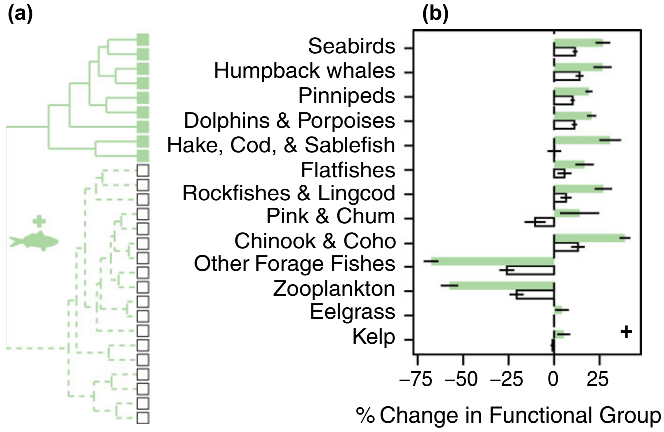


Figure 5 Divergent views among experts driven by variation in perceived impact of herring to the surrounding ecosystem. Dendrogram based on hierarchical cluster analysis of changes in relative abundance of 13 functional groups relative to the steady state (silhouette width 0.32). Dendrogram branch colors and tips correspond to two significant cluster units (open and closed tips, and solid and dashed branches). Barplot of univariate response of each functional group (b) shows the mean (±1 SE) percent change in the relative abundance of each functional group underlying the multivariate clusters. Note the majority of functional groups follow the same directional shifts in relative abundance with the exception of pink and chum salmon, which expert groups perceive responding differently to the simulated herring increase.

the other expert group (Figure 5b). These contrasting perspectives center on the strength of expected declines in relative abundance of zooplankton (typically herring prey) and other forage fish (resource and apparent competitors with herring), and expected increases in herring predators (e.g., groundfish, whales, and seabirds; Figure 5). Background and demographic characteristics did not explain the discordant perspectives between these two expert groups (Table S4). Furthermore, the demographic composition of these two groups is very similar, with 85% of the individuals from the cluster analysis of ecosystem structure found in identical groups that emerged from cluster analysis of simulated increases in herring.

For the increased predator and prey scenarios that led to relative consensus among experts (i.e., lower multivariate dispersion in community response to simulated scenarios), an understanding of differences in perception of herring ecosystem structure would have inappropriately suggested potential for divergent views over ecosystem functioning (Figure 4a). This diminished divergence of expert perceptions did not emerge from the increased herring scenario (Figure 4b). Rather, structural differences in perception of the herring ecosystem were critical predictors of functional differences where herring were the focal point of change.

Discussion

For a wide range of public policy issues, there is an increasing dependence on scientific expertise to inform decision-making (Martin *et al.* 2012) and a broadening expectation for experts to extend their knowledge to more disparate areas (Gibbons 1999). Many of these issues (e.g., coastal defense and Hurricane Sandy/Katrina, Ebola dynamics, and GMO foods) are directly related to how ecosystems will respond to forecasted increases in natural and anthropogenic perturbations (Turner 2010). As in other spheres, because of limited data and the urgency of decision-making, the institutional and governance structures of natural resource and conservation management increasingly rely on expert knowledge (Thuiller *et al.* 2008). This reliance comes despite widespread acknowledgment that expert knowledge is often incomplete, variable, and biased (Martin *et al.* 2012; Drescher *et al.* 2013). We show here that among-expert differences in perceptions of ecosystem structure are logically tied to consequences for how an individual might view the outcomes or impacts of predicted future change. Recognizing this causal chain, and quantifying it explicitly, is the first step toward navigating ecosystem-based conservation decisions that rely on expert knowledge.

Experts are susceptible to known cognitive biases due to heuristics (i.e., informal rules people use to make judgments) such as "availability," the ease with which an idea can be brought to mind, and "anchoring and adjustment," where an individual is provided a particular value or range of values and adjusts from that "anchor" (Morgan 2014). To diminish the likelihood of including these biases in our data set, we attempted to reduce variation in weighted estimates between variables and focus measurement on knowledge variation in terms of network structure, as opposed to variation in probability estimates (Morgan 2014). Through our approach, we show that among-expert differences in perceptions of ecosystem structure are logically tied to consequences for how an individual might view the outcomes or impacts of predicted future change. Recognizing and quantifying causal chains can allow experts to consider multiple factors that influence one another in a complex web of interactions, including feedbacks. The exact reasons underlying differences among expert knowledge and perceptions are unclear. Future studies would benefit from including meta-knowledge about expert knowledge, including dimensions about knowledge confidence in the relationships represented and epistemic orientations (Miller *et al.* 2008), to understand how different "ways of knowing" maybe more or less valued by different expert groups and influence expert knowledge representations.

