HARNESSING THE COLLECTIVE INTELLIGENCE OF STAKEHOLDERS TO UNDERSTAND SOCIAL-ECOLOGICAL SYSTEMS

By

Payam Aminpour Mohammadabadi

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Community Sustainability – Doctor of Philosophy

2020

ABSTRACT

HARNESSING THE COLLECTIVE INTELLIGENCE OF STAKEHOLDERS TO UNDERSTAND SOCIAL-ECOLOGICAL SYSTEMS

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Collective Intelligence (CI) is an amplified, meta-intelligence that emerges when a distributed collective of individuals aggregate their inputs in order to solve a problem, often with the help of communication or knowledge pooling. Importantly, CI outcomes (e.g., solutions, decisions, judgments, wisdom and knowledge) are generally more problem-adequate and therefore seem more "intelligent" than the contribution of any solitary member. CI in human societies can therefore solve key and pressing problems that no individual can resolve alone. Importantly, with recent advances in digital technologies, we now have more potential to harness the full power of human collectives to better address fast-evolving, complex problems facing human societies, many of which are complex issues that are resulted from the interactions between humans and natural ecosystems.

Problems like anthropogenic environmental changes, biodiversity loss, and over-consumption of natural resources, which often take place in so called social-ecological systems (SESs), require adequate knowledge and complete understandings about complex relationships between intertwined social and environmental dimensions. Such understandings are difficult to achieve in many contexts due to data scarcity and scientific knowledge limitations. This dissertation explores the potentials of using CI approaches to leverage the local knowledge of environmental and natural resources stakeholders to better understand SESs, develop adequate knowledge of complex human-environment interactions, and inform sustainability decisions.

First, this dissertation synthetizes key insights from biological, cognitive, behavioral, and management sciences literature to develop a framework that guides the design and generation of CI in human groups. This framework organizes fundamental design elements of CI and thus can help researchers, communities, and policymakers, especially in data-poor situations, design crowd-based approaches to aggregating knowledge of local people and stakeholders in order to achieve accurate and reliable understandings of complex human-environment interactions.

Additionally, this dissertation empirically tests CI approaches using three real-world fisheries case studies. The first empirical study uses an example of inland freshwater pike fisheries to explore how CI of local stakeholders can be harnessed through aggregation of their mental models about human-environment interactions. This study shows that the aggregated model can provide scientifically sound insights about how the ecosystem and humans are coupled, and how their interactions are influenced by various management strategies. The second empirical study uses an example of striped bass fisheries in Massachusetts, to explore the impact of knowledge diversity on the CI of local stakeholders while pooling their local knowledge about the complex human-environment interactions. The final study uses an example of U.S. Atlantic coasts to scale up these CI approaches by crowdsourcing inputs from a very large population of local fishing communities to predict people's perception of, and behavioral responses to climate change impacts on ocean fisheries across a large social and ecological gradient. This study demonstrates perfect match among stakeholder-driven perceptions, their mental models' predictions of behavioral changes, and empirical patterns of climate change disturbances.

In conclusion, this work demonstrates that CI approaches to utilizing stakeholders' local knowledge for understanding the complexity of SESs have considerable implications for dealing with scientific and management uncertainties, while many untapped potentials still remain.

To my beautiful wife.
For her love and support, for all the late nights and early mornings.
I love you.

ACKNOWLEDGMENTS

I would like to express my sincere gratitude to my advisor and great friend Dr. Steven Gray for his guidance, encouragement and motivation, patience, and immense knowledge throughout my Ph.D. research. I have learned a lot from him about how to be a scholar. I could not have imagined having a better advisor for my Ph.D. study and a mentor for my academic and personal life. Thanks for showing me a fantastic example of a scientist that I ever want to be. I would like to extend my thanks to all my research committee members, Dr. Rebecca Jordan, Dr. Maria Claudia Lopez, and Dr. Joshua Introne for their insightful comments and guidance.

I would also like to sincerely thank my external mentors, collaborators, co-authors and research advisers for their support and friendship over the past four years: Dr. Antonie Jetter from Portland State University, Dr. Philippe Giabbanelli from Miami University, Dr. Steven Scyphers and Dr. Jonathan Grabowski from Northeastern University, Dr. Robert Arlinghaus from Leibniz-Institute of Freshwater Ecology and Inland fisheries, Dr. Michael O'Rourke from MSU Center for Transdisciplinarity, Dr. Lex Paulson from UM6P School of Collective Intelligence, and Dr. Carina Antonia Hallin from Copenhagen Business School- the Collective Intelligence Unit. Without their support, advice, and mentorship this research would not be finished. I would also like to thank my many friends in the Department of Community Sustainability for being my second family at MSU.

Last but not least, I owe my deepest gratitude to my wife Niyaz, my parents Foruzan and Mohammadreza, my twin brother Peyman, and my parents−in−law Zahra and Alireza. Thanks for their unconditional love, patience, encouragement and support.

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INTRODUCTION

OVERVIEW OF THE PROBLEM

Many of the world's most pressing issues such as massive climate change, unprecedented biodiversity loss, widespread overexploitation of natural resources, and extensive environmental degradation highlight the substantial scale of human influence on the earth. These far-reaching environmental consequences of anthropogenic disturbances often take place in so called social-ecological systems (SESs) [1,2], wherein humans and the nature interact reciprocally [3]. These couplings between human and natural components typically lead to the emergence of complexity in different contexts and different scales [3,4]. Managing such complexity, however, requires adequate understanding about multiple social and environmental components, their two-sided interrelationships, and their resulting dynamics [4]. This understanding can therefore help us better predict the impacts of environmental and social perturbations on coupled systems, and how these systems respond to various management decisions and environmental changes. Immediate consequences of such predictions would be an improvement in the sustainability of ecosystems and human societies [5].

Notwithstanding, in many cases, adequate understanding about complex SESs is difficult to achieve due to widespread limitations and shortages in scientific data, knowledge, tools, and methods to model these complex systems [4,6,7]. To fill this gap, study of SES has faced an increased interest in the use of local knowledge of stakeholders [6,8,9]—environmental and natural resource users who hold valuable knowledge about social-ecological dynamics, sample the natural environment from their routine interactions with SESs through activities like fishing or hunting [10], and may share information about environmental, policy or social changes across their social networks and generations [11]. These human-nature interactions allow stakeholders to accumulate and refine knowledge and observations across years and locations (e.g., anglers moving among lakes) [12]. This local knowledge (LK), also known as local ecological or traditional knowledge, is considered a rich source of information [13,14], especially in data-poor and data-scare situations where data-driven scientific assessments are very limited, and therefore researchers often attempt to incorporate LK into environmental models and resource management [15,16].

Incorporating relevant stakeholder input into SES modeling, however, remains fundamentally challenging due to methodological insufficiencies [17,18]. One key challenges associated with this process is the inability to quantify and address uncertainty in LK that leads scientific community to question the quality and validity of information provided by non-scientist stakeholders [14]. Although stakeholders represent a free and widespread source of information, almost always, knowledge held by stakeholders represents different levels of expertise and reflects diverse perspectives [19]. Yet, the unknown accuracy and the wide range of variation in stakeholders' inputs considerably rise concerns about the validity and reliability of using this source of information in scientific processes [20].

To overcome these challenges, it is necessary to advance the formal use of LK in the study of SES through development of innovative approaches that incorporate stakeholders' inputs and, at the same time, enhance the reliability and accuracy of these stakeholder-driven inputs. Therefore, it is of utmost relevance to foster methodological developments that allow researchers to harness the LK of nonscientist stakeholders and achieve robust understandings about complex human-environment interdependences while meeting a scientifically acceptable accuracy and reliability.

OVERVIEW OF THE METHODOLOGY

This dissertation explores the potential for harnessing the collective intelligence (CI) of resource stakeholders to advance the formal use of LK in developing better understandings about complex human-environment interdependencies and their resulting dynamics. CI is a term used to describe a group phenomenon that emerges from the interactions of various individuals such that the group ends up being more *intelligent*, i.e., more capable of solving problems, making decisions, or answering questions than any individual within the group. CI methods rely on the problem-solving efforts of groups, often based on a proper aggregation of their individual opinions, judgments and knowledge, which can potentially lead to a superior *intelligence* (aka. a collectively intelligent system). This property of the collective may enable the group to solve complex problems in a way no individual can accomplish [21–23].

According to this definition, CI can first thought to be a natural phenomenon, common to many species like ants, honeybees, birds, and fish. For examples, groups of army ants foraging for food can collectively form complex organizations (i.e., assemblages), such as bridges out of their bodies to reach disconnected areas [24]; and schools of fish can collectively form gigantic masses of fish, while escaping from predators, to become less vulnerable to predator's attack and increase the chances of survival [25]. CI is also a common phenomenon among human societies. At the simplest level, highly synchronized human groups can achieve physical capabilities above and beyond what individual humans can do (e.g., a group can simply lift heavier objects than what individuals can do). In a more sophisticated manner, human societies practice democracy and incorporate public opinions into important decisions to thrive culturally and economically [26] and organizations practice collaborative problem-solving to integrate diverse knowledge and expertise [27]. Importantly, however, in modern days, online interactions among millions of people contribute to shape the public, and yet smart, discourse on health, social, environmental, and political issues: millions of online web users contribute their customized, anecdotal knowledge to the world's biggest encyclopedia (i.e., Wikipedia) [28]; and globally distributed citizen scientists work together collectively to expand the scale of data collection and contribute to better environmental conservation [29].

By looking at these examples from the nature and human societies, one important question that needs to be addressed is "under what conditions, a group's collective intelligence surpasses individual intelligence or problem-solving capabilities?" This has long been a fundamental question for researchers from a range of disciplines to study collectives and has led many theoreticians to explain the underlying factors that make collectives *smarter* than individuals: For example, the Condorcet's jury theorem (1785) [30] explains the power of collective decision making and has been a fundamental theoretical assumption for epistemic democracy and other democratic theories of decision-making characterized by majority voting. In the context of estimation, Francis Galton's observation of 800 people accurately estimating the weight of a dead ox in 1907 introduced the "wisdom of crowds" phenomenon [31]. About a century later, James Surowiecki pushed the term "wisdom of crowds" into spotlight in his 2004 book [23] with a series of examples where the average response from a large crowd of independent individuals accurately estimated various quantities while outperforming the majority of individuals.

Scott Page offers a theoretical explanation for this phenomenon in his 2007 book [32]. He explains that there is noise associated with each individual judgment, and taking the average over a large number of responses filters out the noise of over- and under-estimates, and therefore moving the aggregated response closer to the truth. Based on this theoretical explanation, the crowd error is equal to the mean of individual errors, minus their variance. Consequently, as diversity of judgments increases the variance of individual errors increases, and thus the crowd collective error decreases. For that reason, Page calls it a "*Diversity Theorem.*"

Another form of CI frequently observable in socially interacting animal species is known as "swarm intelligence." [33] Swarm intelligence emerges from the ability of a network of individuals to work together synchronously to accomplish complex tasks. This is therefore a common source of CI among social species like ants and honeybees. However, in 2017, Louis Rosenberg proposed that, once connected into real-time systems with synchronous social interactions among members, humans can also amplify their group intelligence by forming "human swarms," which can outperform the vast majority of individuals when solving problems and making decisions [34]. Even though humans did not evolve the natural ability to form a swarm intelligence, with the aim of networking technologies, humans can also connect with each other to form artificial swarm intelligence. "We just need the right technology to turn those connections into real-time systems." [34]

In the 21st century, by leveraging the power of emerging online technologies, we should be able to more efficiently harness humans' CI to address our complex problems we face today. Internet-based technologies like online surveys, artificial swarming platforms, cyber-enabled micro markets such as Amazon Mechanical Turk, and prediction market tools can help us more conveniently, and at an unprecedented scale, aggregate the knowledge, wisdom, and insights of diverse groups of people distributed all around the world into a single *intelligent* solution to our complex problems. As a result, CI has been shown as a powerful tool for wide-spread application in a range of areas such as innovation management, democratizing policies, medical diagnostics. Despite promising findings scattered in various fields, there lacks an overarching framework that can reconcile these findings and guide the generation of new forms of CI. Considerably less attention has been paid to CI applications in natural resource management and understanding coupled social and environmental changes beyond citizen science. As a result, the degree to which a group of local stakeholders can collectively arrive at an amplified intelligence that provides adequate and reliable understanding of complex human-environment relationships remains a largely unexplored (and potentially underutilized) area. This dissertation aims to reconcile theoretical and empirical findings scattered in various fields, develop a general CI framework, and eventually design and implement new forms of CI to fill these gaps.

DISSERTATION OUTLINE

Firstly, in chapter 1, the past and current states of CI theoretical and empirical research from social sciences, biological sciences, and managerial and political sciences are synthesized to develop an overarching, state-of-the-art framework that guides the generation of new collectively intelligent systems. Based on this framework, new approaches to harness the CI of local stakeholders were designed with the aim of developing robust understandings about complex human-environment interactions in SESs. To empirically test these approaches, three real-world case studies were implemented with fisheries examples.

In chapter 2, the potential for harnessing the CI of local stakeholders in recreational pike fisheries in Germany is explored. This study empirically demonstrates how the knowledge of a crowd of local stakeholders, once aggregated through cognitive mapping techniques, can adequately model social-ecological relationships and predict how the inland freshwater lake ecosystems may respond to different management strategies. This study offers methodological guidance for aggregating the input of crowds of resource users to generate high-quality system models.

In chapter 3, using a case of striped bass fisheries in Massachusetts, the benefits of pooling local knowledge from a diverse group of stakeholders are explored. Using a novel online mental-modeling experiment, based on theoretical work about "wisdom of crowds," [31] and more recent theoretical assumptions about "diversity bonus," [35] this study tests the ideas about how pooling informal knowledge from local people, who interact with the natural resources and may not necessarily hold formal scientific knowledge about their environment, may produce accurate and reliable scientific understandings that can inform sustainability decisions. Results demonstrate that the crowdsourced knowledge, once aggregated from a *diverse* pool of stakeholders as opposed to heterogeneous pools, can generate useful information about complex social-ecological interdependencies, thereby filling in knowledge gaps in light of unavoidable uncertainty.

Finally, in chapter 4, an example of U.S. Atlantic coasts is used to scale up the CI approaches by crowdsourcing inputs from a very large population of stakeholders to predict climate change impacts on ocean fisheries and approximate their behavioral responses to these changes. This study empirically demonstrates that internet-based crowdsourcing approaches can produce accurate patterns of collective perceptions and behavioral responses which are highly aligned with empirical biogeographic patterns of climate change across east coast. These findings, and particularly that human responses to climate change varies regionally and is linked with ecosystem changes, are especially important as society continues developing scientific and management plans that consider climate change. Moreover, this work represents one of the largest studies involving stakeholder mental models and overcomes many of the common logistical constraints (e.g., time and effort of in-person interviews) that have typically limited the scale and spatial coverage of past studies.

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CHAPTER 1

1 BECOMING INTELLIGENT ABOUT COLLECTIVE INTELLIGENCE AND PUBLIC POLICY

ABSTRACT

Twenty-four centuries ago, Protagoras is generally credited for first taking seriously the idea that "two heads are better than one," [1] an idea echoed in Proverbs 11:14 centuries after: "Where *there is* no counsel, the people fall; but in the multitude of counselors *there is* safety." (King James Version of the Bible). Today, thanks to 21st Century technologies, two heads and the counsel of the multitude are possible at the scale of thousands, millions, and beyond. Paradoxically, however, even with these technologies in place, the vast potential of collective counsel is widely underused by policy-makers. Additionally, significant fragmentation across the academic fields that study collectives in humans and non-human animals limits the cross-disciplinary advancements that have far-reaching implications for policy-making. So how can researchers and policy-makers work together to harness the power of collectives to address society's most pressing health and environmental problems? A vast increase in the study of "Collective Intelligence" may provide some insight into these questions but, ironically, it will first require defining "Collective Intelligence" as a collective. Here we present an overarching, state-of-the-art framework for CI that provides guidance for policymakers, communities and researchers in developing new forms of CI for better addressing problems that societies face.

1.1 THE POWER OF THE COLLECTIVE

Collective intelligence (CI) is a term used to describe a group property that emerges from the interactions of various individuals such that the group ends up being more intelligent, i.e., more capable of solving problems, making decisions, or answering questions than any individual within the group. Under the bridge of this definition, CI can be first thought to be a natural phenomenon, common to many species like ants and honeybees but also increasingly as a key form of success in human communities [2]. In many ways, this philosophy acknowledged a natural precursor to modern civilizations leading human societies to thrive culturally and economically. This type of outcome is frequently achieved in human groups through processes ranging from face-to-face deliberation to large-scale judgment aggregation to decentralized problem-solving.

Based on CI observations from nature, various forms of human organization, and theoretical and experimental advances, our knowledge about successful CI conditions is fast expanding in the biological sciences, cognitive and behavioral sciences, political and management sciences. Each of these fields offers a different stream of insight into how collectives navigate both simple and complex problems leading to better outcomes. For example, biologists have demonstrated how groups of modestly capable individuals can collectively succeed in highly complex tasks such as nest construction, navigation of an unfamiliar environment, and cohesive migration, e.g., see ref. 3, or social scientists have demonstrated how humans, once formed into a collective, can amplify their cognitive capability, e.g., see ref. 4.

At the same time, studies specific to computer and information science have offered several opportunities to deliberately design social or cyber-infrastructures to allow collectives to address a particular problem. This enormous potential, however, is not yet fully accessible to policy-makers because of the lack of an overarching framework to inform the generation of new collectively intelligent systems given a specific objective. Structuring such an overarching framework requires responding to several questions: What types of public-policy questions can CI support? What is the nature of the collective and what knowledge is appropriate for different types of questions? How should this knowledge of the collective be integrated to ensure CI emerges and we avoid the madness of mobs?

Here we present (outline) a framework that can guide the design of new collectively intelligent systems and thereby harness collective counsel that can be considered 'intelligent.' Our outline focuses on three primary components: the nature of the policy problem or challenge, the nature of the collective, and the nature of the aggregation mechanism.

1.2 COLLECTIVE INTELLIGENCE FRAMEWORK

1.2.1 The problem

Defining the public need or challenge with clarity (i.e., the ***purpose***) is fundamental to designing a CI system. Such a system can be aimed at addressing a wide range of problems for which individuals have to accomplish various tasks such as data collection, observation, labor services or cognitive tasks such as processing new information (i.e., acquire and organize knowledge), retrieving that information from memory, and use that information at a later time (e.g., for estimation and prediction, making a decision, conducting an analysis, etc.) (Figure 1.1).

In addition, the ***complexity*** of the problem should be taken into account. Here we use a three-point continuum of complexity (i.e., simple, complex, and wicked) to classify problems: Simple problems are clearly defined with an ideal solution that can be obtained in a linear fashion using straightforward techniques. In such cases, there is a clear "correct" solution and participants only have to decide on a single variable value (e.g., numerical estimate of a quantity). Complex problems can eventually be clearly defined, but unlike simple problems, solutions to complex problems are not well-understood. Such problems are not solvable by reductionist or sequential techniques, and solutions to them are often adaptive and can lead to other problems and unintended consequences. Finally, wicked problems are complex problems which are neither clearly defined nor well-understood. These types of problems involve multiple stakeholders with different values and beliefs. Intelligent systems typically seek to manage wicked problems rather than definitively solve them [5].

1.2.2 The collective

Theorists have suggested various characteristics by which collectives may effectively construct a CI system: The ***diversity*** of members of a collective, for example, has been demonstrated to serve a critical role in collective problem-solving [6]. Especially for more complex problems, cognitive diversity is a critical driver of collective performance. Here we use Hong and Page (2004) method [6] to classify diversity: “identity diversity” refers to differences in demographic characteristics, cultural identities and ethnicity; and “functional diversity” refers to differences in people’s representation of a problem and how they solve it.

Further, the ***skills/expertise*** of individual participants are of importance to the collective outcome. Three categories can be used to classify the level of expertise people have in CI systems: lay public (individuals who do not necessarily have intimate knowledge, experience, and professional training in the subject of the problem); local stakeholders/communities (individuals likely to be affected by a management decision, action, or a problem); and subject-matter experts (individuals who possess specialized or professional knowledge of a subject).

Additionally, one important group characteristic is the ***group size*** which has been hypothesized to influence group CI. While some traditional models of collective decision-making, e.g., Condorcet's Jury Theorem (1785) and Galton's wisdom of crowds (1907), proposed that collective accuracy should increase monotonically with group size [7], more recent studies have demonstrated that group size differently impacts the accuracy of collective decision-making given the complexity of environmental cues and the correlation of information driving individual decisions [8].

Participants' ***engagement***, or their level of effort and motivation to solve the problem at hand [9], can influence the design and implementation of a CI system. Here we expand on Malone et al. (2010)'s CI framework [10] and classify engagement into four overarching categories: (1) Monetary incentives; (2) Social responsibility, concerns, and civic duty; (3) Enjoyment, satisfaction and recognition; and (4) Legitimate right, ownership, and liability. A final relevant factor is the ***task management*** process, which explains how a collective manages the distribution of labor or intellectual contributions. A collective is either self-governed (decentralized) with autonomous agents or hierarchically controlled (centralized).

1.2.3 The aggregation mechanism

Group formation can take place once a collective of individuals are either sampled or self-selected. The mechanisms by which individuals' information is aggregated, however, depends largely on two factors. First, the level of **social influence** among individuals, which ranges from highly influenced with collaborative and synchronous interactions to highly independent with no social interactions. In this case, social influence can take various forms: individuals can either communicate through face-to-face dialogue or through online platforms, referred to as artificial *Swarm* platforms [11], which allow users to interact concurrently to make collective decisions. These interactions are synchronous, meaning that users can explore decision-spaces together in real-time. On the other hand, social interactions can occur asynchronously, meaning that individuals are independently exposed to information about others' and/or their collective responses, or they receive correlated environmental cues [8] (e.g., people are exposed to the same social media outlets).

Given the type of policy problem, social influence may undermine or improve collective performance. In simple estimation tasks, for example, a dominating belief is that social influence may drive out beneficial diversity [12]. Those upholding this belief contend that connected individuals are likely to copy their peer's solutions and this tendency to copy results in a smaller range of individual judgments [12]. While this can be problematic in more centralized networks, recent studies, e.g., refs. [4,13] have demonstrated that, in decentralized networks, connected individuals outperform disconnected ones due to the benefits of collective learning. In addition, and especially for complex and uncertain problems, innovation entails social interactions whereby ideas need to be recombined.

Second, a CI solution requires an **aggregation** method by which individual inputs are combined. We have identified five general aggregation rules: average rule (i.e., using a central tendency measure); addition rule (i.e., pooling or crowdsourcing information); majority rule (i.e., using voting mechanisms); convergence rule (i.e., reaching a consensus by deliberation or convergence of opinions); and emergence rule (i.e., self-organized recombination of individual inputs emerges to innovations or better outcomes).

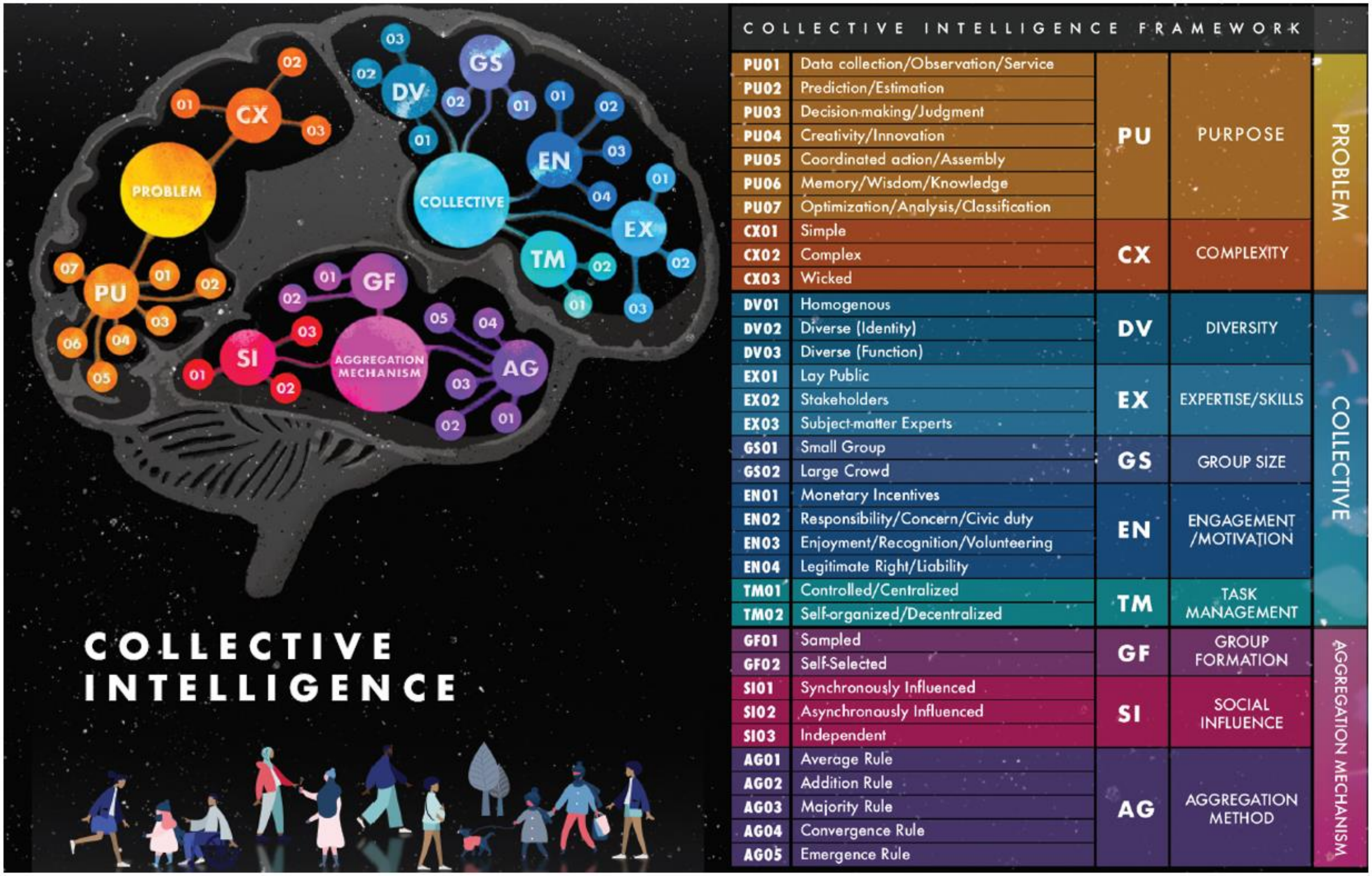

Figure 1.1. Collective intelligence framework for policy-making. This framework provides insights into new hypothetical pathways to aggregate information (i.e., units of knowledge) from a group of individuals and thereby offer solutions that are more optimal than how any single individual could have addressed a particular problem (examples are provided in the Appendix, Figure 1.S1).

1.3 POLICY IMPLICATIONS

While we are only at the beginning of exploring the potential impact of CI methods on public policy, we envision at least three important areas of impact. The first is interdisciplinarity. Choosing the right CI intervention for a given policy challenge will require engaging with fields of knowledge that did not traditionally intersect. The design of a citizen consultation at the level of a large city may benefit from cognitive science and social psychology in question formulation; network science to identify the right diffusion channels; data science and machine learning in the treatment of open-text citizen contributions; and design thinking with behavioral economics to redesign a public service.

And while the field of CI has long been allied with quantitative disciplines such as computer science [14], the next wave of experiments will benefit from the insights of social science disciplines such as participatory democracy, social psychology, management, peacebuilding, and complex mediation. To this end, we see a natural convergence between the framework for CI studies presented here and the closely related discourses of *crowdlaw* and public entrepreneurship [15], epistemic democracy, complex systems, organizational change, and behavioral insights or nudge theory [16].

Second, a common CI framework should allow policymakers to eliminate many of the false choices that dominate current political debates. Harnessing the CI of a community or country does not necessarily mean calling a referendum or overturning a government. On the contrary, the field of CI provides a multitude of methods and techniques at the disposal of policymakers: some relevant to decision-making, but others to collective observation, interpretation, prediction, or preservation of common knowledge. Practitioners of CI may include those seeking radical changes in existing institutions, but so too can they be faithful stewards of them. In all cases, institutionalizing CI methods will require an understanding of how to supplement and not necessarily replace existing representatives and intermediaries.

Finally, a common CI framework can serve as a basis for new coalitions of scientists, policymakers and citizens that will be necessary to take the most promising CI methods to scale. Many promising CI pilots never achieve the necessary institutional buy-in to create a long-term impact. As such, an increasing amount of attention is being given to the conditions for institutionalizing CI processes, including the need to link new participatory channels to performance indicators of managers and public servants [17]. To name only a few, the work of the NYU GovLab, NESTA Centre for Collective Intelligence Design, OECD Future of Democracy Network, World Bank Open Government Unit, Democracy R&D Network, and EU Horizon 2020 CI fund seek to develop the link between scientific research into what works and a hard-nosed understanding of what lasts.

As this research agenda expands, the network of researchers exploring CI principles should itself embody those principles. This means creating more diverse data-gathering channels, including Africa's first cognitive science lab being created at the UM6P School of Collective Intelligence in Morocco. It means more opportunities to pool knowledge in innovative ways, such as the virtual CI conference in June 2020 hosted by Northeastern University and Copenhagen Business School, and it means the epistemic humility practiced by researchers and dialogue facilitators alike: in shaping this new discipline for policy-making, we must be vigilant against our own biases and ever-ready to overturn our presumptions if new evidence comes to light.

What is the future of CI? At a minimum, these methods have already shown the promise of a more agile and inclusive policy-making framework, in which current priorities are more easily achieved and existing institutions reap the benefit of higher effectiveness and greater trust. Conversely, it may entail a more profound paradigm shift in which existing models give way to more radically decentralized or distributed systems. But whether we are able to define, study and implement the field of CI will determine if we can collectively address our shared problems or not.

APPENDIX

APPENDIX

SUPPLEMENTARY INFORMATION

S1 Collective Intelligence Examples

Here we have identified 21 unique approaches that exemplify most of the CI systems that have been implemented to address societies' real-world problems. These examples include citizen science [18], micro-task markets [19] (e.g., *Amazon Mechanical Turk*), human swarm intelligence [20] (e.g., *Swarm AI technology*), traditional wisdom of crowds [7], wisdom of decentralized networked crowds [13], knowledge co-production [21], distributed governance [22] (*Blockchains* technology), epistemic democracy [23], social bookmarking [24] (Folksonomy), Delphi methods [25], prediction markets [26], adaptive co-management and community engaged studies [27], open innovation and broadcast search [28] (e.g., idea competitions), open problem-solving [29] (e.g., *MIT Climate CoLab*), commons-based peer production [30], deliberative democracy [31], mass collaboration [32] (e.g., *Linux*), collective memory [33] (e.g., *Wikipedia*), wisdom of stakeholder crowds in complex problems [34] (e.g., social-ecological modeling), wisdom of crowds in combinatorial problem-solving [35] (e.g., traveling salesperson problem and minimum spanning tree problem), and diversity trumps ability theorem [6]. These examples are shown in Figure 1.S1, each demonstrates a unique array of sub-components from three main CI components: the problem, the collective, and the aggregation mechanism. In addition, the Sankey diagram displayed in Figure 1.S2 is a flow diagram, in which the width of the arrows represents proportionally the flow quantity between two sub-components of the CI framework, based on 21 aforementioned examples.

