Journal of Environmental Psychology 85 (2023) 101906

Contents lists available at ScienceDirect

Journal of Environmental Psychology

journal homepage: www.elsevier.com/locate/jep

Content and complexity of stakeholders' mental models of socio-ecological systems

Karlijn L. van den Broek [a,b,*], Joseph Luomba [c], Jan van den Broek [d], Helen Fischer [e,f]

[a] Copernicus Institute of Sustainable Development, Utrecht University, Princetonlaan 8a, 3584 CB, Utrecht, the Netherlands
[b] Research Centre for Environmental Economics, Heidelberg University, Germany
[c] Tanzanian Fisheries Research Institute, Mwanza, Tanzania
[d] Department of Theoretical Epidemiology, Utrecht University, the Netherlands
[e] Leibniz Institut für Wissensmedien, Tübingen, Germany
[f] Department of Psychology, Mainz, Germany

ARTICLE INFO

Keywords:
Mental models
Systems thinking
Cognitive maps
Causal beliefs
Natural resource conservation
Fisheries

ABSTRACT

Stakeholders' interactions with environmental resources are influenced by their mental models of the socio-ecological system of the environmental resource. Individual differences in such mental models are particularly important to identify, as diverse mental models may be associated with different behaviour or policy preferences and affect collaborative conservation efforts. In the present work, we explore stakeholders' mental models of a socio-ecological system and assess content and complexity differences across fishing experience levels, migration status, and regions. We mapped Tanzanian fishers' ($N = 185$) mental models of the drivers of the Nile perch stock fluctuation at Lake Victoria. The findings show that (1) fishers' mental models were complex and diverse, (2) mental models focused on the causal influence of destructive fishing activities, (3) mental model complexity, but not content, varied across regions, and (4) fishing experience and migration status were not consistently related to mental model complexity or content. These results have important implications for environmental resource management at Lake Victoria.

1. Introduction

Although there is scientific consensus that humanity uses more resources than the planet can sustainably produce (IPCC, 2022), managing common-pool resources remains particularly challenging (Hardin, 1968). To optimise resource conservation, a wealth of research has investigated the perceptions of resource users directly affected by the exploitation or preservation of the resource (Norström et al., 2020). Resource users' perceptions of complex systems or phenomena are cognitively represented in mental models. Mental models affect resource users' decision-making and interaction with the environmental resource system and their collaboration with other users to conserve the resource (Biggs et al., 2011; Güss & Robinson, 2014; Morgan et al., 2002). Consequently, mental models have been identified as leverage points within psychological research for addressing sustainability challenges (Goldberg et al., 2020). Mental model research can provide insights into system thinking (Lezak & Thibodeau, 2016), uncover (in)consistencies in perceptions and beliefs between individuals (Wood et al., 2012), or demonstrate misperceptions that can be addressed in risk communication (Morgan et al., 2002).

1.1. Mental models of environmental resources

Mental models are cognitive representations of the external world and consist of an individual's assumptions about the functioning of a particular system (Bostrom, 2017; Craik, 1943; Johnson-Laird, 1989), including the relevant components of a system or process (e.g. actors, events, or phenomena) and their causal relationships (e.g. causal influences, consequences, Böhm et al., 2018; Böhm & Pfister, 2001; Newell et al., 2014). Mental models are based on individual experience, culture, values, and beliefs (Bender, 2020; Biggs et al., 2011). These perceptions are inherently subjective and may reflect a simplified representation of external reality. Mental models may provide an incomplete view of the system but can complement insights from different knowledge systems (Johnson-Laird, 2010; Morgan et al., 2002; Richter et al., 2022). Individuals are guided by their mental models to filter,

* Corresponding author. Copernicus Institute of Sustainable Development, Utrecht University, Princetonlaan 8a, 3584 CB, Utrecht, the Netherlands.
E-mail address: k.l.vandenbroek@uu.nl (K.L. van den Broek).

https://doi.org/10.1016/j.jenvp.2022.101906
Received 24 December 2021; Received in revised form 24 October 2022; Accepted 6 November 2022
Available online 19 November 2022
0272-4944/

process and store information (Johnson-Laird, 1983; Kempton, 1986).

The concept of mental models has gained momentum within sustainability research and has been investigated in relation to various environmental resources (e.g. Downing et al., 2014; Hobbs et al., 2016). Within the field of environmental psychology, research on mental models of environmental resources is more sparse and has focused on aspects of mental models such as causal cognition (Bender, 2020; Klein et al., 2021), pathways in mental models (Böhm et al., 2019), categories of mental model components (Doran et al., 2018), inferences about the system (Dutt & Gonzalez, 2012; Holmgren et al., 2019) or mental imagery (Böhm et al., 2018).

Having participants draw their mental model by mapping the relevant concepts and the directional relations between them, also known as cognitive maps or influence diagrams, demonstrates the mental model's structure and the causal beliefs within the mental models (Johnson-Laird, 1983; Kaplan & Kaplan, 2009). Arguably, such an approach goes beyond understanding facets of a mental model and provides a more comprehensive account of individuals' perceptions. Research on such mental model representations shows the perceptions of the interrelations between system components and therefore an individual's engagement in systems thinking. Systems thinking reflects one's grasp of the interrelations within a system, meaning that individuals understand that processes do not occur in isolation and that addressing one issue may affect other processes (Lezak & Thibodeau, 2016). Since most sustainability challenges require system changes or imply systemic effects, it is imperative to understand people's views of socio-ecological systems. These perceptions determine what solutions are considered suitable and influence policy support and decision-making (Lezak & Thibodeau, 2016).

1.2. Complexity and content differences in mental models

Differences in mental models can have far-reaching consequences for conservation management collaborations. Similar mental models between stakeholders may indicate agreement on the functioning of a complex system and provide a solid foundation for collaborative efforts to manage environmental resources. Differences in mental models, in contrast, may reflect disagreement about causes and solutions to the particular conservation challenge, obstructing collaborations for management. Hence, identifying such differences in perceptions may be an essential first step toward fostering collaborative environmental resource conservation strategies (van den Broek, 2018; Wood et al., 2012).

Mental models can be similar or different between individuals in terms of their *complexity* (the number of concepts included and the connectivity between concepts) or the *content* of the mental models (which concepts are included and the relative importance of concepts or connections within the mental model). Research has shown that these mental model differences can predict behaviour. Regarding mental model complexity, sufficiently complex knowledge structures may be necessary for making decisions (Calori et al., 1994). Mental models may only help navigate a situation or task requirements if they consist of sufficient model concepts and relationships between these concepts, particularly in complex and dynamic environments (Mohammed et al., 2017). Indeed, longitudinal research showed that groups with more complex mental models (measured at earlier time points) were more likely to succeed in team tasks (measured at later time points), demonstrating the directional relationship between mental model complexity and behaviour (Uitdewilligen et al., 2021).

In terms of content, for example, farmers with mental models that included biological pest control concepts showed higher rates of sustainable conservation practices than farmers who did not perceive biological pest control concepts to be relevant (Bardenhagen et al., 2020). Differences in mental model content have also predicted differences in policy support. For instance, those who perceive carbon emissions to drive climate change were more likely to support policies reducing those emissions than those who attribute climate change to other causes (Bostrom et al., 2012).

1.3. Factors associated with differences in mental models

Social cognition theory describes how individuals acquire knowledge through social interaction and experiences (Bandura, 1986). Social cognition research outlines how situational context, cognitive processes, and behaviour influence each other and underlines the importance of the social environment for making sense of that environment, including the development of mental models. Therefore, individuals growing up in different geographical or cultural regions, who have migrated to another place or who differ in how much experience they have in a socio-ecological system may vary in their mental models of environmental resources. The following sections will provide an overview of three stakeholder characteristics that may predict differences in mental model complexity and content: region, migration status, and experience.

1.3.1. Regional differences

The content or complexity of mental models may differ across geographical locations since these locations may differ in physical attributes, and therefore learning experiences will vary. Indeed, research showed that farmers' mental models from three different winegrape regions in California included region-specific elements such as erosion control or institutions and policy (Hoffman et al., 2014). Regional differences in mental models may also occur because individuals communicate more with others within regions than between regions. When individuals share their knowledge, they may gradually develop converging mental models (Aminpour et al., 2020; Henly-Shepard et al., 2015) and a shared understanding within a culture (Jones et al., 2011).

1.3.2. Native and migrated residents

Communication may also explain why the content of mental models among residents native to the socio-ecological system is likely to differ from those who migrated to the area (Bertolas, 1998). Intergenerational transmission of knowledge shapes perceptions of local environmental issues and how to respond to them (Molina, 2016). Hence, native residents' mental models are more likely to have been shaped by their parents' or grandparents' interaction with the system and subsequent dissemination of these perceptions to the next generation, while this is less likely the case for migrated residents.

1.3.3. Experience

Experience with a system, meaning the amount of system interaction accumulated, has mainly been investigated in relation to mental model complexity. The literature on the link between experience and mental model complexity consistently finds that experience with a system facilitates the identification of more complex causal structures, such as feedback loops and moderation effects (Jaques, 1986; Levy et al., 2018). Individuals with more experience can form mental models with more integrated, stable, overarching patterns, reflecting more abstract representations of the system (Carter et al., 1988; Hmelo-Silver et al., 2007; Tanaka & Taylor, 1991; Trafton et al., 2002).

