Harnessing the Collective Intelligence of Natural Resource Users for Conservation

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1. INTRODUCTION

Local ecological knowledge (LEK) of natural resource users, also known as traditional ecological knowledge is constructed while local people interact with natural ecosystems through their daily routines like fishing, farming or hunting [Arlinghaus and Krause 2013]. Additionally, resource users may share information about environmental, policy or social changes across their social networks [Barnes et al. 2016], allowing them to accumulate and refine knowledge and observations across years and locations. Such LEK constitutes a valuable source of information and can complement scientific knowledge about natural resources abundance, resource dynamics, and interactions with humans in data-poor situations [Gray et al. 2012]. However, information embedded in LEK is predominantly qualitative and thus cannot be easily integrated with scientific assessments which are primarily quantitative [Laborde et al. 2011]. Yet, because of inability to measure uncertainty of information obtained through LEK, and also methodological insufficiency, LEK may not be easily translated into accurate assessments and predictions about natural resources abundance and how they respond to various management strategies or external perturbations. To address these challenges, we explored how emerging internet technologies can be used to harness resource users' collective intelligence (CI) to support natural resource management. Here we present reports of two original research studies [Aminpour et al. 2020 and Gray et al. 2020] in which we used fisheries examples to empirically demonstrate how CI of local fishing communities can be harnessed through pooling their LEK to provide valuable information for sustainable resource management. In these examples, we used synchronous social-swarming technologies [Rosenberg 2015] and asynchronous wisdom of crowds (WOC) [Surowiecki 2004] techniques for harnessing resource users' CI to (a) estimate fish abundance, (b) predict human pressures on fish resources and (c) model complex human-fish interdependences.

2. REPORTS OF TWO ORIGINAL RESEARCH

2.1 Social Swarming, Wisdom of crowds, and *Striped Bass* conservation

In the first study [Gray et al. 2020] we examined how synchronous social-swarming technologies and asynchronous WOC techniques can be used as potential conservation tools for estimating the status of Striped Bass (*Morone saxatilis*) population in Massachusetts. We reached out to three of the largest clubs for recreational Striped Bass fishing in the state, and asked members to independently complete an online survey and participate collectively in an online-swarming activity in the spring of 2017. The online survey prompted anglers to answer questions designed to extract their LEK. To obtain insight about size demographics of the fish population, participants were asked to specify the percentage of Striped Bass caught last year (i.e. 2016) that fell into certain size classes. Anglers were also required to estimate the number of licensed recreational fishermen in Massachusetts. We defined results from the crowd as the average of survey responses to promote WOC effect. The second phase of our experiment encouraged individuals to give estimates through real-time online collaboration. The activity incorporated the use of Swarm AI technology [Rosenberg 2015] as a tool to answer a subset of questions from the first phase. *Swarm* is an online platform that allows users to interact concurrently to make predictions and answer questions [Rosenberg and Pescetelli 2017]. The platform is synchronous, meaning that users can explore decision-spaces together and the software structures these online social groups of users through a process of 'social swarming' in real-time intended to promote group convergence on a preferred solution. In our experiment participants were able to answer questions by collectively moving a "graphical puck" to select a response from among multiple choices (Fig.1c). Individual intent for selecting a particular answer was visible to others by showing small graphical magnets on the screen pulling the puck towards specific directions (i.e. intended choice). Although most questions exactly matched those in the survey, a handful were modified to fit the swarm's format.