S2 Supplementary Figures

Representative examples of CI				Citizen Science	Micro-task markets (*Mechanical Turk*)	Human Swarm	Wisdom of crowds	Wisdom of networked crowds	Knowledge Co-production	Distributed Governance	Epistemic Democracy	Social bookmarking (*Folksonomy*)	Delphi Methods	Prediction Markets	Adaptive Co-management	Open Innovation (*Broadcast search*)	Open problem-solving (*Climate CoLab*)	Commons-based peer production	Deliberative Democracy	Mass collaboration (*Linux*)	Collective Memory (*Wikipedia*)	Wisdom of Stakeholders Crowds	Crowd Combinatorial Problem-solving	Diversity trumps ability theorem
Problem	PU	Data collection/Observation/Service	PU01	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
		Prediction/Estimation	PU02	0	0	0	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
		Decision-making/Judgment	PU03	0	0	1	0	0	0	1	1	0	1	0	1	0	0	0	0	0	0	0	0	0
		Creativity/Innovation	PU04	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0
		Coordinated action/Assembly	PU05	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0
		Memory/Wisdom/Knowledge	PU06	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0
		Optimization/Analysis/Classification	PU07	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	1
	CX	Simple	CX01	1	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
		Complex	CX02	0	1	1	0	0	0	0	0	1	1	1	0	1	0	1	1	1	1	0	1	1
		Wicked	CX03	0	0	0	0	0	1	1	0	0	0	0	1	0	1	0	0	0	0	1	0	0
Collective	DV	Homogenous	DV01	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
		Diverse (Identity)	DV02	1	1	0	0	0	0	1	1	0	0	1	0	0	0	0	1	0	0	0	0	0
		Diverse (Function)	DV03	0	0	0	1	1	1	0	0	1	1	0	1	1	1	1	0	1	1	1	1	1
	EX	Lay public	EX01	1	1	1	1	1	0	0	1	1	0	1	0	0	1	1	0	1	1	0	1	0
		Stakeholders	EX02	0	0	0	0	0	1	1	0	0	0	0	1	0	0	0	1	0	0	1	0	0
		Subject-matter experts	EX03	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	1
	GS	Small Group	GS01	0	0	1	0	0	1	0	0	0	1	0	1	0	0	0	0	0	0	0	0	1
		Large Crowd	GS02	1	1	0	1	1	0	1	1	1	0	1	0	1	1	1	1	1	1	1	1	0
	EN	Monetary incentives	EN01	0	1	0	1	0	0	1	0	0	0	1	0	1	0	1	0	1	0	0	0	0
		Responsibility/Concern/Civic duty	EN02	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
		Enjoyment/Recognition/Volunteering	EN03	0	0	1	0	1	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0
		Legitimate right/liability	EN04	0	0	0	0	0	1	0	1	1	1	0	1	0	0	0	0	0	0	1	1	1
	TM	Controlled/Centralized	TM01	0	1	0	1	1	1	0	1	0	1	0	1	0	0	0	1	0	0	1	1	0
		Self-organized/Decentralized	TM02	1	0	1	0	0	0	1	0	1	0	1	0	1	1	1	0	1	1	0	0	1
Aggregation Mechanism	GF	Sampled	GF01	0	0	1	1	1	1	0	1	0	1	0	1	0	0	0	1	0	0	1	1	1
		Self-Selected	GF02	1	1	0	0	0	0	1	0	1	0	1	0	1	1	1	0	1	1	0	0	0
	SI	Synchronously Influenced	SI01	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0
		Asynchronously Influenced	SI02	0	0	1	0	1	0	0	0	1	1	1	0	0	1	1	0	1	1	0	0	0
		Independent	SI03	1	1	0	1	0	0	1	1	0	0	0	0	1	0	0	0	0	0	1	1	1
	AG	Average rule	AG01	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0
		Addition rule	AG02	1	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0	1
		Majority rule	AG03	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
		Convergence rule	AG04	0	0	1	0	0	0	1	0	0	1	1	0	0	0	0	1	0	0	0	0	0
		Emergence rule	AG05	0	0	0	0	0	1	0	0	1	0	0	1	1	1	0	0	0	0	0	0	0

Figure 1.S1. Examples of collective intelligence (CI). Each example demonstrates a unique approach to harness the CI of a collective by aggregating individual inputs to solve a particular problem. See Figure 1.1 for more information about sub-categories (i.e., *PU*, *CX*, *DV*, *EX*, *GS*, *EN*, *TM*, *GF*, *SI*, and *AG*).

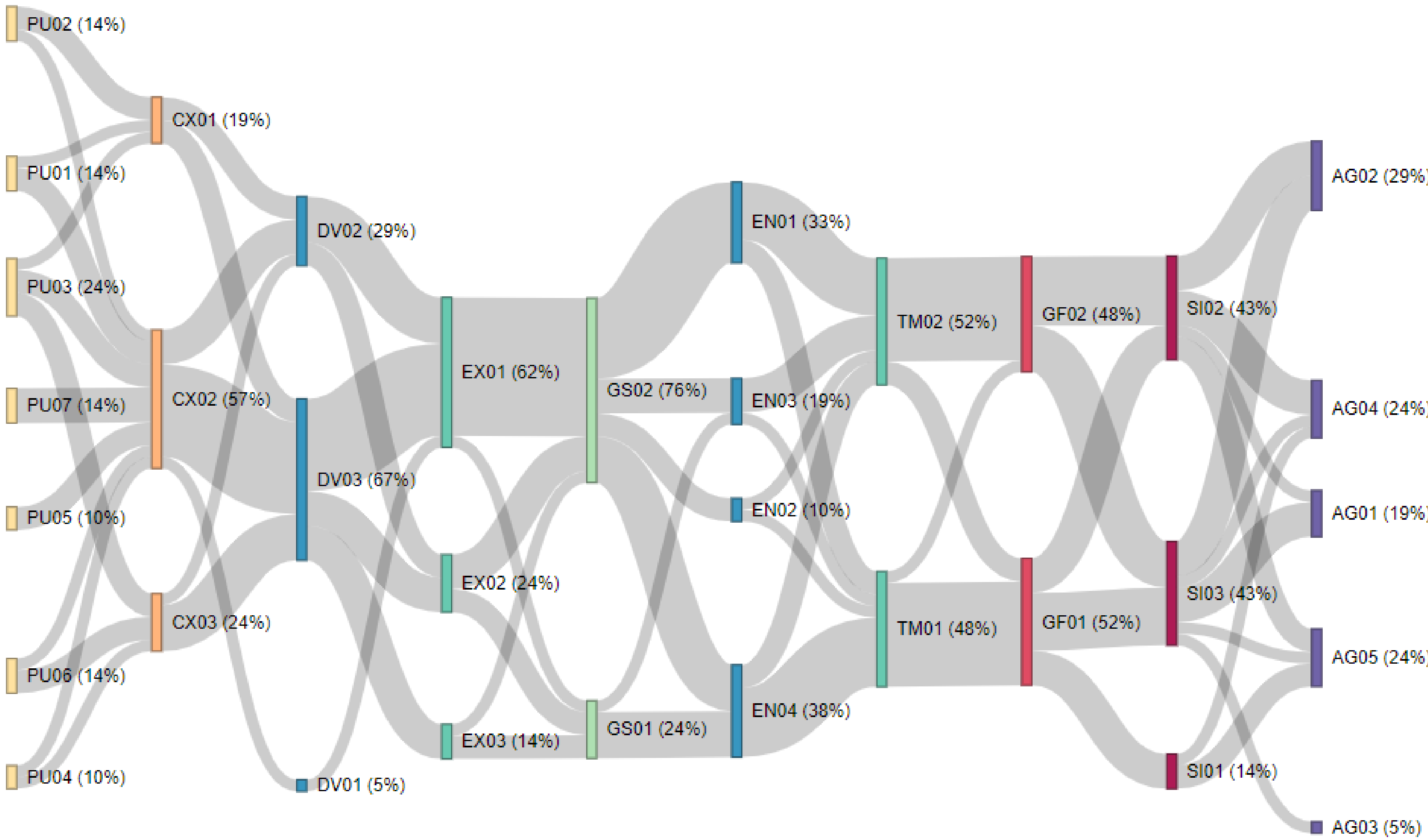

Figure 1.S2. The Sankey diagram showing the flow between sub-components of CI framework. Considering examples from Figure 1.S1, the diagram shows where a CI can come from and where it can end up, with possible intermediate steps, where the width of the connections between two nodes visualizes the quantity of examples used these pairs of nodes (i.e., sub-components).

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CHAPTER 2

2 WISDOM OF STAKEHOLDER CROWDS IN COMPLEX SOCIAL-ECOLOGICAL SYSTEMS

This chapter is a reprint of an original peer-reviewed article published in *Nature Sustainability in 2020*, *volume 3, on pages 191-199.* The original article can be found at: https://doi.org/10.1038/s41893-019-0467-z.

ABSTRACT

Sustainable management of natural resources requires adequate scientific knowledge about complex relationships between human and natural systems. Such understanding is difficult to achieve in many contexts due to data scarcity and knowledge limitations. We explore the potential of harnessing the collective intelligence of resource stakeholders to overcome this challenge. Using a fisheries example, we show that by aggregating the system knowledge held by stakeholders through graphical mental models, a crowd of diverse resource users produces a system model of social-ecological relationships that is comparable to the best scientific understanding. We show that the averaged model from a crowd of diverse resource users outperforms those of more homogeneous groups. Importantly, however, we find that the averaged model from a larger sample of individuals can perform worse than one constructed from a smaller sample. However, when averaging mental models within stakeholder-specific subgroups and subsequently aggregating across subgroup models, the effect is reversed. Our work identifies an inexpensive, yet robust way to develop scientific understanding of complex social-ecological systems by leveraging the collective wisdom of nonscientist stakeholders.

2.1 INTRODUCTION

Many environmental problems that influence human well-being, such as climate change, biodiversity loss, and overexploitation of natural resources, are caused by a combination of social and ecological factors that occur in coupled systems across scales[1]. Managing resources under such complexity requires adequate system representation (i.e., models) [2], so that the system's response to management decisions can be anticipated before action is taking. However, the sheer number of intimately linked social-ecological systems that require management, limited knowledge and resources, and the difficulty to enumerate many system elements cause scientific model creation to lag behind decision-making needs in most natural resource contexts [3,4]. This limits the effectiveness of natural resource management and contributes to the inevitable collapse of many exploited systems, such as fisheries [5].

To address knowledge limitations and data gaps, resource managers frequently receive input and decision-making support from resource stakeholders [6,7]. Resource users sample the natural environment through their routine interactions with social-ecological systems (e.g., while fishing or hunting) [4] and thus accumulate and refine knowledge and observations over years and, frequently, in different locations (e.g., anglers moving among lakes) [8]. Therefore, monitoring and assessment of natural resource dynamics may be improved by leaning on the knowledge of diverse resource stakeholders (e.g., fishers) [7] in ways that harness their collective intelligence (CI) [9] —the ability of a group to solve problems effectively. For example, natural resource management increasingly uses citizen scientists [10] to collect and aggregate observational data (e.g., by observing bird distribution and abundance) [11].

Importantly, the CI held by a group can also be harnessed by pooling judgments, rather than observations, from large, loosely organized collectives or "crowds". The so-called wisdom-of-crowds (WOC) phenomenon was discovered more than a hundred years ago, when the average judgment of the crowd of observers accurately estimated the weight of a dead ox [12]. This phenomenon frequently leads to surprisingly accurate point estimates by averaging the judgments of a large collective [13]. In addition to simple estimation tasks, a WOC effect has also been researched in cases of higher solution complexity, such as combinatorial problems [14,15]. Understanding the complex social-ecological interactions in natural resource ecosystems, however, constitutes a considerably more difficult problem than counting the number of birds [10], guessing the weight of an animal [12], or solving a Euclidean traveling salesperson problem [15]. Natural resource managers frequently have to predict future system states (e.g., in response to a planned management intervention), which requires more complex knowledge about the structure, connection, and dynamic behavior of natural resource systems, often associated with high uncertainty and with no clear "correct or optimum" solution. It is currently unclear if the WOC approach can harness CI for such complex problem-solving conditions.

In this work, we explore if the WOC can be leveraged to provide accurate system knowledge about natural resources. Specifically, using a case from fisheries, we ask: can crowds of non-scientist resource users provide representations of the ecological and social cause-and-effect relationships that drive resource stock dynamics and mirror the best scientific understanding of the same social-ecological context? Given the urgent need to effectively manage globally declining fish stocks [16,17], this is a question of utmost relevance: if stakeholder crowds can provide accurate representations of complex social-ecological relationships, then by using the CI of stakeholders we could create a more complete coverage of localized social-ecological processes than any team of scientists can ever achieve when traditional scientificallydriven assessments are limited and cannot cover the universe of local environmental and social interactions.

One way to elicit system representations from stakeholders is through cognitive maps. These are graphical models of system elements (concepts) and their causal connections (represented as signed arrows). They represent an individual's internal perception of external reality, referred to as mental models [18]. Mental models of complex systems can be represented in special semi-quantitative forms of cognitive maps called Fuzzy Cognitive Maps (FCM) [19,20]. Importantly, individual mental models elicited by FCMs can be aggregated mathematically to create a model that represents the insights of all subjects [19,20]. However, there is a lack of empirical evidence to explicitly demonstrate a WOC effect in averaging a crowd's mental models about complex social-ecological relationships, such as human interactions with natural fish populations [21].

In this study, we explore using WOC principles to establish a presumably accurate understanding of natural resource dynamics by proposing and testing a novel approach for aggregating individual mental models collected from non-scientist stakeholders. We use an example of a recreational fishery ecosystem and independently generated mental models, represented by FCMs, from diverse resource users, composed of individuals who interact with fishery resources in different ways, either through exploiting fish populations (anglers), managing resources (fisheries managers) or governing communities of resource users (angling club managers).

In general, and especially for complex problems with many interrelated components, incorporating diverse knowledge and expertise into collective problem-solving improves the group's performance [22–24]. Similarly, diversity of perspectives has been identified as a critical driver of WOC[13]. Building on earlier theoretical reasoning [22–24], we hypothesize, first, that, a system model generated by aggregating the mental models of a crowd of diverse resource users outperforms the models of more homogeneous groups (H_1).

Yet, it is realistic to assume that users of the same social-ecological system are most likely to be socially influenced by their peers in real life, especially by those from the same stakeholder category (e.g., anglers, club managers, and fisheries managers), due to similarities in the ways they use and interact with the natural resources. Such interactions can be direct through face-to-face communications or indirect through sharing knowledge, information and assumptions over media and through being exposed to a similar set of information sources (e.g., educational material codified in books). Socially influenced subgroups of individuals, however, tend to accumulate and represent correlated knowledge. Despite potentials for social learning and improving the accuracy of the collective judgments, prior WOC studies [25–27] have shown that under such conditions, averaging data points from a larger crowd of individuals increases the risk of amplifying biased knowledge that drives from direct or indirect exposure to social influences, thereby potentially diminishing the WOC effect [25–27]. Therefore, we hypothesize, second, that, when arithmetically averaging mental models of stakeholders with plausible real-life social influence, larger samples of mental models may amplify the negative effect social influence can have on WOC, thereby deteriorating collective performance as crowd size increases (H_2).

To deal with the latter issue, past theoretical and empirical WOC studies [26,28] have suggested that, once there are multiple "modules" within a large crowd (i.e., smaller subgroups of individuals whose opinions are more likely to be directly or indirectly influenced by their subgroup peers), the WOC can be enhanced by averaging responses across modules [26,28]. Assuming that the crowd is suffering from the possible negative effect social influence can have on WOC [27] and building on prior theoretical work [26], we hypothesize, third, that a multi-level aggregation method that averages mental models within modules (i.e., subgroups of stakeholders from the same user type category), followed by a subsequent aggregation across modules, can dampen the negative effect of social influence (H_3). This multi-level aggregation approach may compensate for the possibly harmful biases as a result of social influence, thereby allowing larger crowds to demonstrate an improved WOC effect.

Our work tests the above mentioned three hypotheses and thereby establishes that WOC can be leveraged to crowdsource system knowledge of social-ecological and other complex systems, while also offering methodological guidance for aggregating the input of crowds of resource users to generate high-quality system models similar to those developed by trained scientists. Our findings provide the basis for managing and planning interventions in complex social-ecological systems that are data-poor or even data-deficient, but that have an abundance of local knowledge from resource users.

2.2 EXPERIMENTAL DESIGN

We collected graphical mental models of 218 stakeholders characterized as recreational anglers, angling club managers, and fisheries managers through a fuzzy cognitive mapping task in a series of workshops in angling clubs recruited from north-western Germany. The FCMs represented participant understanding of the fish ecology and fishery management regarding the northern pike (*Esox lucius*) fishery (see a previous publication for more details) [21]. The individually collected mental models graphically displayed the perceived cause-and-effect relationships of ecological and social concepts affecting each other (see *Appendix*, Figure 2.S1). Additionally, we ran two FCM workshops with 17 fishery scientists, each of whom had formal training and scientific knowledge in fishery resource dynamics and pike ecology, to create a scientific reference mental model representing the best scientific understanding about the same ecosystem.

We experimented on various ways to draw and aggregate mental models from a population of stakeholders to explore the impact of diversity, possible biases raised because of real-life social influences, and aggregation methods on the WOC. The effects were quantified by comparing the aggregated mental models against the scientific reference mental model (i.e., experts' group mental model).

We used two aggregation methods: (a) *Single-level* that is accomplished by arithmetically averaging the weights of all individually contributed links in FCMs of group members (see previous publications for more details) [19,20], and (b) *Multi-level* that first divides the stakeholders into separate modules (i.e., smaller subgroups) and arithmetically averages the edge weights of all contributing maps within each module, and then in the second level, it uses the median to aggregate the maps across the modules (see Methods). We proposed to use median in the second level of aggregation because the median has been shown to outperform the arithmetic mean in likely skewed distributions [12,29,30].

We used the single-level aggregation method to form the averaged mental models of *stakeholder-specific* groups with members only from one stakeholder category (i.e., homogeneous groups of anglers, club managers, and fisheries managers). We also aggregated all 218 individual mental models using the multi-level aggregation method to construct a *crowd* mental model composed of diverse stakeholders. To create the scientific reference model we aggregated the mental models generated by 17 scientists (i.e., experts) using single-level aggregation method. We compared stakeholder-derived models against the experts' group mental model (i.e., reference model) in terms of their (a) centrality of concepts representing pike ecology and management, (b) strong cause-and-effect relationships, (c) network geometric structures, and (d) dynamic behavior (see Methods).

In addition, we built a “null-unwise” model by aggregating a set of artificial mental models made by a random graph generator using the probability distribution of edge weights drawn from the population of all participants’ mental models. We used this null-unwise model to test that any observed WOC is not simply an artifact of averaging mental models, and is attributed to stakeholders’ real-world relevant knowledge.

Finally, to test the impact of accumulated biases of socially influenced individuals on the WOC effect and the success of different aggregation methods in filtering out these biases, we formed numerous samples of individuals randomly drawn from the entire population of 218 stakeholders with different sample sizes. For each random sample of individuals we aggregated their mental models using two aggregation methods: single-level and multi-level. We then computed an overall performance error by comparing the aggregated mental model against the expert’s mental model (see Methods for details).

2.3 RESULTS

We find that the structural properties of the crowd mental model match scientific understanding about the social-ecological relationships driving pike fisheries, This was evidenced by evaluating agreement between the crowd model and the scientific model using three metrics: (a) centrality index (which represents the relative importance of a concept in the mental model), (b) strong causal patterns (which represents the arrangement of strong cause-and-effect relationships), and (c) graph eigenvalues (which represent hidden fundamental patterns of geometric structure that has implications for the networked functionality of a mental model). The centrality measures (see Methods) indicated that the three *stakeholder-specific* groups were biased toward specific management strategies (e.g., anglers were biased toward angling pressure being particularly impactful for pike, and fisheries and club managers were biased toward enhancement of habitat quality promoting pike) (Figure 2.1). However, in support of our first hypothesis (H_1), when the mental models of all diverse stakeholders were aggregated, the *crowd* model demonstrated remarkable similarity to the experts (i.e., the reference model) regarding the centrality of six important concepts for possible impacts of fishery management decisions on pike population (Figure 2.1).

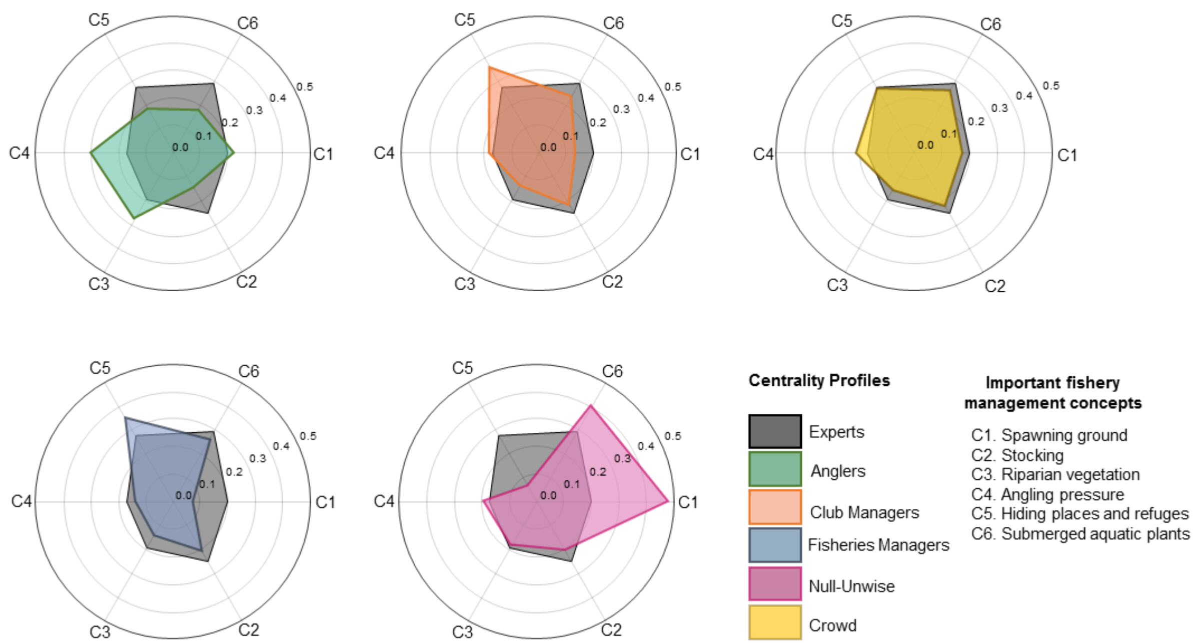

Figure 2.1. Centrality profiles of different groups (in color) and the expert reference model (in black/grey). Axes in the radar charts show the centrality of system elements that are important for fishery management decisions. Katz index is used to measure the centrality (see Methods).

The crowd also showed the highest agreement with the reference model regarding the strongest cause-and-effect relationships in pike ecology and management (Figure 2.2). Additionally, the eigenvalue similarity index (see Methods) also indicated that the structure of the crowd mental model had the most similar fundamental characteristics to the experts, suggesting yet again significant structural agreement (Figure 2.3). We, therefore, conclude that the structure of the mental model of the crowd is very similar to the one produced by experts and thus, a WOC effect is demonstrated.

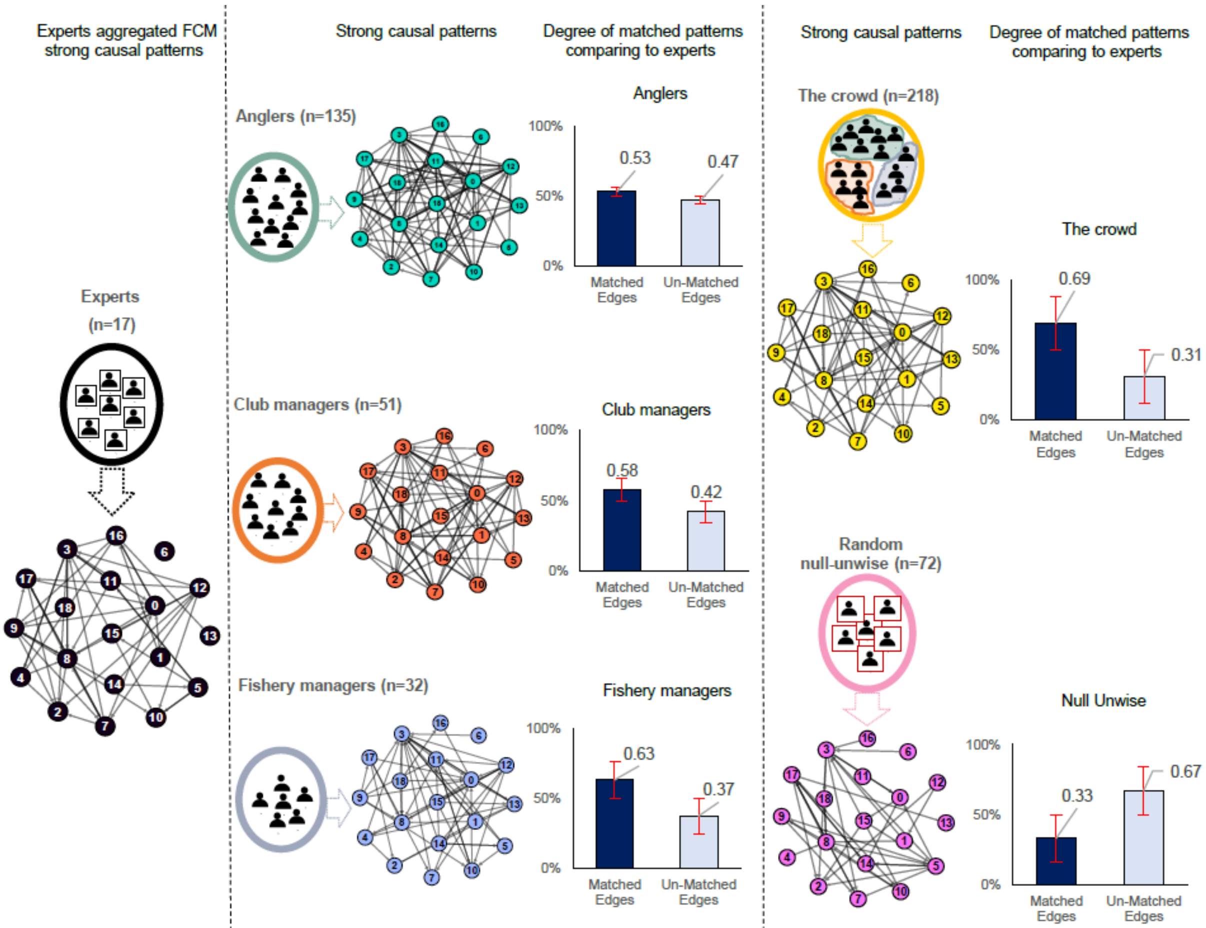

Figure 2.2. Agreement on strong causal patterns in the FCM of stakeholder-specific groups, the crowd and the experts. The crowd map has the highest degree of matched patterns (~70% matched) with experts; the stakeholder-specific groups perform substantially better (among 53% to 63% of correct matches) than the null-unwise model (only ~30% correct matches). Weak relationships with an edge weight less than 0.33 (the first tertile in zero to one continuum, corresponding to the weak interval) were removed from the maps to get the strong causal patterns (see *Appendix*, Figure 2.S2). Error bars display standard errors.

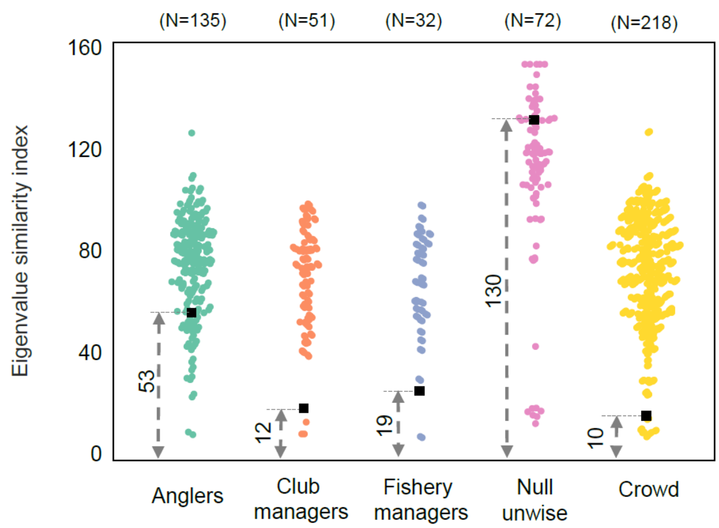

Figure 2.3. Eigenvalue similarity index. Within each group (x axis), each point represents one individual and is placed according to the eigenvalue similarity index (y axis). The similarity index represents the structural mismatch with the experts mental model. The swarm plots reflect the density of points around any distance value, while black squares represent the aggregated mental models for each group. The crowd model has the smallest distance from (highest similarity with) the experts model. Interestingly, for all stakeholder groups, aggregated model is located below the densest area of the plot, illustrating the WOC effect (the average model outperforms most individuals). Yet, this effect is notably higher in the crowd.

Structure does not necessarily provide insights into how the fishery might react under changing social-ecological conditions. We, therefore, assessed the dynamic (i.e., functional) behavior of the FCMs by simulating how changes in one or more system elements of the mental models impacted the state of all system elements (see Methods). We find again in support of H_1 that the functional properties of the crowd mental model accurately match scientific understanding about pike ecology (Figure 2.4). We revealed this agreement using a measure of dynamic distance, which represents the mismatch between two models in terms of the outcomes they produce as a result of changes in the state of one or more concepts. The functional properties of the mental models generated by the crowd and experts aligned, where the mean of the dynamic distance between experts and the crowd was the lowest compared to all stakeholder-specific groups (Figure 2.4).

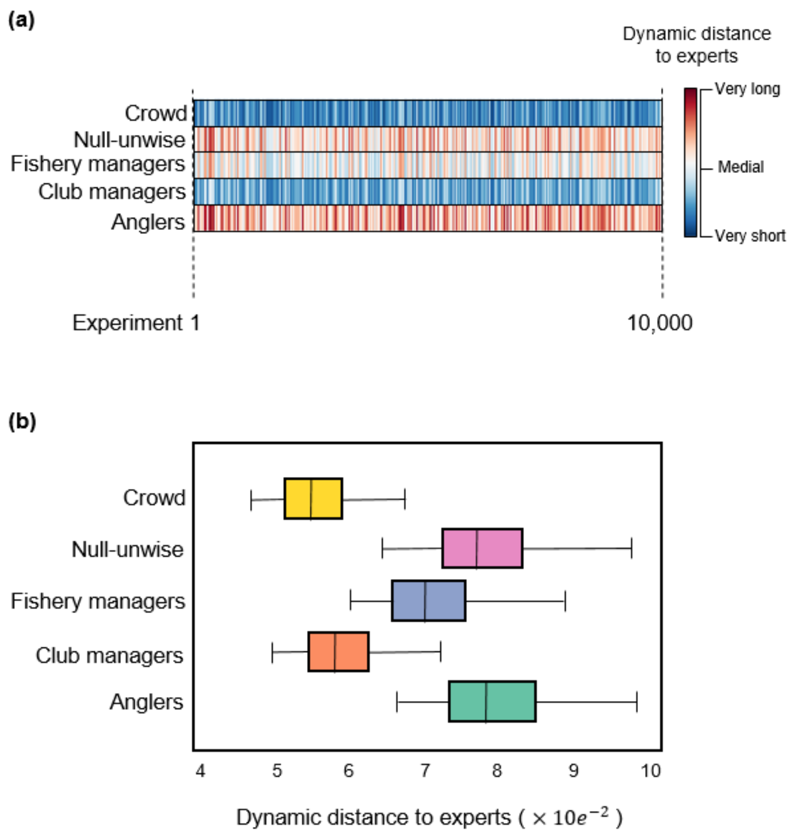

Figure 2.4. The dynamic distance between the experts model and the stakeholder-derived models based on 10,000 randomly generated scenarios (experiments). Each experiment randomly selects a set of concepts (nodes in the FCMs) and changes their values to produce outputs (see Methods). (**a**) Each cell in the color-bar graph represents a random scenario with colors denoting the dynamic distance. (**b**) Boxplots illustrate the distribution of these dynamic distances for each group in 10,000 experiments. The mean of dynamic distances from the reference model is the smallest in the crowd.

We also find that the impact of biases deriving from real-life social influences exhibited two distinct behaviors across different aggregation methods affecting WOC performance (Figure 2.5). For the models built by single-level aggregation larger samples of stakeholders amplify the accumulation of biases, and thus group performance error increases at larger sizes in agreement with H_2 (Figure 2.5 a). By contrast, confirming H_3, for the models built by multi-level aggregation larger samples of stakeholders cancel out the biases, and therefore group performance error decreases monotonically as more data points are drawn from the population of mental models (Figure 2.5 b). Consistent with prior theoretical and empirical works [26,28], we collectively show that the WOC effect is indeed observed for the large crowds, which consist of multiple socially influenced subgroups of stakeholders (i.e., modules), but only if multi-level aggregation, as opposed to single-level aggregation, is used (Figure 2.5). This result supports previous experimental studies [15,27], implying that social influences and their resulting biases, if not appropriately harnessed [31], will undermine the WOC effect in large crowds when averaging individually collected mental models about natural resource dynamics, at least under the conditions of our study context.

