The diversity bonus in pooling local knowledge about complex problems

Payam Aminpour[a,1], Steven A. Gray[a,b], Alison Singer[c], Steven B. Scyphers[d], Antonie J. Jetter[e], Rebecca Jordan[a], Robert Murphy Jr[f], and Jonathan H. Grabowski[d]

[a]Department of Community Sustainability, Michigan State University, East Lansing, MI 48824; [b]Collective Intelligence Research Group, The IT University of Copenhagen, 2300 Copenhagens, Denmark; [c]Department of Biological Sciences, Northern Arizona University, Flagstaff, AZ 86011; [d]Department of Marine and Environmental Sciences, Coastal Sustainability Institute, Northeastern University, Nahant, MA 01908; [e]Department of Engineering and Technology Management, Portland State University, Portland, OR 97201; and [f]Fisheries, Aquatic Science, and Technology Laboratory, Alaska Pacific University, Anchorage, AK 99508

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Recently, theoreticians have hypothesized that diverse groups, as opposed to groups that are homogeneous, may have relative merits [S. E. Page, *The Diversity Bonus* (2019)]—all of which lead to more success in solving complex problems. As such, understanding complex, intertwined environmental and social issues may benefit from the integration of diverse types of local expertise. However, efforts to support this hypothesis have been frequently made through laboratory-based or computational experiments, and it is unclear whether these discoveries generalize to real-world complexities. To bridge this divide, we combine an Internet-based knowledge elicitation technique with theoretical principles of collective intelligence to design an experiment with local stakeholders. Using a case of striped bass fisheries in Massachusetts, we pool the local knowledge of resource stakeholders represented by graphical cognitive maps to produce a causal model of complex social-ecological interdependencies associated with fisheries ecosystems. Blinded reviews from a scientific expert panel revealed that the models of diverse groups outranked those from homogeneous groups. Evaluation via stochastic network analysis also indicated that a diverse group more adequately modeled complex feedbacks and interdependencies than homogeneous groups. We then used our data to run Monte Carlo experiments wherein the distributions of stakeholder-driven cognitive maps were randomly reproduced and virtual groups were generated. Random experiments also predicted that knowledge diversity improves group success, which was measured by benchmarking group models against an ecosystem-based fishery management model. We also highlight that diversity must be moderated through a proper aggregation process, leading to more complex yet parsimonious models.

diversity | social-ecological systems | collective intelligence | local knowledge | sustainability

Local users of natural resources may hold first-hand knowledge about complex social-ecological interdependencies through direct interactions with natural ecosystems, consuming resources, or striking a balance between exploitation and preserving ecosystem functionality (1, 2). They may also inherit traditional ecological knowledge from past generations (3) or share information about environmental, policy, or social changes across their social networks (4). This process can lead to the accumulation of valuable local knowledge (LK) that can complement or be substituted for scientific knowledge, especially in data-poor situations (2, 5, 6).

Yet, LK held by stakeholders may vary across groups, suggesting that different types of stakeholders hold biased and often inadequate perceptions of complex social-ecological interdependencies, which represents only a part of the complex system. These variations may be linked to diverging beliefs and values (7), disparate experiences and interactions with the natural ecosystems (8), and differences in preferred adaptation strategies and management policies (9), and are assumed to be more pronounced across different stakeholder groups (i.e., different user types) than within the same group (10, 11).

In this work, we draw on collective intelligence (CI) theory and hypothesize that the aggregation of LK from diverse stakeholder groups can produce more complete and potentially more accurate representations of complex problems with interconnected social and environmental components. CI is typically defined as a group phenomenon that enables a group to accomplish complex tasks where individuals or any subset within it might fail (12). This group advantage may emerge when a collective of individuals either collaborate or independently aggregate their knowledge to address a problem (12–14). The group may, therefore, benefit from a larger, more refined, or recombined body of knowledge, because aggregation mechanisms filter out errors and biases, compensate for individuals' insufficiencies, or result in innovative solutions (e.g., refs. 15–17).

A growing body of literature suggests that diversity of knowledge, once properly harnessed, is of the utmost importance to improve CI in a group (13, 15, 17–21). In general, and especially for complex problem-solving, theoretical and empirical evidence has demonstrated that diversity is positively correlated with

Significance

Groups can collectively achieve an augmented cognitive capability that enables them to effectively tackle complex problems. Importantly, researchers have hypothesized that this group property—frequently known as collective intelligence—may be improved in functionally more diverse groups. This paper illustrates the importance of diversity for representing complex interdependencies in a social-ecological system. In an experiment with local stakeholders of a fishery ecosystem, groups with higher diversity—those with well-mixed members from diverse types of stakeholders—collectively produced more complex models of human–environment interactions which were more closely matched scientific expert opinions. These findings have implications for advancing the use of local knowledge in understanding complex sustainability problems, while also promoting the inclusion of diverse stakeholders for increasing management success.