Our results show that experts can exhibit divergent views about the structure of a complex ecosystem, independent of commonly identified "bins" of expertise (e.g., local, scientific, traditional). Our inability to predict variability in perceptions through demographic characteristics stands in contrast to examples from other arenas (e.g., political party affiliation and ideologies; Pinello 1999). Yet, expert backgrounds (e.g., years of experience) do not always predict expert performance (Burgman, McBride *et al.* 2011). Our finding reinforces the concept that expert knowledge is more fluid and pluralistic than discrete categories acknowledge (Raymond *et al.* 2010; Krueger *et al.* 2012). However, it is also possible that we did not detect links among background characteristics and perceptions because there were hidden demographic characteristics we did not test, our study was limited in statistical power, or perhaps there was some cognitive bias resulting from our elicitation method (Morgan 2014). Simulated management scenarios using cognitive maps of the herring ecosystem highlighted additional implications based on differences in perceptions of how ecosystems may respond to future perturbations. In particular, simulations of herring recovery using each expert's unique perception of food web structure demonstrated that not all experts perceive herring as having a similar number and strength of connections to the broader ecosystem and that this may lead to different predicted outcomes across the food web. These disparities in perception are particularly significant because herring sit at the center of the food web (Watts & Strogatz 1998), as is common for many marine forage species in coastal ecosystems (Cury *et al.* 2000). Moreover, similar variability in perception is likely to be common for complex networks with the potential to be highly centralized, dynamic, and interactive (e.g., financial systems; May 2013).

Among-expert variability in perceptions of the number and strength of connections between herring and the rest of the food web portends of variable management advice by experts when it comes to: (1) protected species (e.g., seabirds and marine mammals) that consume herring, (2) sustainable harvest of commercially valuable fishes that prey upon herring (e.g., groundfishes and salmon), and (3) marine ecosystem-based management in the Northeast Pacific. For example, experts were divided in their expectations about the impacts of a herring increase on Pink and Chum salmon: one group predicted an increase while the other predicted a decline (Figure 5b). Under the same scenario, one group of experts perceived a simulated increase in herring would lead to an 89% greater increase in whales relative to the other group (Figure 5b). These results suggest managers of the herring ecosystem are confronted with different knowledge systems and diverse perceptions that they must reconcile or reject as they weigh different (and at times divergent) forms of expertise. As in many other environmental decision-making contexts, recognition of these variable perceptions of food web structure may encourage efforts to fill knowledge gaps in areas where experts disagree. Where there is expert consensus, promoting social learning among stakeholders about commonalities in their logical chains of reasoning, despite diverse and cultural backgrounds, may be a positive force in a system where mistrust and differences in values contribute to conflict over common pool resources (Welch 2015). In contrast, mixed demographic composition within a cluster of experts with similar food web perceptions could be associated with differences in values as well as mistrust, making it difficult to find consensus (Burgman, McBride *et al.* 2011). By including diverse sets of expert knowledge, the total space of available knowledge increases and can be particularly useful for exploring events and processes that are outside the normal range or are difficult to test empirically. Furthermore, while variable expert perceptions can lead to conflict, it may also be a positive force through integration with adaptive management. For example, given a set of common ecosystem goals, surveys could be used to describe variation in expert perceptions and to test alternative logical chains of reasoning that compete with one another, and data which support a group of experts' knowledge can be used to validate perceptions empirically. In these cases, conflicting expert knowledge can be considered an asset, as opposed to a liability, since knowledge diversity is likely to lead to scrutiny of expert opinions, leading to more robust conservation decision-making.

Conclusion

Previous research has demonstrated that expert perceptions can vary widely; however, fewer studies have explored the potential implications of diverse expert perceptions for the management of complex SESs. Our findings demonstrate how the composition of expert panels will strongly influence expert perceptions of ecosystem structure, which can have cascading effects on the perceived outcomes of future management actions. As such, binning knowledge into a priori categories based on expert backgrounds can lead to erroneous conclusions; rather, embracing a diversity of knowledge in dialogue surrounding alternative management actions will help address uncertainty, can reduce conflict, and potentially improve management outcomes. Demonstrating the variety of perceptions that exist, and the potential implications of these variable perceptions given future management scenarios, is a critical step to moving forward with ecosystem-based conservation in the face of uncertainty that surrounds complex systems and their dynamics.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's web site:

Table S1. Number of technical experts per affiliation and gender category.

Table S2. Species embedded within each of the 14 functional groups described to participants.

Table S3. IPCC certainty values .

Table S4. Multivariate analysis testing whether demographic characteristics predict variation in food web network metrics.

Table S5. Demographic predictors of three scenarios simulating press perturbations to the food web at the bottom (zooplankton increase), middle (herring increase), and top (whale increase).

Figure S1. The capacity of two clusters of experts (white and green) based on structural properties of the system to predict variation in ecosystem response to three perturbations.