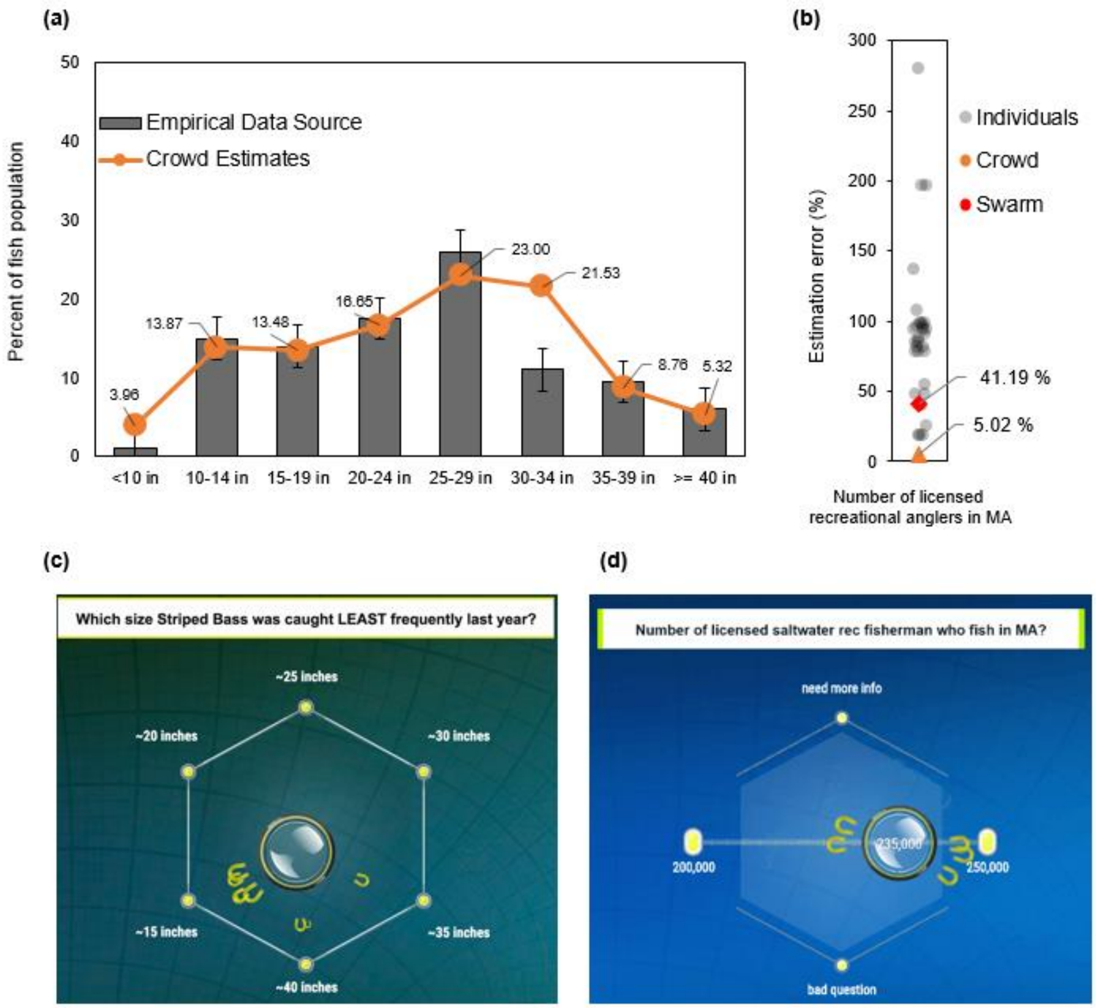

Fig 1. Results of Striped Bass case study. (a) Crowd estimates of percentages of the fish population regarding the size class compared to empirical data. (b) Estimation error of individuals, independent crowd, and the swarm regarding the number of licensed recreational anglers in Massachusetts. (c) The online social-swarming platform asking question about size-frequency. (d) Swarming platform asking question about number of recreational anglers in MA.

Within the framework of our research, participatory websites such as Swarm AI and the online survey served as functional tools to harness stakeholders CI. Based on their performance in our experiments, systems utilizing WOC ideology are more effective at making numeric predictions, compared to those which incorporate swarming, as exemplified by the swarm's lower accuracy than crowd in estimating the number of active recreational anglers in Massachusetts (Fig. 1b). But more empirical data is needed to understand under what conditions these approaches can be applied to more data-poor conditions with high uncertainty. Both approaches, however, can be effective forecasters in certain settings. For example the crowd and swarm yielded valid results when classifying estimates at the extreme ends of the spectrum, such as the sizes of fish that occur most or least frequently. We offer a practical approach for using resource stakeholders to generate highly precise estimates, which mirror the empirical data collected by scientists.

2.2 Wisdom of stakeholder crowds, mental modeling, and *Pike* conservation

In the second study [Aminpour et al. 2020] we explored the potential of harnessing the CI of natural resource stakeholders to produce accurate representations (i.e. models) of complex relationships between human and natural systems. Using an example of freshwater Pike (*Esox lucius*) fisheries in Germany, we showed that by aggregating the LEK held by stakeholders through graphical mental model representations, a crowd of diverse resource users produced an accurate prediction of human–environment relationships that is comparable to the best scientific knowledge. We also showed that the averaged mental model from a crowd of diverse resource users outperforms those of more homogeneous groups (Fig. 2). In this study, 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. To leverage WOC effect, we used mathematical averaging techniques to aggregate the cognitive maps elicited as directed networks of nodes and weighted causal connections. Additionally, we ran two mental modeling 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 found that the network structure of the crowd mental model matched scientific understanding about the social–ecological interdependences driving pike fisheries. This was evidenced by evaluating agreement between the crowd mental model and the scientific mental model using network analysis. We also assessed the dynamics (functional) behavior of the mental models by simulating how changes in one or more nodes of the mental models affected the state of remaining nodes using auto-associative neural network method. We found again that the functional properties of the crowd mental model accurately matched scientific understanding about pike ecology [please see Aminpour et al. 2020 for more detail].