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[1]To whom correspondence may be addressed. Email: aminpour@msu.edu.

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group success (2, 6, 22, 23). However, these efforts have often been made through simplified mathematical models (e.g., ref. 18), computational experiments with artificial agents (e.g., refs. 15 and 24), or laboratory-based controlled experiments with gamified settings and role-playing human subjects (e.g., refs. 8 and 23), and it is therefore unclear whether these discoveries generalize to actual complex problems. To bridge this divide, here we explore whether diversity can improve a group's collective capability in representing a real-world complex problem.

Our experimental design includes the aggregation of LK crowd-sourced from diverse groups of natural resource stakeholders (e.g., resource users and managers). To implement this experiment, we used an example of striped bass (*Morone saxatilis*) population dynamics and fisheries management in Massachusetts (MA), United States. The striped bass fishery is an important component of coastal economies throughout the east coast and is composed of commercial and recreational fishers (see *SI Appendix*, Text S6 for more detail). While various stakeholder groups interact differently with the fishery, they each construct diverse knowledge about ecological dimensions (e.g., predator–prey relationships and recruitment dynamics), human dimensions (e.g., commercial and recreational fishing pressures), and their interrelationships. We explore how this diversity impacts the quality of stakeholders' aggregated knowledge.

We use a semiquantitative knowledge elicitation technique called Fuzzy Cognitive Mapping (FCM) (25) to represent each individual's LK about social-ecological relationships that influence striped bass populations and fisheries management. We collect these FCMs from various types of stakeholders, including recreational fishers, commercial fishers, and local fisheries managers via an online mental modeling technology (www.mentalmodeler.com), in the form of digitalized graph drawings (*SI Appendix*, Figs. S1 and S2). The individuals' drawings are then mathematically combined into a collective model representing the aggregated knowledge of stakeholders (i.e., a causal model). We first combine individual maps by stakeholder types to form homogeneous, stakeholder-specific models. Subsequently, the more diverse crowd model (including all stakeholder types) is created through aggregating models across groups (*Methods* and *SI Appendix*, Fig. S3). These aggregated models can be analyzed in terms of their qualitative compositions (i.e., what concepts are represented), network structure of causal relationships (i.e., how concepts are connected), and dynamic behavior (i.e., how changes in the state of one or multiple concepts initiate a cascade of changes in other concepts) (*Methods*).

In contrast to laboratory-based and computational experiments, in a complex reality, the actual ground truth is not explicitly known. Thus, we evaluate the success (i.e., accuracy and reliability) of stakeholder-driven models, both homogeneous and diverse, by 1) acquiring subjective judgments from a panel of scientific experts and 2) stochastically analyzing their network structures with respect to their representation of complex causality (*Methods*). Our findings revealed that aggregating knowledge from a diverse group of stakeholders produces a causal model of social-ecological interdependencies that can represent the structure of natural resource systems, their interactions with human societies, and their response to external perturbations, and these outcomes, overall, outrank those of more homogeneous groups.

Finally, to test the robustness of our findings, we conduct a Monte Carlo Analysis (MCA) (i.e., the generation of random samples) (26) that reproduces the distributions of stakeholder-driven cognitive maps and measures the success of randomly generated groups that represent various levels of diversity. To measure virtual groups' success, we compare the network structure of their aggregated models to a model of striped bass ecosystem-based fishery management (EBFM) (27). The National Oceanic and Atmospheric Administration (NOAA) has identified EBFM as the most efficient and effective model of fisheries management to maintain interconnected ecosystems and human societies in a healthy, productive, and resilient condition, while considering the full range of trade-offs and complex social-ecological interactions. Therefore, we used EBFM as a plausible benchmark against which the success of group models is measured (*Methods*).

Results

A total of 32 individuals completed the online mental modeling survey including 13 recreational fishers, 11 commercial fishers,