Although ample literature has demonstrated the effect of experience on the inclusion of complex structures within mental models, it remains unclear if individuals with more experience also include a higher number of concepts and connections in their mental models. A study assessing mental models of the Northeast Pacific Ocean herring ecosystem among 27 rather diverse experts (scientists, residents and traditional experts) did not find a relation between experience and the number of concepts and connections in their mental models (Stier et al., 2017). However, the small and diverse sample of participants may have resulted in considerable variability in mental models, which may have obscured any effect of experience on the complexity of the mental models. Hence, more research is needed among a larger, more homogenous sample to assess if individuals with more system experience create more complex mental models regarding the concepts and connections in their mental models.

1.4. The present study

Previous research suggests that differences in mental models may be particularly prone between regions, native and migrated residents, and system experience levels. However, current literature leaves room to investigate mental model content and complexity differences (i) across different regions, (ii) across native individuals and those who have migrated to the area during their lifetime, and (iii) across similar stakeholders with varying levels of system experience. To gain insight into how individual characteristics are associated with differences in mental models, we investigate resource users' mental models of a shared socio-ecological system in East Africa.

1.4.1. Study area

Lake Victoria is Africa's largest lake, shared by Tanzania, Uganda, and Kenya, and has the largest small-scale freshwater fishery worldwide (Njiru et al., 2008). This multi-species fishery is dominated by the Nile perch fishery, which supports the livelihoods of many individuals in the region (Njiru et al., 2018). This fishery makes a suitable case study for the present work for two reasons. First, Lake Victoria's fishers' diversity makes comparisons regarding the variables of interest relevant to resource management. Fishers differ in their amount of system experience in different regions. Furthermore, some fishers migrated to Lake Victoria for economic opportunities, while others were born there. Second, Lake Victoria provides a context in which perceptions are critical for resource conservation. Because of the diversity of regulations across regions and low enforcement rates in many areas (Njiru et al., 2018), individual decisions and behaviour are imperative for sustainable fishing practices.

This study investigated differences between the Mara region, the Mwanza region, and Ukerewe Island. The Mara region is one of the most rural regions in Tanzania, while the Mwanza region is more urban and includes a large island called Ukerewe (Tanzanian National Bureau of Statistics, 2013). This island is primarily inhabited by another ethnic group with different cultural practices than the ethnic groups dominating the Mwanza and Mara regions (Onyango, 2014). Due to its geographical distance from the mainland and cultural differences, this district was grouped separately from the Mwanza region.

1.4.2. Aims

This study aimed to (i) describe the characteristics of Tanzanian fishers' mental models of the Nile perch stock fluctuations at Lake Victoria and (ii) explore which individual differences are associated with differences in fishers' mental models. Specifically, we investigate differences in terms of the complexity and content of the mental models depending on fishers' landing site region, whether they are native or migrated to the area and their fishing experience. Differences in mental model complexity may signal differences in systems thinking. Content differences in mental models may demonstrate differences in causal attribution concerning the depletion of the natural resource and may provide insights into what processes and actors are perceived to be critical for natural resource conservation. This study, therefore, contributes to the literature on stakeholders' mental models of socio-ecological systems and the body of literature explaining differences in mental models.

2. Methods

The data collected for the current study were also analysed to validate the tool used to capture mental models in Study 2 by van den Broek, Luomba, et al., (2021). Therefore, the following sections merely summarise the methods of this study, and we refer readers to van den Broek, Luomba, et al., (2021) for more details.

2.1. Participants

The sample consisted of 185 fishers from 13 randomly selected landings sites, who were predominantly male (0.5% female) and varied in age ($age_{mean} = 38.64$, $age_{SD} = 10.73$). These sample characteristics match those of prior research on the fishery (Chitamwebwa et al., 2009; Luomba, 2013; Msuku et al., 2011; Onyango et al., 2006), and the sample size is large compared to typical mental model research (Özesmi & Özesmi, 2004). We employed a time-location sampling strategy, which first involves random sampling of locations where individuals of interest can be found and then taking a random sample from those who are present at the sampled locations at the time of sampling (Karon & Wejnert, 2012). Since no previous mental model research has been conducted with a similar research design and analysis, we did not have any effect sizes and variation indicators to conduct a power analysis. Hence, the sampling strategy aimed to maximise the sample size, considering the practical limitations and resource-intensive sampling strategy for this hard-to-reach population.

2.2. Instruments and materials

2.2.1. Mapping mental models

We elicited mental models with M-Tool (van den Broek, Klein, et al., 2021), a standardised tool with which participants create visual representations of their mental models. The tool has previously been applied using a similar study design to capture mental models of the drivers of COVID-19 transmission (see de Ridder et al., 2022). Participants created mental models consisting of driver concepts connected by weighted arrows to indicate directional relationships, showing their causal beliefs regarding the drivers and the target variable of Nile perch stock fluctuation. Participants first chose relevant drivers from a set of pictograms and then connected the pictograms with weighted arrows. The set of drivers (Fig. 1, see Table A1 in Appendix A for the definitions) was derived from an interview study with Lake Victoria stakeholders ($N = 67$) (van den Broek, 2019).

M-Tool was populated with these driver icons and the audio instructions and was administered as described in the paper by van den Broek, Luomba, et al., (2021). Through mental model interviews, the set of drivers was validated in the three regions in Study 1 by van den Broek, Luomba, et al., (2021). Participants conducted a mental model mapping practice task, after which the set of drivers was presented to participants (Fig. 2, Panel A). On the mapping screen (Fig. 2, Panel B), participants created their mental model by selecting the relevant drivers and connecting them with weighted arrows, working towards the target variable of the Nile perch stock fluctuation that was fixed on the right side of the mapping screen (Fig. 2, Panel C). Participants were encouraged to think out loud during the task to verify they had understood the task and drivers.

2.2.2. Survey

A survey collected demographic information (age, gender, education, role in fishery, type of fishing gear) and individual characteristics expected to be associated with differences in mental models (landing site region, years of fishing experience, and migration status). Additional variables included in the paper by van den Broek, Luomba, et al., (2021) are not reported further.

2.3. Procedure

Data were collected in collaboration with the Tanzania Fisheries Research Institute (TAFIRI Mwanza). Two trained research assistants collected data in one-to-one sessions. After providing informed consent, participants drew their mental model with M-Tool, and answered the survey questions at the end of the session. Participants were thanked, debriefed and financially compensated for their time according to local standards.

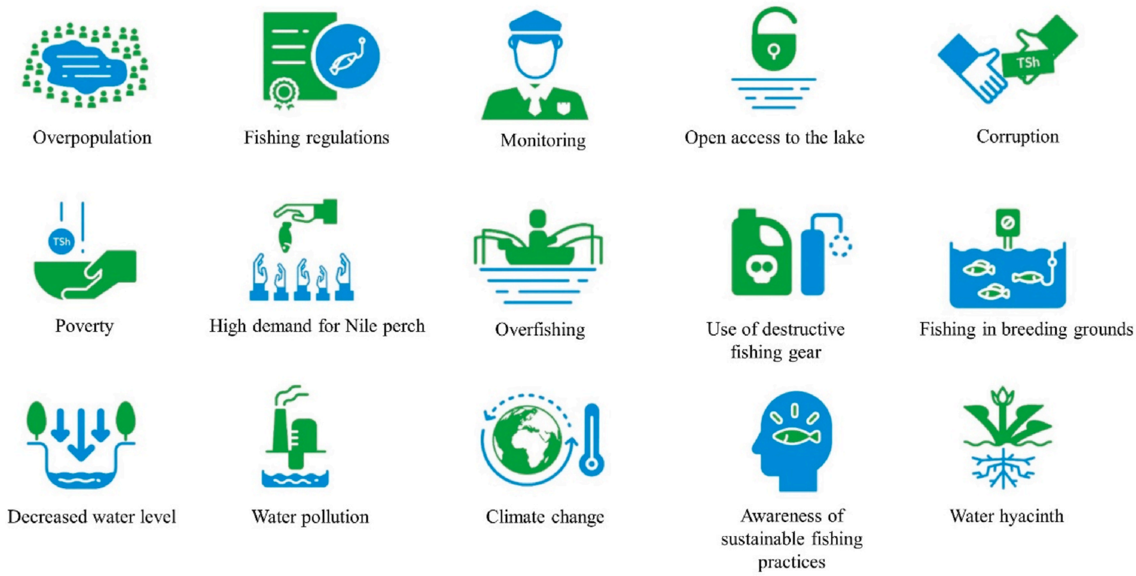


Fig. 1. The set of driver concepts participants could use to create their mental model in M-Tool.