Figure S2. Positive correlation between a structural property of each expert's mental model of the food web and the amount the ecosystem fluctuates in response to the increased herring scenario.

References

Ainsworth, C.H., Pitcher, T.J., Heymans, J.J. & Vasconcellos, M. (2008) Reconstructing historical marine ecosystems using food web models: Northern British Columbia from pre-European contact to present. *Ecol. Model.*, **216**, 354-368.

Beaudreau, A.H., Levin, P.S. & Norman, K.C. (2011) Using folk taxonomies to understand stakeholder perceptions for species conservation. *Conserv. Lett.*, **4**, 451-463.

Biernacki, P. & Waldorf, D. (1981) Snowball sampling: problems and techniques of chain referral sampling. *Sociol. Method. Res.*, **10**, 141-163.

Biggs, D., Abel, N., Knight, A.T., Leitch, A., Langston, A. & Ban, N.C. (2011) The implementation crisis in conservation planning: could "mental models" help? *Conserv. Lett.*, **4**, 169-183.

Burgman, M., Carr, A., Godden, L. *et al*. (2011) Redefining expertise and improving ecological judgment. *Conserv. Lett.*, **4**, 81-87.

Burgman, M.A., McBride, M., Ashton, R. *et al*. (2011) Expert status and performance. *PLoS ONE*, **6**, e22998.

Cleary, J.S. (2014) Stock assessment and management advice for British Columbia pacific herring: 2013 status and 2014 forecast. *Canadian Sci. Adv. Sec.*

Cury, P., Bakun, A., Crawford, R.J. *et al*. (2000) Small pelagics in upwelling systems: patterns of interaction and structural changes in "wasp-waist" ecosystems. *ICES J. Mar. Sci.: Journal du Conseil*, **57**, 603-618.

de la Mare, W., Gales, N. & Mangel, M. (2014) Applying scientific principles in international law on whaling. *Science*, **345**, 1125-1126.

Dietz, T. (2013) Bringing values and deliberation to science communication. *P. Natl. Acad. Sci.*, **110**, 14081-14087.

Doswald, N., Zimmermann, F. & Breitenmoser, U. (2007) Testing expert groups for a habitat suitability model for the lynx Lynx lynx in the Swiss Alps. *Wildlife Biol.*, **13**, 430-446.

Drescher, M., Perera, A., Johnson, C., Buse, L., Drew, C. & Burgman, M. (2013) Toward rigorous use of expert knowledge in ecological research. *Ecosphere*, **4**, 1-26.

Ford, J.K. (2009) *An assessment of the potential for recovery of humpback whales off the Pacific coast of Canada*. Canadian Science Advisory Secretariat = Secrétariat canadien de consultation scientifique.

Gibbons, M. (1999) Science's new social contract with society. *Nature*, **402**, C81-C84.

Gray, S., Chan, A., Clark, D. & Jordan, R. (2012) Modeling the integration of stakeholder knowledge in social–ecological decision-making: benefits and limitations to knowledge diversity. *Ecol. Model.*, **229**, 88-96.

Gray, S.A., Zanre, E. & Gray, S. (2014) Fuzzy cognitive maps as representations of mental models and group beliefs. Pages 29-48. *Fuzzy cognitive maps for applied sciences and engineering*. Springer.

Hey, J., Waples, R.S., Arnold, M.L., Butlin, R.K. & Harrison, R.G. (2003) Understanding and confronting species uncertainty in biology and conservation. *Trends Ecol. Evol.*, **18**, 597-603.

Iniesta-Arandia, I., del Amo, D.G., García-Nieto, A.P., Piñeiro, C., Montes, C. & Martín-López, B. (2015) Factors influencing local ecological knowledge maintenance in Mediterranean watersheds: insights for environmental policies. *Ambio*, **44**, 285-296.

IPCC. (2014) *Climate change 2014: impacts, adaptation, and vulnerability. Part A: global and sectoral aspects. Contribution of working group II to the fifth assessment report of the Intergovernmental Panel on Climate Change*. In Field, C.B., Barros, V.R., Dokken, D.J. *et al.*, editors. Cambridge University Press, Cambridge, UK and New York.

Jones, R., Rigg, C. & Lee, L. (2010) Haida marine planning: first nations as a partner in marine conservation. *Ecol. Soc.*, **15**, 12. http://www.ecologyandsociety.org/vol15/iss1/art12/

Jones, N.A., Ross, H., Lynam, T., Perez, P. & Leitch, A. (2011) Mental models: an interdisciplinary synthesis of theory and methods. *Ecol. Soc.*, **16**.

Krueger, T., Page, T., Hubacek, K., Smith, L. & Hiscock, K. (2012) The role of expert opinion in environmental modelling. *Environ. Modell. Softw.*, **36**, 4-18.