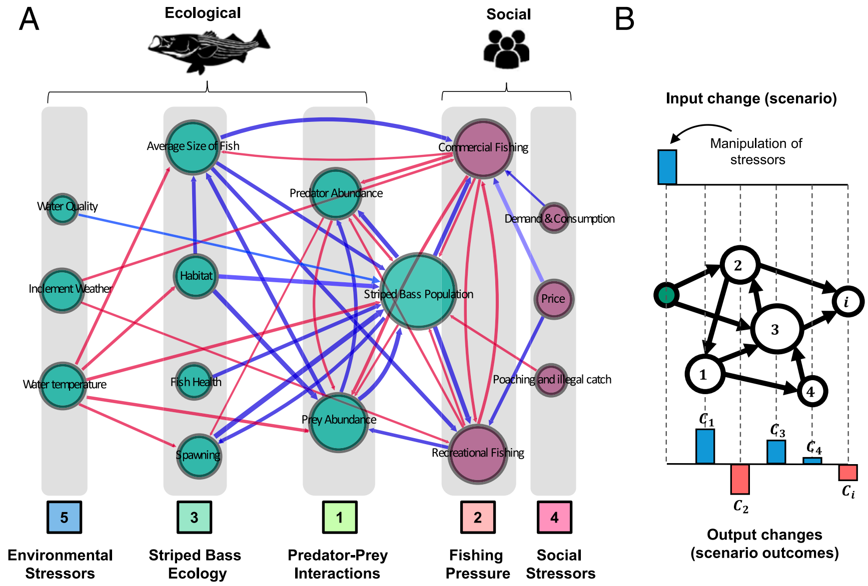

Fig. 1. Models' structural and dynamic components used in experts' subjective evaluations. (*A*) An example of a causal structure between 15 overlapping concepts (i.e., nodes that are shared among all stakeholder groups). Green/purple nodes in *A* are ecological/social concepts, blue/red links are positive/negative causal relationships, and node sizes correspond to the degree centrality (i.e., number of connections linking the node to other nodes). (*B*) Schematic illustration of model dynamics. For each of the six social and environmental stressors in *A*, the stressor's activation value is computationally manipulated to trigger a cascade of changes in other concepts that are causally connected. Scenario outcomes in *B* are relative changes in the activation of concepts as a result of artificial manipulations in the activation of stressors (*Methods* and *SI Appendix*, Figs. S10–S12).

and 8 fisheries managers. Computing the matrix distances between pairs of cognitive maps, both within groups and across groups (*Methods*), revealed that individuals within each group construct maps that are more similar to one another compared to members of other groups (*SI Appendix*, Fig. S4). These results confirmed the assumption that members of the same stakeholder type represent more correlated knowledge.

Aggregation of individual cognitive maps within stakeholder types resulted in three averaged models representing the perception of three homogeneous groups (*SI Appendix*, Figs. S5–S7). Group aggregated models varied widely in the number of nodes and connections (*SI Appendix*, Table S1), as well as the qualitative composition of concepts used to represent social-ecological relationships. For example, recreational fishers placed more emphasis on social concepts influencing fish populations (e.g., economy, coastal development, socioeconomic status of residents), while commercial fishers tended to incorporate more biological concepts (e.g., striped bass interactions with other species like mackere and herring), and managers emphasized management aspects (e.g., bycatch, poaching and illegal catch, undersized fish mortality) more frequently than other groups (*SI Appendix*, Fig. S9). These results may provide support for the claim that groups' specific interests drive their mental models of the external world. Additionally, aggregation across stakeholder types yielded a "diverse crowd model" (*Methods*). This latter model integrated the diverse knowledge of all three stakeholder-specific groups by preserving a median level of information presented by them (*SI Appendix*, Fig. S8).

Experts' subjective evaluations of homogeneous group and diverse crowd models first explored the "model structure" based on the patterns of causal relationships that represent 1) striped bass predator-prey food web, 2) the effect of fishing pressures on striped bass, 3) striped bass connection to ecology and habitat, 4) socioeconomic stressors, and 5) environmental stressors affecting the striped bass population (Fig. 1*A*). These causal patterns represent interdependences between 15 concepts that are shared among all groups and, therefore, used for comparisons. In addition, experts' evaluations were conducted to examine the "model dynamics" based on how models responded to computational manipulations (i.e., scenarios) of social and environmental stressors (Fig. 1*B*). These computational manipulations simulated perturbations in 1) inclement weather for fishing, 2) water temperature, 3) water quality, 4) price of fish, 5) demand and consumption, and 6) poaching and illegal catch.

Experts, on average, rated the diverse crowd model as the most accurate map among the four models because it most adequately and correctly represented the causal relationships and feedback loops in the striped bass fishery SES. Overall, scientific experts assessed that the causal structure of the crowd model was 65% accurate, followed by 55% accuracy for fisheries managers, 48% for recreational fishers, and 43% for commercial fishers (Fig. 2*A*). Similarly, experts rated the crowd model as the most accurate regarding models' responses to simulated manipulations of social and environmental stressors. On average, scientific experts determined that the diverse crowd model was most accurate (75%) regarding simulated dynamics, while the fisheries managers' model ranked second in this category with 50% accuracy. The models of commercial fishers and recreational fishers were assigned 39% accuracy by the expert panel (Fig. 2*B*). All experts located the diverse crowd model in the upper-right quartile in Fig. 2*C*, indicating accurate structure and dynamics, while for homogeneous models, there exists at least one expert that located the model in one of the quartiles that represent inaccuracy in either structure or dynamics.