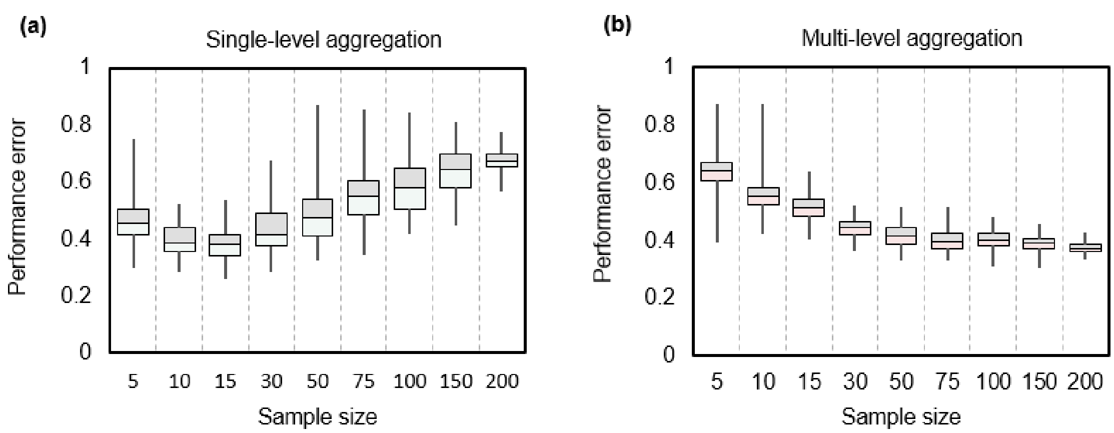

Figure 2.5. The sampling and averaging effect on performance error in crowds built by drawing and aggregating mental models using two aggregation methods. (**a**) Single level aggregation. (**b**) Multi-level aggregation. Samples were formed by randomly drawing individuals from all 218 participants. Data are shown for 100 repeats per sample size. (Test of > 100 random crowd assignment show no significant difference).

2.4 DISCUSSION

This study advances the science of CI by examining how the WOC can be leveraged to crowdsource mental models of social-ecological systems. We demonstrate that a large-enough group of diverse and informed stakeholders, who pool their mental models, can provide system descriptions that mirror the representations of system knowledge by scientific experts (Figures 2.1-2.3). This is an important finding because there is a widespread lack of monitoring data and scientific models in many freshwater and small-scale coastal fisheries and other exploited ecosystems with which resource users regularly interact [5]. Our work supports an earlier hypothesis[4] that the knowledge of these local resource stakeholders can be mined to provide the insights necessary for sustainably managing exploited ecosystems and preventing their collapse.

Consistent with Page's (2007) diversity theorem [22], we found that the system model generated by a crowd of diverse individuals could potentially outperform the models of stakeholder-specific groups. However, assuming that the crowd is suffering from the negative effect social influence can have on WOC, and consistent with recent theoretical work [25,26], we also demonstrate that larger crowds do not necessarily perform better. Instead, aggregating more data points (i.e., individual mental models) in larger crowds may decrease performance under certain conditions (Figure 2.5 a). Our work thus extends prior theoretical work [25,26] by providing empirical evidence that shows the importance of knowledge distribution and aggregation methods in WOC tasks where correlated information could decrease performance with increasing group size.

The multi-level aggregation method that we present offers a solution: it first creates subgroup-level models for user groups assumed to be under group-specific social influences, based on the arithmetic mean (i.e., filtering out system aspects the subgroups did not agree on, thus reducing variance). It subsequently aggregates those initially formed subgroup models, using the median of the mean values (i.e., reintroducing variance). This approach benefits from both modularity that creates a situation of optimum knowledge variation [26] and compensates for a skewed distribution of opinions through using the median rather than mean, thereby enabling improved performance in larger crowds (Figure 2.5 b). This is a very important finding for guiding the application of the methods we present in a natural resource context. Even though simple aggregation can provide accurate models with an optimal (small) sample size (Figure 2.5 a), in our case, this optimal sample size that minimizes the group performance error [25] is not theoretically quantifiable due to the unknown correlation between individual beliefs. Our multi-level aggregation method addresses this issue by triggering a WOC effect that monotonically improves with relatively larger sample sizes. This is of practical relevance for sustainable natural resources management, where often no robust criterion exists for exclusion of some stakeholders, and contrarily, an unbounded inclusion of all stakeholders' perspectives is highly encouraged for democratic reasons [32] (see *Appendix*, Supplementary Discussion and Figure 2.S3).

A few limitations are worth outlining. First, we used a particular format, namely FCM [33], to capture, represent, and aggregate mental models, as well as to explore the structure and dynamic behavior of the system these models represent. Other system formats may lead to different results. Also, while great care went into the selection of experts, knowledge elicitation, modeling, and model testing, we cannot claim that the reference model is the best possible representation of the participating scientists' knowledge of pike ecology, nor does it necessarily represent the best known science. However, because any existing limitation of the reference model equally applies to the other models in this study, our conclusions regarding the WOC for obtaining system knowledge from stakeholders remain robust. A further limitation is that our findings were generated from a specific natural resource management context with a unique governance system: in Germany, local level-angling clubs are self-managing their privately owned fishery resources [34], and both managers and anglers have to pass training that exposes them to concepts of aquatic ecology, fisheries management and conservation and fisheries legislation [35,36]. This, in addition to the workshop settings for data collection, which likely attracted more avid and experienced anglers, means that our sample likely included ecologically interested and rather educated anglers. It is therefore uncertain whether our results translate one-to-one to other natural resource systems, where resource users are less heavily engaged in the local management of resource systems. Also, in our experiments, all participants were provided with a standardized list of system components (see Methods) in favor of model comparability [37]. Therefore, the extent to which our findings would apply to situations where there are considerable debates concerning the constituents of a system is unknown. Finally, while our findings demonstrate that WOC can be leveraged to provide accurate system representations, it is unknown whether the crowd has the ability to quantify the status of natural resources, assess human pressures on them, and derive sustainable harvest rates – all of which are critical components of sustainable management [4,5]. These are important directions for future research.

When looking at possible applications of our findings, importantly, the crowd's model not only approximated the structure, but also the dynamic behavior of the scientist-provided model in response to changes (Figure 2.4). This is very relevant for designing inclusive processes and adaptive co-management practices that require stakeholders, managers, and scientists first model likely outcome scenarios and then jointly agree on possible management actions for uncertain ecosystems [6,38]. While frequently proposed to manage uncertainty in social-ecological systems, such adaptive management approaches often suffer from a lack of readily available simulation models [6,39]. Based on our work, we instead recommend proactively involving local stakeholders in system simulation by aggregating individual mental models resulting from online or other survey means.

To conclude, we found that robust scientific information of complex ecosystem dynamics can be generated from a group of informed stakeholders. In fact, when done at the right scale and for the appropriate problem, leveraging the CI of stakeholders through a crowd-sourcing approach can be a stepping-stone for fostering institutional fit [40] and accommodating nested governance in environmental decision-making [41,42]. For example, certain natural resource problems are local in orientation (e.g., overfishing of a coastal fishery for non-migratory fish, such as coastal pike), but are still data-deficient and in need of urgent conservation action that is agreed-upon by local communities of resource users. Here, harnessing local stakeholder knowledge through a systematic approach, as proposed in our study, can provide much-needed information for sustainability. When this information is paired with also granting local users sovereignty for making local conservation decisions, we can anticipate increased legitimacy of the resulting management actions [17]. Management authorities at larger scales (e.g., regional, national, or international) can, in turn, focus on environmental problems operating at those scales, yet their decisions might also be influenced by harnessing the CI of regionally operating stakeholders. Ultimately, collecting system understanding may operate in a nested fashion by first organizing understanding at lower levels through user group-specific mental models, with ultimate decisions being coordinated at higher levels through across-group models (see Supplementary Discussion).

Despite its promise, our work also clearly shows the importance of carefully designing WOC approaches in natural resource contexts. In particular, if the wrong aggregation method is chosen, increasing sample size can produce a solution worse than one produced by intermediate sample sizes, and because the size for optimum performance is not known, the crowd's response may become unreliable. Fortunately, perhaps, when using the right aggregation method, as we show, a large enough crowd of diverse stakeholders can produce a science-like understanding of even complex social-ecological dynamics. While further research is needed to confirm the application of WOC to natural resource contexts, it has considerable potential for addressing pertinent problems of unsustainable natural resource use and biodiversity loss.

2.5 METHODS

2.5.1 Description of study system and context

Many global fisheries are in trouble [5,43]. Harvest regulations and stocking practices have been promoted as a common management response in inland and marine fisheries [44]. While stocking is a common management practice for freshwater fisheries around the world, researchers have recently begun questioning the sustainability of these decisions, given their negative consequences and the highly uncertain context in which many of these decisions are made [45]. Alternative and complementary management options to stocking include social wellbeing-oriented measures (e.g., decreasing angling pressure through input controls) and habitat rehabilitation policies (e.g., increasing spawning habitat, increasing refuge, and increasing riparian vegetation) [46]. The degree to which different fishery decision-makers understand the ecological and social tradeoffs of management decisions is currently not well understood [47], and there is abundant documentation that fisheries stakeholders and managers find themselves in disagreement about which policy to follow [48]. Moreover, it is notoriously difficult to understand social-ecological interactions and how various ecological factors affect the productive capacity of renewable natural resources striving in the natural ecosystem. The problem is elevated in inland fisheries given the multitude of ecosystems that exist in water-rich landscapes. The multifaceted origin of the fisheries system gives rise to a complex social-ecological problem with substantial data-deficiencies, which lends itself for an investigation of WOC effect for complex system modeling: stakeholders who either use or manage the fisheries interact with the system in different ways and thus accumulate diverse system knowledge that results in different mental models of the structure and function of the system [21]. These different mental models could be mined in WOC applications to harness their CI.

Germany offers a compelling case for application of WOC as many local recreational fisheries are managed by angler communities, organized in angling clubs [34]. As opposed to open access systems in the USA and other regions of the world, in Germany as in much of central Europe, angler communities own or lease fishing rights from water owners and in this position have sovereignty to engage in certain management actions (e.g., stocking, increasing harvest regulations). Angling clubs range in the number of 10,000 in Germany alone, meaning that there are 10.000 or more individual decision makers born out the natural resource user community themselves. Roles in angling clubs differ with some anglers becoming elected as club managers, mainly tasked with running the voluntary body. On the other hand, selected anglers take training courses in fisheries management and become fisheries managers or water bailiffs taking over the management tasks. A further group entails ordinary anglers who in Germany also have to pass a 30 hour training course to acquire a fishing license and be allowed to join angling clubs. The content of the angling course is mainly directed to legal and practical issues [35,36]. Participants' fisheries knowledge and education metrics assessed using questionnaires after the mental model exercises (see *Appendix*, Table 2.S3).

2.5.2 Mental models

Mental models about social-ecological systems, and in fact any type of system, can be elicited and represented as Fuzzy Cognitive Maps (FCM) [33]. These can be analyzed with regard to structure and dynamic behavior of the system [49]. Moreover, FCMs from individuals can be aggregated into a larger FCM that represents the collective knowledge of all contributors [20] and thus provide a tool for WOC. In this study we used the FCM format to collect data from a crowd of 218 stakeholders who manage their own lake and river section fisheries in Germany [34]: recreational anglers, who are organized in clubs, fishery club managers, and fisheries managers, who are responsible for the entire ecosystem. In addition, we collected the system models from 17 fishery scientist and used their model for comparison.

Between 10 and 20 anglers, managers and club heads of Lower Saxony, Germany, were invited to one of our 17 workshops (for details see a previous publication) [36], where graphic mental model representations of the ecology and fishery management of the model species "pike" were individually collected through Fuzzy Cognitive Mapping technique. We used pike populations as an example case because it is a valuable species in the study region in high demand by anglers [21]. To standardize the collection of FCMs for this study, all participants received the same set of ecological concepts, which represented key factors affecting pike population dynamics. These factors were derived from independent focus groups with anglers and mental model pre-tests with both anglers and experts to identify key concepts relevant to the pike fishery. We also completed a thorough review of the pike literature to identify key aspects of their life history and what determines population dynamics (e.g., macrophyte abundance) [50]. We added human-centered concepts represented angling impacts (e.g., fishing pressure) to outline a social-ecological, rather than merely an ecological, system. The task was to arrange the concepts and draw connections between them based on their own understanding and knowledge ("please indicate the factors of importance to the pike population biology and their relationships in terms of direction of influence and strength of influence"). The participants were given freedom to add additional concepts (participants received blank cards to be able to outline concepts not mentioned so far) and instructed that not all concepts had to be used in their model (see *Appendix*, Table 2.S1 for a complete list of concepts). The final drawings were photographed for further analyses (*Appendix*, Figure 2.S1). It is worth noting that the mental models were obtained at the beginning of the workshops before any influence could have happened by the team of researchers and workshop organizers and before any other type of information was exchanged with the stakeholders.

The visualizations that result from FCM modeling (see *Appendix*, Fig. 2.S1) are similar to so-called causal maps, which can be structurally explored in terms of network characteristics. Furthermore, FCM models are also quantitative simulation models that can be used to assess the dynamic behavior of the system under study. FCM computation shows the changes in the state of system's elements given a particular input or combination of inputs (i.e., input scenario) [51]: when one concept increases (or decreases) this triggers a cascade of changes to other system elements until the system converges to a so-called "steady state" [52]. FCM can thus answer "what if" questions, such as how an increase in one concept (e.g., angling pressure) affects all other elements in the system [52].

In a nutshell, FCMs are directed graphs, and therefore, using graph theory, they can be analyzed structurally to represent system knowledge regarding the elements and connections of the system. Also, to represent how the system behaves in response to input changes, FCM can be analyzed dynamically (i.e., functionally), based on fuzzy causal algebra for simulating causal propagation [33] (see Methods, Dynamic analysis and Inferences). Moreover, FCM from different participants can be mathematically aggregated if their matrices are brought to the same size and thus include information about every system element that is mentioned in any of the contributing maps.

2.5.3 Mental model aggregation

Individual FCMs can be aggregated mathematically to create a model that represents the insights of all study participants and thus provide a tool for testing WOC. There are two aggregation methods used in this study to build the crowd model: (a) *Single-Level aggregation*; aggregation is obtained in one step:

$$A_{ij}^{FCM_{crowd}} = \sum_{p=1}^{N} A_{ij}^{FCM_p} \,/\, \sum_{p=1}^{N} (1 \mid A_{ij}^{FCM_p} \neq 0) \quad (\mathbf{2.1})$$

where A^{FCM_p} is the adjacency matrix used to represent the FCM of participant *p*, *N* is the total number of participants, and $A_{ij}^{FCM_p}$ indicates the element of this matrix with the value equals to the weight of the edge between node *i* and *j*. FCM_{crowd} represents the crowd's FCM with the corresponding adjacency matrix $A^{FCM_{crowd}}$.

And (b) *Multi-level aggregation*; aggregation is obtained in two steps: Step (1) is computing the mean FCM of each subgroup:

$$A_{ij}^{FCM_G} = \sum_{p \in G} A_{ij}^{FCM_p} \,/\, \sum_{p \in G} (1 \mid A_{ij}^{FCM_p} \neq 0) \quad (\mathbf{2.2})$$

Where FCM_G represents the aggregated FCM of subgroup *G* and $A_{ij}^{FCM_p}$ indicates the element of adjacency matrix with the value equals to the weight of the edge between node *i* and *j*.

And step (2) is averaging subgroup means. We can use the arithmetic mean of subgroup means to average them; however, forming subgroups which consist of individuals with the same role in the fishery club carries the risk of amplifying stakeholder-specific biases in each subgroup and can be expected to increase the skewness of subgroup models distribution. Biases are likely to exist in our sample as prior work has shown that there is considerable bias in anglers' understanding of fishery management [53,54], which is the largest group in our dataset. Most importantly, to further remove the effect of biases, to form collective solutions, rather than using the arithmetic mean of subgroup means, we propose to aggregate subgroup means using the median. Earlier studies, in which the crowd is asked to provide single variable estimates, and in which there are significant biases in individual judgments, show that the median outperforms the arithmetic mean [12,29,30]. Thus we used the median to combine group means in the second level of the aggregation.

$$A_{ij}^{FCM_{crowd}} = Median\left(A_{ij}^{FCM_{G1}}, A_{ij}^{FCM_{G2}}, \dots\ , A_{ij}^{FCM_{Gn}}\right) \ (\mathbf{2.3})$$

Additionally, to remove the effect of subgroup biases, we can also use weighted-mean and geometric mean in the second level of aggregation based on prior theoretical and empirical studies [27,55–57]. We measured the performance of the crowd model built by different averaging methods in the second level of aggregation, and our result showed that the median had the best performance amongst other aggregation methods (see *Appendix*, Table 2.S2).

2.5.4 FCM analyses

FCM concepts (nodes) represent the qualitative characteristics of the system with an absolute value between 0 and 1, characterizing their so-called "activation level" in the model [52]. Arrows (edges) are characterized by a number in the interval of [-1, +1], corresponding to the strength, direction, and sign of causal relationships between concepts. The steady state that an FCM reaches in response to an input change (i.e., a forced change in the activation of one or more of its concepts), depends on how the activated concept(s) is connected to other concepts in the system. How nodes and edges are arranged is thus of great importance and frequently used to analyze FCM. A common measure to investigate this connectivity is centrality: A concept's centrality shows the contribution of this concept in a cognitive map which is determined by accumulating the strength of causal relationships linking this node to the other nodes [52]. One individual considers concepts with higher centrality more important since they are more strongly linked to the other system elements and consequently play more important roles in the dynamic of the system. Comparing the centrality of particular sets of concepts in different cognitive maps translates the differences in the system definition and its important components. In this study, we used Katz centrality index [58], since it is expected to provide the most appropriate centrality measurement for comparing aggregated maps with higher density and presumably higher abundance of feedbacks [59].

2.5.4.1 Structural analysis

In this study, we compared the structure of FCMs using three approaches: The first approach is to compare the centrality of six concepts of central relevance to fishery management decisions, namely "Stocking", "Spawning ground development", "Angling pressure management", "Enhancement of hiding places and refuges", "Enhancement of riparian vegetation", and "Enhancement of submerged aquatic plants" by making the centrality profiles. Each centrality profile displays the Katz centrality of these six concepts in a radar chart (Figure 2.1). We calculate the Katz centrality of each node *i* with:

$$X_i = \alpha \sum_j A_{ij} X_j + \beta \quad (\mathbf{2.4})$$

where X_i is the Katz centrality of node i, A is the adjacency matrix of FCM, α is the Attenuation factor, and β is the extra weight attributed to the immediate neighborhood. What Katz centrality measures is the relative influence of a node within the FCM by taking into account the weight of the immediate neighbors and also all other nodes in the FCM that connect to the node through these immediate neighbors. Extra weight would be given to the nodes located in the immediate neighborhood through parameter β (in our case $\beta = 0.5$). Connections made with distant neighbors are penalized by the attenuation factor α (in our case $\alpha = 0.3$). The Katz centrality of each node is a function of the Katz centrality of other nodes. Thus, this centrality computation is an iterative process (in our case maximum number of iterations is $10e^4$, and the error tolerance used to check convergence is $10e^{-6}$).

The second approach to analyzing and comparing the structure of FCMs is an investigation of agreement of strong causal patterns. This patterns emerge when we remove weak edges with absolute weights less than 0.33 from aggregated FCMs (Figure 2.2). The remaining edges illustrate the strong causal patterns used for model description.

$$U_g = \{EDG_g^{0.33}\} \cup \{EDG_{Exp}^{0.33}\} \quad (2.\mathbf{5})$$

$$M_g = \{EDG_g^{0.33}\} \cap \{EDG_{Exp}^{0.33}\} \quad (2.\mathbf{6})$$

$$PM_g = \frac{Size(M_g)}{Size(U_g)} \quad (\mathbf{2.7})$$

where $\{EDG_g^{0.33}\}$ is the set of strong edges with $Weight \geq 0.33$ in the FCM of group g, $\{EDG_{Exp}^{0.33}\}$ is the set of strong edges with $Weight \geq 0.33$ in the FCM of experts, M_g is the intersection of strong edges in FCMs of the group g and experts (i.e., set of matched edges), U_g is the union of strong edges in FCMs of the group g and experts, and PM_g is the proportion of matched edges between group g and experts.

Furthermore, we can compare the network structure of FCMs with regards to the quantitative aspects of their graph geometric shapes. In this study, we evaluate combinatorial and geometric properties of FCM graphs using a graph similarity index, namely “Eigenvalue graph similarity” [60,61] . Given two graphs, this index evaluates how similar they are in terms of the important features of their structures. Therefore, it provides a comparison between each FCM and the expert FCM regarding their fundamental structure. In fact, eigenvalue similarity index measures the *Euclidean* distance between two graphs in a new coordinate system wherein coordinates represent eigenvalues. In this coordinate system, each graph is determined by a point and the distance between two points demonstrates the structural similarity between these two graphs. The shorter the distance, the more similar the graphs are in terms of the essential components of their structures (Figure 2.3). To measure eigenvalues similarity index, we first calculate the eigenvalues of Laplacian of adjacency matrices of both FCMs. For each FCM the Laplacian matrix is calculated by.

$$L = D - A \quad (\mathbf{2.8})$$

where L is the Laplacian matrix, D is the diagonal matrix, and A is the adjacency matrix.

Then, for each Laplacian matrix, we find the smallest k such that the sum of the k largest eigenvalues constitutes at least 90% of the sum of all of the eigenvalues [60]. If the values of k are different between the two graphs, we use the smaller one. Thus, the eigenvalues similarity index is the sum of the squared differences between the largest k eigenvalues of the group g and experts FCMs. This gives us a number in the range [0,∞), where values closer to zero are more similar:

$$sim_g = \sum_{i=1}^{k} \left(\lambda i_{L_{Exp}} - \lambda i_{L_g}\right)^2 \quad (\mathbf{2.9})$$

where sim_g is the eigenvalue graph similarity index, $\lambda i_{L_{Exp}}$, is the i^{th} eigenvalue of the Laplacian matrix of experts FCM, λi_{L_g}, is the i^{th} eigenvalue of the Laplacian matrix of group g FCM.

2.5.4.2 Dynamic analysis and inferences

In addition to network structure, we analyze the dynamic behavior of FCMs. As prior studies suggested, the dynamic behavior of FCMs can be assessed through analyzing their responses to several "what if" scenarios [49,62]. To do so, in each scenario, we change the value of one or more concepts (i.e., nodes) in a map and record the alterations of the system state from the "steady state"[52]. The value of each concept in the steady state is calculated using:

$$c_i^{(k+1)} = f\left(c_i^{(k)} + \sum_j c_j^{(k)}.A_{ji}\right) \quad (\mathbf{2.10})$$

where $c_i^{(k+1)}$ is the value of concept C_i at iteration step k+1, $c_i^{(k)}$ is the value of concept C_i at iteration step k, $c_j^{(k)}$ is the value of concept C_j at iteration step k, and A_{ji} is the weight of the edge relationship between C_j and C_i. Function $f(x)$ is the "threshold function" used to squash the values at each step [49]. Our threshold function is a sigmoidal function:

$$f(x) = \frac{1}{1 + e^{-\lambda x}} \quad (\mathbf{2.11})$$

where λ is a real positive number (in our case $\lambda = 1$) which determines the steepness of the function f.

To run a "what if" scenario, we force the system to take fixed activation value in one or multiple concepts and use (Eq. 2.10) to compute the value of other concepts. The scenario results are the differences between the values of the system's concepts when the system is self-administered (i.e., steady state) and when it is bounded by fixed manipulations in the state of some concepts (i.e., scenario). For each concept C_i the change in its value as a result of running a scenario is:

$$d_i^{sc} = c_i^{ss} - c_i^{sc} \qquad \mathbf{(2.12)}$$

where d_i^{sc} is the change in the value of concept C_i, c_i^{ss} is the value of concept C_i in the steady state, and c_i^{sc} is the value of concept C_i after converging into a new steady state while scenario concepts are clamped on fixed values.

Comparing the scenario outcomes in different FCMs gives us a clear picture of how differently the system dynamic behavior is perceived by different mental models. To compare dynamic behavior of each group mental model with experts (i.e., reference model), we compute the *Euclidean* distance between their outputs of a scenario (Figure 2.4). The mean of these distances in all of the scenarios (i.e., 10,000 random scenarios in our case) represents the degree of agreement on simulation outcomes and therefore compare their dynamic behavior:

$$DD^g = \frac{1}{N}\sum_{j=1}^{N}\sqrt{\sum_i \left(d_i^{sc_{j_{Exp}}} - d_i^{sc_{j_G}}\right)^2} \quad \mathbf{(2.13)}$$

where DD^g is the dynamic distance between group *G* and experts, $d_i^{sc_{j_{Exp}}}$ is the result of scenario *j* in concept C_i in experts map, $d_i^{sc_{j_G}}$ is the result of scenario *j* in concept C_i in the group map, and *N* is the total number of scenarios.

2.5.4.3 Normalized error and performance

The normalized dynamic and structure errors are respectively the standardized dynamic and structure distances between the crowd and expert models:

$$ES_{normal} = \frac{Sim_{crowd}}{\max_g(Sim_g)} \quad \textbf{(2.14)}$$

$$ED_{normal} = \frac{DD_{crowd}}{\max_g(DD^g)} \quad \textbf{(2.15)}$$

where ES_{normal} is the normalized structure error, and ED_{normal} is the normalized dynamic error. The normalized total error is the mean of normalized dynamic and structure error:

$$ET_{normal} = \frac{1}{2}(ES_{normal} + ED_{normal}) \quad \textbf{(2.16)}$$

Finally, the Normalized Performance is calculated by subtracting the normalized total error from one:

$$P_{normal} = 1 - ET_{normal} \quad \textbf{(2.17)}$$

APPENDIX

APPENDIX

SUPPLEMENTARY INFORMATION

S1 Supplementary Methods

S1.1 Alternative multi-level aggregation methods

In Multi-level method the aggregated model is obtained in two steps: (1) Computing the mean FCM of each subgroup,

$$A_{ij}^{FCM_G} = \sum_{p \in G} A_{ij}^{FCM_p} \ / \sum_{p \in G} (1 \mid A_{ij}^{FCM_p} \neq 0) \quad (\mathbf{2.S1})$$

where A^{FCM_p} is the adjacency matrix used to represent the FCM of participant *p*, $A_{ij}^{FCM_p}$ indicates the element of this matrix with the value equals to the weight of the edge between node *i* and *j*, and *G* is the set of individuals in the subgroup. And (2) combining subgroup means: The simplest way to combine subgroup means is to use the arithmetic mean, which is called "Multilevel Mean-Mean"

S1.1.1 Multilevel Mean-Mean

This method uses the arithmetic mean of subgroup means to aggregate the maps.

$$A_{ij}^{FCM_{crowd}} = \frac{1}{N_G} \sum_{G=1}^{N_G} A_{ij}^{FCM_G} \quad (\mathbf{2.S2})$$

Most importantly, to further remove the effect of biases, to form collective solutions, rather than using the arithmetic mean of subgroup means, we can aggregate subgroup means by alternative aggregation techniques in the second level.

S1.1.2 Multilevel Mean-W Mean

Firstly, we can weigh subgroup means, resulting in "Multilevel Mean- W Mean". This approach builds on the works of Mannes *et al.* [55] and Budescu and Chen [56]. However, we were not able to identify justifiably reliable criterion to calculate contribution weights, instead, and based on Kao and Couzin's [26] suggestion, we simply weighted the subgroups by the reverse order of their proportional size. It uses the weighted mean of subgroup means to aggregate the maps.

$$A_{ij}^{FCM_{crowd}} = \sum_{G=1}^{N_G} W_G . A_{ij}^{FCM_G} \qquad and \qquad \sum_{G=1}^{N_G} W_G = 1.0 \quad (\mathbf{2.S3})$$

S.1.1.3 Multilevel Mean-Geo Mean:

Secondly, to account for the fact that estimates of edge weights are not necessarily normally distributed, we can calculate "Multilevel Mean- Geo Mean" building on the works of Lorenz *et al.* [27] and van Dolder & van den Assem [57]. This can be expected to perform better than the arithmetic mean when the data is right skewed because most people estimate small causal strengths and a few estimate very strong effects. It uses the geometric mean of subgroup means to aggregate the maps.

$$A_{ij}^{FCM_{crowd}} = \left(\prod_{G=1}^{N_G} A_{ij}^{FCM_G} \right)^{\frac{1}{N_G}} \quad (\mathbf{2.S4})$$

where *N* is the total number of participants, and $A_{ij}^{FCM_p}$ indicates the element of this matrix with the value equals to the weight of the edge between node *i* and *j*. FCM_G represents the aggregated FCM of group *G*. FCM_{crowd} represents the crowd FCM. N_G is the number of different subgroups and W_G is the contribution weight of group G used in weighted mean calculation (in our case $W_{Anglers} = 0.1, W_{ClubManagers} = 0.3, W_{FishManagers} = 0.6$). There is no quantitative criterion to compute contribution weights, and the weights are qualitatively chosen in the opposite order of proportional group sizes.

We measured the performance of the crowd model built by different aggregation methods, and our result showed that the Multilevel Mean-Med had the best performance amongst other aggregation methods (see *Appendix*, Table 2.S2).

S1.2 Participants' demographics and education

The three stakeholder groups (anglers, club managers and fisheries managers) as well as the fisheries experts' knowledge metrics assessed using identical questionnaires after the mental model exercises. The educational variables that were measured included three levels of formation: (1) school-level education (secondary education), (2) work-related education (tertiary education), and (3), in Germany, anglers are legally obliged to take a 30-hour training course in principles of aquatic ecology, legal conditions and how to treat fish from a welfare perspective (fisheries related education and training). Fisheries managers elected from angling clubs are further obliged to receive specific training in principles of fisheries management, usually offered by angler associations and assisted by fisheries agencies in each of the 16 German states. In addition, anglers, managers and club heads can also self-teach themselves in ecological principles. We therefore specifically assessed the degree of ecology-related training outside formal educational formation through schools or professional training for the job market.

In addition to assessing education at three levels, in the three angler groups (anglers, club managers, fisheries managers), we also measured the self-rated knowledge over a range of fish ecological and fisheries management topics to measure self-perception of ecological knowledge. We asked about participants' self-perception of their knowledge about aquatic ecology, fish stocking in general, Pike (*Esox lucius*) stocking practices, Carp (*Cyprinus carpio*) stocking practices, and measures for the sustainable care and management of water-bodies.

To describe the differences among the four surveyed groups, we conducted statistical tests using ANOVA on metrical variables and Chi²-test for distributional variables. Importantly, in addition to examining mean values we were interested in the within group heterogeneity of variables to index the degree of diversity present in each of the four groups we surveyed.

S1.2.1 Demographics

The four groups did not statistically differ in average age, and all four samples were heavily biased towards males (>94% of all surveyed people, which is the default in the study population). However, there was substantial more within group variation in age in the angler sample (as indexed by SD), and age variation was also higher in club managers relative to the more homogenous groups of fisheries managers and fisheries scientists.

S1.2.2 Education

The angler group revealed the largest heterogeneity in the distribution of the highest school education degree compared to the other three groups. On the other extreme, the scientists were the most homogenous sample with over 94% of the respondents holding a university-entrance qualification (Abitur) – the highest school degree possible in Germany. Fisheries managers were more homogenous compared to club managers in terms of school education. A similar pattern was revealed in terms of the distribution of the highest degree of professional training. While the fisheries scientists were most homogenous (predominantly having either a university degree or a PhD), the anglers exhibiting the most spread in tertiary degrees compared to club managers or fisheries managers. Finally, in terms of specific official or voluntary education in natural scientific and ecological topics related to aquatic systems and fisheries, fisheries managers showed the largest and most homogenous degree of ecological training, followed by club managers and then the angler group. For example, while only 7% of anglers had completed a one-week fisheries management training course, 18% of club managers and 85% of fisheries managers that responded to our survey completed this training. Similarly, 21% of anglers regularly attended public seminars on fish biology topics, while 32% of club managers and 64% of fisheries managers acknowledged such training. Overall, the degree of ecological training in fish ecology question thus was most homogenous and more pronounced in fisheries managers, followed by club managers and lastly anglers.