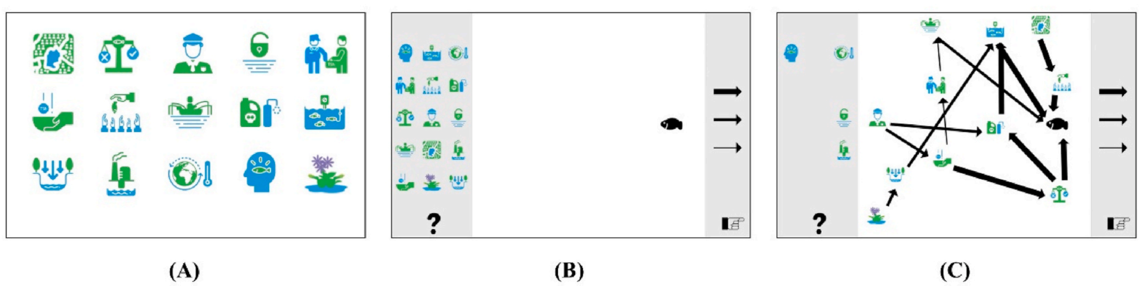


Fig. 2. Screenshot of M-Tool. (A) Set of driver concepts (B) mapping screen (C) example of a mapped mental model.

2.4. Ethics statement

The Tanzanian Commission for Science and Technology conducted an Ethical review following local legislation and institutional requirements and provided a research permit for this study (No. 2019-490-NA-2019- 272).

2.5. Measures and statistical procedure

The data were analysed using a network analysis approach, as the mental model data for each participant can be represented as a network (Newman, 2010). In these networks, the drivers in the mental model and the target variable are the nodes of the networks, and the weighted arrows are the edges. The connection weights were coded as follows: a thin arrow:1, a medium arrow:2, a thick arrow:3.

2.5.1. Dependent variables

For each driver (node) in each participant's mental model, we calculated four values: (i) a binary variable indicating driver selection (ii) the in-strength of the driver, (iii) the out-strength of the driver, and (iv) the betweenness of the driver. The latter three measures constitute centrality measures that provide insights into the location and importance of a variable within the network (Krebs, 2000). These centrality indicators are recommended for directed weighted networks (Zweig, 2016) to represent diverse aspects of the importance of each driver in the mental model. The centrality measures were not computed for the target variable Nile perch stock fluctuation since this node was in every participant's model and, therefore, cannot be compared to the drivers of the Nile perch stock fluctuation in the mental models. The four measures of the 15 drivers served as indices of participants' mental models and as dependent variables to investigate differences in mental models and are further explained below.

2.5.1.1. Driver selection. Driver selection reflects whether the participants selected the driver to be included in their mental model or not. When a participant did not select a driver, this variable had a value of zero.

2.5.1.2. In-strength. The in-strength of a node is computed by summing the values of the edge weights of incoming edges of that node (Hevey, 2018). Hence, in-strength takes the number of incoming arrows of a particular driver and the weights assigned to those arrows into account. In-strength reflects the driver's importance based on the influence the driver receives from connected drivers.

2.5.1.3. Out-strength. The out-strength of a node is computed by summing the values of the edge weights of outgoing edges of that node (Hevey, 2018). Hence, out-strength takes the number of outgoing arrows of a particular driver and the weights assigned to those arrows into account. Out-strength reflects the driver's importance based on the influence the driver has on its connected drivers.

2.5.1.4. Betweenness. The betweenness of a node (e.g. note A) is the sum of the number of times that node is on the shortest path between any two other nodes (e.g. B and C), divided by the total number of shortest paths between the two nodes (B and C) (Brandes, 2001). Betweenness indicates whether a driver provides an important link between other drivers (Hevey, 2018). We computed the weighted betweenness, where the weights of the connections reflect the distance between two nodes (Brandes, 2001). Hence, paths with higher weights were considered shorter, and nodes on higher-weighted paths obtained higher betweenness values. The higher the betweenness, the more important a driver is in connecting other drivers with each other. Drivers at the start of a chain of drivers obtained a value of zero.

2.5.2. Predictors

The predictors included landing site region, migration status and fishing experience (Table 1). A median split was conducted for the responses for fishing experience, dividing the respondents into 10 years of fishing experience or less, and more than 10 years of experience. The survey responses for migration status (native or migrant) and fishing experience (up to 10 years of experience vs. more than 10 years) were dummy-coded. Landing sites were grouped into the Mwanza region, Mara region, and Ukerewe district.

2.5.3. Statistical analysis

Separate regressions were conducted for driver selection, in-strength, out-strength, and betweenness as dependent variables, with driver ID, landing site region, migration status, and years of fishing experience as predictors, as well as the two-way interactions between driver ID with landing site region, between driver ID and migration status and between driver ID and years of fishing.

Because each measure was computed for each driver for each participant, the data reflected a long data format with a repeated measure structure of 15 rows for each participant, one for each driver. Hence, all regressions included random intercepts for subjects in a multilevel model to reflect the dependence across drivers within participants. Since one regression was conducted on the selection or centrality indices for all 15 drivers, each regression included a variable 'driver ID' to distinguish each driver's selection or centrality scores. A main effect for this variable would indicate different selection or centrality measure scores between drivers. No pairwise comparisons between drivers were performed when differences were found in centrality scores between drivers. Instead, we refer the reader to section 3.1.3 for the mean centrality scores for each driver.

2.5.3.1. Mental model complexity and content. The driver selection, in-strength, out-strength and betweenness of all 15 drivers served as the dependent variables to compare *complexity* and *content* differences in the mental models between landing site regions, participant migration status and experience levels (see Table 2).

The *complexity* of a mental model is reflected by *the number of drivers* included in the mental model, indicated by the mean probability of driver selection for the 15 drivers, or the *connectedness of the drivers*, indicated by the mean in-strength, out-strength and betweenness values for the 15 drivers. Differences in the complexity of the mental model were investigated by looking at the main effect of each predictor for the driver selection, in-strength, out-strength and betweenness. Main effects for landing site region, migration status and years of fishing would indicate group differences in the *complexity* of the mental models. For example, a main effect of region on driver selection would suggest that the mean probability of the drivers being selected for the mental model differs across regions. Hence, this would show that participants in some regions tended to include more drivers than participants in other regions, indicating mental model complexity differences between regions. Furthermore, a main effect of region on the connectedness indicators (in-strength, out-strength and betweenness) would indicate differences in the mean connectedness of the drivers between participants from different regions, indicating complexity differences across regions in terms of the connectedness of the mental model.

The *content* of the mental model was investigated by honing in on the predictor effects across the different drivers by looking at the interaction between the predictor and driver ID. An interaction between a predictor and driver ID on the driver selection would indicate that the effect of the predictor on driver selection differs across the drivers, demonstrating differences between drivers in the probability that they were included in the mental model. Hence, such an interaction can demonstrate *which drivers tend to be included* for different predictor levels. For example, an interaction between region and driver ID on driver selection would indicate that the differences in the selection of the drivers vary across regions. Hence, such an effect would suggest that participants in different regions tend to include drivers in their mental models with different probabilities.

An interaction between a predictor and driver ID on the connectedness indicators (in-strength, out-strength and betweenness) would indicate that the effect of the predictor on the connectedness indicators differs across drivers. Hence, such an interaction would show differences in the connectedness of the drivers, revealing *which drivers tend to be highly connected* for different levels of the predictor. For example, an interaction between region and driver ID on the connectedness indicators would demonstrate that the regional differences in the connectedness of the drivers differ across drivers. Hence, this interaction would suggest that the mental models of participants in different regions differ in terms of which drivers tend to be highly connected in their mental model. Such a finding would indicate that participants from different regions varied in the ascribed importance across drivers regarding the influence drivers are perceived to have on other drivers or the target variable in their mental model.

2.5.3.2. Model selection. We used Akaike's information criterion (AIC) for model selection, which estimates the relative amount of (Kulback-Leibler) information lost by one model compared to another and is an indicator of out-of-sample predictive accuracy. With this method, various models are compared, and the model with the lowest AIC value is deemed to have the least estimated information loss (Burnham & Anderson, 2002). Akaike's Information Criterion minimises the out-of-sample error and makes a stepwise regression a suitable method to obtain the most accurate model (Hastie et al., 2017). A backward stepwise selection procedure was applied, starting with the full model and removing the term with the lowest AIC value in each step until the AIC value for the entire model was lower than the AIC value for the terms in the model. For the final model, the model fit was checked by inspecting deviance residual plots. We report 95% profile likelihood confidence intervals, since these are particularly suitable for non-linear models and asymmetric confidence intervals (Royston, 2007).

Table 1
Frequency distribution of predictor variables.

		N	Percentage
Landing site region	Mara	70	38%
	Mwanza	87	47%
	Ukerewe	26	14%
	Missing	2	1%
Migration status	Native	107	58%
	Migrant	78	42%
Fishing experience	≤10 years of fishing experience	78	42%
	>10 years of fishing experience	107	58%

3. Results

3.1. Mental models of the Nile perch stock fluctuation

The following sections will first describe the patterns in the mental models across the entire sample and then investigate differences in mental models across participant groups in section 3.2.

Table 2
Interpretation of regression effects.