Kosko, B. (1986) The role of expert opinion in environmental modelling, **24**, 65-75.

Leschine, T.M., Pavia, R., Walker, A.H., Bostrom, A. & Starbird, K. (2015) What-if scenario modeling to support oil spill preparedness and response decision-making. *Hum. Ecol. Risk Assess.*, **21**, 646-666.

Levin, D.A. (1979) The nature of plant species. *Science*, **204**, 381-384.

Lynam, T. & Brown, K. (2011) Mental models in human-environment interactions: theory, policy implications, and methodological explorations. *Ecol. Soc.*, **17**, 24. http://www.ecologyandsociety.org/vol17/iss3/art24/

Mantua, N.J. & Hare, S.R. (2002) The Pacific decadal oscillation. *J. Oceanogr.*, **58**, 35-44.

Martin, T.G., Burgman, M.A., Fidler, F. *et al.* (2012) Eliciting expert knowledge in conservation science. *Conserv. Biol.*, **26**, 29-38.

May, R.M. (2013) Networks and webs in ecosystems and financial systems. *Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*, **371**.

Miller, T.R., Baird, T.D., Littlefield, C.M., Kofinas, G., Chapin, III F.S. & Redman, C.L. (2008) Epistemological pluralism: reorganizing interdisciplinary research. *Ecol. Soc.*, **13**, 46. http://www.ecologyandsociety.org/vol13/iss2/art46/

Morgan, M.G. (2014) Use (and abuse) of expert elicitation in support of decision making for public policy. *P. Natl. Acad. Sci.*, **111**, 7176-7184.

Özesmi, U. & Özesmi, S.L. (2004) Ecological models based on people's knowledge: a multi-step fuzzy cognitive mapping approach. *Ecol. Model.*, **176**, 43-64.

Pinello, D.R. (1999) Linking party to judicial ideology in American courts: a meta-analysis. *Justice Syst. J.*, **20**, 219-254.

Raymond, C.M., Fazey, I., Reed, M.S., Stringer, L.C., Robinson, G.M. & Evely, A.C. (2010) Integrating local and scientific knowledge for environmental management. *J. Environ. Manage.*, **91**, 1766-1777.

Redpath, S.M., Young, J., Evely, A. *et al.* (2013) Understanding and managing conservation conflicts. *Trends Ecol. Evol.*, **28**, 100-109.

Ryder, D.S., Tomlinson, M., Gawne, B. & Likens, G.E. (2010) Defining and using 'best available science': a policy conundrum for the management of aquatic ecosystems. *Mar. Freshwater Res.*, **61**, 821-828.

Samhouri, J.F., Levin, P.S. & Ainsworth, C.H. (2010) Identifying thresholds for ecosystem-based management. *PLoS ONE*, **5**, e8907.

Schweigert, J.F., Boldt, J.L., Flostrand, L. & Cleary, J.S. (2010) A review of factors limiting recovery of Pacific herring stocks in Canada. *ICES J. Mar. Sci.: Journal du Conseil*.

Thuiller, W., Albert, C., Araújo, M.B. *et al.* (2008) Predicting global change impacts on plant species' distributions: future challenges. *Perspect. Plant Ecol. Evol. Systemat.*, **9**, 137-152.

Turner, M.G. (2010) Disturbance and landscape dynamics in a changing world. *Ecology*, **91**, 2833-2849.

Venables, W.N. & Ripley, B.D. (2002) *Modern applied statistics with S*, 4th ed. Springer-Verlag, New York.

Waples, R.S. (1991) Pacific salmon, Oncorhynchus spp., and the definition of "species" under the Endangered Species Act. *Mar. Fish. Rev.*, **53**, 11-22.

Watts, D.J. & Strogatz, S.H. (1998) Collective dynamics of 'small-world' networks. *Nature*, **393**, 440-442.

Welch, C. (2015) Fighting over herring—the little fish that feeds multitudes. *Natl. Geogr*.

Classification: SOCIAL SCIENCES

SUPPLEMENTARY INFORMATION

Table of Contents

I. Cognitive Maps

Cognitive maps have their historical roots in cognitive mapping (Axelrod et al. 1976), originally developed by Kosko (1986) as a semi-quantitative soft computing method to structure expert knowledge similar to the way the human mind makes predictions based on logical chains of reasoning. Cognitive maps are graphical representations of a system that visually illustrate the relationships or edges between key concepts (nodes) of the system, including feedback relationships. The justification for representing cognition by means of structural maps is derived from constructivist psychology (Gray et al. 2014), which suggests that individuals interactively construct knowledge by creating internal associative representations that help catalogue, interpret and assign meaning to environmental stimuli and experiences (Raskin 2002). This organized understanding can then be used to make predictions about the dynamics of the external world, and therefore, are thought to be the basis of human reasoning. Therefore, cognitive maps can be considered external representations of internal 'mental models' (Jones et al. 2011). Individuals assimilate external events and accommodate information into these mental model structures to facilitate reasoning and exchange understanding (Craik 1943; Piaget 1976).