S1.2.3 Self-rated ecological knowledge on fisheries topics

Following the training in fish biological topics, the mean self-rating index of ecological knowledge was significantly highest among fisheries scientists, followed by fisheries managers, club managers and anglers. Importantly, however, the variation in self-rated knowledge (as indexed by SD) was higher in the angler group than in the fisheries manager group. Interestingly, also the scientists showed quite high variation in the self-rated knowledge, most likely because the self-rated knowledge with very specific domains (such as stocking the species of carp or pike) was assessed, which is unlikely to be something fisheries scientists regularly engage with in their practical world. Overall, a picture emerged that the angler group was the most heterogeneous of all three stakeholder groups and the fisheries manager group was the most homogenous in relation to education, with club managers ranging in between. On the other extreme, fisheries scientists overall were mainly academically trained (*Appendix*, Table 2.S3).

S2 Supplementary Discussion:

S2.1 Distinct impact of different aggregation methods on WOC

The distinct impact of different aggregation methods on WOC can be explained with biases resulting from real-life social influences. Despite potentials for learning from others and thus developing more integrated understanding of the system, in our study, participants were socially influenced only through their real-life interactions, where we had no control on the social network structure to avoid accumulation of biases. Becker *et al.* [31] theoretically and experimentally demonstrated that under certain conditions, and in highly decentralized networks, social influence may produce learning dynamics that potentially improves the WOC; however, we cannot assert that real-life social network structure is decentralized. Thus, we hypothesized that social processes may undermine the WOC effect, and the negative impact can be aggravated in larger crowds where the accumulation of biases magnifies the skewness of the distribution of individual data points. In a crowd built by single-level aggregation, as we draw and average more mental models, the group performance initially approaches its optimal point owing to the benefits of information pooling, but drawing more mental models undermines the crowd performance because knowledge that is shared by many members of the group (i.e., commonly agreed upon knowledge that relates to easily observable system elements) is downplaying the specialized mental models that deviate from this common knowledge (see Appendix, Figure 2.S3). By contrast, we show that in a crowd built by multi-level aggregation, the group performance improves monotonically as more mental models are drawn and averaged because the specialized knowledge is not downplayed in favor of commonly agreed upon knowledge (see *Appendix*, Figure 2.S3). The multilevel process first acknowledges group-specific knowledge using the mean (i.e., it reduces within-group variability). Then, in the second level of aggregation, it reintroduces some levels of variability by aggregating maps across different stakeholder groups; however, it uses median which reduces the negative influence of group-specific biases that deviate too much from the “norm” (i.e., the collective knowledge all stakeholder groups agreed upon).

S2.2 Fostering institutional fit and nested governance

Our WOC approach has potential implications for operationalizing local institutions to fit the complex social and ecological aspects of large-scale coupled human-natural systems by suggesting a novel structure for a nested governance system. This nested governance system integrates actions at local levels (i.e., aggregating local knowledge of stakeholders to create role-based subgroups) and coordinates decisions at higher levels with larger scales management authorities (i.e., aggregating across sub-groups). This application can be supported by findings of the recent works of Bodin and Nohrstedt [63] on collaborative management networks and McGlashan *et al.* [64], demonstrating how actions in complex system components could be directly related to how a multitude of actors collaborate to collectively represent a complex system by identifying parts of the system on which they can intervene.

S3 Supplementary Figures

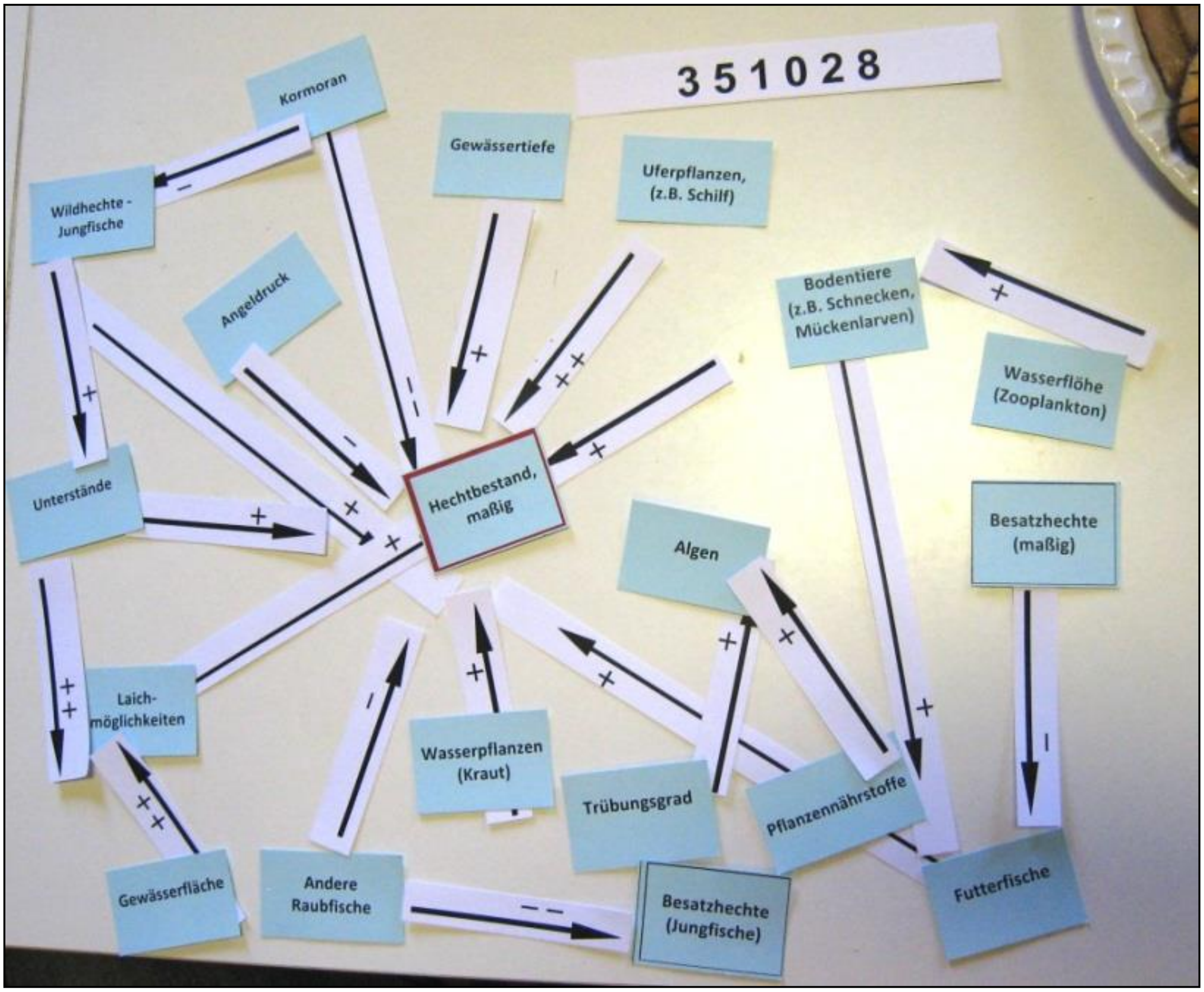

Figure 2.S1. An example of pike ecology and management fuzzy cognitive map generated by one participant in the workshops: The individually collected mental models graphically display the perceived cause-and-effect relationships of ecological and social concepts affecting each other (e.g., how habitat quality affects juvenile pike that later grow into harvestable size, or how fish-eating birds, stocking, or angling pressure affect the pike population). Note that the concepts' names are in German.

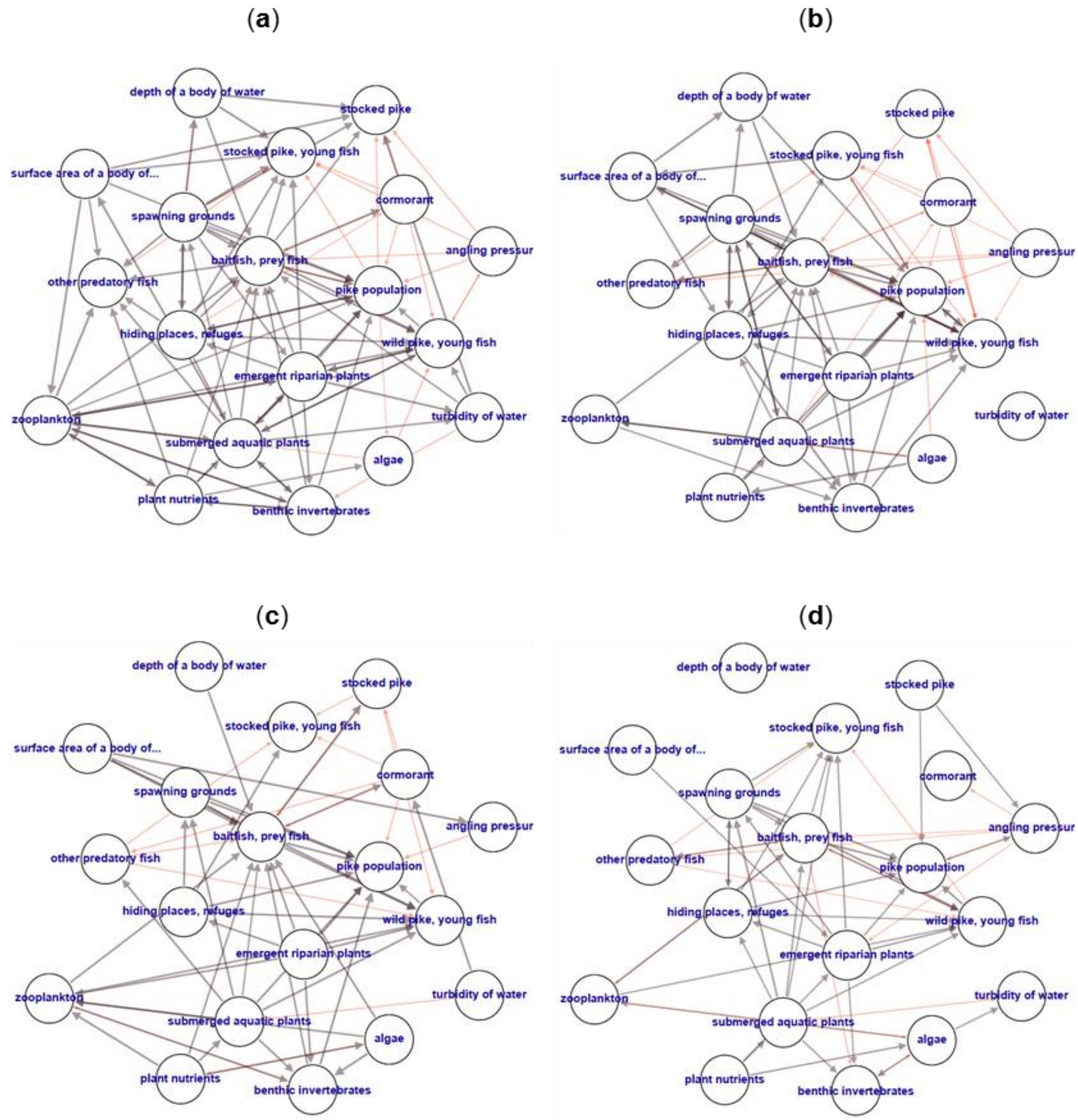

Figure 2.S2. The aggregated fuzzy cognitive maps of pike ecology and management in different groups of stakeholders: (**a**) Map generated by aggregating anglers' models, (**b**) Map generated by aggregating club managers' models, (**c**) Map generated by aggregating fisheries managers' models, (**d**) Map generated by aggregating all 218 individual models using multi-level aggregation method, and (**e**) Map generated by aggregating 17 scientists' models used as the reference model. Red arrows represent negative relationships, and blue arrows represent positive relationships between concepts. Weak relationships with a weight less than 0.33 were removed from the maps for a more clear illustration.

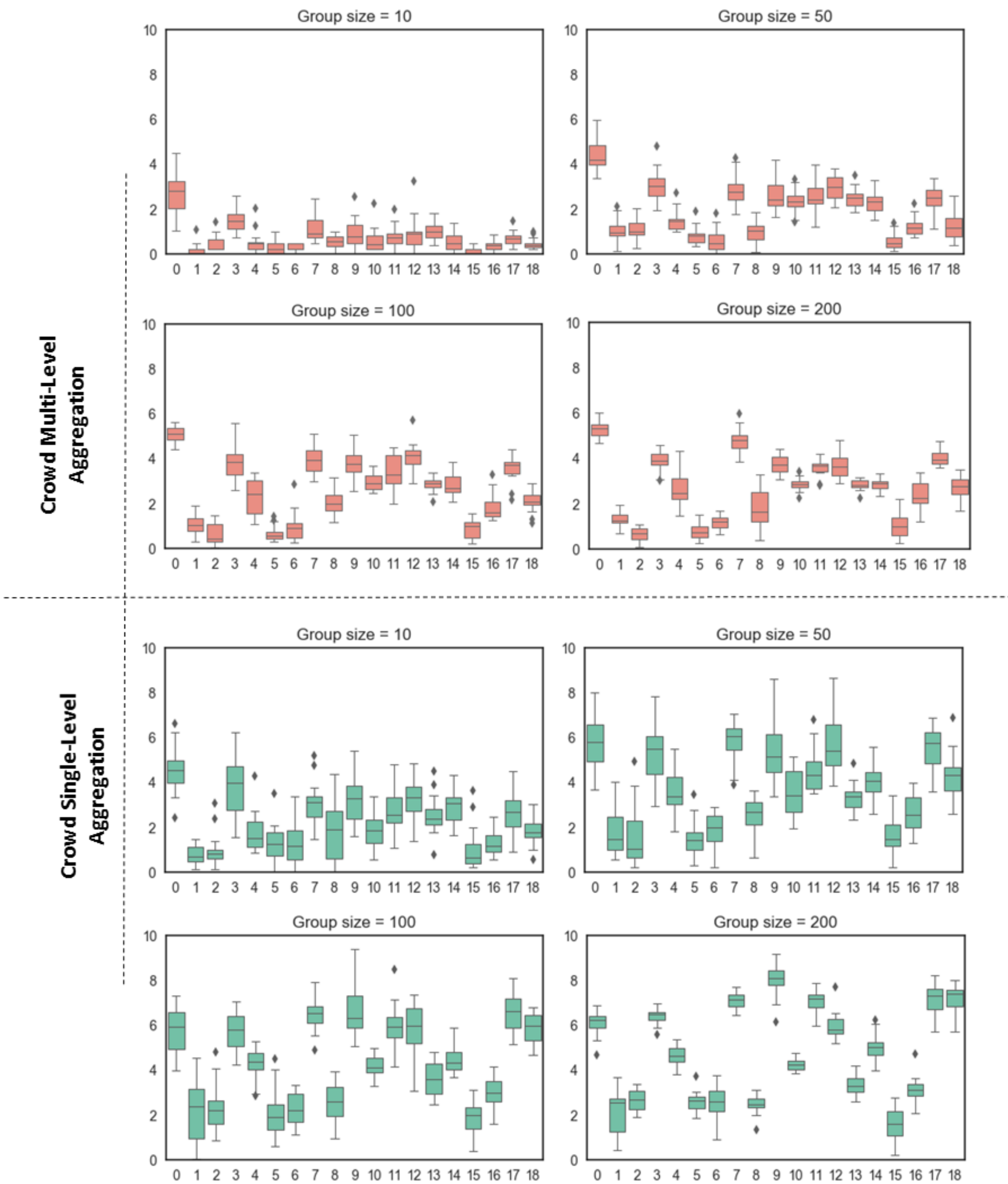

Figure 2.S3. Distribution of group emphasis on different concepts and its variation with group size: The graphs show the boxplots of all concepts' degree centrality in a crowd aggregated model. Given each specific group size N, we randomly sampled 100 groups by drawing N individual mental models. Each chart has 19 box plots (one for each concept in the model), each shows the distribution of degree centrality of a concept in 100 random samples. Degree centrality represents the perceived importance of the concept, based on its connections to other concepts

(i.e., the number of inward and outward facing arrows). The x-axis shows the 19 concepts coded from 0 to 18 (see *Appendix*, Table 2.S1 for the name of the concepts). The y-axis indicates the degree centrality of each concept.

As group size increases, initially high and low-centrality concepts move further apart in the bottom row (single-level aggregation), but much less so in the top row (multi-level aggregation). In the case of single-level aggregation, initially highly central concepts become relatively much more emphasized than other concepts, thus crowding out more specialized knowledge. These emphasized concepts are easily-observable and more correlated knowledge, such as node 3 = baitfish/prey fish, node 7 = spawning, node 9 = riparian plants like reeds, node 11 = zooplankton, node 17 = hiding places and refuges, and node 18 = surface area of a body of water. These concepts (i.e., nodes) can be expected to be part of all or most contributing models. However, their centrality is outsized in comparison to other concepts as group size increases. By contrast, in multi-level aggregation, the larger groups do not intensively overemphasize common knowledge shared by the majority, nor do they underemphasize specialized, and yet important, concepts. In this case, as crowd size increases, it quickly achieves a stable, and yet approximately unbiased, distribution of emphasis on different concepts, and this stable pattern does not significantly change in relatively larger sizes.

S4 Supplementary Tables

Table 2.S1. The list of all concepts used to build fuzzy cognitive maps. The list of factors were derived from independent focus groups with anglers and mental model pre-tests with both anglers and experts, to identify key concepts relevant to the pike fishery. Participants were given the freedom to add additional concepts and the final list of all identified concepts was 19 concepts coded from node 0 to node 18 in all fuzzy cognitive maps.

Node number	Concept's Name
0	pike population (adult, over the legal size limit)
1	stocked pike (adult, over the legal size limit)
2	stocked pike, young fish (under the legal size limit)
3	baitfish, prey fish
4	other predatory fish
5	Algae
6	depth of a body of water
7	spawning grounds
8	wild pike, young fish (under the legal size limit)
9	emergent riparian plants (e.g., reeds and other bank vegetation)
10	Benthic invertebrates (snails, crustaceans etc.)
11	zooplankton
12	submerged aquatic plants
13	cormorant
14	plant nutrients
15	turbidity of water
16	angling pressure
17	hiding places, refuges
18	surface area of a body of water

Table 2.S2. The performance of the crowd model generated by different aggregation methods. The last column shows the overall performance of the crowd models generated by different aggregation methods. The overall performance is calculated by subtracting the normalized total error from one. The normalized total error itself is the mean of normalized dynamic and structure errors. The normalized dynamic and structure errors are respectively the standardized *Euclidian* dynamic and structure distances between the crowd and expert models as described in Methods section. Therefore, the normalized performance serves as an interpretive criterion to rank the accuracy of aggregated models in approximating the structure and dynamic behavior of the scientific expert model.

Aggregation method	**Method details**	**Normalized Structure Error**	**Normalized Dynamic Error**	**Normalized Total Error**	**Overall Performance**
Single-level	The arithmetic mean of all individuals	0.337	0.94	0.64	0.36
Multilevel Mean-Mean	The arithmetic mean of subgroup means	0.164	0.721	0.44	0.56
Multilevel Mean-W Mean	The weighted mean of subgroup means	0.124	0.687	0.41	0.59
Multilevel Mean-Geo Mean	The geometric mean of subgroup means	0.093	0.667	0.38	0.62
Multilevel Mean-Med	The median of subgroup means	0.084	0.623	0.35	0.65

Table 2.S3. Fisheries knowledge and education metrics assessed using questionnaires after the mental model exercises. Ecological Knowledge index is based on Chronbach's Alpha reliability of 0.84. Statistical test on mean differences is based on ANOVA, with Post-hoc test Tukey B for homogenous variances, and Dunnett-T-3 for heterogeneous variances.

	Anglers	**Club Managers**	**Fishery Managers**	**Scientists**
Age (years)	48.5(14.13)	47.8(13.28)	46.3(11.6)	40(9.8)
Gender	98% Male 2 % Female	96% Male 4% Female	97% Male 3% Female	94% Male 6% Female
Self-rated Ecological Knowledge	Mean(SD) N=135	Mean(SD) N=52	Mean(SD) N=31	Mean(SD) N=17
Ecological Knowledge index	**13.6(3.2)a*****	**15.2(3.0)ab*****	**17.7(2.1)b*****	**19.7(4.2)c*****
Aquatic ecology	2.9(0.8)a***	3.1(0.7)b***	3.7(0.5)c***	4.2(0.7)d***
Fish stocking in general	2.7(0.7)a**	3.2(0.7)b**	3.7(0.5)c***	4.35(0.6)d***
Pike (*Esox lucius*) stocking practices	2.5(0.8)a***	2.8(0.8)b**	3.2(0.7)c***	3.9(1.1)d***
Carp (*Cyprinus carpio*) stocking practices	2.6(0.8)a***	2.9(0.8)b**	3.4(0.5)c**	3.3(1.4)c**
management of water-bodies	3.0(0.7)a***	3.3(0.9)b**	3.8(0.6)c**	4.0(0.9)c**
Fisheries Related Education and Training				
Educational course in preparation for the state angling exam	89%	94%	85%	NA
Training as a fisheries manager	7%a***	18%b***	85%c***	NA
University degree in biology or ecology	0%	0%	5%	NA
Attendance of fisheries biology presentations, or other natural science presentations	21%a***	32%b***	64%*c***	NA
Self-education by means of technical literature (books, magazines, internet)	50%	69%	100%	NA
Secondary Education				
Certificate of secondary education	24.8%a***	23.8%a***	37.5%***	0.0%b***
General Certificate of secondary education	24.8%a***	23.8%a***	18.8%a***	0.0%b***
Advanced technical college certificate	10%a**	16.3%a**	3.1%b**	5.9%b**
University entrance qualification (Abitur)	7.8%a***	2.5%a***	6.3%a***	94.1%b***
Did not complete school degree	0.7%	0%	0%	0.0%
Tertiary Education				
Apprenticeship	33.3%	35.0%	37.5%	0.0%
University degree of technical degree of higher education	7.8%a***	6.3%a***	3.1%a***	41.2%b***
No tertiary education	0.7%	0.0%	0.0%	0.0%
Master Craftsman	10.6%a***	15.0%***	9.4%***	0.0%b***
Technician	6.4%a***	8.8%a***	12.5%a***	0.0%b***
PhD	0.0%a***	0.0%a***	3.1%a***	58.8%b***
Still studying	1.4%	1.3%	0.0%	0.0%

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CHAPTER 3

3 THE DIVERSITY BONUS IN POOLING LOCAL KNOWLEDGE ABOUT COMPLEX PROBLEMS

A revised version of this chapter is in press for publication in *Proceedings of the National Academy of Sciences (PNAS)* (https://www.pnas.org/).

ABSTRACT

Recently, theoreticians have hypothesized that diverse groups, as opposed to groups that are homogeneous, produce several assets— all of which lead to better performance in solving complex problems. As such, understanding complex environmental or social issues, for which scientific information is typically limited, would likely benefit from the integration of diverse types of local expertise. Yet, capturing knowledge distributed across diverse types of local experts is not straightforward and consequently rarely evaluated, which often hinders applying knowledge-pooling to sustainability decision-making. To address these challenges, here we show how emerging internet technologies, semi-quantitative cognitive mapping techniques, and principles of collective intelligence theory can merge into a novel crowdsourcing approach to aggregate diverse expertise. Using a case of striped bass fisheries in Massachusetts, we show how our approach can be used to pool local knowledge of resource stakeholders to produce a model of complex social-ecological interdependencies. First, subjective evaluation of stakeholder models revealed improved performance of the diverse group compared to more homogeneous ones, as evidenced by blind reviews conducted by an expert panel. Second, objective evaluation of stakeholder models using a stochastic network analysis indicated that a diverse group more adequately modeled complex interdependencies and feedbacks where homogeneous groups were more likely to fail. Our work empirically validates the previous

theoretical assumption that knowledge diversity and pooling are important for understanding complex problems, while also highlighting that diversity must be moderated through an aggregation process leading to more complex yet parsimonious models.

3.1 INTRODUCTION

Determining which management strategies lead to sustainable outcomes in social-ecological systems (SES) is challenging, and are often made based on the *best available* sciences [1]. Specifically, in natural resource management, a number of laws and regulations mandate the use of best scientific information available (BSIA) in decision-making (e.g., the Magnuson-Stevens Fishery Conservation and Management Act of 1976; and the 2012 Forest Service Planning Rule). In many cases, BSIA is comprised of empirical data, peer-reviewed information, expert knowledge, and local and traditional knowledge. This scientific information can be used to implement management strategy evaluation (MSE) [2]—a decision-support tool (e.g., computational models) to examine the implications of alternative management and policy scenarios before any action is taken. However, in data-poor cases across a wide range of local sustainability contexts, scientific information is frequently inadequate for effective decision-making [3,4]. In such cases, traditional or local knowledge (LK) of people who interact with local ecosystems can constitute a rich source of scientific information and plays a key role in decision-making [5–8]. However, there are two primary challenges associated with pooling LK from local stakeholders that need to be addressed:

First, it is often difficult to quantify the scientific or management uncertainties associated with utilizing LK, which limits its formal or even legal use in environmental assessments and decision-making [6,9]. This is in part because the information embedded in stakeholders' LK is predominantly qualitative and may be considered "anecdotal" [1] and thus cannot be easily integrated with scientific assessments, which are often quantitative [6,10,11]. This limitation undermines the potential use of LK to develop statistically rigorous inferences or computationally executable simulations with the ability to represent the true condition of the system and “accurately” predict system responses to various management strategies or natural and anthropogenic perturbations.

Second, LK held by stakeholders demonstrates considerable variations across different groups that represent biased and sometimes conflicting perceptions of complex social-ecological interdependencies. These variations may be linked to differences in preferred adaptation strategies [12,13]; diverging beliefs and values [14]; disparate experiences and interactions with ecosystems [15]; and are thought to undermine the “reliability” [9] of integrating LK into management strategies [16–18].

In this article, we draw on collective intelligence (CI) theory [19] to test if LK—once aggregated from diverse stakeholders— produces accurate and reliable scientific information for complex problem-solving. CI is typically defined as a group phenomenon, enabling a group to accomplish complex tasks where individuals or any subset within it fail [20]. This group phenomenon may emerge when a collective of individuals either collaborate or independently pool their knowledge to address a problem [19,21,22]. The group may therefore benefit from a larger, more refined, or recombined body of knowledge, whereas the aggregation mechanism filters out errors and biases, compensates individuals’ insufficiencies, or allows for recombining the pool of knowledge in new ways that can result in innovative solutions, which is unlikely that any of the individual members would be able to come up with (e.g., ref. 23–25). CI has been a growing area of investigation with implications for improving decision-making in different fields. Importantly, new information technologies have substantially increased human capacities to pool knowledge and participate in decision-making [20]. For example, online crowdsourcing technologies such as *Human DX* and *Sermo* facilitate medical collaboration by building partnerships between medical societies and the public to improve medical training and clinical decision-making [26,27]. Prediction Markets, as another example, leverage internet technologies to harness the CI of online crowds and accurately predict the probabilities of various events occurring [21].

A growing body of literature now suggests that diversity of knowledge, once properly harnessed, is of utmost importance to improve CI in a group, thereby helping a group achieve better performance at the aggregate level [21,23,28–32]. In general, and especially for complex problem-solving such as those related to the sustainability of local SESs, theoretical and empirical evidence has demonstrated that knowledge diversity is a critical driver of collective performance [4,33–35]. But, how can we harness the CI of natural resource stakeholders via pooling LK to model social-ecological interdependencies? How does the factor ‘diversity’ impact the group’s collective performance in modeling a complex system?

Here we explore how emerging internet technologies, semi-quantitative cognitive mapping techniques, and CI theoretical principles can be integrated into a novel crowdsourcing approach to address the challenges associated with using LK as an accurate and reliable source of information to understand local sustainability issues. Our approach results in the aggregation of LK that is elicited from diverse groups of natural resource stakeholders through mental modeling. This knowledge elicitation and aggregation mechanism can yield a computationally executable representation (i.e., model) of social-ecological dynamics that combines local stakeholders’ perceptions. To implement this approach, we used an example of striped bass (*Morone saxatilis*) population dynamics in Massachusetts (MA), U.S.A. The striped bass fishery is an important component of coastal economies throughout the east coast and is composed of commercial and recreational fishers. While various stakeholder groups interact differently with the fishery, they each construct diverse knowledge about resource dynamics including both ecological dimensions (e.g., predator-prey relationships) and human dimensions (e.g., commercial and recreational fishing pressures), as well as their interrelationships.

We crowdsourced mental models using a semi-quantitative technique called Fuzzy Cognitive Mapping (FCM) [36] to represent each individual's LK about social-ecological relationships that influence striped bass populations and fisheries. We collected these FCMs using an online mental modeling technology (www.mentalmodeler.com), in the form of digitalized graph drawings from a diverse crowd of local stakeholders, including recreational fishers, commercial fishers, and fisheries managers (see *Appendix*, Figures 3.S1 and 3.S2). The individuals' drawings were then mathematically combined into a collective model representing the aggregated knowledge of stakeholders. 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) (see *Materials and Methods*).

Given the numerous social and ecological concepts potentially influencing the striped bass population and the likely differences in stakeholders' perceptions, we explored how this diversity impacts the accuracy and reliability of stakeholders' aggregated knowledge. Aggregation took place once all individual mental models were transformed into adjacency matrices—a mathematical representation of a directed graph [37]. We first combined individual mental models by stakeholder types to form homogeneous, stakeholder-specific models using the arithmetic mean of their adjacency matrices elements [38] (see *Materials and Methods*).

Subsequently, the more diverse crowd model (including all stakeholder types) was created through aggregating stakeholder-specific models using the median of their adjacency matrices elements. This "multi-level aggregation" mechanism (see *Appendix*, Figure 3.S3) has been previously identified as the most reliable and effective method for combining the mental models of stakeholders to mediate the diversity of models and cancel out group specific biases [33].

We evaluated the performance of stakeholder-driven models, both homogeneous and diverse by (*i*) acquiring subjective judgments from scientific experts, and (*ii*) analyzing the network structure of their aggregated mental models (see *Materials and Methods*). Our findings demonstrate that aggregating knowledge from a diverse group of stakeholders produces a CI model of social-ecological interdependencies that can generate outcomes similar to scientific methods in anticipating the structure of natural resource systems and their response to management strategies and external perturbations, and these outcomes in general, outperform those of more homogeneous groups. Our study, therefore, provides tools and methods for synthesizing the knowledge held by diverse groups of local stakeholders, which can advance the formal use of LK in understanding and making decisions about integrated environmental, health, and social issues and can potentially enhance our ability to resolve local sustainability problems.

3.2 RESULTS

A total of 32 individuals completed the online mental modeling survey including 13 recreational fishers, 11 commercial fishers, and 8 fisheries managers. To allow for standardization, but also capture knowledge diversity, participants were asked to include 5 concepts in their models (recreational fishing, commercial fishing, striped bass population, prey abundance, and water temperature) while other components in their concept maps could be freely associated based on their perceptions (see *Appendix*, Table 3.S1).

Aggregation of individual mental models by stakeholder types resulted in three averaged FCMs representing the overall perception of each homogeneous group (see *Appendix*, Figure 3.S4-3.S6). Group aggregated FCMs varied widely in the number of nodes and connections, as well as the qualitative composition of concepts used to represent social-ecological relationships. For example, recreational fishers focused on social concepts influencing fish populations, while commercial fishers tended to incorporate biological concepts, and managers emphasized management aspects (see *Appendix*, Figure S8).

Aggregation across diverse stakeholder groups using the median of group means yielded a "crowd model" with a parsimonious set of concepts and connections (23 concepts and 59 connections) (see *Appendix*, Figure 3.S7). This "crowd model" reflected the different expertise of all three stakeholder-specific groups by preserving a moderated level of information presented from each of them, blended knowledge diversity, and represented the overall understanding of the whole community about striped bass dynamics.

The review of concepts in three stakeholder-specific models and the diverse crowd model revealed that there were 15 overlapping core concepts shared by all 4 models; however, these concepts were connected to each other differently in different models (Figure 3.1). Expert evaluations of model structure were conducted by a panel of fisheries scientists based on the patterns of causal relationships among those 15 concepts to examine and compare the performance of four models. This evaluation was conducted in five steps: examining 1) striped bass predator-prey relationships, 2) the effect of fishing pressures on striped bass, 3) striped bass connection to ecology and habitat, 4) social drivers affecting the striped bass population, and 5) environmental drivers affecting the striped bass population.