	Dependent variable	
	Driver selection	In-strength, out-strength, betweenness
Main effects: Landing site region Migration status Fishing experience	*Complexity* differences in mental models: differences in the *number of drivers* included (the mean probability of selection across all 15 drivers) in a mental model	*Complexity* differences in mental models: differences in the *connectedness of drivers* (the mean connectedness across all 15 drivers)
Interactions: Landing site region*driver ID Migration status*driver ID Fishing experience*driver ID	*Content* differences in mental models: differences in *which drivers tend to be included* for different levels of the predictor	*Content* differences in mental models: differences in *which drivers tend to be highly connected* for different levels of the predictor

3.1.1. Mean mental models

The aggregated mental model for the entire sample is displayed in Fig. 3. On average, participants included 10.99 drivers ($SD = 2.51$) out of the 15 drivers that were presented in M-Tool. The mean number of connections was 12.10 ($SD = 2.85$), meaning, on average, a driver was connected with 1.10 arrows ($SD = 0.12$), thus connecting it to 1.10 other drivers or the target variable.

The most common connections in the mental models are displayed in Table 3. Out of the 185 participants, 81.62% connected *fishing in breeding grounds* to *Nile perch stock fluctuation*, with a mean weight of 2.86 (from a possible range of 1–3), indicating that the majority of participants agreed that this was an important cause for Nile perch stock fluctuations. Other common connections, such as *use of destructive fishing gear – fishing in breeding grounds*, *awareness of sustainable fishing practices – Nile perch stock fluctuation*, *water level – Nile perch stock fluctuation*, and *monitoring – fishing regulations*, were included by 34.06–43.24% of participants. These connections were also regarded as very important, as mean weights were >2.50 (except for the connection *water level – Nile perch stock fluctuation*).

3.1.2. Mean centrality measures

The driver selection, in-strength, out-strength and betweenness values of each driver are displayed in Fig. 4 and Table B1 in Appendix B. The driver selection was highest for *use of destructive fishing gear* and *fishing in breeding grounds.* The in-strength measure also demonstrated substantial variability across drivers, with the highest in-strength values for *fishing in breeding grounds, use of destructive fishing gear* and *overfishing*, highlighting that they receive strong influences from connected drivers in the mental model. For the out-strength measure, *monitoring* obtained the highest value, suggesting this driver may be a key driver influencing other drivers in the mental model. The betweenness measure demonstrated great differences across drivers, with high scores for the *use of destructive fishing gear*, *overfishing*, and *fishing in breeding grounds,* showing that these drivers are essential in connecting other drivers and hence, key for the Nile perch stock fluctuations. The concepts with the lowest driver selection, in- and out-strength and betweenness include *water hyacinth*, *decreased water level*, and *climate change*.

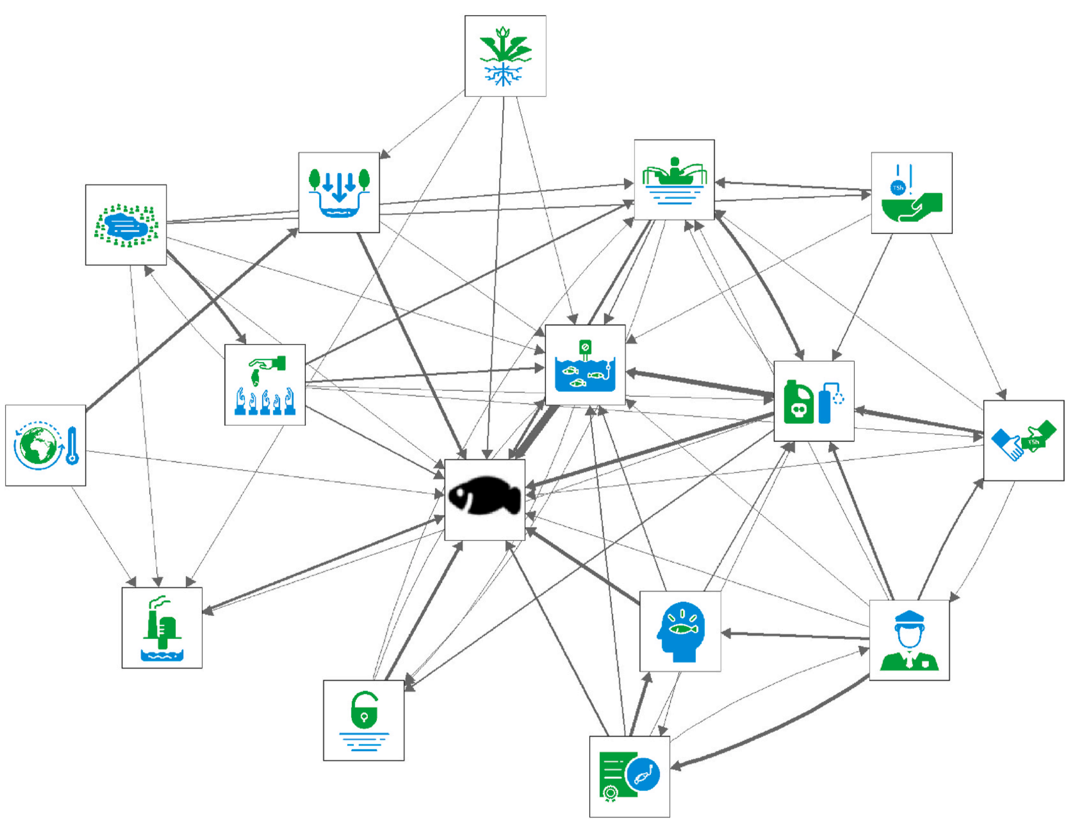


Fig. 3. The aggregated mental model of the entire sample. Arrow width indicates the sum of the weights of the connections of the individual mental models (thicker arrows indicate stronger connections). The nodes' locations in this figure were determined by the algorithm by Fruchterman and Reingold (1991) that optimises the display of the connections, and does not accurately reflect the nodes' centrality. Note: only connections with a minimum aggregated weight of 20 are displayed.

Table 3
Most frequently included connections in the mental models.

Connection	% of participants	Mean weight
Fishing in breeding grounds-Nile perch stock fluctuation	81.62	2.86
Use of destructive fishing gear – Fishing in breeding grounds	43.24	2.85
Awareness of sustainable fishing practices – Nile perch stock fluctuation	43.24	2.56
Water level – Nile perch stock fluctuation	43.24	2.15
Monitoring – Fishing regulations	39.46	2.70

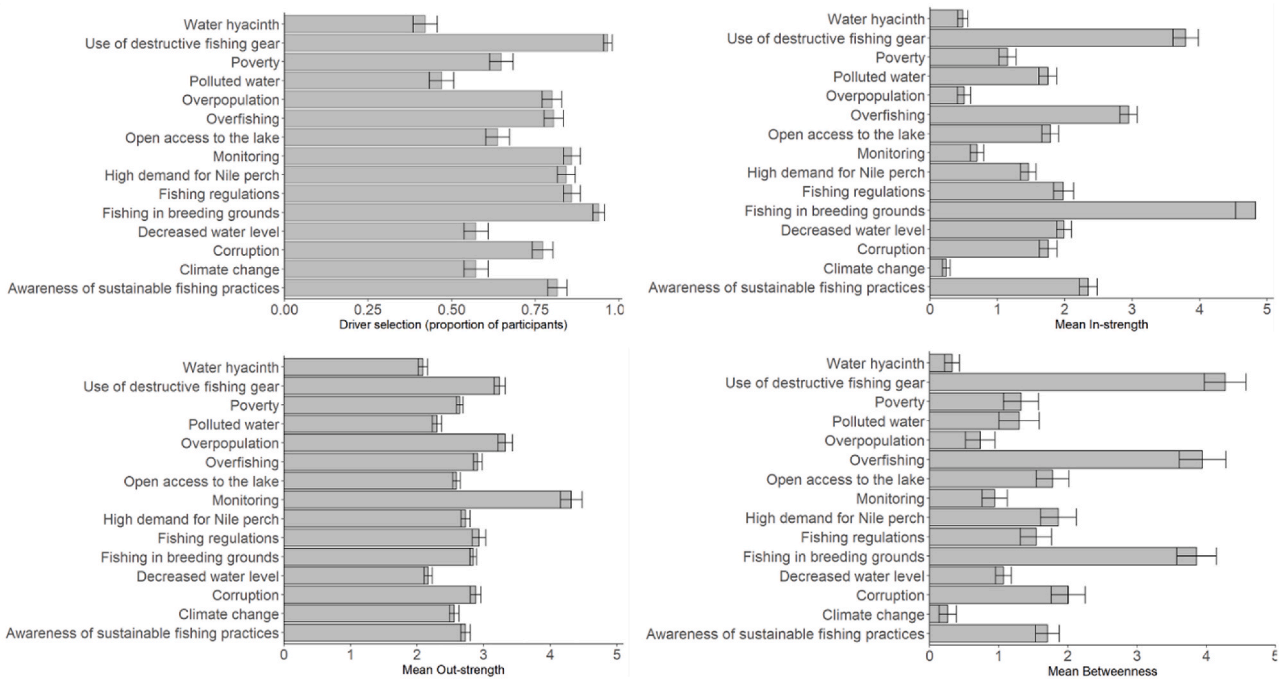


Fig. 4. The driver selection, in-strength, out-strength and betweenness values of each driver. Error bars display the standard error for each driver.