Also, experts' qualitative evaluations of "model composition" revealed the number of false negatives or false positives (i.e., not including necessary system components or including unnecessary and redundant ones, respectively). These qualitative assessments included all concepts, aside from 15 overlapping concepts that all three stakeholder groups mentioned in common and, therefore, complemented experts' subjective evaluations of model structure. Comparing the proportion of "false" errors in four aggregated models revealed that, on average, the expert panel identified 20% of the crowd model's composition as false positive or false negative, whereas false error rates ranged from 32 to 55% for the stakeholder-specific models (*SI Appendix*, Figs. S15 and S16).

In addition, we evaluated the extent to which system complexities were captured by each model via a stochastic network analysis that measured the prevalence of complex micromotifs in a model (i.e., complex microstructures including bidirectionality, indirect effect, multiple effects, and feedback loop) (see ref. 28). Fig. 3 shows the deviations of motif counts from their expected value as a measure of motifs' prevalence (*Methods*). Our results demonstrated that the aggregated model of the diverse crowd had a higher prevalence for all complex motifs compared to the expectation, thereby representing a higher perception of complex causality. The aggregated model of recreational fishers also had high prevalence for all tested motifs while managers had a low prevalence of the motif "indirect effects," indicating a lower appreciation of cascading impacts (29). The aggregated model of commercial fishers, however, had low prevalence for all tested complex motifs, indicating that commercial fishers tended to perceive the system as more linear with hierarchal casual structures.

Finally, results of the MCA with 10,000 reproductions of cognitive maps distributions revealed that the aggregated models of randomly generated diverse crowds, as opposed to homogeneous groups, demonstrated higher similarity to a benchmark model of EBFM for striped bass (Fig. 4 *A* and *B*). Additionally, virtual combinations of random individuals from three stakeholder types resulted in groups with different levels of diversity (Fig. 4*C*). The model computed the success of these virtual groups via measuring their matrix similarity to EBFM and predicted that group diversity and performance (i.e., success) were positively correlated (Fig. 4*D*).

Discussion

Our results provide insights into how knowledge diversity affects the success of a group in effectively representing a complex problem with interconnected social and environmental dimensions (i.e., a SES). We used an example of striped bass fisheries in MA to implement our experiment in a real-world context with local individuals. This special example is a natural resource system with diverse stakeholders, which represents a wide range of complex feedback between humans and the natural ecosystem. Our results may therefore apply to a more general domain of complex problems (e.g., disease spread, large-scale natural disasters, social inequities) that are shared among academics, policymakers, and businesses and impact large numbers of individuals who collectively may help us understand and address these issues.

In our case, individuals interact with natural resources, observe changes, and sample ecosystems in different ways, and this may lead them to construct diverse perceptions about social-ecological interdependencies (5, 10). Yet, we showed that LK of stakeholders in a SES are more likely correlated with their peers of the same stakeholder type than members of other types (*SI Appendix*, Fig. S3). This could be a consequence of similarities in values and interests, the similar ways they use and interact with natural resources, their more frequent communications and knowledge sharing, and their likely exposure to a similar set of information sources (e.g., media outlets). Therefore, each group may accumulate knowledge that is biased to some degree (*SI Appendix*, Fig. S9).

Consistent with past theoretical studies (e.g., "diversity trumps ability" theorem) (18), we found that the aggregation of LK obtained from a diverse group of stakeholders produces a system representation that outperforms those of homogeneous groups. However, to be successful, the aggregation needs to mediate the

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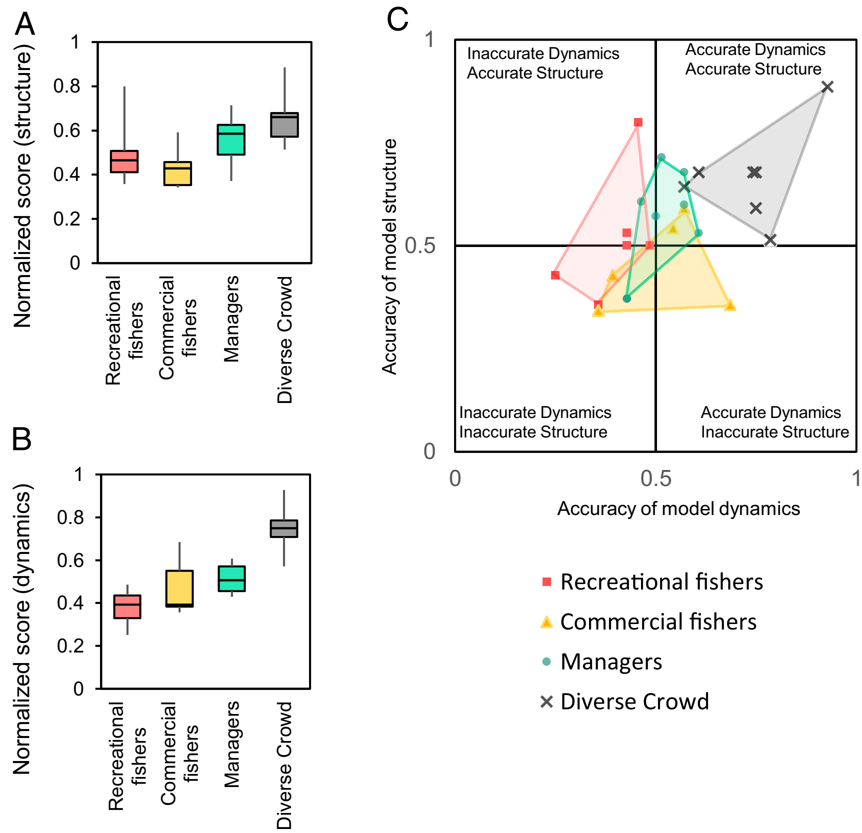