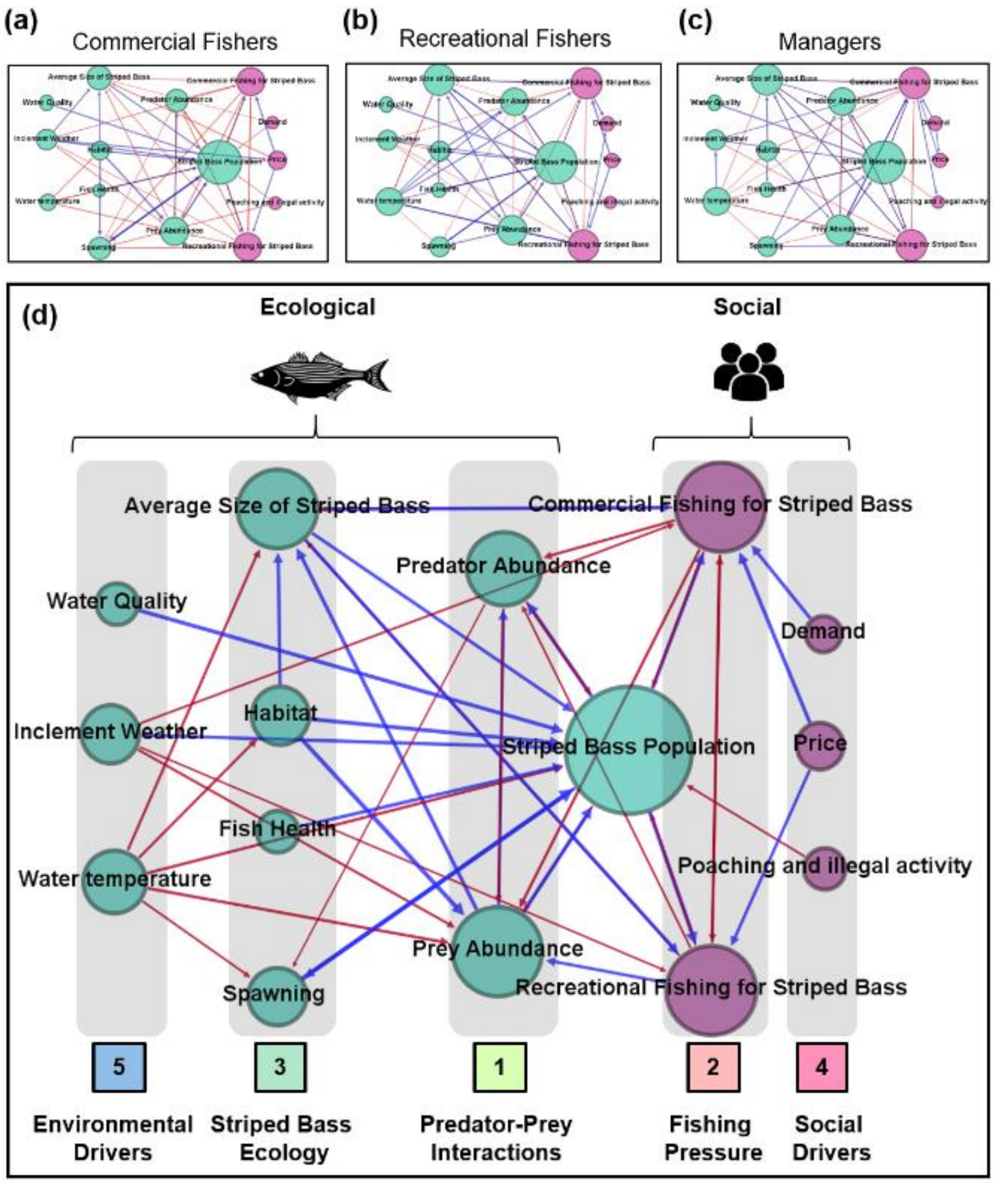


Figure 3.1. The representation of cause-and-effect relationships between 15 overlapping concepts shared by all stakeholder groups and the diverse crowd. Ecological components are green and social components are purple. The aggregated graphs of (**a**) commercial fishers, (**b**) recreational fishers, (**c**) fisheries managers, and (**d**) the diverse crowd were evaluated by scientific experts to assess their accuracy in terms of causal relationships and feedback loops. Evaluations were conducted in 5 steps as shown in (**d**).

In addition, the four aggregated models were computationally manipulated to determine how perceived social-ecological dynamics vary for each model (see *Appendix*). We computed the models' prediction of changes under six scenarios: increased inclement weather for fishing, increased water temperature, decreased water quality, increased price of fish, increased demand, and increased poaching and illegal activities (Figure 3.2).

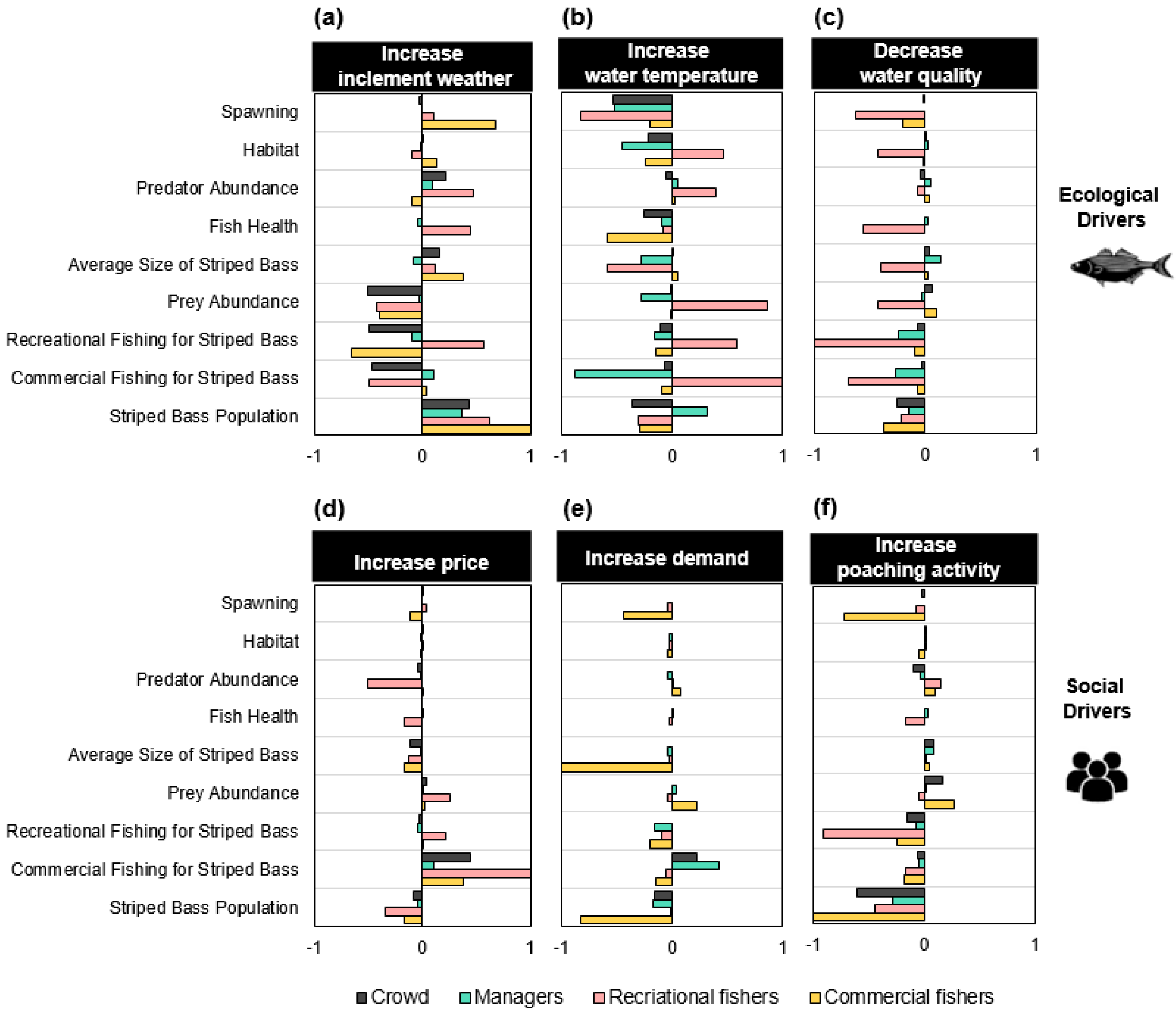


Figure 3.2. Fishery response (i.e., relative normalized changes in value of concepts) to six different scenarios simulating (**a**) increased inclement weather for fishing, (**b**) increased water temperature, (**c**) decreased water quality, (**d**) increased price of fish, (**e**) increased demand, and (**f**) increased poaching and illegal activities.

Expert evaluations of model functionality were conducted to examine and compare models' dynamic behavior under these six scenarios. Expert evaluation of models' structure and dynamic behavior revealed that the diverse crowd model outperformed stakeholder-specific models of homogeneous groups (i.e., recreational fishers, commercial fishers, and fisheries managers). Experts, on average, rated the crowd model as the most accurate map among the four models because it most adequately represented the causal relationships and feedback loops in striped bass fishery SES. Overall, scientific experts assessed that the structural performance of the crowd model was 65% accurate, followed by 55% accuracy for fisheries managers, 48% for recreational fishers, and 43% for commercial fishers (Figure 3.3 a). For the models' dynamics, experts rated the crowd model as the most accurate map among four blinded models owing to models' prediction of changes. On average, scientific experts determined that the crowd model's dynamic performance was most accurate (75%), 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 experts according to the model's dynamic performance (Figure 3.3 b). This implies that aggregating diverse knowledge of different stakeholder groups may improve the overall accuracy of their combined LK and can potentially lead to higher scientific alignment (Figure 3.3 c).

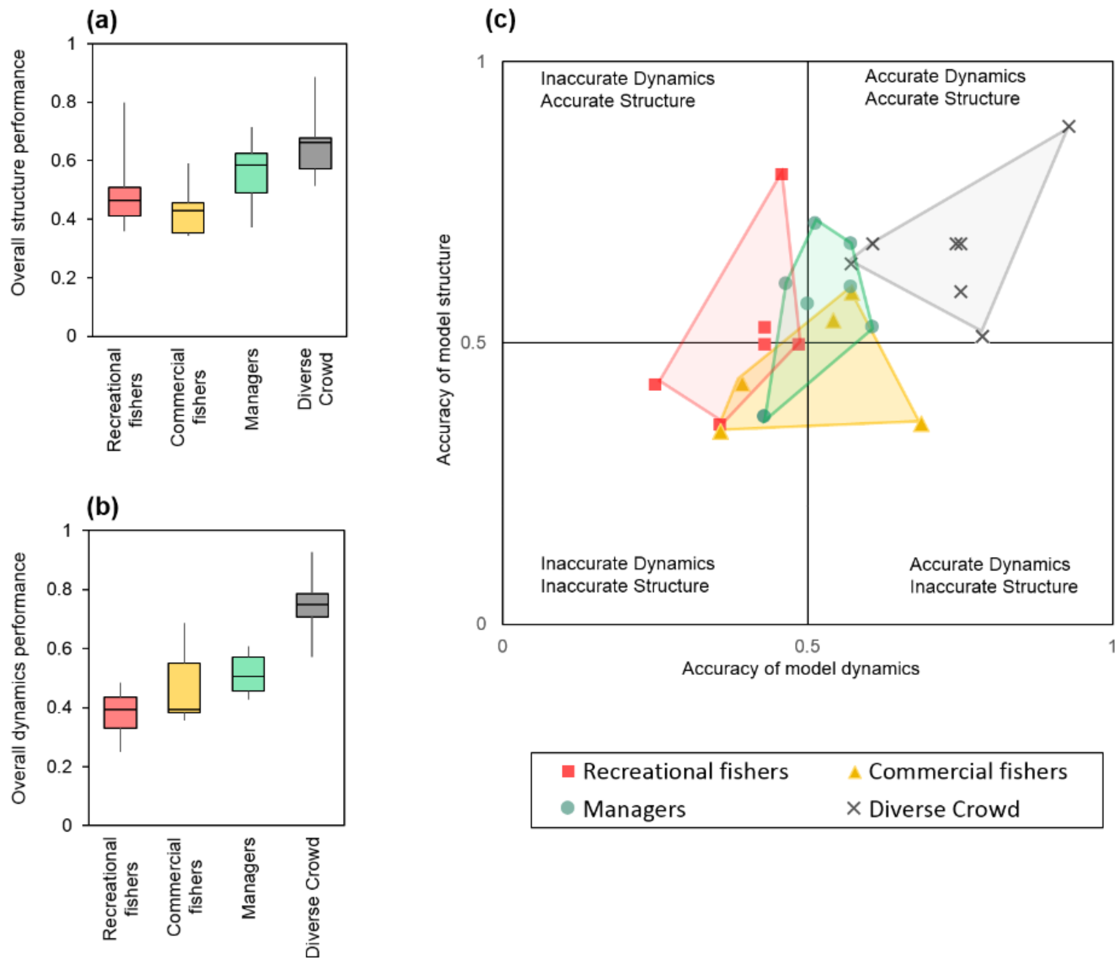


Figure 3.3. Expert evaluation of aggregated models. The box plots represent the distribution of experts' opinions regarding models' (**a**) structure and (**b**) dynamic performance. The performance was measured using a 7 point Likert scale for each item of interview sheets (see *Appendix*). The assigned accuracies of structural items (i.e., five sub-structures illustrated in Figure 3.1) were averaged and normalized to a scale between 0 and 1. Similarly, the assigned accuracies of dynamic items (six scenarios illustrated in Figure 3.2) were averaged and normalized to a scale between 0 and 1. The 2D scatter plot in (**c**) shows the overall score given to four models by each expert, where x-axis is the accuracy regarding models' dynamics and y-axis is the accuracy regarding models' structure.

In addition to 15 overlapping concepts that appeared in all four aggregated models, we asked experts to examine the other concepts that did not appear in all 4 models. Expert qualitative evaluation of models' composition revealed the number of false negatives or false positives (i.e., not including necessary system components and including unnecessary ones, respectively). An evaluation was conducted based on experts' scientific knowledge of the system's fundamental components versus trivial or redundant components which were considered superfluous in modeling the striped bass population. This qualitative assessment of the model composition determined "false" errors in four aggregated models revealing that, on average, expert panel identified 20% of the crowd model's composition as false positive or false negative, which is the smallest among all other stakeholder-specific models with overall false errors ranging from 32% to 55% (see *Appendix*, Figure 3.S9).

The stochastic network analysis of model structures revealed the prevalence of complex motifs (i.e., bi-directionality, indirect effect, multiple effects, and feedback loop micro-structures) in a model (see ref. 39). We quantified the expected value of counts for complex motifs given the size and density of networks of each group FCM (see *Materials and Methods*). Deviations of motif counts from their expected value were used as measures of motifs' prevalence (Figure 3.4). Our results demonstrate that the FCM of the diverse crowd has a higher prevalence for all complex motifs compared to the expectation, thereby representing a higher perception of complex causality.

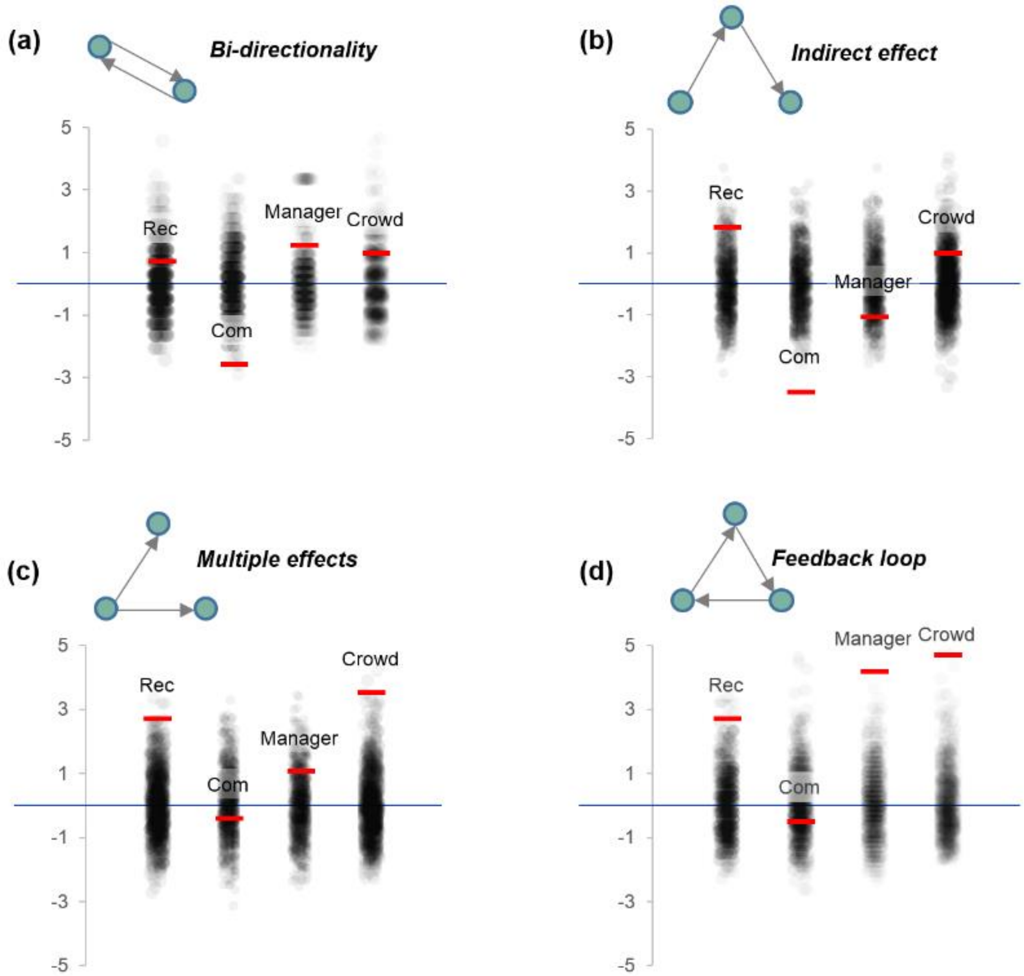


Figure 3.4. Deviation of the prevalence of complex causal motifs in aggregated models relative to uniform random graphs for (**a**) bi-directionality, (**b**) indirect effect, (**c**) multiple effects, and (**d**) feedback loops. Black dots represent 10,000 random graphs and the blue line shows the expected value of motif counts. Red dashes represent the deviation of each model from the expected value.

3.3 DISCUSSION

This study advances the use of LK for understanding complex problems by leveraging the assets of knowledge diversity (i.e., "diversity bonus") [29]. We draw on CI theoretical principles to combine diverse stakeholders' LK and produce comprehensive models of complex interrelationships in social and environmental problems that human societies face. Our study offers a novel approach to collect and aggregate knowledge diversity across various groups of individuals to provide an improved understanding of complex problems. We used an example of striped bass fisheries in MA to empirically test our approach. Our results demonstrate that once harnessed properly, pooling diverse LK would likely yield accurate representations of complex interdependencies between humans and the environment that govern a natural resource system. The resulting aggregated model can also generate reliable and accurate predictions of system responses to natural and anthropogenic perturbations (Figure 3.3). This study, therefore, adds to a growing body of literature that investigates the use of LK in scientific assessments and the management of natural resources [8,10,11,40,41].

Stakeholders interact with natural resources differently, and this may lead them to construct diverse perceptions about social-ecological interdependencies. The semi-quantitative FCM approach we used here enables us to highlight these variations in stakeholders' LK in terms of perceived system composition, structure of interdependencies, and dynamic behavior [42,43]. Even though a large body of literature has been dedicated to measuring these variations using FCMs (e.g., ref. 44), few studies have explored the benefits of knowledge aggregation [33,38,45,46]. Here we focused on how diversity impacts stakeholders' collective perception of a complex problem.

Consistent with past theoretical studies (e.g., "diversity trumps ability" theorem) [28], 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 be mediated, filtering out the biases associated with each group's LK. We used the principles of CI, and specifically, the wisdom of crowds (WOC) ideology to aggregate mental models and operationalize the diversity "bonuses" [29]. As such, the aggregation method we used here is based on a two-step averaging mechanism (Figure 3.S3) to let stakeholder-specific biases cancel each other out and also knowledge insufficiencies be complemented by pooling diverse expertise (see ref. 33 for more details about the aggregation method).

In this study, we used both subjective and objective evaluations to measure the performance of aggregated FCMs. We asked a group of experts with a wide range of scientific knowledge and expertise to assess the performance of the stakeholder-driven models based on their personal opinions and knowledge. Even though experts represented a wide range of academic disciplines (e.g., fisheries ecology, economics, etc.) and professional expertise, a clear majority of experts rated the diverse crowd model as the most accurate one, compared to stakeholder-specific, homogeneous models. Additionally, stochastic network analysis provided an objective evaluation of the model's performance in representing complex causalities driving the system. The FCM of diverse crowd demonstrated a higher prevalence for all complex motifs compared to the expectation. The aggregated map of recreational fishers also demonstrated high prevalence for all tested motifs while managers demonstrated low prevalence of motif “indirect effects”, which represents a lower appreciation of cascading impacts [45]. The aggregated map of commercial fishers, on the other hand, demonstrated low prevalence for all tested complex motifs indicating that commercial fishers tend to perceive the system as more linear with hierarchal casual structures (Figure 3.4).

Additionally, managing uncertainty is a key challenge for policy and decision-making. In natural resources management, two common types of uncertainties include scientific uncertainty (related to data sources) and management uncertainty (related to the ability to predict management success/outcomes). To address the former, laws and regulations frequently mandate the use of BSIA (e.g., Magnuson-Stevens Fishery Conservation and Management Act of 1976). However, the interpretation of such laws has led natural resource management to overvalue minimizing scientific uncertainty, often to the detriment of properly handling management uncertainty. Similarly, researchers have suggested that managing the latter requires that stakeholders, managers, and scientists first predict how systems respond to management strategies through scenario analysis and then collectively achieve a shared understanding about possible management actions [47]. Such adaptive co-management practices, however, often suffer from a lack of ready-to-use simulation models, in addition to the high amount of time and resources necessary to elicit diverse knowledge. Here we demonstrate that the use of internet technology to crowdsource LK through an online mental modeling platform can help achieve efforts to manage both types of uncertainties.

Even though these mental modeling practices are commonly organized through workshops (e.g., ref. 43) and interviews (e.g., ref. 44), we demonstrated that once provided with simple instructions (e.g., short videos and written directions) (see *Appendix*), participants can comfortably interact and familiarize themselves with the online platform, and thus knowledge elicitation process can be automated. Our study demonstrates a novel CI approach for aggregating and integrating stakeholders' LK to produce reliable, computationally executable modeling systems for understanding and promoting the sustainability of complex social-ecological systems.

3.4 METHODS

3.4.1 Mental models and fuzzy cognitive maps

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 many researchers have suggested the importance of eliciting and measuring mental models [18,38,44,48,49]. However, many mental model elicitation techniques often yield qualitative representations of associative rules between concepts/ideas and logical chains of reasoning, with few standardized methods to analyze them as computational simulations of the system they represent [38]. Here we used FCM—a semi-quantitative technique— to bridge the divide between highly computational system modeling and easy-to-construct qualitative cognitive or concept mapping. FCMs are graphical representations of an individual's perception showing a network of cause and effect relationships (edges) among different concepts (nodes) and, yet, 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 individuals' knowledge about dynamics of the system they represent [37]. By increasing or decreasing a concept in the map (e.g., water temperature or predator abundance), "what-if" scenarios can be simulated using the auto-associative neural network method [50] (see *Appendix*).

3.4.2 Online crowdsourcing implementation

We collected mental models from diverse groups of stakeholders including commercial fishers, recreational fishers, and fisheries managers. We used a contact list of recreational and commercial fishers including all MA licensed fishers. In addition, we used a contact list of fisheries managers including individuals from NOAA, Massachusetts Division of Marine Fisheries, and Atlantic States Marine Fisheries Commission - striped bass board. Random sampling methods were used to select 100 individuals from each list. Individuals who indicated their willingness to participate were 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.

Participants were given a written step-by-step manual (see *Appendix*) and a series of short videos instructing them how to brainstorm, identify, and add components via an online graphical interface, representing all concepts that they believe impact either their fishing effort and/or the striped bass population. 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 component affects another. This exercise was completed when the participant could no longer think of additional relevant concepts or linkages among concepts. Participants had to save their mental model contributions and send them to the project's email address.

3.4.3 Collective intelligence and knowledge pooling

To harness the CI of local stakeholders for natural resource system modeling we expanded a well-documented method called the "wisdom of crowds" (WOC) [21,51]. WOC refers to the finding that groups of people, under certain conditions, are collectively smarter than individuals in problem-solving, decision making, innovating, and predicting. For example, in simple estimation, the average of individual judgments often outperforms the judgment of the majority of the contributing individuals and sometimes even the best individual judge [21]. WOC has been applied to many situations from people contributing to medical diagnostics [52] to predicting the winners of major sporting events [53], often with high rates of success. 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 over- and under-estimates, thus moving the aggregate response closer to the ground truth [21,54].

We used WOC principles to aggregate mental models of stakeholders about the striped bass SES. According to Surowiecki [21], crowd-based solutions, can be reliable when (a) the study participants represent diverse opinions, (b) make their judgments independent of each other and without outside influences, (c) are able to draw on their local knowledge, and (d) there exist some aggregation mechanisms to combine individual contributions into a collective response. We similarly aggregated individuals' graphical mental models from a diverse group of stakeholders whose LK and perceptions were elicited independently using an online mental modeling technology in the form of FCMs. Once the individual FCMs were standardized (i.e., using unique terminologies for similar concepts) (see ref. 55), models were combined using their adjacency matrices and matrix algebra to create a model that represented the collective knowledge of stakeholder groups and thus provided a tool for leveraging WOC (see *Appendix*).

3.4.4 Expert evaluation of models' performance

To evaluate the accuracy and overall performance of the stakeholder-driven models we conducted in-depth interviews with fisheries experts. Experts were recruited from the National Oceanic and Atmospheric Administration (NOAA), Northeast Fisheries Science Center, Massachusetts Division of Marine Fisheries, and an academic institution. A purposeful sampling method was used to select a sample of fisheries scientists with diverse scientific expertise and educational background—also being involved in management, assessment, and conservation of striped bass fish stocks in MA. Eight experts participated with academic background in environmental sciences; natural resource management; ecology, evolution and marine biology; environmental conservation; environmental and natural resource economics; marine sciences and fisheries biology; and social sciences. Interviews with experts were semi-structured with a combination of pre-established questions and a series of interactive model evaluation practices requiring scientific experts to examine 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). Each expert independently interacted with the stakeholder-driven models and expressed their opinion about the accuracy of models' composition, structure, and dynamics using a 7 point Likert scale (1 = very inaccurate, 7 = very accurate) as a proxy measurement for models' performance.

3.4.5 Network analysis of stakeholder-driven models

To identify the extent to which each aggregated model represented complex causal processes we used stochastic network analysis of causal micro-structures. Building on network theory and cognitive map analyses of complex causal structures developed by Levy et al. [39], we compared the aggregated FCMs according to their network motifs (i.e., micro-structures 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). 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. Theoretical and empirical studies have frequently suggested that four particular motifs exemplify more complex patterns of causation [39,45,46,49,56–58]; therefore, their prevalence in a cognitive map indicates higher perception of complex interdependencies: bi-directionality, multiple effects, indirect effect, and feedback loop (see Figure 3.4 and ref. 39). 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 [59]. We measured the count of motifs in the model's network and how this count compared to the expected value of counts in 10,000 randomly generated networks of the same size and density with uniform distribution of edges.

APPENDIX

APPENDIX

SUPPLEMENTARY INFORMATION

S1 Supplementary Methods

S1.1 Mental Models and Fuzzy Cognitive Maps (FCM)

Mental models [60] are simplified internal representations of reality that allow humans to perceive patterns of cause-and-effect relationships through reasoning and to make decisions. Mental models consist of beliefs and subjective knowledge that are constructed as individuals observe, interact with, and experience the world around them and concurrently develop an internal model to understand and predict how it functions [61]. As such, they synthesize knowledge that is acquired through experiential, social, and formal learning.

Mental models that represent causal knowledge (e.g., how social and ecological components are interconnected in a natural resource system) can be elicited through cognitive mapping [62]. Cognitive maps are representations of mental models in the form of directed graphs. Nodes represent concepts that are part of the mental model and edges (arrows) are used to show the causal relationship between the concepts.

Fuzzy Cognitive Maps (FCM) [36] extend causal cognitive maps in order to add a dynamic component to their analysis. These are graphical models of system components (nodes) and their causal relationships (edges), forming a weighted directed graph (Figure 3.S1). Relationships (edges) are characterized by a number in the interval of [-1, +1], corresponding to the strength and sign of causal relationships between nodes. They, therefore, provide a semi-quantitative system modeling technique, based on auto-associative neural networks and fuzzy set theory that make cognitive maps computable (see FCM computation section of this *Appendix*).

A total of 32 individuals completed the online mental modeling survey including recreational fishers, commercial fishers, and fisheries managers, each creating their own FCM (Figure 3.S2). Table S1 shows the number of participants from each stakeholder type. In addition, the mean and standard deviation of number of concepts (i.e., nodes) and connections (i.e., edges) used by individuals to construct FCM representing their mental models about striped bass population dynamics are shown in Table S1.

S1.2 Mental Models Aggregation

S1.2.1 Stakeholder-specific models (homogenous groups)

Individual mental models represented as FCMs can be aggregated mathematically using matrix algebra operations on their adjacency matrices. These aggregated models—also referred to as "community maps"—can be used to represent the knowledge and perception of a group of participants and thus provide a tool for knowledge-pooling [63]. To combine mental models of a homogenous group with individuals from a specific stakeholder type (e.g., recreational fishers, commercial fishers, or managers) we calculated the arithmetic mean (i.e., simple average) of edge weights that are shared in all FCMs (see also ref. 64 for more details):

$$A_{ij}^{FCM_g} = \sum_{p=1}^{N} A_{ij}^{FCM_p} \;/\; \sum_{p=1}^{N} (1 \mid A_{ij}^{FCM_p} \neq 0) \quad (\mathbf{3.S1})$$

where A^{FCM_p} is the adjacency matrix of the FCM of participant *p*, *N* is the total number of participants in a group, and $A_{ij}^{FCM_p}$ indicates the element of this matrix with the value equals to the weight of the edge between node *i* and *j*. FCM_g represents the aggregated FCM of a group with the corresponding adjacency matrix A^{FCM_g}.

We used the above aggregation method to create stakeholder-specific (homogenous) models of recreational fishers (Figure 3.S4), commercial fishers (Figure 3.S5), and fisheries managers (Figure 3.S6).

S1.2.2 Crowd model (diverse group)

To build an aggregated mental model of diverse stakeholders (i.e., the crowd model), we used a multi-level aggregation technique (Figure 3.S3). The first level of aggregation was achieved by adding mental models of individuals from the same stakeholder type and averaging the weights of shared edges (see Eq. S1). At the second level, we aggregated the averaged stakeholder-specific models. At this level, we could have used the arithmetic mean of averaged maps to aggregate across the stakeholders; however, forming stakeholder-specific models that consist of same-type individuals could likely amplify the accumulation of stakeholder-specific biases. To address this issue, and similar to what described in Aminpour *et al.* (2020), here we used the median of stakeholder-specific averaged models to further remove the effect of biases:

$$A_{ij}^{FCM_{crowd}} = Median\left(A_{ij}^{FCM_{g1}}, A_{ij}^{FCM_{g2}}, \dots\ , A_{ij}^{FCM_{gn}}\right)\ \mathbf{(3.S2)}$$

where $A_{ij}^{FCM_{crowd}}$ indicates the element of the adjacency matrix of crowd model with the value equals to the weight of the edge between node *i* and *j*. In our case, there are three types of stakeholders: recreational fishers, commercial fishers and fisheries managers. Thus, we used the median of edge-weights across three arithmetically averaged stakeholder-specific maps (i.e. FCM_{g1}, FCM_{g2}, and FCM_{g3}) to build the diverse crowd model (Figure 3.S7).