3.2. Explaining differences in mental models

The following sections report on the regressions conducted of mental model driver selection, in-strength, out-strength, and betweenness. All four regressions demonstrate regional differences in mental model complexity but not mental model content. The regional differences follow the same patterns across regressions, showing that participants from Ukerewe created the least complex mental models and Mwanzan participants created the most complex mental models. Across all four regressions, participants' migration status was not related to mental model complexity or content. Only the regression on the betweenness of the drivers demonstrated an effect of fishing experience on the mental model complexity but not mental model content.

3.2.1. Drivers selection

A logistic regression of the selection of the drivers, on driver ID, landing site region, migration status, and years of fishing experience as independent variables, the interaction of each of the latter three with driver ID and including random subject intercepts was conducted. The full model (AIC = 2768.40) was reduced based on the AICs (for the regression estimates of the full model see Tabel C1 in Appendix C, for the changes in AIC values for each step in model reduction, see Table D1 in Appendix D). The final model included driver ID and landing site region, meaning that the odds of the drivers being selected for the mental models differed between drivers and between regions (AIC = 2729.40).

The confidence intervals of the odds ratios for landing site region (see Table E1 in Appendix E) show that the mean odds ratio of a driver being chosen was 0.59 times lower [95% profile likelihood $CI_{OR} = 0.36, 0.94$] in Ukerewe ($M_{Odds} = 2.88$) compared to Mara ($M_{Odds} = 4.92$). The mean odds ratio of a driver being chosen was 1.53 times higher [95% profile likelihood $CI_{OR} = 1.06, 2.22$] in Mwanza ($M_{Odds} = 7.56$) compared to Mara ($M_{Odds} = 4.92$).

These results demonstrate the regional differences in mental model complexity in terms of the number of drivers that were included in the mental models. Participants from Ukerewe created the least complex mental models, and Mwanzan participants created the most complex mental models (Fig. 5). See also Appendix F for the aggregated mental model figures for each region, which illustrate the increased complexity of the models moving from Ukerewe (F1), to Mara (F2) and Mwanza (F3). Since no interaction between driver ID and another predictor was included in the final model, we did not find support for mental model content differences (see section 2.5.3.1).

3.2.2. In-strength

A regression with a negative binominal distribution with random subject intercepts was conducted of the in-strength of all drivers. This type of regression was selected because the in-strength measure reflects values with discrete data and high variance (McCullagh & Nelder, 2019). The full model included driver ID, landing site region, migration status, fishing experience as predictors, the interaction of each of the latter three with driver ID, and random subject intercepts (AIC = 7485.90). A stepwise backwards regression led to the final model, including driver ID and landing site region, meaning there were differences in the in-strength values between drivers and between regions (AIC = 6869.90).

The confidence intervals of the ratio of the means for landing site

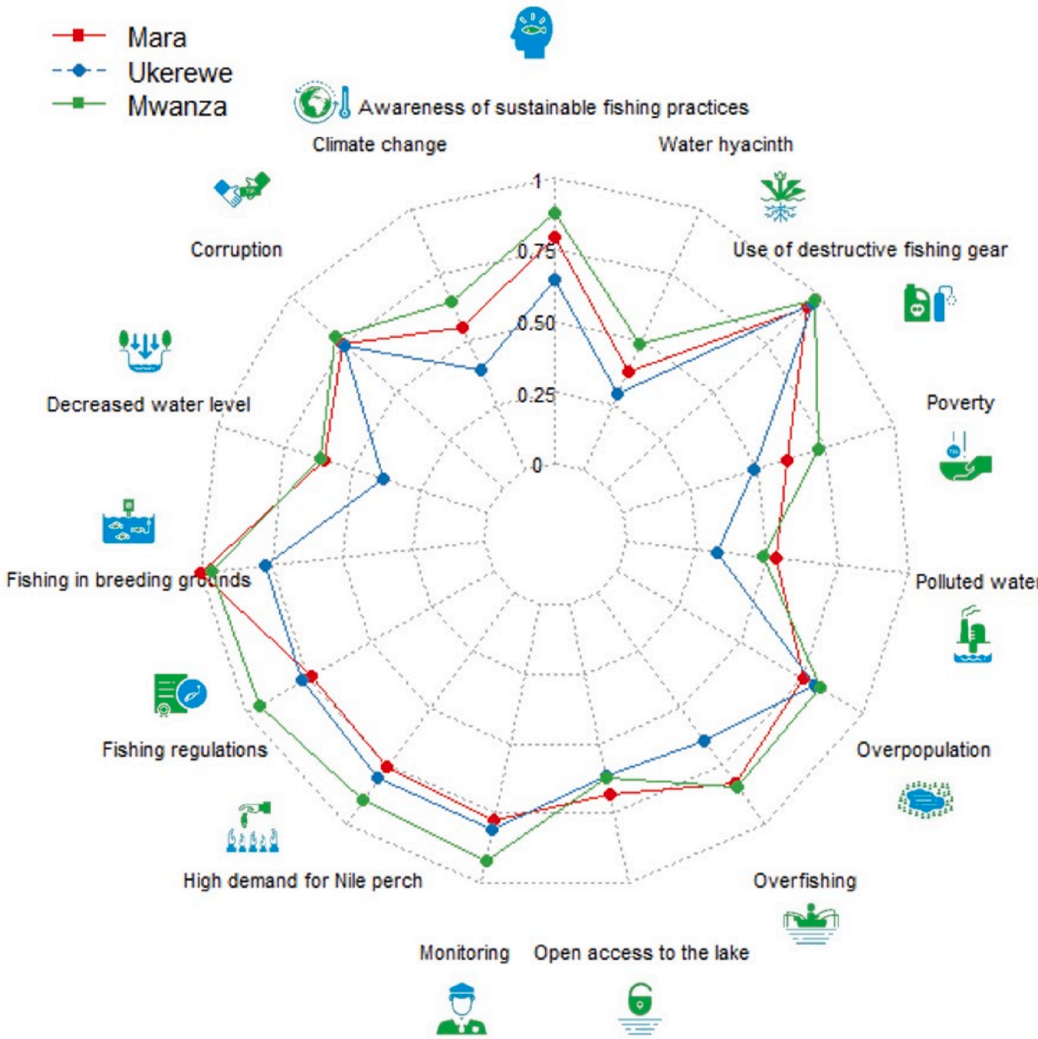


Fig. 5. Radar chart of the selection of each driver per region. Axes in the radar charts show the proportion of participants per region that included the particular driver in their mental model.

region (see Table E1) show that the mean in-strength of a driver was 0.81 times lower [95% profile likelihood CI = 0.69, 0.94] in Ukerewe ($M = 1.92$) compared to Mara ($M = 2.37$). The mean in-strength of a driver was 1.13 times higher [95% profile likelihood CI = 1.03, 1.25] in Mwanza ($M = 2.68$) compared to Mara ($M = 2.37$).

These results show that the complexity of the mental models varied across regions in terms of the drivers' connectedness. That is, the influence drivers tended to receive from connected drivers in participants' mental models differed across regions. The regional differences showed that participants from Ukerewe created the least complex mental models (drivers in their mental models received the least influence from connected drivers), and Mwanzan participants created the most complex mental models (drivers in their mental models received the most influence from connected drivers) (see Fig. 6). Since no interaction between driver ID and another predictor was included in the final model, we did not find support for mental model content differences.

3.2.3. *Out-strength*

A regression with a Poisson distribution with random subject intercepts was conducted for out-strength, since a regression with a negative binomial distribution did not converge. The full model included driver ID, landing site region, migration status, and fishing experience as predictors, the interaction of each of the latter three with driver ID, and random subject intercepts (AIC = 6818.20). The backward stepwise selection procedure resulted in a final model that included driver ID and region (AIC = 6726.70), meaning there were differences in the out-strength values between drivers and between regions.

The confidence intervals of the ratio of the means for landing site region (see Table E1) show that the mean out-strength of a driver was 0.95 times lower [95% profile likelihood CI = 0.87, 1.03] in Ukerewe ($M = 2.56$) compared to Mara ($M = 2.70$). The mean out-stength of a driver was 1.03 times higher [95% profile likelihood CI = 0.97, 1.09] in Mwanza ($M = 2.78$) compared to Mara ($M = 2.70$).

These results again show that the complexity of mental models varied across regions in terms of connectedness. Specifically, the influence drivers tended to have on connected drivers in participants' mental models differed across regions. The same pattern of results emerged across regions as for drivers selection and in-stength: participants from Ukerewe created the least complex mental models (drivers in their mental models tended to have the lowest level of influence on connected drivers), and Mwanzan participants created the most complex mental models (drivers in their mental models tended to have the highest level of influence on connected drivers) (see Fig. 7). Again, no interaction between driver ID and another predictor was included in the final model, meaning we found no support for mental model content differences.