II. Expert Elicitation Methods

We performed an expert elicitation of the number and strength of interactions between pairs of 14 functional groups within the herring-centric food web of Haida Gwaii, British Columbia. To build cognitive maps of the herring ecosystem in Haida Gwaii, we constructed a food web with 14 functional groups (Table S2), based on published literature, our natural history knowledge of important ecosystem interactions, and through pilot testing with 5 experts to check survey length and ensure the clarity and intelligibility of the question format and terminology.

Experts were defined as having technical or local knowledge and/or practical experience in Haida Gwaii ecosystems and were identified through stratified chain referral sampling (Biernacki and Waldorf 1981). In total, we contacted 46 potential experts by email. A total of 31 responded positively, 5 declined to participate and 10 did not respond. Authors administered the survey either in person (13 people) or by phone (18 people), and of the 31 people who participated, we obtained a total of 27 completed species matrices for analysis. After completing the 27 surveys we had exhausted the pool of local experts using the stratified chain referral sampling produced.

The elicitation consisted of a series of demographic questions detailing information that could potentially influence responses (e.g., age, gender, years of experience, professional affiliation, training, and place of residence) (Table S1). and an interaction matrix with 14 functional groups (Table S2).

Table 1: Number of technical experts per affiliation and gender category. Circles represent the percentage of the total group (27 experts) represented by a given affiliation or gender category.

	Affiliation				Gender	
	Academic	Agency	Haida	Residents	Male	Female
	30%	31%	19%	44%	59%	41%
Respondents	8	9	5	12	16	11

Table S2. Species embedded within each of the 14 functional groups described to participants.

Functional Group	Common Name	Scientific Name
Seabirds*	Gull species	*Larus spp.*
	Scoter species	*Melanitta spp.*
	Sea ducks, e.g. Common merganser	*Mergus merganser*
	Marbled murrelet	*Brachyramphus marmoratus*
Humpback whales	Humpback whale	*Megaptera novaeangliae*
Pinnipeds	Northern elephant seal	*Mirounga angustirostris*
	Harbor seal	*Phoca vitulina*
	Northern fur seal	*Callorhinus ursinus*
	California sea lion	*Zalophus californianus*
	Steller sea lion	*Eumetopias jubatus*
Dolphins & porpoises	Orca	*Orcinius orca*
	Pacific white sided dolphin	*Lagenorhynchus obliquidens*
	Dall's porpoise	*Phocoendoides dalli*
	Harbour porpoise	*Phocoena phocoena*
Hake, cod & sablefish	Hake	*Merluccius productus*
	Pacific cod	*Gadus macrocephalus*
	Walleye pollock	*Theragra chalcogramma*
	Sablefish	*Anoplopoma fimbria*
Flatfishes	Pacific halibut	*Hippoglossus stenolepis*
	English sole	*Parophrys vetulus*
	Rock sole	*Lepidopsetta bilineata*
	C-O sole	*Pleuronichthys coenosus*

	Starry flounder	*Platichthys stellatus*
Rockfishes & lingcod	Rockfish	*Sebastes spp.*
	Lingcod	*Ophiodon elongatus*
Pink & chum salmon	Pink salmon	*Oncorhynchus gorbuscha*
	Chum salmon	*Oncorhynchus keta*
Chinook & coho salmon	Chinook salmon	*Oncorhynchus tshawytscha*
	Coho salmon	*Oncorhynchus kisutch*
Herring	Pacific herring	*Clupea pallasii*
Other forage fishes	Northern anchovy	*Engraulis mordax*
	Sand lance	*Ammodytes hexapterus*
	Surf smelt	*Hypomesus pretiosus*
	Sardine	*Sardinops sagax*
	Capelin	*Mallotus villosus*
	Eulachon	*Thaleichthys pacificus*
Zooplankton*	Krill	*Thysanoessa spinifera*
	Copepod	*Calanoida species*
	Tunicate	*Oikopleura spp.*
	Barnacle larvae	*Cirripedia nauplii*
Eelgrass	Eelgrass	*Zostera marina*
Kelp	Giant kelp	*Macrocystis pyrifera*
		Macrocystis integrifolia
	Ground cover kelps	*Laminariales*
	Bull kelp	*Nereocystis luetkeana*

*Functional group may include other species in addition to those listed here.

We asked respondents how they perceived the strength of interaction between each species group. To guide respondents in completing the interaction matrix, authors asked respondents "does Species X have a strong negative, weak negative, neutral, weak positive or strong positive direct effect on Species Y?" Respondents were also given an opportunity to comment on the species groupings, include new species groups, and provide information on their uncertainty about interactions. To capture uncertainty, we followed the IPCC protocol (Table S2), where we assigned the default level of certainty at IPCC level 4 (Likely, 66-100% probability), and asked respondents to indicate if their certainty values were different than the default.