S1.3 Concept Categorization

We categorized concepts used by participants into two main categories: (1) Ecological-dimension and (2) Human-dimension. The ecological-dimension was divided into two sub categories of biological concepts and habitat related concepts. In addition, the human-dimension was divided into two sub categories of social concepts and management related concepts. We measured the frequency and relative percentage of each sub-category across stakeholder types to determine stakeholder-specific biases (Figure 3.S8).

S1.4 FCM computation

FCM models are semi-quantitative simulation models [65] that can be used to assess the perceived dynamic behavior of the system they represent [63,66,67]. Here, we used FCM computational analysis to demonstrate how stakeholders, based on their collective perceptions and knowledge, predicted the changes in the state of system's elements (e.g., striped bass population) given an initial change in one or combination of concepts (i.e., scenario inputs) (e.g., water quality or water temperature) (also see ref. 68 for details about scenario analysis). An increase (or a decrease) in a concept initiates a cascade of changes to other system concepts (typically normalized between 0 and 1), and this iterative propagation of the initial change evolves into a so-called new "system state" [69]. By comparing the system states (i.e., the value of concepts) before and after initiation of a change, FCM can be used to implement "what if" scenario analysis, and therefore represent perceived dynamic behavior of the system (in this case, striped bass fisheries).

To run a scenario, the value of one or more concepts (i.e., scenario nodes) in a FCM was changed and forced to stay at either +1 (an increase) or -1 (a decrease). This initial change passes through the network of nodes and connections including feedback loops until the system reaches a new state. The consequent alterations in the state of other system concepts were calculated by subtracting their initial values from their values after the scenario was introduced and system evolved into a new state. The initial value of each concept—also known as steady state—is calculated using the following formula:

$$c_i^{(k+1)} = f\left(c_i^{(k)} + \sum_j c_j^{(k)}.A_{ji}\right) \quad (\mathbf{3.}\boldsymbol{S}\mathbf{3})$$

where $c_i^{(k+1)}$ is the value of concept C_i at iteration step k+1, $c_i^{(k)}$ is the value of concept C_i at iteration step k, $c_j^{(k)}$ is the value of concept C_j at iteration step k, and A_{ji} is the weight of the edge relationship between C_j and C_i. Function $f(x)$ is the "threshold function" that was used to squash the concept values at each step to a normalized interval between -1 and 1. In this study, we used a hyperbolic tangent function (see ref. 70 for more details about hyperbolic tangent function):

$$f(x) = Tanh\,(\lambda x) = \frac{e^{\lambda x} - e^{-\lambda x}}{e^{\lambda x} + e^{-\lambda x}} \quad (3.\boldsymbol{S}\mathbf{4})$$

where λ is a real positive number (in our case $\lambda = 1$) which determines the steepness of the function f.

The value of each concept under a scenario was computed using the same formula (Eq. S3), but this time scenario nodes were forced to take fixed values (either +1 or -1). The scenario outcomes were then calculated as the differences between the values of the system's concepts when the system was self-administered and when it was forced by fixed manipulations in the state of scenario concepts [63,69]. For each concept C_i the change in its value as a result of running a scenario is:

$$D_i^{sc} = c_i^{ss} - c_i^{sc} \qquad (3.\boldsymbol{S5})$$

where D_i^{sc} is the change in the value of concept C_i, c_i^{ss} is the value of concept C_i in the steady state, and c_i^{sc} is the value of concept C_i after converging into a new state while scenario concepts are clamped on fixed values.

S1.5 Online mental modeling instructions

The individuals who participated in online mental modeling survey were given a step-by-step instruction how to build a FCM model using the online mental modeling technology. Mental Modeler online tool is modeling software that helps individuals and communities capture their knowledge in a standardized format that can be used for scenario analysis. Based in FCM, users can develop semi-quantitative models of complex social and environmental issues by defining the important components of a system and also the relationships between these components [71]. The step-by-step direction showing in Figure 3.S10 was used to instruct participants.

S2 Supplementary Figures

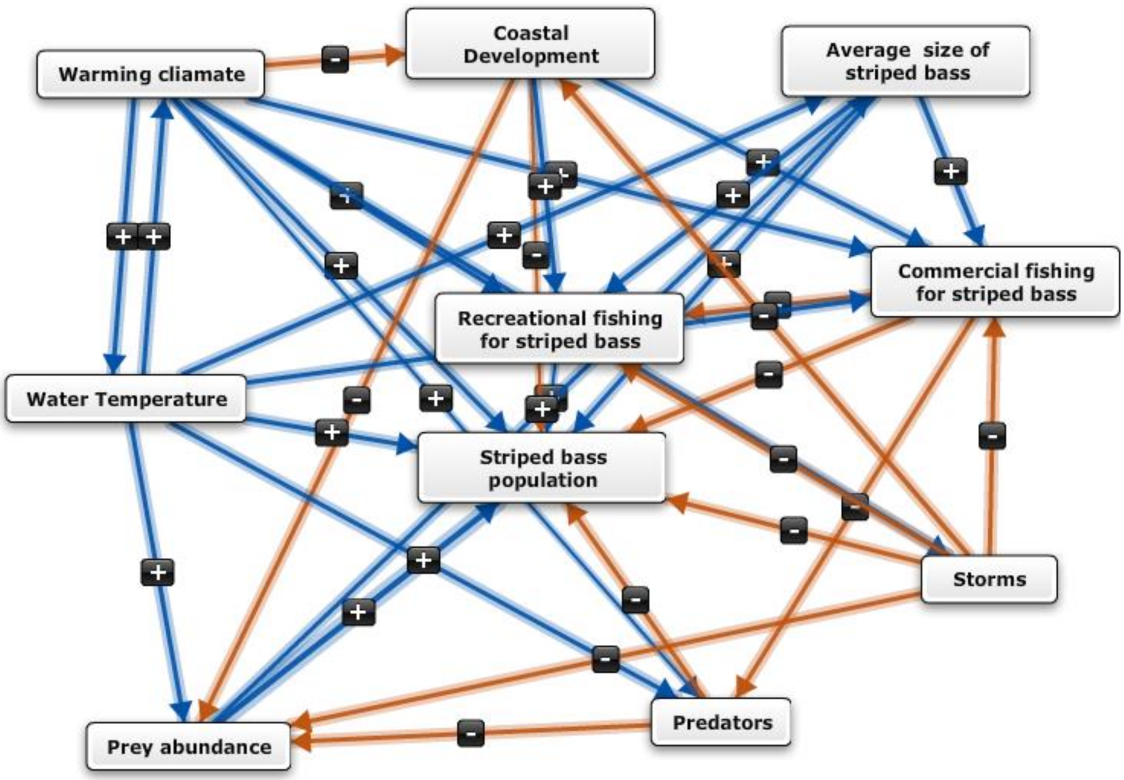


Figure 3.S1. An example of a fuzzy cognitive map (FCM) representing a mental model about striped bass fishery. The FCM was created using Mental Modeler online platform at www.mentalmodeler.org. Boxes demonstrate system concepts defined by the individual modeler and arrows indicate causal relationships between concepts.

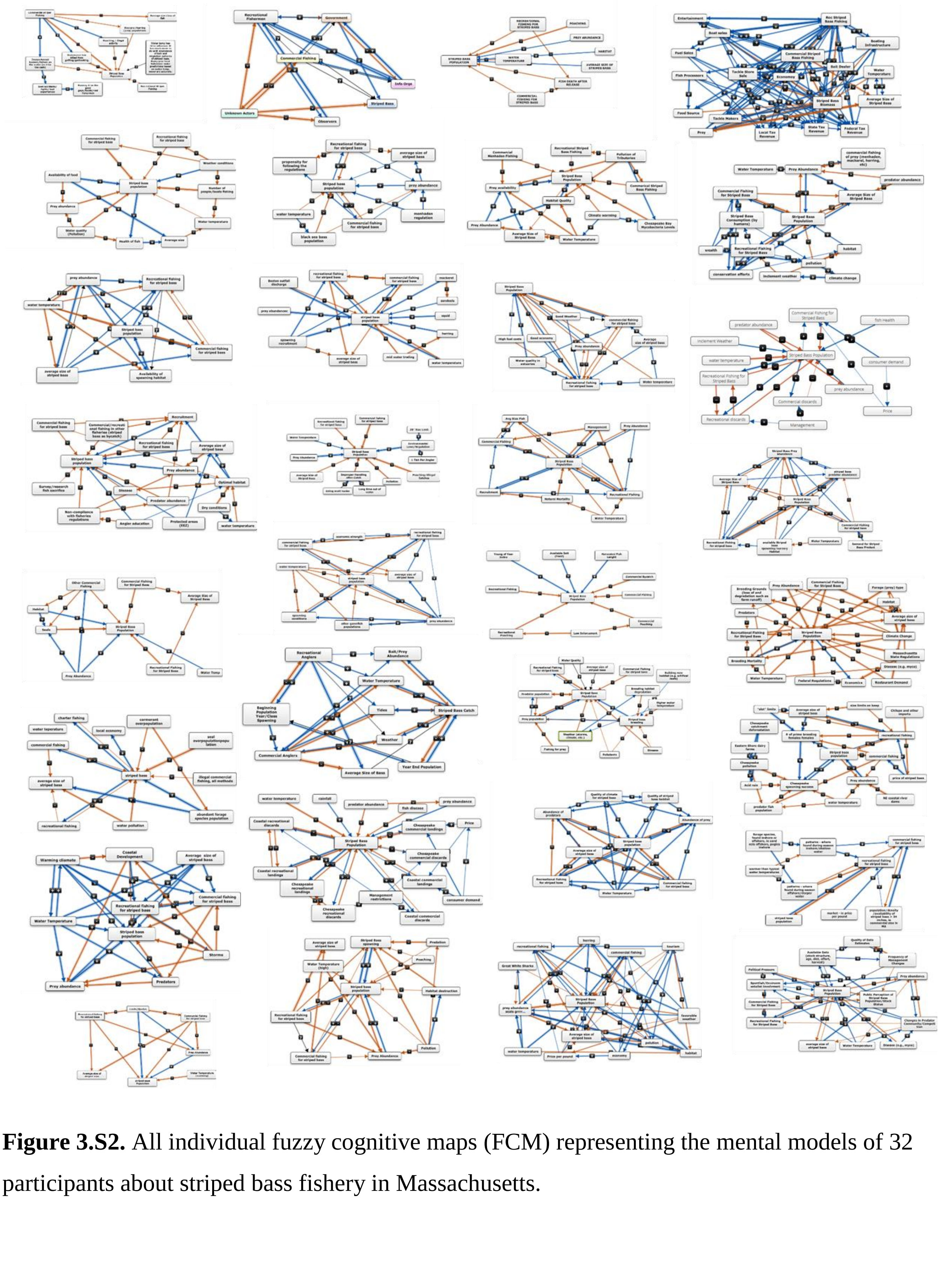


Figure 3.S2. All individual fuzzy cognitive maps (FCM) representing the mental models of 32 participants about striped bass fishery in Massachusetts.

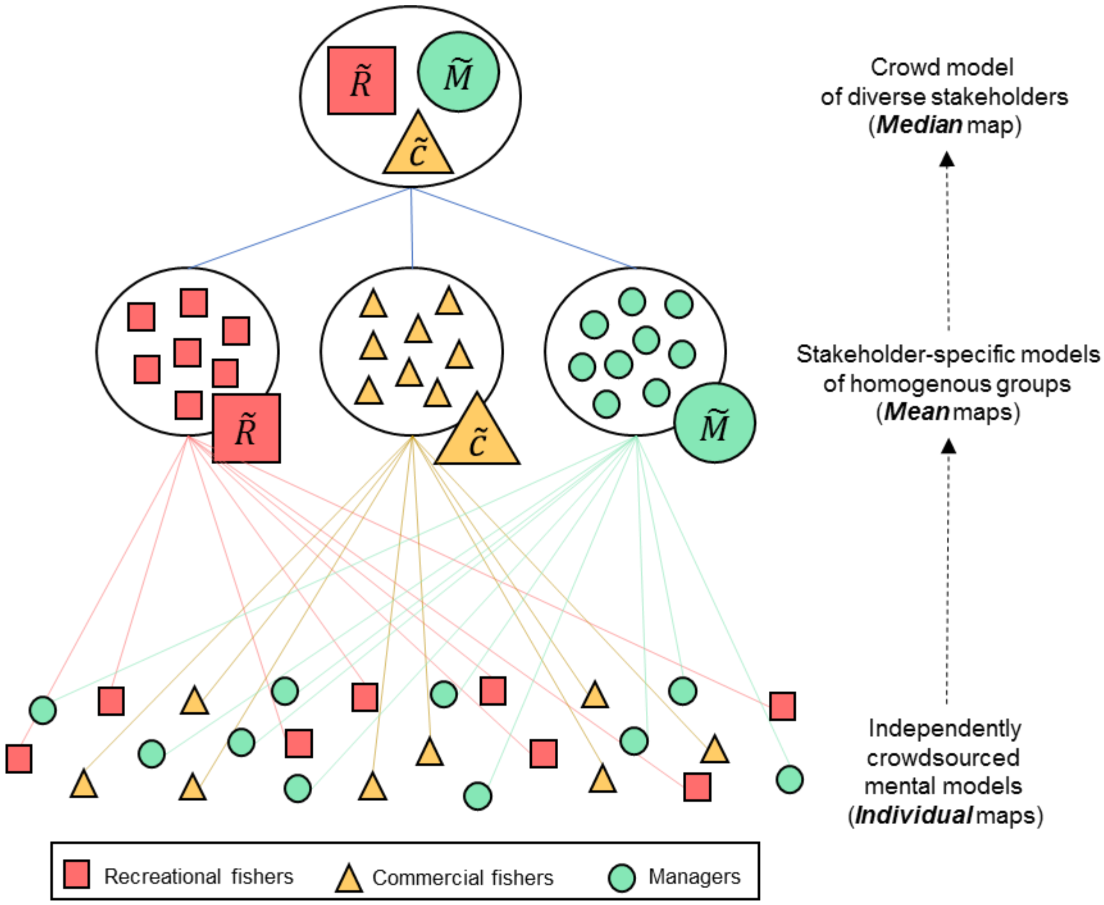


Figure 3.S3. Multi-level aggregation method. At the first level, individual maps are aggregated by stakeholder groups using the arithmetic mean of their fuzzy cognitive maps' edge weights. In the second level, the resulting group means are aggregated using the median of their edge weights to produce the crowd model.

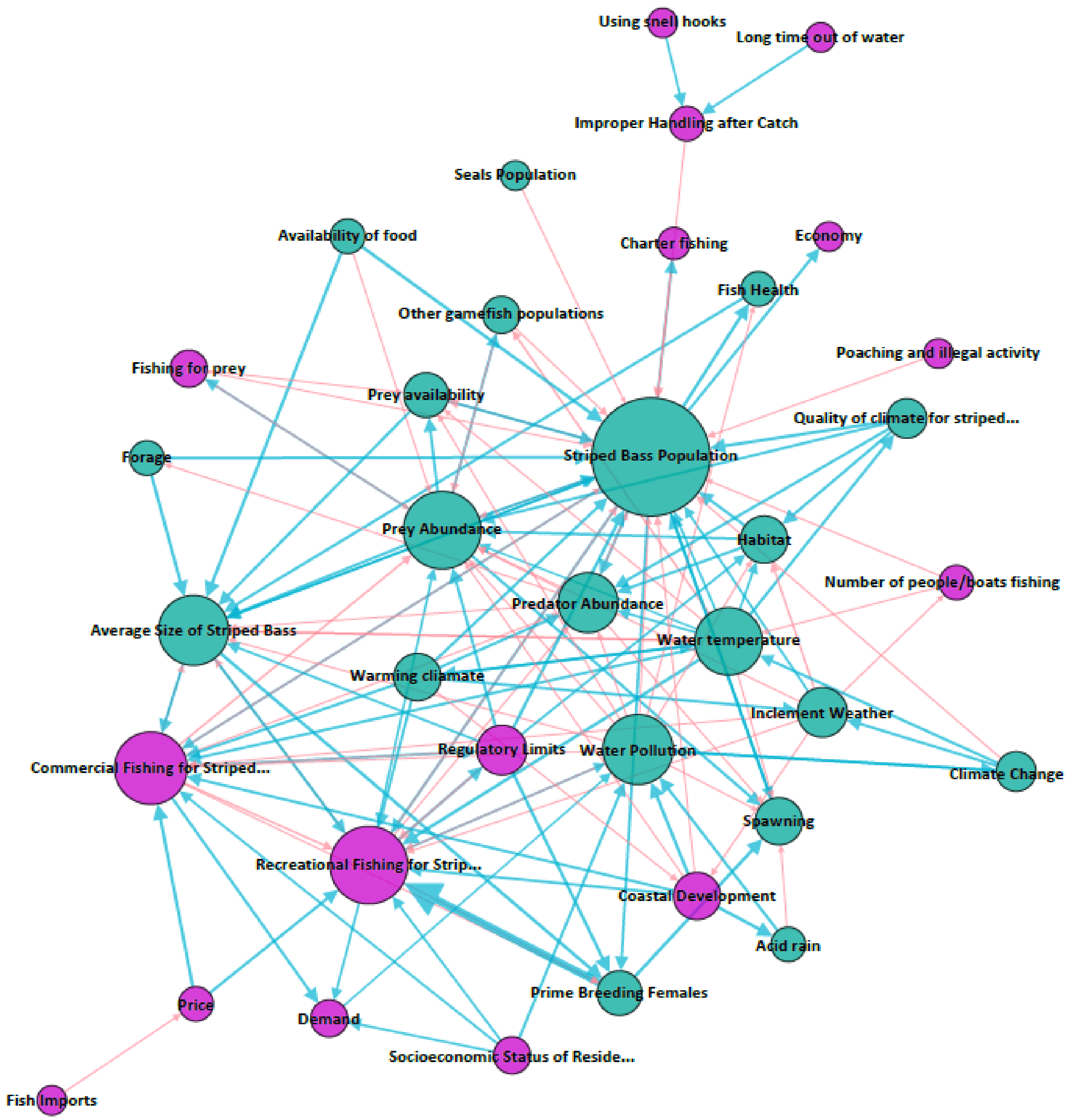


Figure 3.S4. Aggregated mental model of recreational fishers. Circles demonstrate unique system concepts mentioned by the individuals of type recreational fisher. Ecological-dimension concepts are green and human-dimension components are purple. Weighted blue/red arrows indicate positive/negative causal relationships between concepts. The arrows thickness represents the strength of the causal relationships ranged from -1 to +1. The weight of the arrows are computed using equation 3.S1.

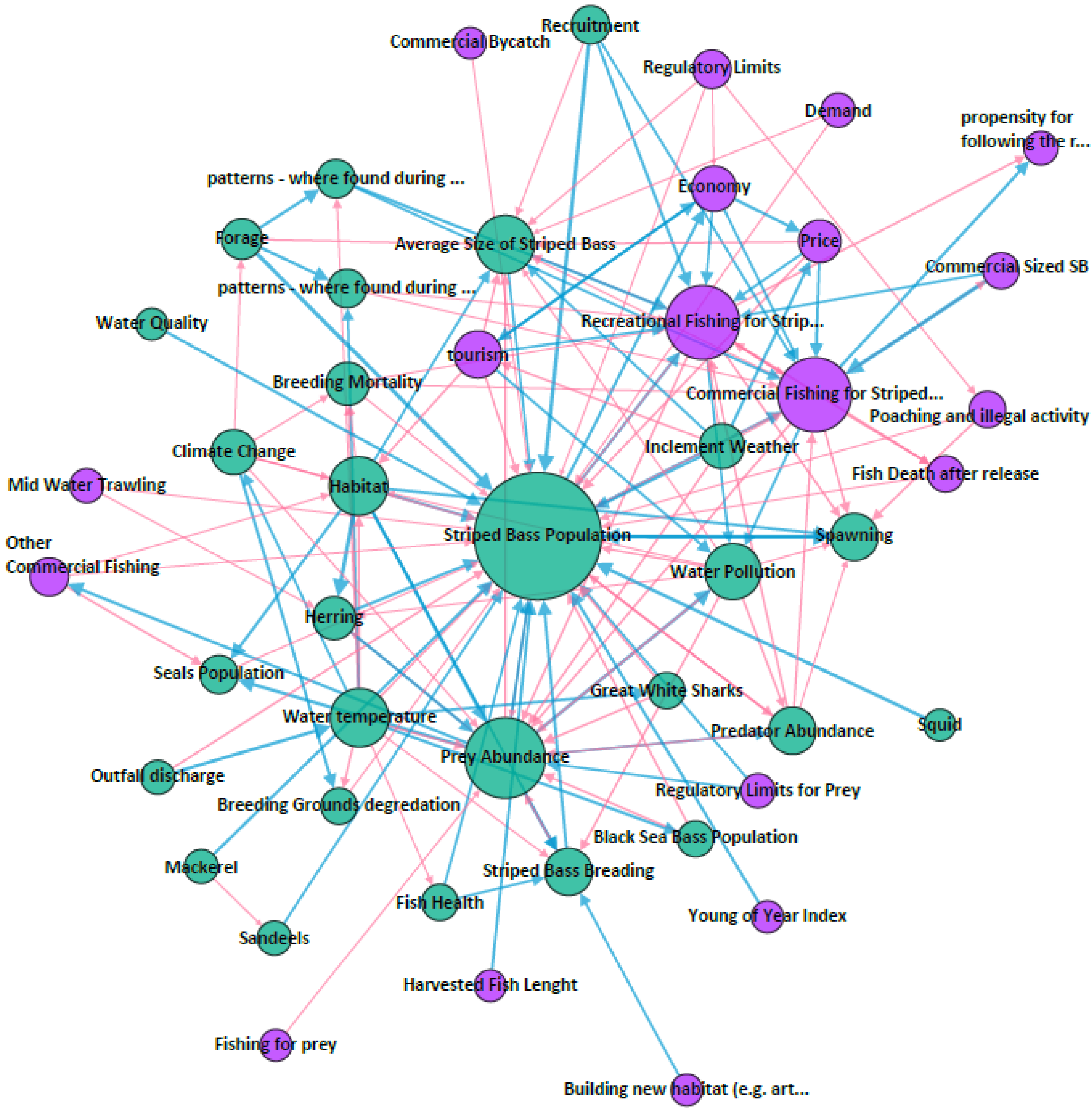


Figure 3.S5. Aggregated mental model of commercial fishers. Circles demonstrate unique system concepts mentioned by the individuals of type commercial fisher. Ecological-dimension concepts are green and human-dimension components are purple. Weighted blue/red arrows indicate positive/negative causal relationships between concepts. The arrows thickness represents the strength of the causal relationships ranged from -1 to +1. The weight of the arrows are computed using equation 3.S1.

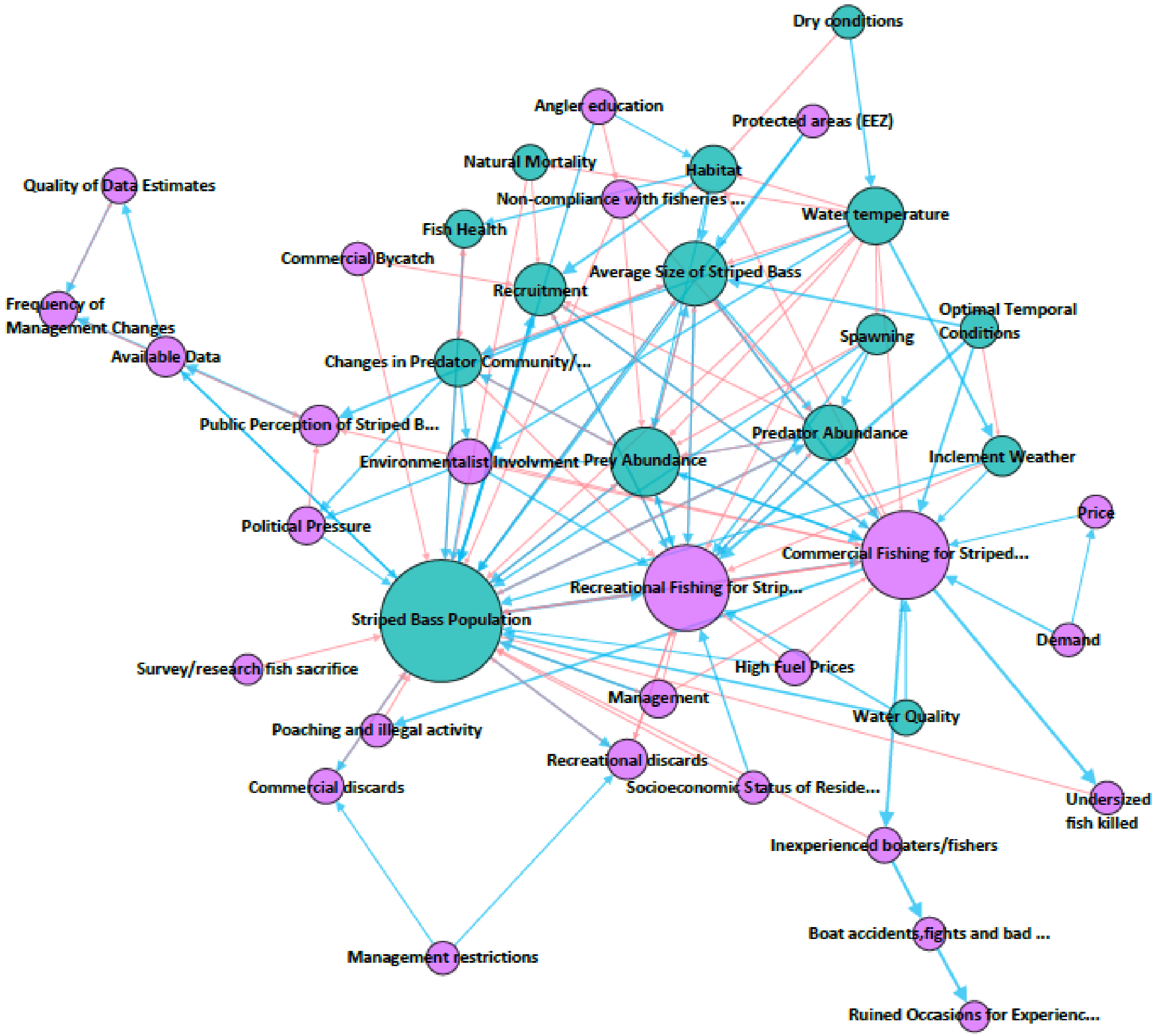


Figure 3.S6. Aggregated mental model of fisheries managers. Circles demonstrate unique system concepts mentioned by the individuals of type manager. Ecological-dimension concepts are green and human-dimension components are purple. Weighted blue/red arrows indicate positive/negative causal relationships between concepts. The arrows thickness represents the strength of the causal relationships ranged from -1 to +1. The weight of the arrows are computed using equation 3.S1.

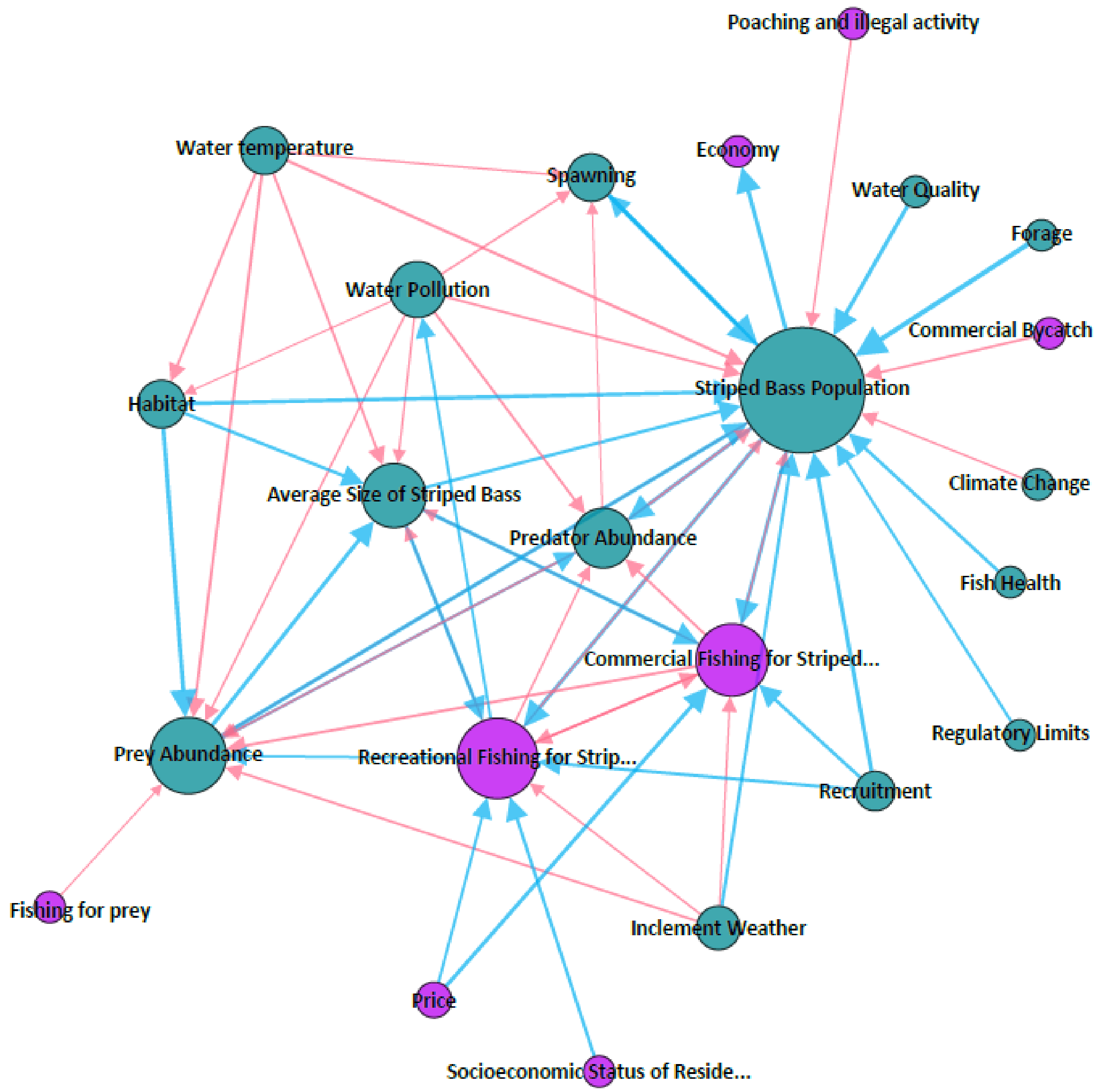


Figure 3.S7. Aggregated mental model of the diverse crowd. Circles demonstrate a parsimonious list of system concepts mentioned by all individuals of all stakeholder types. This parsimonious list of system concepts is obtained by a multi-level aggregation method. Ecological-dimension concepts are green and human-dimension components are purple. Weighted blue/red arrows indicate positive/negative causal relationships between concepts. The arrows thickness represents the strength of the causal relationships ranged from -1 to +1. The weight of the arrows are computed using equation 3.S1.

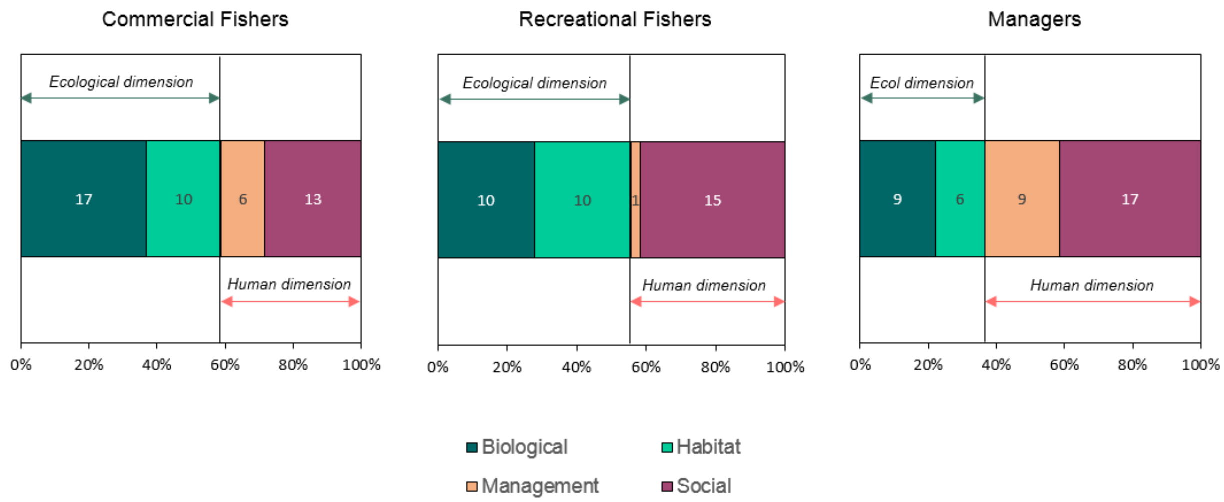


Figure 3.S8. The frequency and the relative percentage of each category of system concepts across three stakeholder groups. The numbers on bar-graphs indicate the frequency of concepts under each specific category. x-axis shows the relative percentage.