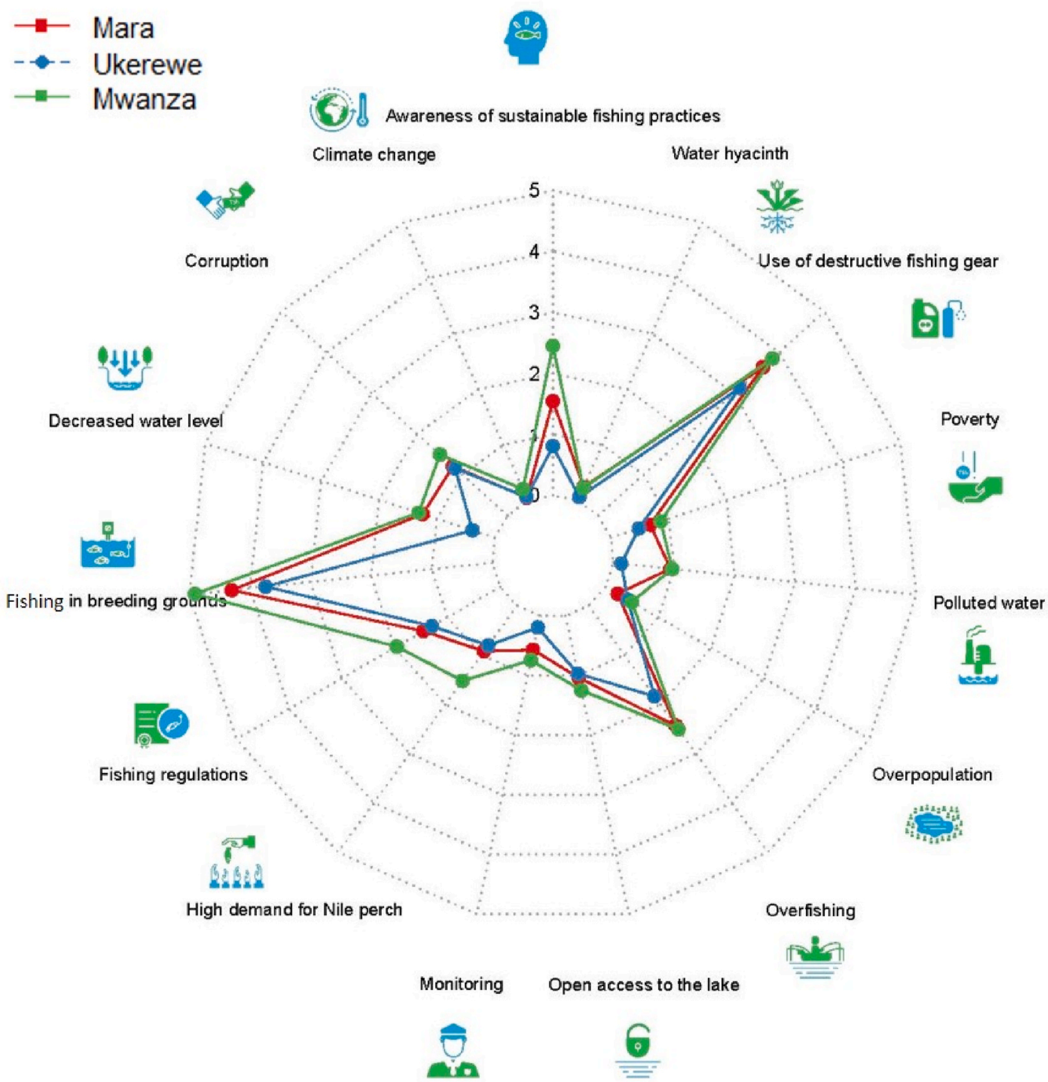


Fig. 6. Radar chart of the in-strength of each driver concept per region. Axes in the radar charts show the mean in-strength of each driver per region.

3.2.4. Betweenness

A regression with a negative binomial distribution with random subject intercepts was conducted of the betweenness of all drivers, because, similar to the in-strength measure, the betweenness measure consisted of a discrete character and high variance. The full model included driver ID, landing site region, migration status, and fishing experience as predictors, the interaction of each of the latter three with driver ID, and random subject intercepts (AIC = 6872.10). The final model included driver ID, landing site region and fishing experience as predictors (AIC = 6804.00). These findings indicate differences in complexity between regions and between levels of fishing experience.

The confidence intervals of the ratio of the means for landing site region (see Table E1) show that the mean betweenness of a driver was 0.65 times lower [95% profile likelihood CI = 0.51, 0.84] in Ukerewe ($M = 1.28$) compared to Mara ($M = 1.97$). The mean betweenness of a driver was 1.22 times higher [95% profile likelihood CI = 1.03, 1.44] in Mwanza ($M = 2.40$) compared to Mara ($M = 1.97$).

These results again show mental model complexity differences in terms of the connectedness of the drivers between regions. Specifically, the extent to which drivers served as important links between other drivers differed between regions. Similar to the previous results, participants from Ukerewe created the least complex mental models (drivers in their mental models were least likely to connect other drivers with each other), and Mwanzan participants created the most complex mental models (drivers in their mental models were most likely to connect other drivers with each other) (see Fig. 8).

The confidence intervals of the ratio of the means for fishing experience (see Table E1) show that the mean betweenness for fishers with more than 10 years of experience ($M = 1.73$) was 0.88 times lower [95% profile likelihood $CI_{OR} = 0.76, 1.02$] compared to fishers with less than 10 years of experience ($M = 1.97$). These results indicate that more experienced fishers created less complex mental models in terms of the connectedness of the drivers in their mental models (drivers were less likely to connect other drivers with each other) compared to less experienced fishers.

Similar to the previous three regressions, no interaction between driver ID and another predictor was included in the final model, meaning we found no support for mental model content differences.

4. Discussion

This study found rich and complex mental models among Tanzanian fishers at Lake Victoria, more complex than mental models in other studies with comparable study designs (de Ridder et al. 2022).The key drivers in most fishers' mental models, either thought to affect the Nile perch stock directly or indirectly, were *fishing in breeding grounds*, *use of*

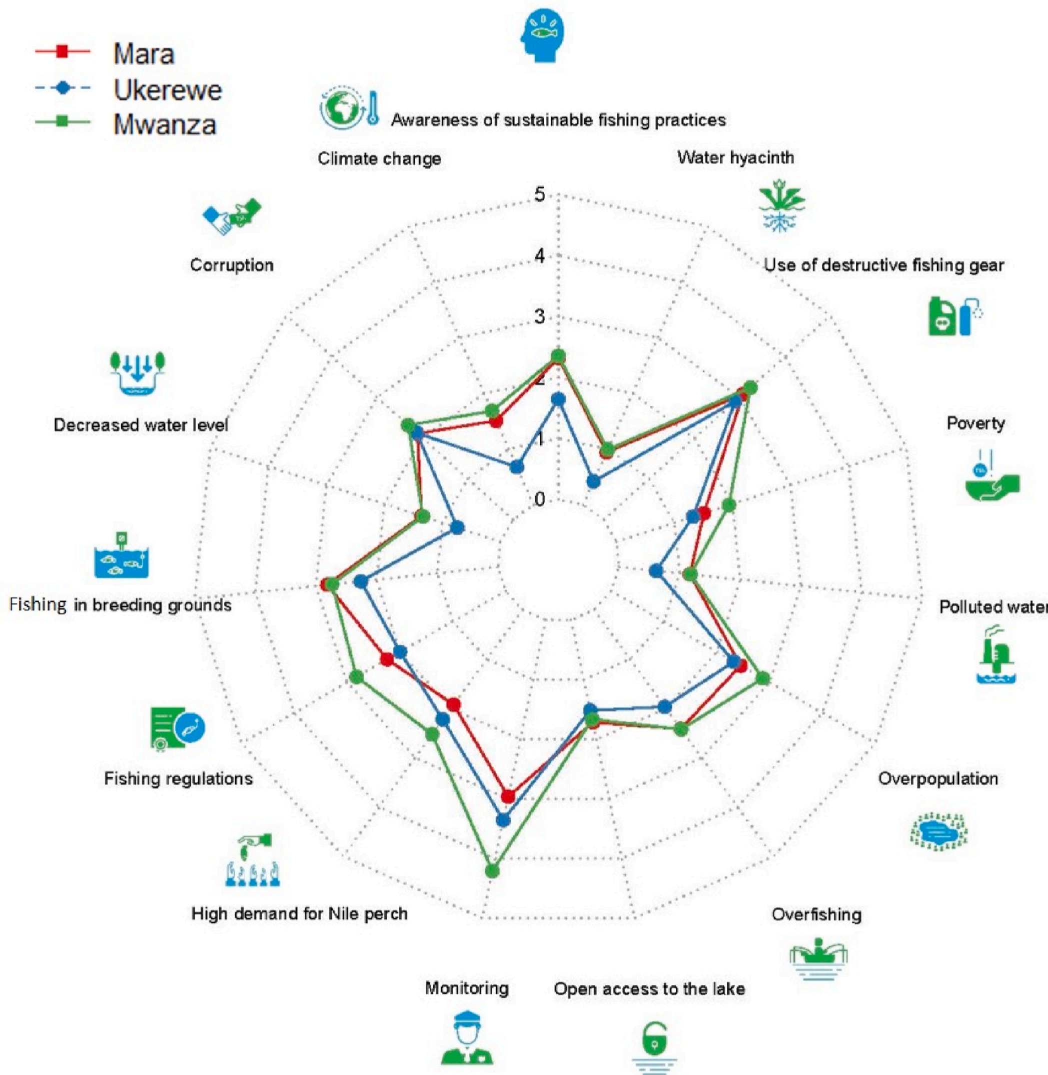


Fig. 7. Radar chart of the out-strength of each driver concept per region. Axes in the radar charts show the mean out-strength of each driver per region.

destructive fishing gear, *overfishing* and *monitoring*. Hence, the results demonstrate the perceived importance of the behaviour of fishers themselves. These findings may suggest that fishers feel some sense of control or responsibility for their impact on the Nile perch stock. The findings consistently demonstrate that the complexity of mental models varied across regions, but no differences in mental model content were observed across regions. Fishing experience and migration status did not consistently relate to mental model complexity or content.