Fig. 2. Experts' subjective evaluation of aggregated models. The box plots represent the distribution of experts' opinions regarding models' structure (*A*) and dynamic accuracy (*B*). The accuracy was measured using a seven-point Likert scale for each item of interview sheets (*SI Appendix*, Figs. S13 and S14). The subjective accuracies designated to each model's causal structures (i.e., five substructures illustrated in Fig. 1*A*) were averaged and normalized to an interval between 0 and 1. Similarly, subjective accuracies designated to each model's dynamics (i.e., outcomes under six scenarios illustrated in *SI Appendix*, Fig. S10) were averaged and normalized to an interval between 0 and 1. The two-dimensional scatter plot in *C* shows the distribution of normalized accuracy scores given to four models by individual experts, where *x* axis is the accuracy regarding models' dynamics and *y* axis is the accuracy regarding models' structure.

accumulation of likely correlated knowledge of members of the same stakeholder type, filter out the biases associated with each group's LK, and most effectively combine diverse expertise across multiple groups (30, 31). To that end, our aggregation method expands prior theoretical and empirical findings about the optimum aggregation of judgments or predictions of unknown quantities from a group of independent individuals—traditionally known as the wisdom of crowds (WOC) effect (32)—to instead aggregate mental models (*Methods*).

In this study, we used both subjective and objective evaluations to measure the performance of aggregated models. Although experts who subjectively judged the accuracy of the stakeholder-driven models represented a wide range of academic disciplines and professional expertise (e.g., fisheries ecology, economics), a clear majority of experts rated the diverse crowd model as more accurate than the homogeneous models. Additionally, stochastic network analysis revealed that the diverse crowd model demonstrated a more thorough representation of complex micro motifs as building blocks of complex causality. While, the higher prevalence of complex causal representations does not necessarily relate to how well the model works, when considered in conjunction with the experts' subjective evaluations, our study suggests that pooling diverse crowds' LK, as opposed to homogeneous groups, may result in system models that are more complex and more closely match the opinions of a group of diverse experts.

Similar to our experiment with actual human subjects, results of random experiments with virtual agents suggested that more diverse groups better succeeded in system modeling compared to homogeneous ones (Fig. 4). To measure the success in MCA, we compared each group's aggregated model to an EBFM model. Although an EBFM model does not fully represent the complex reality of the social-ecological interdependencies and is not considered a ground truth, it takes into account striped bass interactions with other species in the food web; the effects of environmental changes, pollution and other stressors on habitat and water quality; and the impact of socioeconomic conditions, and it is recommended by NOAA Fisheries (27). Therefore, it represents a credible reference point for determining social-ecological interdependences in striped bass fisheries (*SI Appendix*, Fig. S17).

These results have important implications for the sustainability of SESs: First, addressing uncertainty is a challenge for policy and decision-making, especially in data-poor situations. Uncertainties are typically related to the absence of empirical data and formal scientific knowledge (i.e., scientific uncertainties), and the inability to predict management success/outcomes (i.e., management uncertainties). Our study provides evidence for the benefits of pooling LK held by diverse groups of local stakeholders to overcome both types of uncertainties. As such, even in data-rich situations, scientific communities should bring in inputs from local people to inform resource and environmental management to not only complement the knowledge developed by professional science, but to also overcome management uncertainties (33).