Table S3. IPCC certainty values

Certainty Level	Description
1	Very unlikely 0-10% probability
2	Unlikely 0-33% probability
3	About as likely as not 33-66% probability
4	Default. Likely 66-100% probability
5	Very likely 90-100% probability

Expert Elicitation Protocol

Below we provide a detailed description of the expert elicitation protocol.

Step 1. Potential respondents were contacted in advance via email to invite their participation in the elicitation, as follows:

> Dear ***Respondent***,
> I am writing to invite your participation in a research survey. The purpose of this research survey is to determine how perceptions of key socioeconomic and ecological interactions related to Pacific herring in Haida Gwaii vary among different groups of technical experts. We have identified you as a technical expert on Pacific herring in Haida Gwaii, Canada.
>
> This survey is being conducted by scientists affiliated with the Ocean Tipping Points project (http://www.oceantippingpoints.org), including myself.
>
> We will conduct the survey by phone [in person], at a time that is convenient for you. It will require up to 1 hour of your time. Individual responses will remain anonymous, except to the small group of researchers conducting the survey at the National Oceanic and Atmospheric Administration, Stanford University, and the University of California Santa Barbara.
>
> Please let me know if you are available on the following dates and times for the survey:
>
> Thank you in advance,
> ***Interviewer Y***

Step 2. We confirmed each respondent's participation, either by phone or in person, and a date and time for the interview. We then alerted the respondent that s/he would receive and email on the day of the interview with a few additional instructions. For both phone and in person interviews, we suggested to the respondent that s/he remain in front of a computer during the interview.

Step 3. Prior to the elicitation, we sent the respondent a blank species matrix (Table S1) and the demographic information questions:

Step 4: Our team conducted one-on-one interviews with respondents over the phone or in person. Interview protocol took approximately 1-2 hours, depending on the respondent. Each interviewer conducted the elicitation using a generic script below, asking each technical expert to answer some demographic questions and to fill in the species matrix guided by the interviewer.

SCRIPT

a) *Preamble:* Before beginning the survey we'd like to ask a few quick questions about you. You'll find this in the "Survey Instructions" folder in a file called: "Blank_Demographic_Info.xlsx". It includes questions about your educational background, area of expertise, experience with Haida Gwaii, etc.
b) *Intro:* Our interview comprises a set of questions related to species interactions. We have

sent you the matrix of interactions as an excel file, and you can start by focusing on the first column while we ask you the first set of questions. The general format of the questions is:

i) Does Species X have a *weak positive, strong positive, neutral, weak negative or strong negative* direct effect on any of the species in the list in front of you?
ii) We define an effect as something that is sufficient to cause a noticeable increase (positive effect) or decrease (negative effect) in the number of individuals in a population.

c) *Time horizon:* Please focus on a time horizon of the last 5 years and the next 5 years.
d) Certainty: describe IPCC uncertainty levels in Table S2
e) Recording: We would like to record this conversation in the event we need to go back and clarify any of your responses. Is that ok with you?
f) Ask respondent if s/he has any questions or needs clarification.
g) Open the empty interaction matrix:

i) Ask respondent to make sure s/he has the species descriptions table in front of her/him.
ii) Begin elicitation
    (1) Fill in responses for species interactions- Responses are filled in as positive (2,1) or negative (-1,-2) or neutral (0). Asking the respondent does Species X have a strong negative, weak negative, neutral, weak positive or strong positive direct effect on Species Y?
iii) Prompt respondent with: Are there any species not represented here that are substantially positively or negatively affected directly by herring?
iv) Read back responses to confirm you have captured what was said.
v) Note that for the *other forage fish* group, it was efficient for us to ask the respondent if their responses would differ from the ones they gave related to herring.
vi) Note that some respondents choose to respond differently for the species that are grouped into functional groups. It is ok to ungroup them.

h) BE SURE TO THANK YOUR RESPONDENT!!
i) Save your respondents answers and any notes associated with them carefully labeled with both respondent information and your information so we know who conducted the survey if we have questions.

Step 5: Interviewers sent an email to respondents thanking him/her for his/her time.

III. Cluster Analysis

We evaluated the optimal number of clusters using the silhouette coefficient (Kaufman and Rousseeuw 2009) We estimated the silhouette coefficient for 2 to 26 groups and selected the cluster groupings that yielded the highest average silhouette coefficient. Significant clusters were identified as groups that have average coefficients > 0.25 (Kaufman and Rousseeuw 2009). We used the *hclust*, *cluster.stats*, and *pam* functions in R.3.1.1 to conduct all cluster and partitioning analyses (R Development Core Team 2014).