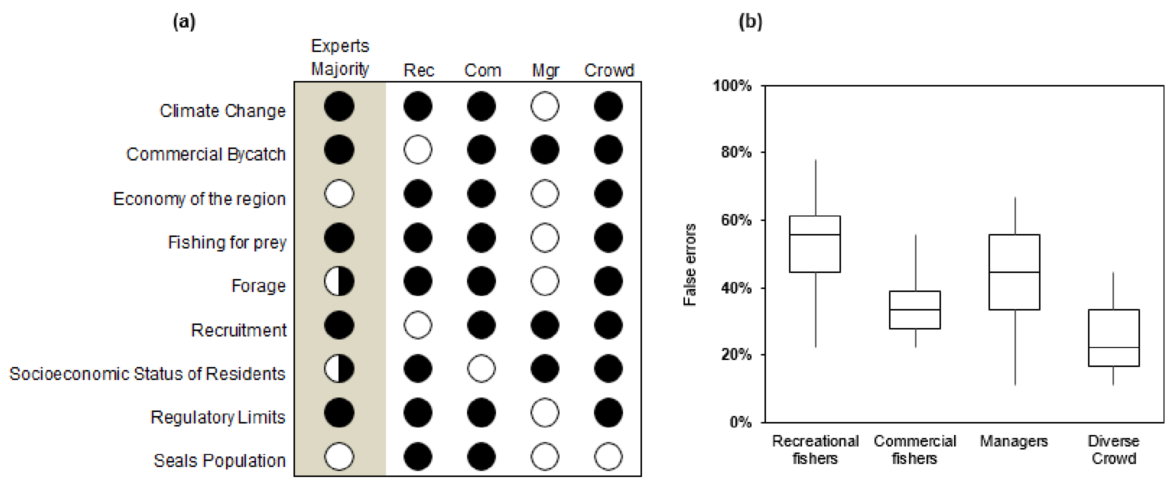


Figure 3.S9. Expert evaluation of models' components (i.e., nodes). Evaluated concepts were those appeared in more than one model, but not all models. The opinion table in (**a**) shows experts' majority opinion about whether a component is necessary (black), superfluous (white) or there is no consensus among experts (half-black, half-white). The percent of false errors according to the experts' majority opinion is shown in (**b**).

"

Modeling the Striped Bass Fishery

The purpose of this activity is to create a cognitive map that represents your understanding of the striped bass fishery, and the impacts of recreational and commercial fishing on its overall health.

How to make a model with Mental Modeler

To create your model, you will use the free Fuzzy Cognitive Mapping (FCM) software Mental Modeler (link to the software found below). FCM represents knowledge by defining three characteristics of a system:

- The components ("parts) of the system
- The positive or negative relationships (e.g. influence) between the components
- The degree of influence that one component can have on another, defined using qualitative weightings (e.g. high, medium, or low influence)

Before you begin:

Please watch these two brief videos. In total the videos are 15 minutes long.

https://www.youtube.com/watch?v=By24uhIbBn4

https://www.youtube.com/watch?v=UbKzyDctkrY&t=28s

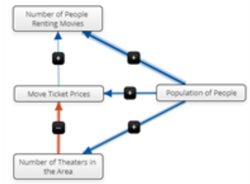
1. Access Mental Modeler at www.mentalmodeler.org. Click the "Software" tab at the top of the page, then the "Use the Online Mental Modeler" link. When prompted, enter the following information:

Username: mentalmodeler
Password: mentalmodeler

Once you have access to the online program, you will then build your model of the striped bass fishery by defining the following characteristics based on your understanding: (1) the components that are relevant to the system (boxes), (2) the directional relationships between these components (arrows), and (3) the degree of positive or negative influence that one component has on another (+/- on a sliding scale)

Example Model:

Here is an example of a mental model (see figure below). Let's start with movie ticket prices as our central variable. Now we can think about factors that affect prices, such as the surrounding population or the number of theaters in the immediate area. We can also think about factors that are affected by movie ticket prices such as the number of the people that rent movies. In the model, as the population increases, it increases the number of people renting movies and increases movie ticket prices and increases the number of theaters in the area (blue arrows) Conversely as the number of theaters increase, it decreases movie ticket prices (see red arrow).



2. Add components you think are important by clicking the "add component" button at the top of the modeler window. Enter text to label a component, and drag the box to reposition it. Components must be variables that can increase or decrease <u>in quality or quantity</u>. Although the components you define in your model will be up to you based on your understanding, please begin by adding the following components:

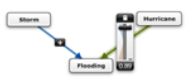
- Striped bass population
- Recreational fishing for striped bass
- Commercial fishing for striped bass

3. Build your model by adding additional components to the three initial components, and defining the relationships between them. Think about other components that are part of the striped bass fishery (what factors influence bass abundance?), etc. When you add a component, make sure that you think about its relationship to all the other components, and define them accordingly. The following tips will help you create your model

Tip #1: **"Defining Components"** (e.g. boxes) need to be things that can increase or decrease in quality of quantity. For example, these may be things like (a) access to healthy food, (b) food prices, (c) cropland, (d) greenhouse gas emissions. All of these things can increase or decrease. The components should not be things like (e) policy, since "policy" is not something that can increase or decrease. You can add as many components as you think is necessary to represent the system, by clicking on the "add component" button at the top of the modeling screen.

Tip #2: **"Defining Relationships"** between components can either be positive or negative. For example, as the amount of sunlight increases, the process of photosynthesis may also increase. Therefore, you might draw a positive arrow from the component "sunlight" to the component "photosynthesis".

<u>*Tip #3:*</u> **"Defining Degree of influence"** is the weightings you give to the positive or negative relationships that you define between components. For example a rain-storm may increase the amount of flooding slightly (represented by a small positive relationship defined between these two components) but a hurricane may increase the amount of flooding a great deal (represented by a high positive relationship defined between these two components)



4. Add the final components. Once your model is complete, please add the following two components if they are not already included:

- Prey abundance
- Water temperature

Then define any relationships between these new components and the existing component.

5. Your model is complete when you feel comfortable with the components you have included and how they interact with each other.

6. Save the model and email it to the project email address. "

Figure 3.S10. Step-by-step written instructions for participants to direct them how to use online mental modeling tool and create fuzzy cognitive maps repressing their perception of striped bass fisheries in MA and social-ecological relationships driving this system.

S3 Supplementary Tables

Table 3.S1. The number of participants from each stakeholder type and the number of nodes and connections used in their mental models. The mean and standard deviation of number of concepts (i.e., nodes) and connections (i.e., edges) are shown by stakeholder types.

Stakeholder group	**Number of Participants**	**Number of Nodes**	**Number of Connections**
		Mean (SD)	**Mean (SD)**
Recreational fishers	13	11.54 (4.01)	29.85 (20.53)
Commercial fishers	11	11.45 (2.84)	23.45 (12.41)
Fisheries managers	8	12.00 (3.21)	27.25 (7.87)
Total	32	11.63 (3.35)	27.00 (15.32)

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CHAPTER 4

4 CROWDSOURCING MENTAL MODELS FOR PREDICTING BEHAVIORAL RESPONSES TO CLIMATE CHANGE

This chapter is in review for publication in *Global Environmental Change* (https://www.journals.elsevier.com/global-environmental-change).

ABSTRACT

Understanding and modeling human behavioral responses to changing environmental conditions is difficult, especially at large social and environmental scales. This is due less to scientific understanding of how environmental conditions are predicted to change, and more of an issue of how environmental change is perceived by humans and how these perceptions are integrated with intended behavioral responses. We developed a method for utilizing the collective knowledge and perceptions of stakeholders to predict local scale responses to climate change. Specifically, by crowdsourcing mental models of 1,464 recreational fishers across a large social-ecological gradient along the U.S. Atlantic coast, we show that simulations of warming waters and increased storminess reveal mental model predictions about environmental change that explain divergent behavioral responses across regions, measured as the number of intended days fishing. Importantly, these diverging responses align with empirical patterns of environmental change. More broadly, our approach could be applied to predict human behavioral responses to environmental or even social changes across biogeographic scales and social-ecological contexts.

4.1 INTRODUCTION

Climate change is projected to impact oceans through a wide range of environmental changes and pulses of disturbance which vary widely at local scales [1,2]. While the environmental impacts of climate change have received significant attention, there is considerable uncertainty regarding the social impacts resulting from climate change, especially in understanding how environmental change will impact peoples' perceptions and behavior across large social and ecological gradients [3–6]. Here, we show that crowdsourcing mental models of 1,464 recreational fishers distributed across a large social-ecological gradient from U.S. north to south Atlantic reveals latitudinal patterns of perceptions and intended behavioral responses (i.e., fishing days) to climate change (e.g., increased storminess and warming water temperatures). Harnessing local-scale knowledge or "wisdom" of a large network of resource stakeholders who interact with ecosystems may provide considerable insight, decreasing uncertainty on how society and ecosystems may react to climate change.

Predicting how individual fishers and fishing communities may be impacted or are able to adapt to the consequences of climate change has been an increasingly high priority for fisheries social scientists [7,8]. For instance, warming ocean waters are expected to induce biogeographic shifts for many fish species [9–11], which may impact fishing communities through the decline or disappearance of traditionally predominant species, as well as the increasing prevalence of formerly rare or novel species [7]. In addition, sea level rise and increased storminess may directly impact fishing communities by decreasing the number of fishing trips and damaging facilities. However, such complex scenarios could promote a multitude of social and economic outcomes for fishing communities that are difficult to predict and may therefore increase uncertainty regarding climate change.

Many studies have increasingly demonstrated that the behaviors and responses of stakeholders to environmental and management changes are often complex and can be strongly influenced by a number of factors including knowledge, perceptions, and concerns about these changes [12]. Likewise, understanding the dynamics of human institutions is often essential for predicting outcomes of coupled systems such as fisheries, as stakeholders' behaviors can strongly influence ecosystem structure and function [13]. Understanding climate-influenced changes and creating appropriate adaptive management strategies to optimize trade-offs will require integrated modeling of numerous ecological and social variables. However, uncertainties associated with human behavioral responses to climate-driven changes, such as storms and ecosystem changes, are compounded by inadequate tools and methods to quantify them [14].

We developed an online survey method with fuzzy-cognitive mapping (FCM) to crowdsource mental models of climate change among 1,464 recreational fishers across the states of Massachusetts (MA), North Carolina (NC), and Florida (FL). By defining positive or negative pairwise relationships between components in a networked structure, individual FCMs represent individual-level perceptions about the social and ecological impacts of climate change, as well as intended behavioral responses [15] (see Methods). Additionally, once mathematically aggregated, these individual mental model representations can be scaled up to represent community beliefs, referred to as a "community map" [16] (see Methods--mental model aggregation). Importantly, causal connections in FCMs are numerically parameterized using fuzzy logic [17]. These mental models are therefore quantitative simulation tools that can be used to assess individual or community level predictions about changes in the state of a system's components given a scenario (i.e., an activation vector that makes changes in one or a set of components, which triggers a cascade of changes in other system components until the system reaches a new attractor) (see Methods).

We used mental models to explore stakeholders' perceptions of how climate change may impact coastal recreational fisheries across three states representing higher to lower latitudes of the U.S. Atlantic Coast (Figure 4.1). Specifically, this paper focuses on three questions: 1) to what extent do survey responses regarding fishers' concerns about climate-influenced ecological changes align with empirical patterns of climate change disturbances?, 2) how do recreational anglers perceive the individual and combined effects of warming coastal waters and increased storminess on their primary target species?, and 3) how might fishing behaviors change under these same scenarios?

4.2 RESULTS

4.2.1 Overall Climate Concern

We compared the individual responses regarding the concerns of recreational fishers in MA, NC, and FL about (1) ocean warming, (2) severe storms, and (3) fish declines. Across the three states, respondents in MA demonstrated significantly higher concerns about global warming and increased ocean temperature (Figure 4.2 a), while NC respondents were most concerned about increased severe storms (Figure 4.2 b). In terms of the fish decline and the status of fisheries, FL respondents demonstrated the lowest concerns, while inter-state comparisons revealed a latitudinal gradient in concern that increased from south to north (Figure 4.2 c).

In addition, we used empirical data for changing ocean patterns over the past 20 years at the regional ecosystem scales to obtain latitudinal patterns of (1) sea surface temperature (SST) trends, (2) the trends of frequency of stormy days in coastal regions, and (3) the proportion of fish stocks that are overfished/experiencing overfishing as a proxy measure for fish declines (Figure 4.2 d-f). All of these data support the differential angler perceptions that we measured. In particular, water temperature increases have been greatest in MA (Figure 4.2 d), while NC has experienced the highest increase in frequency of stormy days (Figure 4.2 e), and MA is in the federal fisheries management region (New England) that has experienced the highest percentage of overfished stocks. In general, survey responses largely aligned with observed empirical patterns, suggesting a strong conformity between subjective stakeholder perceptions and objective measures of environmental changes.

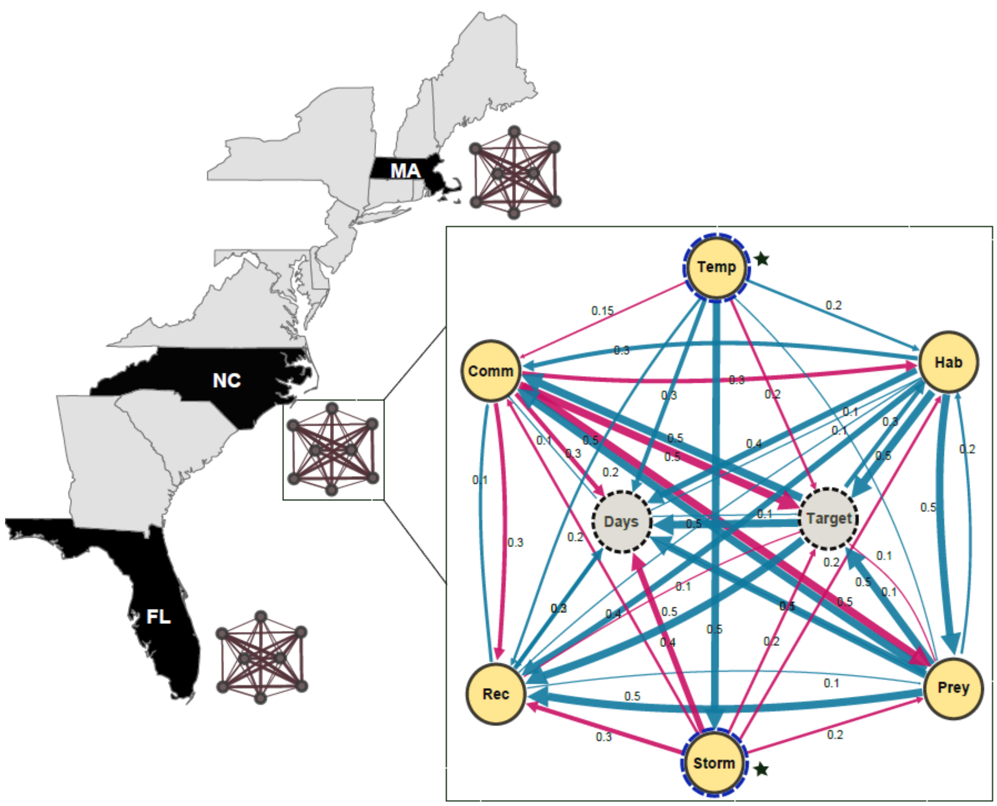


Figure 4.1. Community maps of three study regions representing Florida (FL), North Carolina (NC), and Massachusetts (MA) built by aggregating individual FCMs from each region. The inset shows the NC community model with details (see *Appendix*, Figure 4.S1 for details about other states). Blue/red arrows indicate positive/negative causal relationships between concepts. Edge weights represent perceived strength of the causal links.

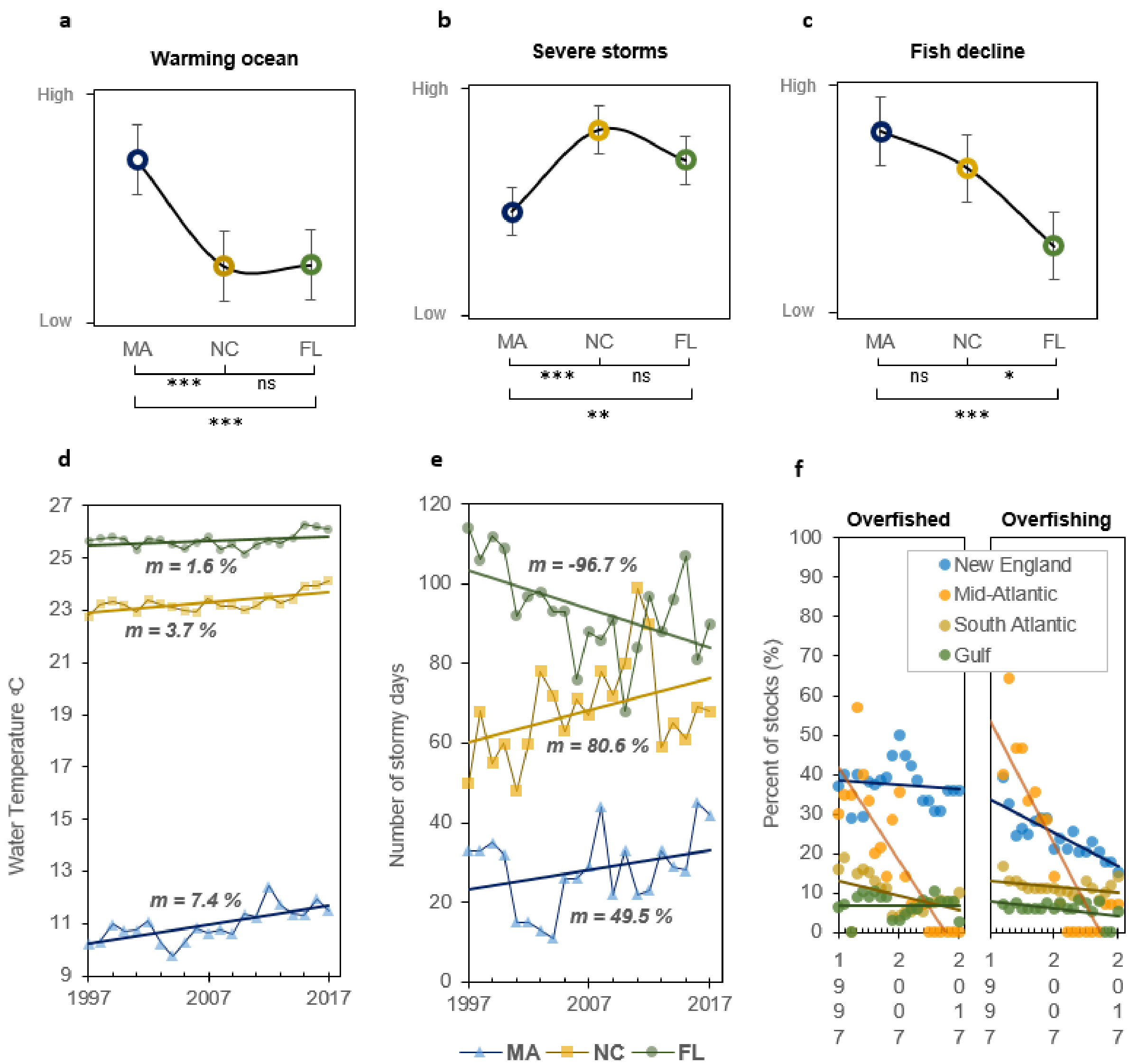


Figure 4.2. Anglers' concern for warming oceans (**a**), storminess (**b**), and fish decline (**c**) alongside patterns of empirical data on water temperature (**d**), storminess (**e**), and fisheries stock status (**f**) trends. Levels of significance are illustrated in (**a-c**) by asterisks (*p*-value< 0.05, *p*-value< 0.01, and *p*-value< 0.001 are shown by one, two, and three asterisks respectively). (Note: stock status trends are missing 1997-98 data points due to the unavailability of information for the number of overfishing stocks. In addition, stock status data are classified based on NOAA fisheries regions: MA is included in New England; NC is partially included in the mid and south Atlantic; and FL is partially included in the south Atlantic and Gulf).

4.2.2 Fishing Characteristics

One question of the online survey documented the primary target species of respondents, which was later used as a concept in the mental model section of the survey. Primary target species varied considerably across our study regions. As shown in (Figure 4.3 *a*), in the Northeast (i.e., MA), Striped Bass dominates recreational fisheries with 63.2% of respondents listing it as their primary target species. The next closest fish species, Bluefish, represents 4.5% of primary target species. In the Mid-Atlantic (i.e., NC), the most targeted species of Red Drum represents 23% of all target species. The next closest fish species, Summer Flounder and Spotted Seatrout, represent 10.9% and 10.1% respectively. In the Southeast (i.e., FL), where empirical measures of fish diversity demonstrate higher species richness, the most targeted species of Snook, Red Drum, Red Snapper, and Spotted Seatrout respectively represent 15.4%, 13.3%, 10.7%, and 10.3% of all target species. To quantitatively measure diversity of target species in each state, we used Shannon diversity index (H) by accounting for both the number of unique species and the evenness of their distribution across participants' responses (Figure 4.3 *b*). Quantification of H index indicates that the diversity of primary target species increases from North to South Atlantic, which aligns with the biogeographical patterns increasing species richness with decreasing latitude.

4.2.3 Simulating Climate Change in Mental Models

We aggregated mental models by states to build regional fishing community maps. Arrays of scenario analyses with various activations of water temperature and water storminess were carried out to show the mental model predictions of changes in target species abundance (Figure 4.4) and intended fishing days (Figure 4.5) under a range of climate change scenarios. We find simulations of warming waters on the community map of FL recreational fishers generally produce favorable perceived outcomes of increased abundances of target species. In contrast, warming water scenarios on community maps of MA and NC yield more negative perceptions with decreasing abundance of target species. Moreover, simulations of increased water storminess on the community mental model of NC produce negative outcomes of drastic declines in target species abundances, while these undesirable outcomes are smoother in FL and are completely flattened in MA (Figure 4.4).

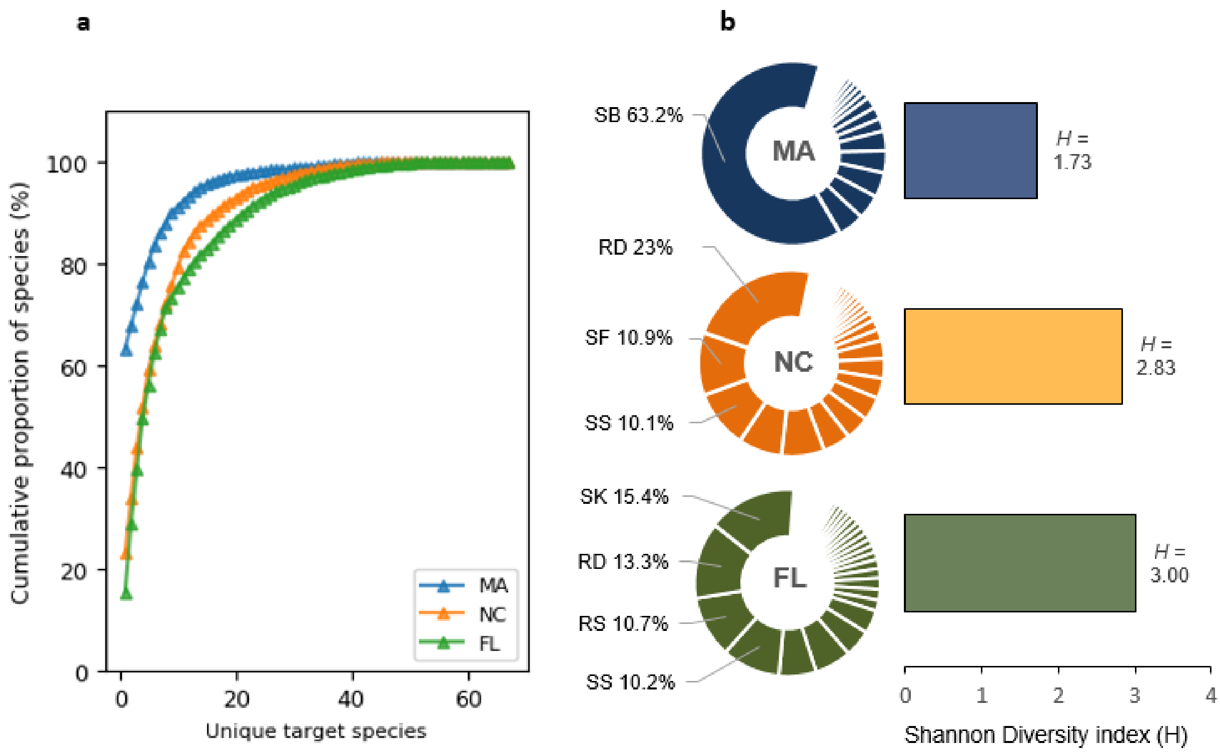


Figure 4.3. Diversity of target species across regions. (**a**) Species accumulation curves shows the cumulative percentage of total primary target species reached by a given number of unique species. (**b**) Circular chart for each region shows the target species and their percentage. Only target species with more than 10% are labeled for each region: Striped Bass (*SB*), Red Drum (*RD*), Summer Flounder (*SF*), Spotted Seatrout (*SS*), Snook (*SK*), and Red Snapper (*RS*). The horizontal bar charts show the calculated Shannon diversity index (H).

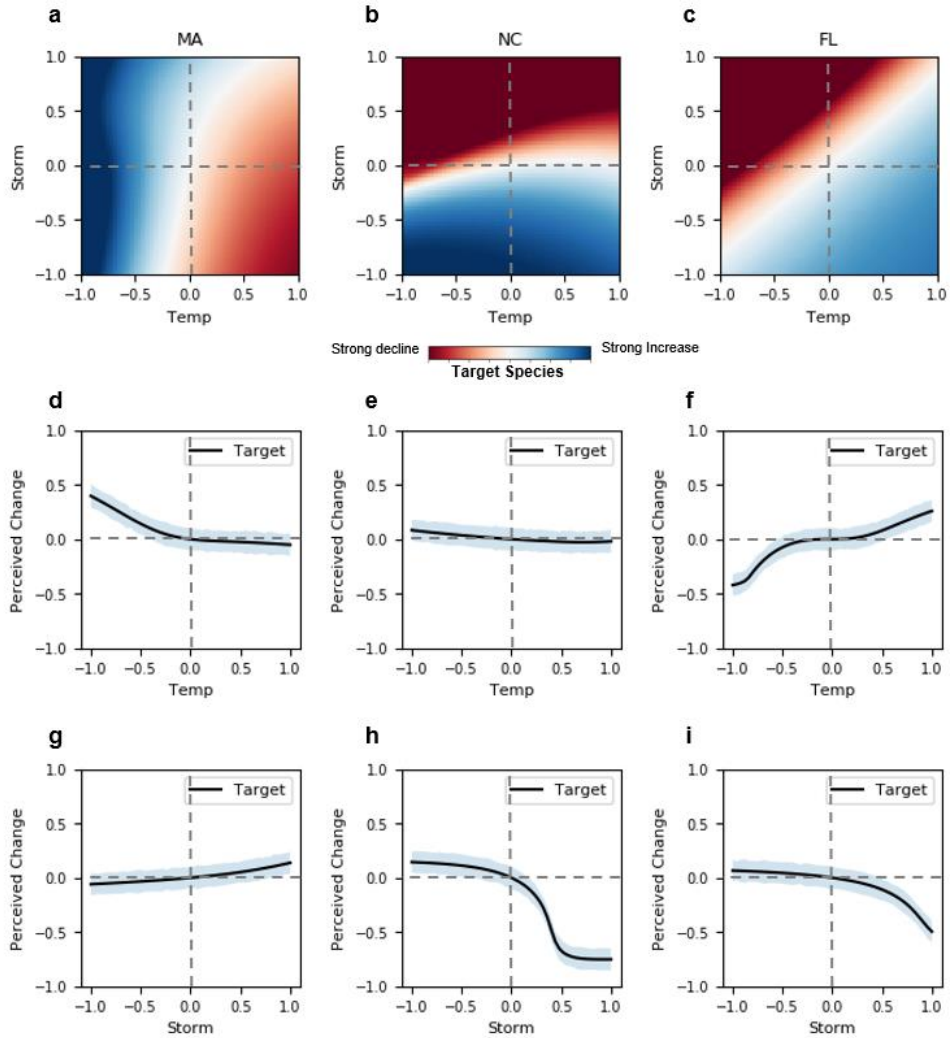


Figure 4.4. Results of scenario analyses showing the community maps' perceived changes in target species abundance. For each state results are shown for various combinations of water temperature and storminess jointly (**a-c**); water temperature individually (**d-f**); and water storminess individually (**g-i**). Axes show the normalized changes in variables' perceived values from high decrease (-1) to high increase (+1). Heat map shows the perceived changes in target species abundance from high decrease (dark red) to high increase (dark blue).

In addition, patterns of behavioral responses to climate change vary across regions. Specifically, increased water temperature is predicted to variably alter intended fishing days across all three states, with the NC map indicating a stronger positive relationship and the FL map having almost no sensitivity to warming water temperature. However, decreased water temperature is perceived to slightly raise intended fishing days in MA, while the NC and FL community maps predict declines in fishing days, and these declines are more abrupt in FL when water temperature drops considerably. Moreover, simulation of increased water storminess is likely to lead to decreased fishing days across all three states, with these changes being smoother in FL and more intense in NC (Figure 4.5).

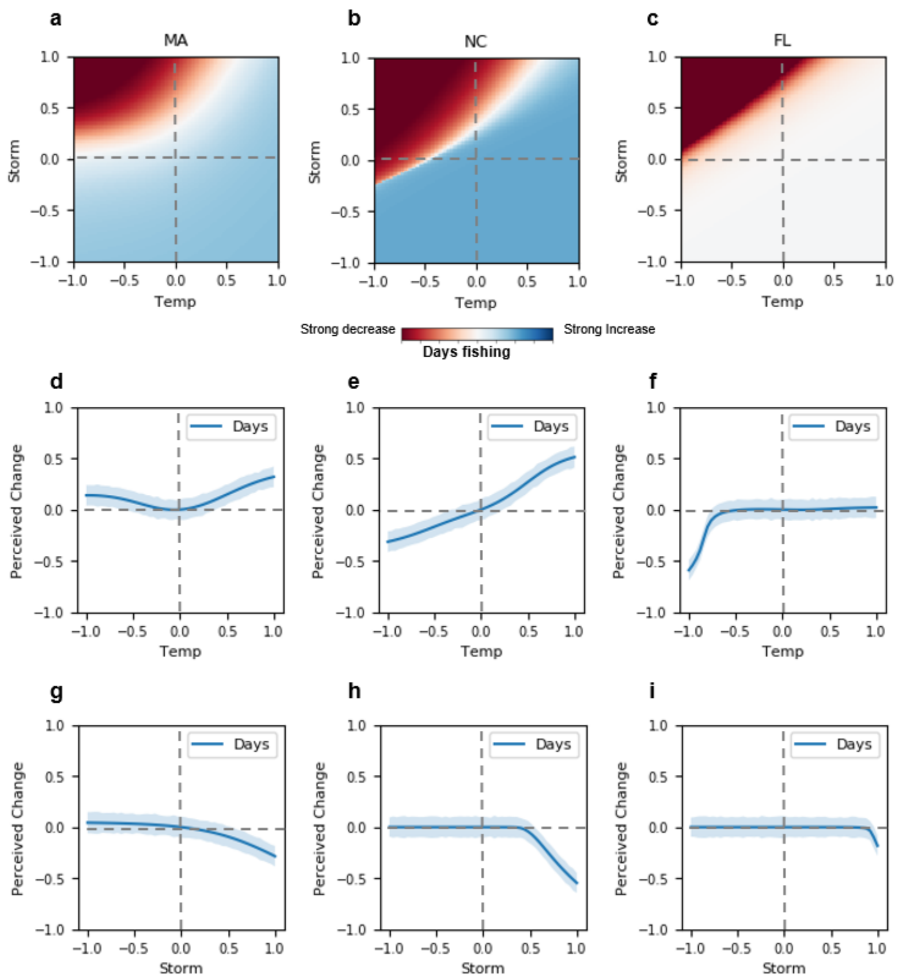


Figure 4.5. Results of scenario analyses showing the community maps' behavioral responses regarding the intended fishing days. For each state results are shown for various combinations of water temperature and storminess jointly (**a-c**); water temperature individually (**d-f**); and water storminess individually (**g-i**). Axes show the normalized changes in variables' perceived values from high decrease (-1) to high increase (+1). Heat map shows the intended number of days fished from high decrease (dark red) to high increase (dark blue).