Second, our findings have applications for designing inclusive processes and adaptive comanagement practices (34). Such approaches encourage the participation and involvement of relevant stakeholders and may enhance the credibility and legitimization of

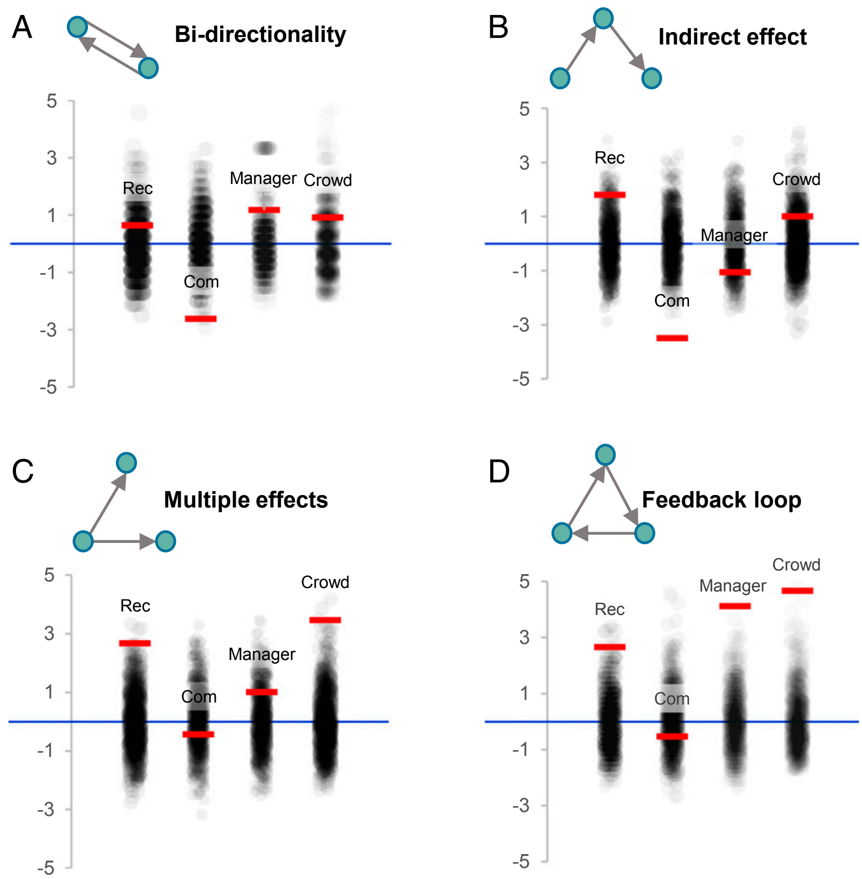

Fig. 3. Deviation of the prevalence of complex causal motifs in aggregated models relative to uniform random graphs for bidirectionality (*A*), indirect effect (*B*), multiple effects (*C*), and feedback loops (*D*). Black dots represent 10,000 random graphs, and the blue line shows the expected value of motif counts. Red dashes represent the deviation of each model from the expected value.

management strategies while resource users, managers, and scientists bridge their divides and jointly agree on possible management actions for uncertain ecosystems (35). Furthermore, an inclusive process with buy-in from stakeholders could have positive feedbacks, such as greater support for and compliance with management measures. Despite these promising successes, adaptive comanagement practices often suffer from a lack of readily available models by which complex social-ecological interdependences are adequately described and probable outcome scenarios are anticipated. We therefore recommend proactively involving local stakeholders in complex system representations and modeling by pooling their LK resulting from online mental modeling means.

Materials and Methods

Mental Models and FCMs. In this study, we used FCMs to represent stakeholders' mental models about striped bass fisheries in MA. To understand stakeholders' perceptions and knowledge about natural resources, researchers have suggested the importance of eliciting and measuring mental models (11, 36–39). However, many mental model elicitation techniques yield qualitative representations of associative rules between concepts/ideas, with few standardized methods to compare, aggregate, and computationally manipulate them (37). Here, we used FCM—a semiquantitative technique—to bridge the divide between highly computational system modeling and easy-to-construct qualitative cognitive or concept mapping. FCMs are graphical models of an individual's perception showing a network of cause-and-effect relationships (edges) among different concepts (nodes) and can be computationally manipulated due to the numerical parametrization of the strength of causal relationships. These models are therefore simulation tools that can be used to assess an individual's knowledge about dynamics of the system they represent (40). By increasing or decreasing a concept in the map (e.g., water temperature), "what-if" scenarios can be simulated using the autoassociative neural network method (41) (*SI Appendix*, Text S1).

Online Crowdsourcing Implementation. This study was conducted with approval of Michigan State University's Institutional Review Board (IRB) (STUDY00000074), and informed consent was acquired from all participants. We used a contact list of recreational and commercial fishers licensed in MA, and a contact list of fisheries managers including individuals from NOAA, the Massachusetts Division of Marine Fisheries, and the Atlantic States Marine Fisheries Commission. An iterative sampling approach was used, until we reached a desired sample size of 10–15 responses from each type of stakeholders. Individuals who indicated their willingness to participate received instructions through email. Each individual participated independently in an online mental modeling survey, where they used an online mental modeling technology (www.mentalmodeler.org) to make an FCM about striped bass population dynamics and social-ecological factors that impact fish population and fishery management.