IV. Supplementary Tables and Methods

Table S4. Multivariate analysis testing whether demographic characteristics predict variation in food web network metrics. To test whether demographic characteristics predict variation in the food web structural metrics we used multivariate permutation tests (PERMADISP and PERMANOVA Anderson et al. 2011; Anderson et al. 2006) to assess whether different a priori groupings differ in multivariate mean (left column) and multivariate dispersion (right column). Similar to MANOVA, PERMANOVA compares dissimilarity variance components within a group versus between groups; however, rather than using a standard *F*-ratio, a pseudo *F*-ratio (which we call F^{π} following Chase 2007) is calculated through permutations of the dissimilarity matrix. Because of multiple non independent comparisons, we adjusted p-values using a Benjamini-Hochberg correction (Benjamini and Hochberg 1995).

	Multivariate Mean		Multivariate Dispersion	
Demographic Characteristic	F^{π}	*P-value*	F^{π}	*P-value*
On or Off Island	1.244	0.762	2.86	0.762
Haida	1.584	0.762	0.357	0.762
Canadian Government	0.632	0.82375	0.564	0.823
DFO	0.995	0.762	0.135	0.762
Parks	0.388	0.838	1.501	0.838
Academic	0.683	0.82375	0.389	0.823
NGO	0.66	0.82375	0.752	0.823
Haida Government	0.468	0.838	1.319	0.838
Gender	1.174	0.762	0.237	0.762
Age	1.69	0.762	2.72	0.762

Table S5. Demographic predictors of three scenarios simulating press perturbations to the food web at the bottom (zooplankton increase), middle (herring increase), and top (whale increase). To test whether demographic characteristics predict variation in food web structural metrics we used multivariate permutation tests (PERMADISP and PERMANOVA Anderson et al. 2011; Anderson et al. 2006), which ask whether different a priori groupings differ in multivariate mean (left column) and multivariate dispersion (right column). We also demonstrate how post hoc groupings that emerged from network structural metrics (listed as “Structural Clusters” below) effectively predict variation in response to each of the three simulated scenarios (Fig. S1). Because of multiple non independent comparisons, we adjusted p-values using a Benjamini-Hochberg correction (Benjamini and Hochberg 1995).

Scenario					
Zooplankton increase		Multivariate Mean		Multivariate Dispersion	
	Demographic Characteristic	F^{π}	*P-value*	F^{π}	*P-value*
	On or Off Island	0.878	0.645	0.06	0.838
	Haida	1.634	0.350	0.689	0.630
	Canadian Government	1.959	0.350	2.43	0.386
	DFO	1.742	0.350	0.233	0.776
	Parks	0.351	0.941	7.51	0.108
	Academic	0.383	0.941	0.307	0.776
	NGO	0.914	0.599	2.074	0.386
	Haida Government	1.367	0.458	3.873	0.216
	Gender	0.582	0.936	0.101	0.838
	Age	1.572	0.350	1.318	0.582
	Structural Clusters	2.534	0.035	11.343	0.008

Herring		Multivariate Mean		Multivariate Dispersion	

increase

Demographic Characteristic	F^{π}	*P-value*	F^{π}	*P-value*
On or Off Island	1.431	0.4704	1.554	0.401
Haida	0.647	0.667	0.356	0.610
Canadian Government	1.023	0.667	4.51	0.164
DFO	2.166	0.213	6.538	0.072
Parks	0.632	0.667	0.566	0.527
Academic	0.948	0.667	0.044	0.845
NGO	0.729	0.667	0.771	0.511
Haida Government	0.628	0.667	2.425	0.271
Gender	2.425	0.213	2.46	0.276
Age	0.763	0.667	1.058	0.511
Structural Clusters	14.154	0.001	3.376	0.082

Whale Increase

	Multivariate Mean		Multivariate Dispersion	
Demographic Characteristic	F^{π}	*P-value*	F^{π}	*P-value*
On or Off Island	1.048	0.464	0.056	0.840
Haida	1.127	0.451	0.351	0.727
Canadian Government	1.817	0.156	3.506	0.332
DFO	1.398	0.390	1.326	0.477
Parks	0.236	0.972	1.842	0.332
Academic	2.386	0.104	2.294	0.332

NGO	0.526	0.707	1.867	0.332
Haida Government	1.459	0.390	0.190	0.764
Gender	1.279	0.411	0.638	0.611
Age	1.133	0.451	0.649	0.611
Structural Clusters	9.738	0.036	2.385	0.115

Links Between Mental Model Structure and Response of Mental Models to Scenarios

The number of connections and interaction strengths described in expert's cognitive maps are effective predictors of how the perceived ecosystem of each expert responded to simulated future scenarios. For example, structural groupings predict significant variability in the multivariate response of the ecosystem to all three scenarios (Fig. S1), and a correlation test reveals greater ecosystem reorganization in food webs with higher average interaction strength (Fig. S2, $r = 0.67$, $p = 0.0001$). This link between cognitive map structure and function highlights the mechanism underlying among-expert variation in perceived ecosystem response to simulated perturbations.