4.3 DISCUSSION

Predicting how people respond to climate change across spatial scales is extremely challenging and faces both conceptual and methodological barriers [6,7,9]. Our approach of using online surveys to crowdsource mental models provides a powerful tool for studying human behavior in complex social-ecological systems and therefore overcome these barriers. However, it should be noted that online surveys may limit the representation of all perceived important concepts for SESs due to the lack of freedom given to participants to include additional customized concepts [16]. Although our fixed-concept approach to represent mental models may not capture the full complexity of the system, it provides a standardized way to collect variation across how stakeholders perceive socially and environmentally relevant interdependencies that influence their local-scale understanding of system dynamics and how they behaviorally respond to scenarios of environmental change. Yet, the high level of alignment between stakeholder concerns, mental model variations, and empirical patterns adds confidence on the validity of the survey data collected to construct mental models.

Our study demonstrates the power of harnessing local knowledge for both understanding the changing dynamics of fisheries and other resources, as well as predicting the individual and collective behavioral responses of groups of stakeholders to environmental changes. More broadly, our study demonstrates a novel online approach for crowdsourcing the mental models of stakeholders to predict diverging patterns of how humans respond to climate change across scales, but also has implications for understanding disparate behavioral responses given other large-scale social changes (e.g., globalization, massive political changes, or large-scale pandemics). From a methodological standpoint, our study demonstrates an approach to greatly increase the scale of data collection including mental models. This approach allowed us compare mental models across largely distributed biogeographic regions with broad implications for other desired contexts that are typically infeasible or limited by the labor intensive traditional approaches for representing mental models [15,16].

In the specific context of fisheries science and management, a key finding of the models and simulations in our study is that perceptions and intended behavioral responses to environmental change (i.e., water temperature, storminess) align with empirical patterns. In particular, we found that stakeholders in Florida seem more resilient to environmental change, with the exception of very cold conditions, than stakeholders in the mid-to-north Atlantic regions. In addition, stakeholders in the northeast perceived more negative impacts on fisheries as a result of increased water temperature (Figure 4.5). We hypothesize that varying patterns of environmental change and disturbances, as well as biogeographical patterns of increasing species richness with decreasing latitudes, drive these regional differences in stakeholder perceptions and intended behavioral responses. For instance, along the U.S. Atlantic coast, ocean waters off northeastern New England have experienced the greatest warming, up to 3°F, while ocean warming along the Florida Gulf coastal waters is about 0.5°F over the past century [18,19]. Meanwhile, the diversity of fish species is the highest in the southeast compared to mid and north Atlantic.

In addition, the implications of increased storminess for fisheries have multiple dimensions. Numerous studies have suggested that climate change is likely to increase the intensity of tropical cyclones [20] and may also increase their frequency [21]. In the wake of these extreme events, fishing communities, as well as fishing infrastructure and opportunities, may be severely disrupted. Coastal and marine fisheries are also often constrained by wind and weather patterns of much lesser intensities as studies have shown that wind speed is an effective predictor of fishing effort, particularly for offshore recreational fisheries [22]. In our study, concern for storms was greatest in North Carolina (Figure 4.2 b), which aligns with empirical patterns of having the highest increase in the frequency of stormy days reported by the National Weather Service between 1997 and 2017 (Figure 4.2 e). Moreover, our results indicate that concern for fisheries declines was greatest in New England, a region with a considerably higher proportion of fisheries stocks categorized as overfished or experiencing overfishing [23].

While there is a wealth of growing physical evidence for changing ocean patterns at the global and regional ecosystem scales [24], the social impacts and behavioral responses are often not well-understood at local to regional scales. Our study may fill this gap by demonstrating relationships among empirical patterns, stakeholders' perceptions, and their mental model predictions of behavioral responses to environmental changes and conditions. This study thus supports the idea that crowdsourced mental models can provide robust and valuable tools for predicting societal or stakeholder behavioral responses to climate change and other scenarios. Such approaches to leveraging local knowledge, therefore, may be particularly valuable when empirical data is scarce or unavailable [25].

As climate change continues to reshape the dynamics of fisheries and other social-ecological systems, our study provides a methodology for understanding complex stakeholder perceptions and predicting human behavioral responses. Notably, fisheries stock assessments and management plans routinely highlight fishing behavior as among the largest contributors to management uncertainty [26,27]. Others have argued that participatory modeling and scenario analyses of mental models offer valuable tools for understanding the human dimension of fisheries, including behavioral intentions, as well as decreasing overall uncertainty [28,29]. However, historically, the complexity and spatial coverage of these studies has been limited by logistical constraints of conducting in-person interviews to elicit mental models. Our study demonstrates an internet-based approach to overcome these limitations and collect robust mental model data for understanding complex social-ecological systems. Such internet-based approaches may provide a way to understand how perceptions of environmental dynamics vary across social or ecological scales not previously possible.

4.4 METHODS

4.4.1 Ethics Statement

This study was conducted with approval of Northeastern University's Institutional Review Board (IRB #13-07-16) and electronic consent was acquired from all survey participants.

4.4.2 Survey Instrument

4.4.2.1 Overview

The survey instrument was designed and administered using Qualtrics Survey Research Suite. The full survey instrument included 66 questions, and the data described in this paper represent the following core sections: Fishing Characteristics, Climate and Hazard Concerns, Mental Models, and Demographics (e.g., education, income, gender, race, birth year).

4.4.2.2 Survey items for eliciting mental models

A primary section of the survey was designed to collect data necessary to assemble individual fuzzy-logic cognitive maps to represent variation in fishers' mental models of climate impacts on marine ecosystems. Mental models are simplified internal representations of the external world that allow individuals to perceive patterns of cause-and-effect relationships and associations. These internal mental models, therefore, enable humans to make decisions through internal processes of reasoning [30]. Mental models that represent causal knowledge (e.g., how social and ecological components are interconnected in a fishery ecosystem) can be graphically obtained through cognitive mapping techniques [31] in the form of directed graphs. Graph nodes represent concepts (i.e., system components) and graph edges (arrows) represent the causal relationships between the concepts. In addition, Fuzzy Cognitive Maps (FCM) are augmented forms of conventional qualitative cognitive maps [32], which are computationally executable and can thus perform dynamic simulations of the complex system they represent. These are semi-quantitative graphical models of system components and their causal relationships in the form of weighted directed graphs [33]. In FCMs, causal connections (i.e., edges) are assigned a numerical value in the interval of [-1, +1], corresponding to the magnitude and sign of the relationships. In our case, responses to Likert-scale questions were mapped into numerical values to determine edge weights. These numerical parametrizations of causal relationships enable FCM computations to represent system dynamics based on neural networks and fuzzy set theory [15].

Our survey instrument involved a series of questions designed to select FCM concepts and assign edge weights. First, we used a two-question series to assess the relative importance of individual target species. The first question asked participants: "What fisheries species do you consider to be the most important for your fishing? (Select one)" (see *Appendix*, Figure 4.S3). Next, we asked "Are there any other fish that you consider important for your fishing? (Select All that Apply)". To assign edge weights, we asked a series of pairwise questions for all concepts, with an example being: "How would you expect an increase in water temperature to influence <Selected Target Species> populations?" (See *Appendix*, Figure 4.S4).

4.4.3 Survey Data Collection

We conducted email surveys of licensed recreational anglers in Florida, North Carolina, and Massachusetts. The data presented in this paper represent 1,464 responses from a splitsample design of 3,000 total respondents across the coastal states of Florida, North Carolina, and Massachusetts (1,000 each). Email addresses were acquired from state managed license databases. Data collection occurred through an online survey of licensed anglers over an 8 week period in October and November 2017. We used an iterative sampling (4 waves) approach, involving an initial email contact and two reminder emails [34], until we reached a desired sample size of 1,000 complete responses. We used a three stage process to assure data quality and validity including filtering out participants who completed the survey in less than ⅓ of the average completion time, failed to accurately complete attention check questions, or would not "thoughtfully confirm that they would give their best answers" in an initial screening question. The adjusted response rate for the survey was 14.9% after adjusting for bounced, blocked, and unopened emails.

4.4.4 Empirical Data

4.4.4.1 Ocean Warming Data

To visualize recent changes in ocean temperature, we mapped mean sea surface temperature (SST) and SST trends from 1997-2017. Daily mean sea surface temperature data were acquired from the NOAA OI SST V2 High Resolution Dataset. (https://psl.noaa.gov/data/gridded/data.noaa.oisst.v2.highres.html) SST trends for the three study states were determined from 1997-2017 using the annual mean SST for the area from the state's coastline to the edge of the Exclusive Economic Zone (EEZ) (*Appendix*, Figure 4.S2). Simple linear regression models were fitted on annual data points to determine the trends in SST over the 20-year period.

4.4.4.2 Storminess Data

For the purposes of our study, we estimated storminess as the annual number of days with a designated severe weather event in a coastal county from 1997-2017. Severe weather events were determined using NOAA's Severe Weather Data Inventory; non relevant items such as drought and wildfire events were excluded from analysis. Coastal counties were determined through NOAA Economics: Ocean Watch Now (ENOW). Simple linear regressions were performed through the annual mean data to determine annual trend.

4.4.4.3 Fisheries Stock Status Data

We gathered data from NOAA Fisheries' Annual Status of U.S. Fisheries Reports to Congress to visualize stock status from years 1997 to 2017 (https://www.fisheries.noaa.gov/national/population-assessments/fishery-stock-status-updates). The data was assembled from the following fisheries management regions: New England Fisheries Management Council (NEFMC), Mid-Atlantic Fisheries Management Council (MAFMC), South Atlantic Fisheries Management Council (SAFMC) and the Gulf of Mexico Fisheries Management Council (GMFMC). For each region, we quantified the total number of stocks assessed, the total number of stocks overfished, and the total number of stocks experiencing overfishing. Percent overfished and percent overfishing were calculated by dividing the respective stock numbers by the total number of stocks assessed in that region.

4.4.5 Analyses

We used the PyFCM package (https://github.com/payamaminpour/PyFCM/wiki) to conduct FCM aggregation and computational analyses. We conducted sensitivity analyses by simulating 10,000 scenarios of climate change on the community models across states. These scenario analyses were conducted to simulate the perceived impacts of climate changes (individual and joint impacts of perturbations in water temperature and water storminess) on fish abundance and consequent behavioral responses regarding the intended number of days fishing.

4.4.5.1 FCM aggregation

Individual mental models elicited by FCMs can be aggregated mathematically by averaging the elements of their adjacency matrices— a square matrix used to represent the FCM graph where elements of the matrix indicate the numerical values of connections (i.e., edge weight) between pairs of nodes that are adjacent in the graph (see *Appendix,* Figure 4.S5). These aggregated models, which are referred to as "community maps," represent the collective mental models (i.e., as a tool for harnessing the collective wisdom) from a group of individuals [16] and therefore can be used to model a group's aggregated knowledge and perception [17]. To build aggregated maps of different states, we calculated the median of edge weights that are shared in all FCMs of individuals who belong to the same state. In contrast to conventional aggregation mechanisms that use arithmetic mean (i.e., simple average) of edge weights to combine FCMs [35,36], we use median here as an alternative measure of central tendency to avoid outliers (i.e., maps with extreme deviations from the mean of the group). One main advantage of this aggregation method is that the community maps built by the median more precisely represent group-specific biases, and therefore better highlight inter-group variations in comparisons. The adjacency matrix of aggregated FCM of each state was obtained as follows:

$$\begin{bmatrix} \overline{W}_{0,0} & \cdots & \overline{W}_{0,n} \\ \vdots & \ddots & \vdots \\ \overline{W}_{n,0} & \cdots & \overline{W}_{n,n} \end{bmatrix} = Median\left(\begin{bmatrix} \omega_{0,0}^{(1)} & \cdots & \omega_{0,n}^{(1)} \\ \vdots & \ddots & \vdots \\ \omega_{n,0}^{(1)} & \cdots & \omega_{n,n}^{(1)} \end{bmatrix}, \begin{bmatrix} a_{0,0}^{(2)} & \cdots & a_{0,n}^{(2)} \\ \vdots & \ddots & \vdots \\ a_{n,0}^{(2)} & \cdots & a_{n,n}^{(2)} \end{bmatrix} \dots , \quad \begin{bmatrix} a_{0,0}^{(m)} & \cdots & a_{0,n}^{(m)} \\ \vdots & \ddots & \vdots \\ a_{n,0}^{(m)} & \cdots & a_{n,n}^{(m)} \end{bmatrix} \right) \; (\mathbf{4.1})$$

Therefore:

$$for\ \forall\ i,j\ \in \{N\}, \qquad \overline{W}_{i,j} = Median\left(\omega_{i,j}^{(1)}, \omega_{i,j}^{(2)}, \dots\ \omega_{i,j}^{(m)}\right) \; (\mathbf{4.2})$$

where $\{N\}$ is the set of nodes (i.e., concepts) used to build FCMs with n unique concepts, $\overline{W}$ is the adjacency matrix of the aggregated FCM, and $\omega^{(i)}$ is the adjacency matrix of the individual i^{th} in the set of m individuals who belong to the same state.

4.4.5.2 FCM Computation

FCM models can be computationally manipulated to assess the perceived dynamic behavior of the system they represent. We used FCM computational analysis to demonstrate how fishers of a state, collectively, perceive/predict the changes in the abundance of their target species and the number of days they intend to fish, given an initial change in one or combination of climate change concepts (i.e., water temperature and water storminess). In FCM formulation, each concept has a state known as its “activation”. A change in the climate change scenario concepts initiates a cascade of changes to other system concepts based on how they are connected, and thus alters their so called “activation”. This iterative propagation of the initial change continues until the system evolves into a new “system state” [15]. By comparing the system states before and after implementing a scenario, FCM can represent perceived dynamic behavior of the system.

The initial activation of each concept—also known as the activation of concepts in the “steady state”—is calculated using the following activation rule, namely Kosko rule [32]:

$$A_i^{(k+1)} = f\left(\sum_j c_j^{(k)}.w_{ji}\right) \quad \mathbf{(4.3)}$$

where $A_i^{(k+1)}$ is the activation of concept C_i at iteration step $k+1$, $A_i^{(k)}$ is the activation of concept C_i at iteration step k, $A_j^{(k)}$ is the value of concept C_j at iteration step k, and w_{ji} is the weight of the edge relationship from C_j to C_i. Function $f(x)$ is the “threshold function” that was used to squash the concept activations at each step to a normalized interval between 0 and 1. In this study, we used a sigmoid function as the most common squashing function used in FCM studies:

$$f(x) = \frac{1}{1 + e^{-\lambda x}} \quad \mathbf{(4.4)}$$

where λ is a real positive number (in our case $\lambda = 5$) which determines the steepness of the function f. The value of parameter λ was determined such that the system dynamics were optimally represented [37,38].

To run a scenario, the value of scenario concepts (i.e., water temperature and/or water storminess) was forced to a fixed activation value, and the activation of other concepts were computed using equation (4.3). The scenario outcomes were then calculated as the differences between the activation of the system's concepts at the steady state and their activations in the new state the system evolved to as the result of forced manipulation of scenario concepts. For each concept C_i, the change in its value as a result of running a scenario is:

$$D_i^{sc} = A_i^{ss} - A_i^{sc} \quad \mathbf{(4.5)}$$

where D_i^{sc} is the change in the value of concept C_i, A_i^{ss} is the value (i.e., activation) of concept C_i in the steady state, and A_i^{sc} is the value of concept C_i after converging into a new state while scenario concepts are clamped on fixed values.

APPENDIX

APPENDIX

SUPPLEMENTARY INFORMATION

S1 Code availability

Codes for mental model aggregation and FCM analyses are publically available and can be obtained on GitHub at https://github.com/payamaminpour/PyFCM/wiki.

S2 Supplementary Figures

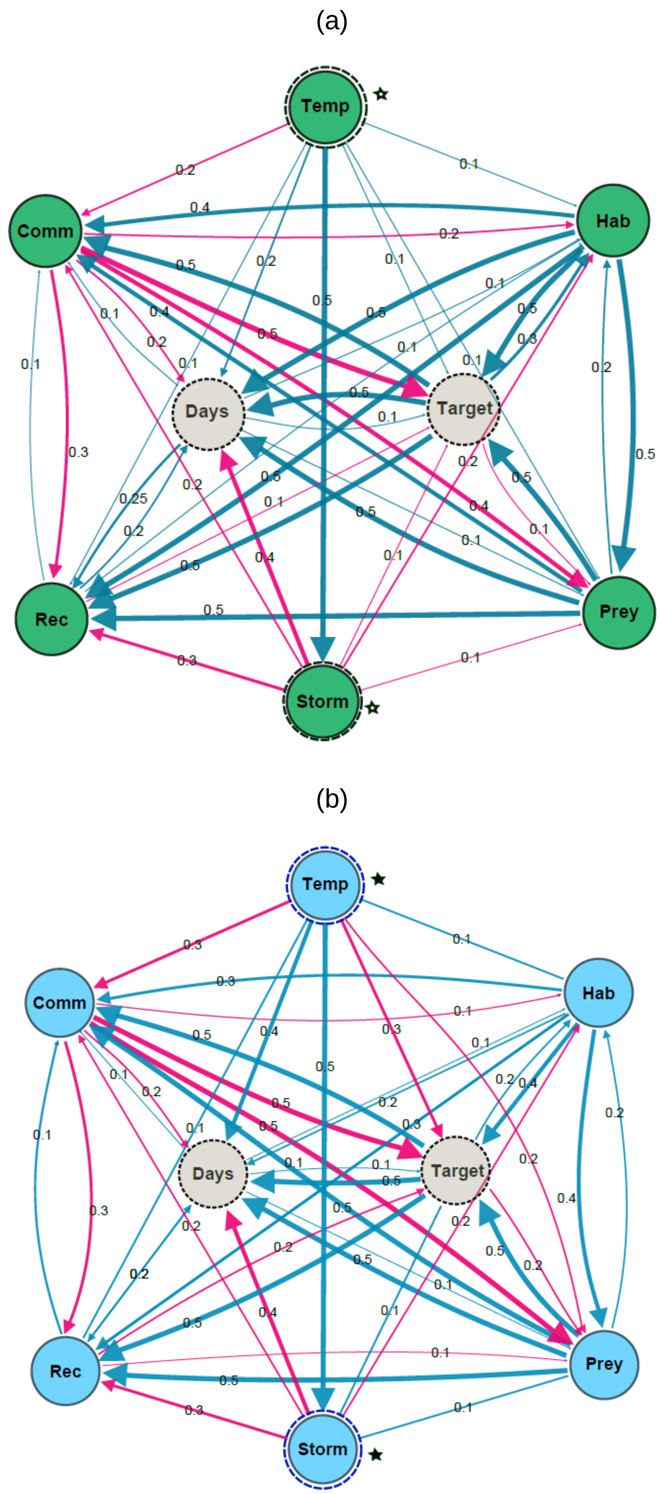
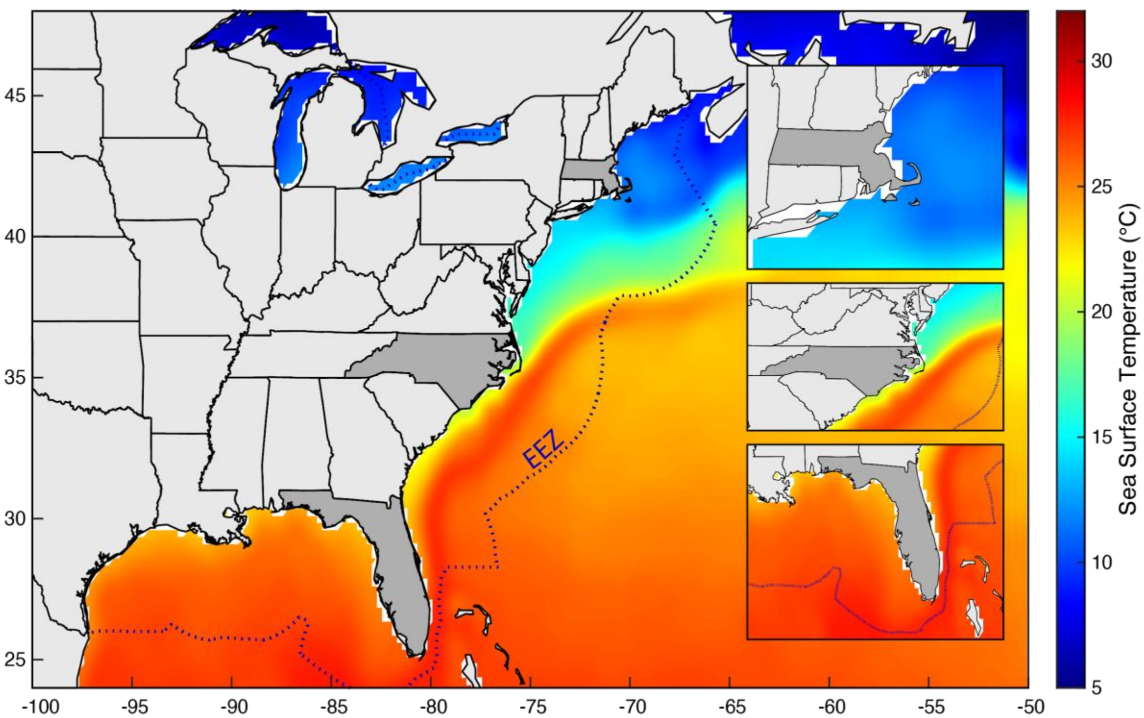


Figure 4.S1. Community maps of study regions representing (**a**) Florida (FL) and (**b**) Massachusetts (MA) built by aggregating individual FCMs from each region.

(a)



(b)

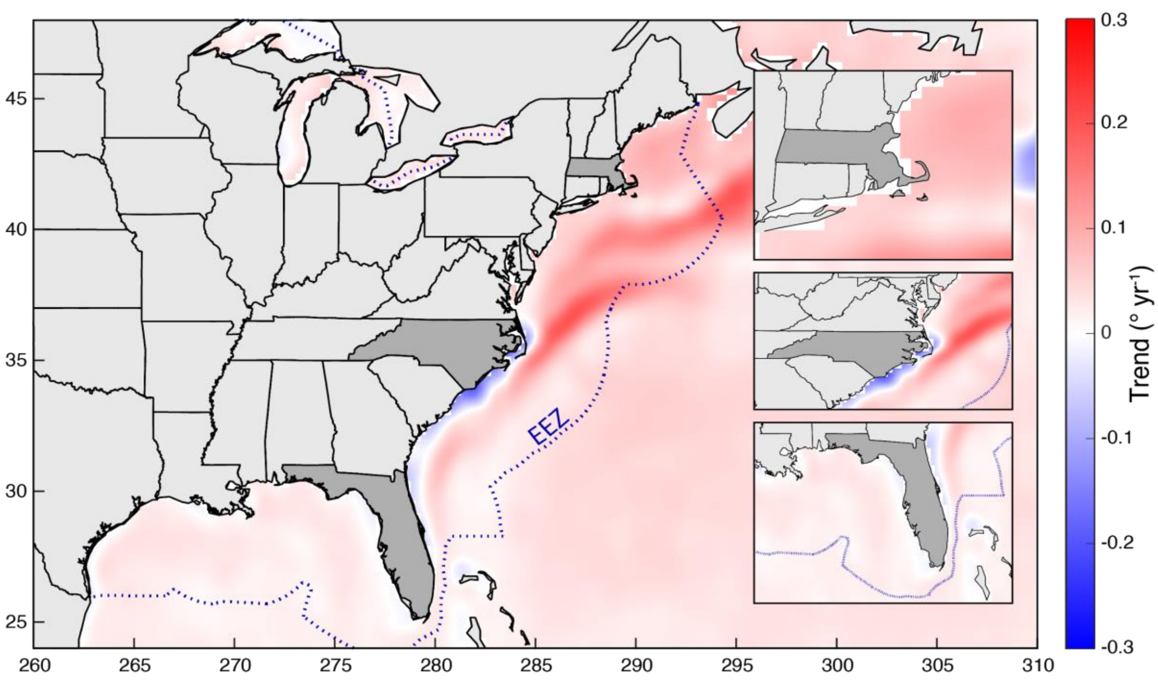


Figure 4.S2. (**a**) Mean sea surface temperature for 2017. (**b**) Trends in monthly mean sea surface temperature from 1997-2017.

What fisheries species do you consider to be the ***most important*** for your fishing? (Choose One)

Greater Amberjack	Gag Grouper	Spot
Alewife	Goliath Grouper	Spotted Seatrout
American Eel	Nassau Grouper	Summer Flounder
American Shad	Red Grouper	Tarpon
Anchovies	Haddock	Tautog
Atlantic Cod	Hardhead Catfish	Tilefish
Atlantic Croaker	Monkfish (Goosefish)	Gray Triggerfish
Atlantic Halibut	Gulf Kingfish	Tripletail

Figure 4.S3. Screenshot of survey question used to determine survey respondents target species. The answer to this survey question was then populated into the subsequent mental model survey questions.

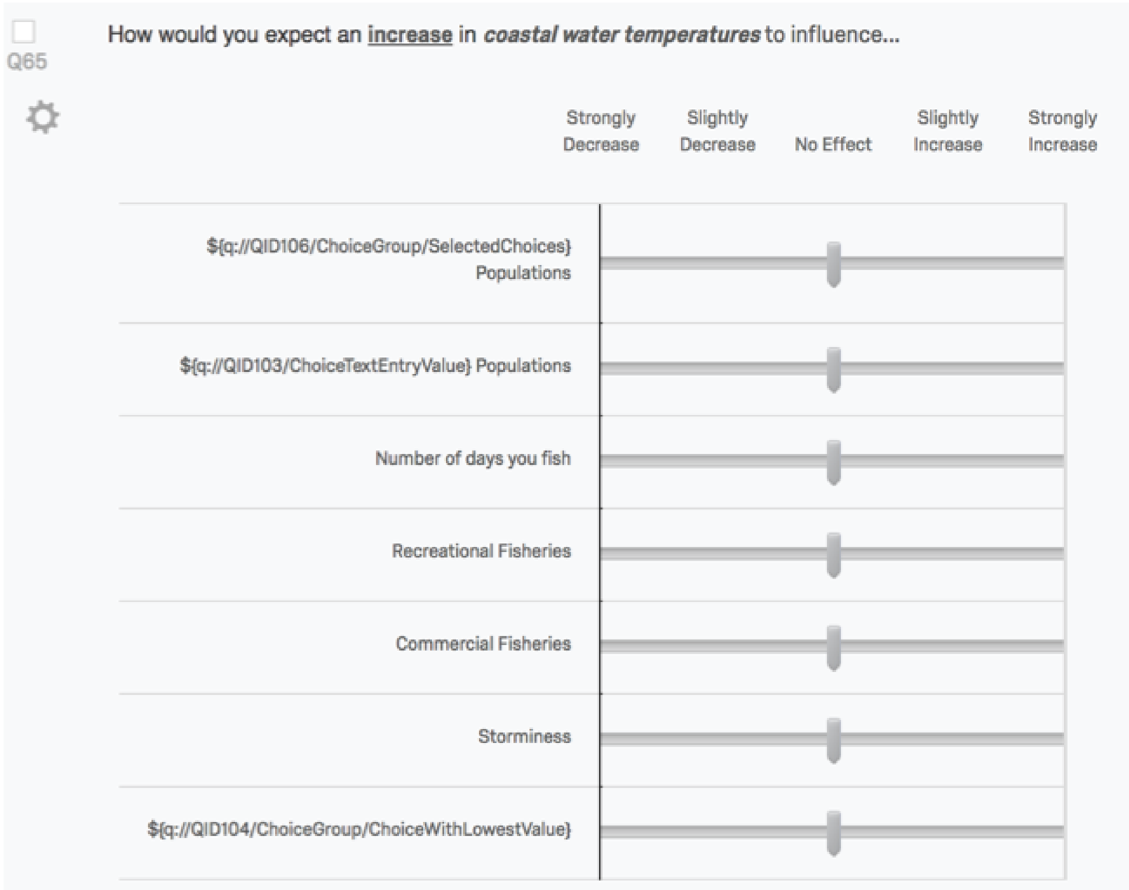


Figure 4.S4. Screenshot of survey question used to ascribe edge weight relationships among concepts.

	Striped Bass Populations	Squid Populations	Rock or Rubble	Warming Coastal Waters	Number of Days You Fish	Recreational Fisheries	Commercial Fisheries	Storminess
Striped Bass Populations		0.5			1	0.7	0.3	
Squid Populations	1				1	1	1	
Rock or Rubble	1	-0.1			1	1	-0.1	
Warming Coastal Waters	0.7	1			1	1	0.1	0.08
Number of Days You Fish	-0.1	-0.1						
Recreational Fisheries								
Commercial Fisheries	-1	-1				-1		
Storminess	-1	-1	-1	-1			-1	

Figure 4.S5. Adjacency matrix showing the corresponding relationships among model concepts derived from the online survey.

S3 Supplementary Tables

Table 4.S1. Survey sample demographics and fishing characteristics of respondents within each state.

	FL		NC		MA	
	Frequency	**Percent**	**Frequency**	**Percent**	**Frequency**	**Percent**
Education						
Less than high school	8	1.1%	4	0.5%	5	1.1%
High school diploma or GED	97	12.8%	77	10.2%	62	13.1%
Some college or 2 year degree	255	33.7%	245	32.4%	116	24.6%
Bachelor's degree	253	33.5%	256	33.9%	165	35.0%
Master's degree	95	12.6%	121	16.0%	78	16.5%
Law or MD	31	4.1%	24	3.2%	23	4.9%
Doctorate (PhD)	17	2.2%	29	3.8%	23	4.9%
Income						
$25k or less	29	3.8%	18	2.4%	7	1.5%
$25,001 to $35k	29	3.8%	17	2.2%	8	1.7%
$35,001 to $50k	47	6.2%	47	6.2%	27	5.7%
$50,001 to $75k	85	11.2%	86	11.4%	35	7.4%
$75,001 to $100k	130	17.2%	128	16.9%	71	15.0%
$100,001 to $150k	134	17.7%	186	24.6%	98	20.8%
$150,000 to $250k	106	14.0%	102	13.5%	87	18.4%
More than $250k	81	10.7%	60	7.9%	54	11.4%
Prefer not to answer	115	15.2%	112	14.8%	85	18.0%

Gender						
Male	635	84.0%	658	87.0%	438	92.8%
Female	109	14.4%	80	10.6%	25	5.3%
Other	1	0.1%	2	0.3%	0	0.0%
Prefer not to answer	11	1.5%	16	2.1%	9	1.9%
Race						
White	659	87.2%	688	91.0%	408	86.4%
Black or African American	1	0.1%	17	2.2%	8	1.7%
American Indian or Alaska Native	11	1.5%	11	1.5%	2	0.4%
Asian	10	1.3%	7	0.9%	12	2.5%
Native Hawaiian or other Pacific Islander	2	0.3%	3	0.4%	1	0.2%
Hispanic or Latino	34	4.5%	6	0.8%	9	1.9%
Prefer not to answer	48	6.3%	37	4.9%	41	8.7%
Age						
less than 21	6	0.8%	7	0.9%	9	1.9%
22-30	49	6.5%	38	5.0%	31	6.6%
31-40	108	14.2%	95	12.6%	67	14.2%
41-50	162	21.4%	170	22.5%	80	16.9%
51-64	379	50.1%	314	41.5%	192	40.7%
65+	52	6.9%	132	17.5%	93	19.7%

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