Participants were given a written step-by-step manual (*SI Appendix*, Text S2) and a series of short videos instructing them how to brainstorm, identify, and add components via an online graphical interface—all concepts that they believe impact either their fishing effort and/or the striped bass population and fishery. Participants were then asked to use this modeling technology to draw lines between concepts and assign a relative value between 0 and 1 (either positive or negative) to each link based upon the degree to which one concept affects another. This exercise was completed when the participant could no longer think of additional relevant concepts or linkages among concepts. Participants saved their models and sent them to the project's email address.

The Wisdom of Crowds and Knowledge Aggregation. To aggregate stakeholders' LK, we expanded a well-documented method called the WOC (13, 32). WOC refers to the finding that groups of people, under certain

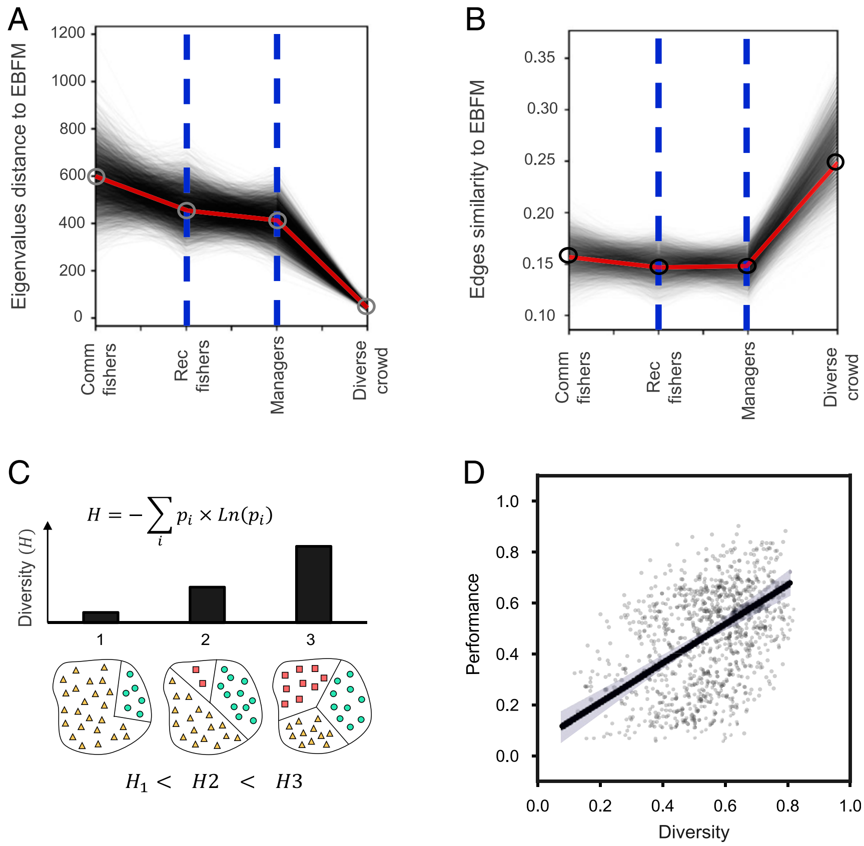

Fig. 4. The Impact of diversity on group performance in 10,000 replicates of the MCA. (*A*) Eigenvalues distance (*Methods*) between group models and the EBFM. (*B*) Edges similarity (*Methods*) between group models and EBFM. (*C*) Three mockup examples of virtual groups with the same size but different levels of diversity from low to high, which is measured by Shannon entropy formula (H), taking into account both the number of unique stakeholder types and the evenness of their proportions in a group. (*D*) Correlation between group diversity and group performance. Group performance in *D* is a normalized score measuring group model similarity to EBFM (*Methods*), and shaded area corresponds to 95% CI.

conditions, are collectively smarter than individuals in problem-solving, decision making, and predicting. Notably, in simple estimation tasks, the average of individual judgments often outperforms the judgment of the majority of the contributing individuals and sometimes even the best individual judge (13). A theoretical explanation for this phenomenon is that there is an error associated with each individual judgment, and taking the average over a large number of responses filters out the noise of gross overestimates and underestimates, thus increasing the accuracy of the aggregate response (13, 42).