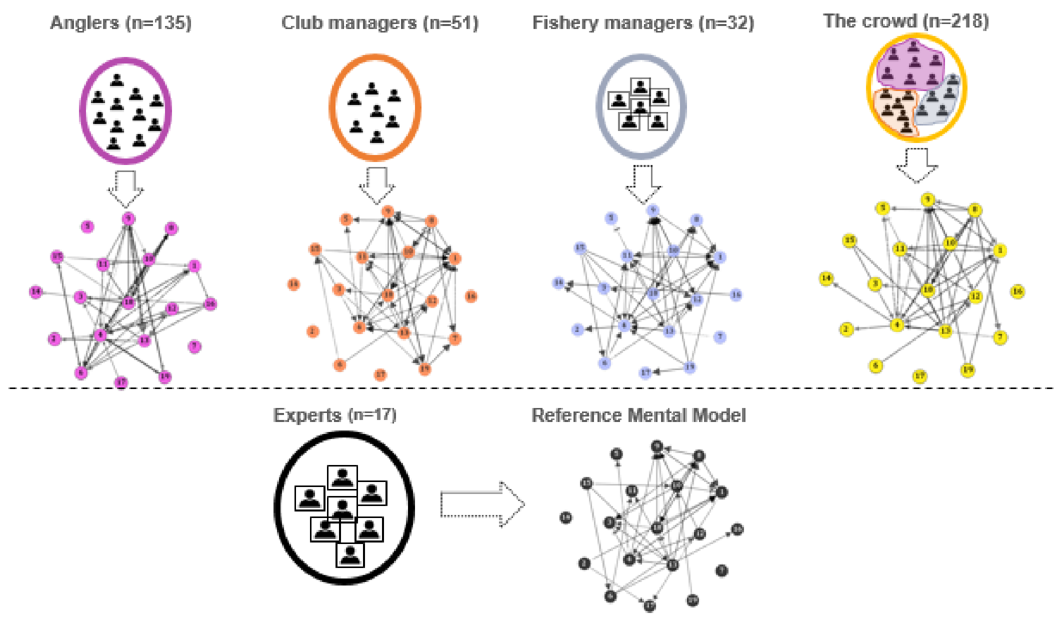

Fig. 2. Aggregated mental models of fisheries stakeholder groups from left: recreational anglers, club managers, fishery managers, and the crowd of all stakeholder types. The mental model at the bottom shows the aggregation of scientific experts cognitive maps used as the reference point to evaluate the performance of stakeholder-driven mental models. The crowd model showed the highest similarity to the reference model.

Although each group had biases leading to larger disagreements with scientific reference model, when combined together, the crowd model demonstrated remarkable similarity to the scientific experts (i.e., reference model), with highest agreement in terms of structure and dynamic behavior [see Aminpour et al. 2020 for the methods and visualization of the results]. Our work opens an avenue to involving stakeholders proactively in difficult management decisions, including system simulation, based on models that aggregate individual mental models resulting from online or other survey means. This can lead to improved analyses, the inclusion of LEK, and more equitable discussions.

3. CONCLUSION

Our work applies to a broad domain of resource management problems in which stakeholders have relevant but diverse system knowledge. It is very encouraging that scientific information of complex ecosystem dynamics can be generated from a group of informed stakeholders. Thus, our work offers a practical approach for using crowds of resource users to generate high-quality system models which mirrors the knowledge of highly trained academics. These crowd models can be used as a concrete basis for developing strategies for better managing ecosystems in participatory and adaptive ways across many different natural resource and biodiversity conservation contexts, especially in data-poor situations.

REFERENCES

Aminpour, P., Gray, S. A., Jetter, A. J., Introne, J. E., Singer, A., & Arlinghaus, R. (2020). Wisdom of stakeholder crowds in complex social–ecological systems. *Nature Sustainability*, 1-9.

Arlinghaus, R., & Krause, J. (2013). Wisdom of the crowd and natural resource management. *Trends in ecology & evolution*, *28*(1), 8-11.

Barnes, M. L., Lynham, J., Kalberg, K., & Leung, P. (2016). Social networks and environmental outcomes. *Proceedings of the National Academy of Sciences*, *113*(23), 6466-6471.

Gray, S., Aminpour, P., Reza, C., et al. (2020). Harnessing the Collective Intelligence for Conservation, *Frontiers in Ecology and the Environment* (Accepted).

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

Laborde, S., Imberger, J., & Toussaint, S. (2012). Contributions of local knowledge to the physical limnology of Lake Como, Italy. *Proceedings of the National Academy of Sciences*, *109*(17), 6441-6445.

Rosenberg, L. B. (2015). Human Swarms, a real-time method for collective intelligence. In *Artificial Life Conference Proceedings 13* (pp. 658-659). MIT Press.

Rosenberg, L., Pescetelli, N. 2017. Amplifying prediction accuracy using swarm AI. In 2017 Intelligent Systems Conference: IEEE.

Surowiecki, J. (2004). The wisdom of crowds: why the many are smarter than the few and how collective wisdom shapes business, economies, societies and nations, First edn, Doubleday, New York.