Mental models differed across geographical regions in Tanzania in terms of complexity but not content. The pattern of differences across the three regions was consistent across all four measures of complexity (driver selection, in-strength, out-strength and betweenness): participants from Ukerewe tended to create mental models with the fewest drivers and with the lowest connectedness between drivers, whereas Mwanza participants created mental models with the most drivers, and with the highest connectedness between drivers. These findings may indicate a more complex and nuanced view of the process that affects the Nile perch stock fluctuation and higher levels of systems thinking in Mwanza compared to Mara and Ukerewe, and lower levels of systems thinking in Ukerewe compared to Mara and Mwanza. This study, therefore, demonstrates that it is possible to systematically map the complexity of mental models across stakeholder regions.

These geographical differences concur with prior research that has identified complexity differences in mental models between different regions or cultures (Atran et al., 2002). These differences may stem from communication within a culture, affecting mental models (Jones et al., 2011) and may mirror previous research demonstrating strong communication between common-pool resource users (Ostrom, 1990). Communication within a culture may entail sharing knowledge, experiences and assumptions about a system, which is likely to result in more similar, or "shared" mental models (Aminpour et al., 2020; DeChurch & Mesmer-Magnus, 2010; Henly-Shepard et al., 2015; Mathevet et al., 2011). One key cognitive mechanism behind the formation of convergent mental models within one culture or social group is that individuals holding common mental models are more likely to encode their joint interpretations into shared language and understanding (Denzau & North, 1994).

We did not find an influence of the fishers' migration status on the complexity and content of their mental models. Although research has shown that intergenerational transmission of knowledge shapes perceptions of environmental challenges (Molina, 2016), this did not translate into differences in mental models between migrated and native fishers in this study. The absence of an effect of migration status on the mental model indices may suggest that mental models within a region are more similar than the differences in mental models between native and migrated fishers within that region. Hence, migrated fishers may

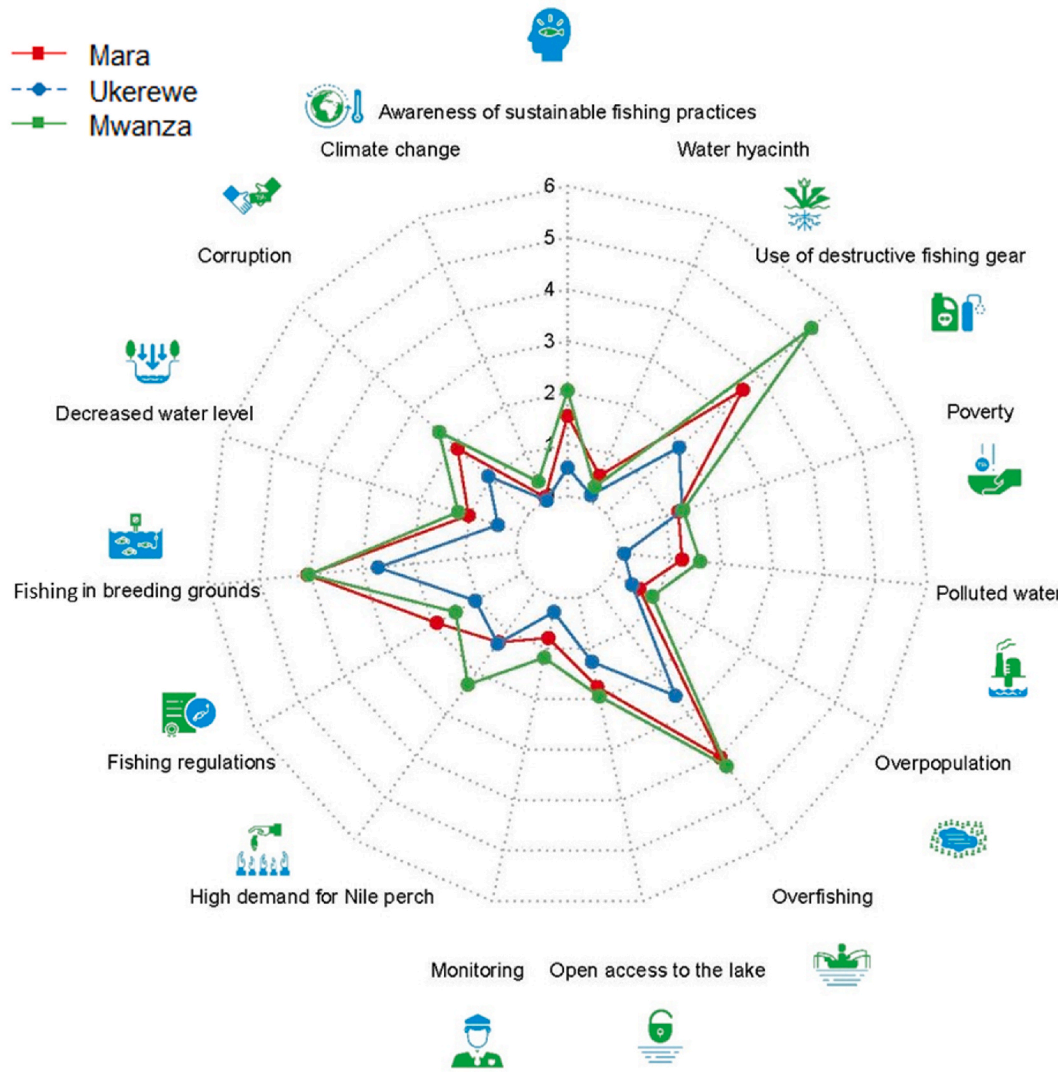


Fig. 8. Radar chart of the betweenness of each driver per region. Axes in the radar charts show the mean betweenness of each driver per region.

tend to assimilate their thinking about the socio-ecological system to the mental models of local fishers. However, the limited sample size may also have suppressed (interaction) effects. Hence, more research is needed on mental model differences between those native to the socio-ecological system and those who migrated to the system.

The findings also did not consistently demonstrate complexity or content differences in mental models between less and more experienced fishers, except for the effect of fishing experience on the betweenness of the drivers in the mental models. These findings concur with previous research that showed that those with more system experience do not necessarily include more connections or concepts in their mental models than less experienced individuals (Stier et al., 2017). Previous research has found that more experienced individuals tend to form more abstract representations of complex problems (Carter et al., 1988; Hmelo-Silver et al., 2007; Trafton et al., 2002). Hence, system experience may affect the type of concepts included (i.e. more abstract concepts) and the complexity of structures included (i.e. feedback loops), but not the number of concepts and connectivity of the mental models. However, the current study did not assess the level of abstraction of the concepts or the complexity of structures included in the mental model. Future research could investigate if system experience indeed enhances the cognitive ability to identify more abstract and complex interrelations of the system, but does not affect perceptions of the number of concepts or interrelations within the system.

4.1. Limitations

A few limitations of the study design need to be noted. First, some of the study variables might be confounded with other constructs. For example, the differences in mental models between regions might result from either communication or the different features of the environmental resource between regions. Enriching the findings of the current field study with experiments disentangling the single mechanisms could provide insights into underlying causal mechanisms.

Although the mental model elicitation method provided rich data on participants' systems thinking, the present research does not provide in-depth insights into fishers' thinking. For example, participants mapped the connections between drivers, but we did not capture *why* or *how* they envisioned these connections. Future research could complement the findings with interview data or use a greater variety of arrows depicting negative and positive effects. Such studies can provide a more detailed account of participants' perceptions of causal relations by demonstrating *how* concepts in a model influence each other. For example, the findings showed that participants' perceived a strong influence of *Monitoring* on *Fishing regulations*, but did not show if increased monitoring was thought to results in more or less fishing regulations, or changes the type of fishing regulations. Mental model studies in which participants can use positive or negative arrows to indicate the direction of the relationship or elaborate on the meaning of the relationship could provide more detailed and in-depth insights into the perceptions of these causal relations.

Finally, the mental models created by participants were fairly complex, which may have reflected comprehensive mental models of Lake Victoria's socio-ecological system but may also have resulted from the standardised elicitation process. Participants may have felt obligated to use most of the 15 drivers presented and, as a result, may have created the mental models on the spot. Hence, these mental models may demonstrate more elaborate systems thinking processes than representative of daily thinking. For a more in-depth reflection on the use of the M-Tool in this study, we refer readers to the validation of the M-Tool van den Broek, Luomba, et al., (2021).