WOC solutions can be reliable when 1) the study participants represent diverse opinions, 2) they make their judgments independent of each other and without outside influences, 3) each individual can draw on their decentralized local knowledge, and 4) there exist some aggregation mechanisms to combine individual contributions into a collective response (13). However, in many real-world cases, rather than being completely independent, crowds demonstrate "modular structures," whereby individuals are more likely socially influenced by their certain peers (i.e., modules) than by others. Our sample, too, demonstrates modular structure (*SI Appendix*, Text S3). In such cases, the WOC effect may be enhanced once the aggregation takes place in two levels: aggregating responses within the modules followed by an aggregation across the modules (30, 31).

We expanded these theoretical findings to aggregate individuals' graphical cognitive maps from a diverse group of stakeholders. This aggregation requires each individual cognitive map to be transformed into an adjacency matrix—a mathematical representation of a directed graph (40). Once the individual FCMs were standardized (i.e., using unique terminologies for similar concepts) (see ref. 43) and brought to the same size, maps were aggregated by treating each element of the matrix as a scalar and creating an averaged model, representing the collective knowledge of stakeholder groups. We first combined individual maps by stakeholder types to form homogeneous, stakeholder-specific models using the arithmetic mean of their adjacency matrices. Subsequently, the more diverse crowd model (including all stakeholder types) was created through aggregating models across homogeneous groups using the median of their averaged matrices (*SI Appendix*, Text S4).

Expert Subjective Evaluation of Models. To evaluate the accuracy and overall performance of the stakeholder-driven models we conducted in-depth interviews with fisheries experts. This data collection has been determined to be exempt by Michigan State University's IRB (STUDY00002479). A purposeful sampling method was used to select a sample of fisheries scientists with diverse scientific expertise and educational background (e.g., natural resource management, conservation, economics, fisheries biology, and social sciences) involved in management, assessment, and conservation of striped bass fisheries. Eight experts participated in semistructured interviews where they examined the accuracy of four aggregated models: three models from homogeneous groups (recreational fishers, commercial fishers, and managers), and one diverse crowd model. Models were blinded (i.e., experts had no information about which model represented which group). They were first given pictures of group models (i.e., graphical maps of causal connections) to score the structure of causal relationships using a seven-point Likert scale (1 = very inaccurate, 7 = very accurate) as a proxy measurement for models' performance (*SI Appendix*, Fig. S13). Second, experts were shown bar charts visualizing the results of six scenarios that simulated each model's responses to social and environmental stressors (*SI Appendix*, Text S5 and Fig. S10). They compared these scenario outcomes across models and judged their accuracy using a similar seven-point Likert scale (*SI Appendix*, Fig. S14).

Network Analysis of Models. To identify the extent to which each aggregated model represented complex causal processes, we used stochastic network analysis of causal microstructures. Building on network theory and cognitive map analyses of complex causal structures developed by Levy et al. (28), we compared the aggregated FCMs according to their network motifs (i.e., microstructures that are constructed by two or three nodes and some unique patterns of connections between them, which shape the underlying elements of perceived causation in a cognitive map). These microstructures—also known as graphlets—"encode important information about the structure of the network and provide a valuable tool for comparison" (44). The extent to which one cognitive map can represent complex interdependencies among social and ecological components of a natural resource system is thus linked to the distribution of complex micro motifs within its network. Studies have frequently suggested that four particular motifs exemplify more complex patterns of causation (28, 29, 38, 45–48): bidirectionality, multiple effects, indirect effect, and feedback loop (Fig. 3). Therefore, their prevalence in a cognitive map indicates a higher perception of complex interdependencies. The prevalence of each motif was measured using uniform random graph tests, which compared the count of motifs in a network with the expected value of counts in randomly generated networks of the same size and density with uniform distribution of edges (49).

MCA. We performed MCA by creating virtual agents (i.e., random individuals) from each type of stakeholders, where their cognitive maps were randomly generated. Specifically, each edge exists proportional to the number of people who included that edge, and the edge weight is randomly drawn from a normal distribution with a mean and SD representing the group. We then assessed how often the diverse model outcompeted homogeneous ones. To measure the group success, we calculated the similarity between the group aggregated map and the EBFM model as the reference point via a bilateral (graph-spectral graph) matrix similarity index (50). This measure of success integrates the structural and compositional agreement of the models with EBFM using measures of edges similarity and eigenvalues distance. Also, to measure each group's diversity, we used Shannon's entropy formula because it accounts for both the richness (i.e., how many unique stakeholder types exist in a group) and evenness of each group (i.e., how even the proportions of stakeholder types are). Our MCA includes 10,000 replicates (*SI Appendix*, Texts S6 and S7). Finally, we used MCA to more comprehensively demonstrate how median outcompetes mean in aggregating models across diverse groups, while group size increases (*SI Appendix*, Text S7 and Fig. S18).

Data Availabilty. All necessary data supporting the findings of this study are available as supporting information and on GitHub (https://github.com/payamaminpour/Diversity_bonus_in_pooling_LK) (51).

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