Figure S1. The capacity of two clusters of experts (white and green) based on structural properties of the system to predict variation in ecosystem response to three perturbations. Left hand side describes non-metric multidimensional scaling plots where blue circles and green squares each represent expert's perceived multivariate change in functional group relative abundance. Right hand side describes corresponding mean +/- 1SE ecosystem reorganization index for each of the scenarios. Overall, structural clusters significantly predict ($P < 0.05$, Table S4) variation in changes in mean functional group relative abundance for all three scenarios.

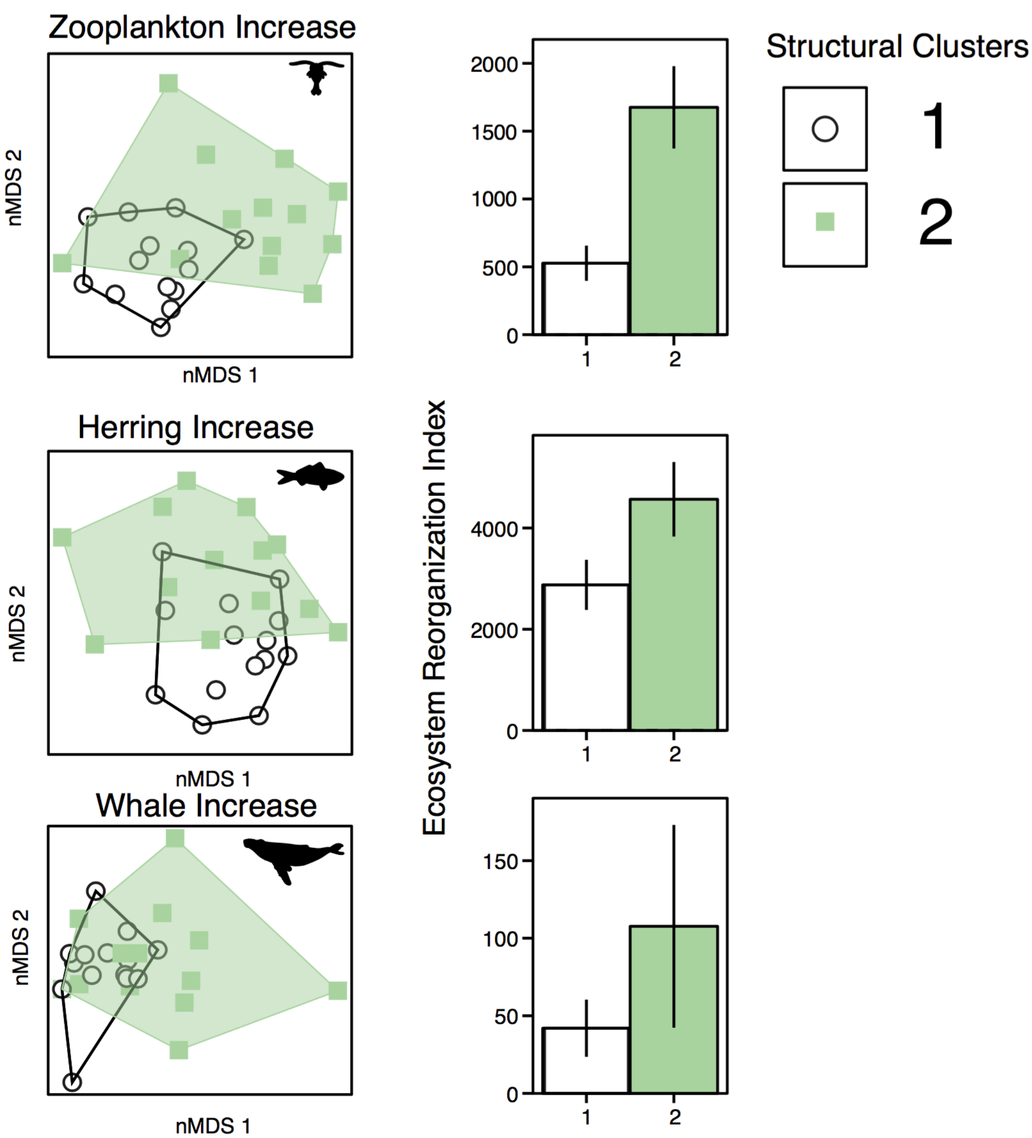

Figure S2. Positive correlation between a structural property of each expert's mental model of the food web and the amount the ecosystem fluctuates in response to the increased herring scenario. Each point represents a single expert, and point color and shape corresponds to the group in which each expert fell in the hierarchical cluster analysis (Fig. 1). See main text for additional details on calculation of the ecosystem reorganization index.