4.2. Future research avenues

Future research could investigate the impact of different types of mental models on behaviour or policy support. For example, research can investigate if those whose mental models tend to focus on the use of destructive fishing gear also differ in their own use of destructive fishing gear, and consequently their support for policy that restricts the use of such gear. Similarly, future research could investigate if the centrality of drivers in the mental models are related to the sense of control resource users perceive to have on these concepts. Another worthwhile research avenue is to investigate if similar mental models result in more successful environmental resource management collaborations (van den Broek, 2018), or whether more diverse perspectives are needed to develop strategies to conserve environmental resources.

4.3. Policy implications

The findings of this study have direct implications for managing the Lake Victoria ecosystem. First, the pertinent role of fishing activities in fishers' mental models may provide a leverage point to dissuade fishers from engaging in unsustainable fishing activities. In addition, this study sheds light on the limited impact of current interventions at Lake Victoria that aim to conserve the Nile perch stock, which tend to take a top-down approach, focusing on enforcement and regulations. A bottom-up approach, in which fishers' responsibility to conserve the Nile perch stock is central, might be more fruitful as it aligns with fishers' perceived causes of the changes in the Nile perch stock.

Second, fishers' mental models could be evaluated for their accuracy, and any misperceptions that may be counterproductive for conservation practices may be addressed (Bruine de Bruin & Bostrom, 2013). Third, differences in mental models are important to consider when developing or communicating conservation policy. Perceptions of natural resource systems can differ greatly on local levels, even between regions in close proximity to each other (Richter et al., 2022). Policy communication could be adapted to local mental models or target a specific region. For example, communication campaigns targeting fishers to convey local conservation policy may be aligned with the differences in complexity across regions. Since tailoring communication with the recipient's beliefs and values tends to increase the persuasiveness of messages (van den Broek et al., 2017), such communications may be more successful because they resonate with those at the heart of resource conservation.

Similar ways of leveraging insights into mental models for policy-making and communication could be helpful beyond the Lake Victoria region. For global challenges, such as climate change, a larger-scale approach may be valuable for understanding differences in mental models across different types of actors and regions. Such approaches may be instrumental in effectively developing joint efforts to address conservation challenges.

5. Conclusion

The present study was the first to apply a mental model approach to understanding conservation challenges at Lake Victoria. What emerges from the current research is how geographical dispersion prompts differences in mental model complexity, while differences could not consistently be found between native and migrated fishers and those with different experience levels. These findings highlight the importance of assessing resource users' mental models and understanding differences in mental models. This study provides important implications for environmental resource management at Lake Victoria and other complex socio-ecological systems in general.

Author statement

Karlijn L. van den Broek: Conceptualization, software, methodology, validation, Investigation, Writing original draft, Writing - review & editing, Supervision, Project administration, Funding acquisition. **Joseph Luomba**: Investigation, Resources, Writing - review & editing, Supervision. **Jan van den Broek**: Formal analysis, Writing - review & editing, Visualization. **Helen Fischer:** Conceptualization; Writing - review & editing.

Funding statement

This research was funded by Field of Focus 4, Heidelberg University, grant number: ZUK 49/Ü 4.1.070 and Bundesministerium für Bildung und Forschung, Grant/Award Number: 01LC1706A & 01LC1822A.

Data availability statement

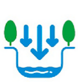
The R script developed to analyse the data is available at the following link: https://osf.io/8v3x9/. The data is available upon request.

Acknowledgements

We would like to thank Lake Victoria Fisheries Organisation (LVFO), and the Tanzanian Fisheries Research Institute (TAFIRI) for their partnership, which helped realise this research. We are also very grateful to our research assistants Musa Ngosha and Elizabeth Mlahagwa at TAFIRI for their help with the data collection. Thanks also goes out to the district executive directors and fisheries officers who facilitated the fieldwork at the landing sites. We are grateful for the help of Dr. Stijn de Vos and Wouter van Boxtel with the visualization of the data, and Natalie Davis for reviewing the analysis section. We also thank Dr. Sina Klein for her contribution to the manuscript and critical review of earlier versions of this manuscript. We would like to thank Konrad Kühn and Judith Massa from Lambdaforge for developing the software for M-tool. Thanks also goes out to the MultiTip team for their contributions for the development of this project. Finally, we would like to thank our research participants, without whom this research would not have been possible.

Appendix A. Icons and definitions of mental model driver concepts

Table A1
Icons and definitions of mental model driver concepts

Icon	Driver	Definition
	Overpopulation	*This image shows overpopulation, this means that there are too many people living around Lake Victoria.*
	Fishing regulations	*This image shows fishing regulations, this means the requirements the government set for fishing, such as the size of the boat and the mesh size of the nets.*
	Monitoring	*This image shows monitoring, this means the surveillance by the government to check that everyone follows the fishing regulations.*
	Open access to the lake	*This image shows open access to the lake, this means that anyone can go fishing at Lake Victoria, and that no permits are required.*
	Corruption	*This image shows corruption, this means that people take bribes.*
	Poverty	*This image shows poverty, this means that people are poor.*
	High demand for Nile perch	*This image shows a high demand for Nile perch, this means that many people want to buy Nile perch.*
	Overfishing	*This image shows overfishing, this means that there are too many fishers and boats at Lake Victoria.*
	Use of destructive fishing gear	*This image shows the use of destructive fishing gear, this means the use of poison, dynamite, nets with small mesh size or small hooks.*
	Fishing in breeding grounds	*This image shows fishing in breeding grounds, this means fishing at a place where many immature Nile perch are.*
0 	Decreased water level	*This image shows a decreased water level, this means that there is less water in Lake Victoria.*
	Water pollution	*This image shows polluted water, this means that the water of Lake Victoria is dirty.*
	Climate change	*This image shows climate change, this means that the climate is changing and will continue to change in the future.*

(*continued on next page*)

Table A1 (*continued*)

Icon	Driver	Definition
	Awareness of sustainable fishing practices	*This image shows awareness of sustainable fishing practices, this means that people know how to fish without harming the future fish stock.*
	Water hyacinth[a]	*This image shows water hyacinth, this is a plant that grows on the lake.*

[a] Water hyacinth is an invasive plant species at Lake Victoria associated with negative social impacts including lack of clean water, increase in vector-borne diseases, migration of communities, social conflict and difficulty in accessing water points (Mailu, 2001).

Appendix B. Means of centrality measures for each mental model variable

Table B1
Mean driver selection, in-strength, out-strength and betweenness values of each driver concept (standard error in parentheses).

	Driver selection [proportion of participants]	In-strength	Out-strength	Mean betweenness
Use of destructive fishing gear	0.97 (0.01)	3.79 (0.19)	3.24 (0.08)	4.27 (0.30)
Fishing in breeding grounds	0.94 (0.02)	4.83 (0.30)	2.84 (0.05)	3.86 (0.29)
Fishing regulations	0.86 (0.03)	1.98 (0.15)	2.93 (0.10)	1.54 (0.22)
Monitoring	0.86 (0.03)	0.70 (0.10)	4.31 (0.16)	0.94 (0.18)
High demand for Nile perch	0.84 (0.03)	1.46 (0.11)	2.73 (0.07)	1.86 (0.26)
Awareness of sustainable fishing practices	0.82 (0.03)	2.35 (0.13)	2.73 (0.07)	1.71 (0.17)
Overfishing	0.81 (0.03)	2.94 (0.13)	2.91 (0.07)	3.95 (0.34)
Overpopulation	0.80 (0.03)	0.51 (0.10)	3.32 (0.11)	0.74 (0.21)
Corruption	0.77 (0.03)	1.76 (0.13)	2.88 (0.08)	2.00 (0.25)
Poverty	0.65 (0.04)	1.15 (0.13)	2.64 (0.05)	1.32 (0.25)
Open access to the lake	0.64 (0.04)	1.79 (0.12)	2.59 (0.06)	1.78 (0.23)
Decreased water level	0.57 (0.04)	2.00 (0.11)	2.17 (0.06)	1.07 (0.11)
Climate change	0.57 (0.04)	0.24 (0.06)	2.56 (0.07)	0.26 (0.12)
Water pollution	0.47 (0.04)	1.74 (0.13)	2.30 (0.07)	1.30 (0.29)
Water hyacinth	0.42 (0.04)	0.49 (0.07)	2.09 (0.07)	0.33 (0.11)

Appendix C. Regression results of full models

Table C1
Regression estimates of the full model before stepwise model selection for landing site region, Driver ID and fishing experience predicting driver selection, in-strength, out-strength and betweenness of the drivers in the mental models.

	Driver selection		In-strength		Out-Strength		Betweenness	
	Estimates(odds & odds ratio's)	Profile likelihood 95% confidence interval	Estimates (mean & ratio of means)	Profile likelihood 95% confidence interval	Estimates (mean & ratio of means)	Profile likelihood 95% confidence interval	Estimates (mean & ratio of means)	Profile likelihood 95% confidence interval
Intercept	8.55	[3.05, 23.94]	1.98	[1.53, 2.55]	2.94	[2.37, 3.63]	1.69	[1.1, 2.62]
Landing site region (0 = Mara, 1 = Ukerewe)	0.34	[0.11, 1.09]	0.63	[0.4, 1]	0.88	[0.63, 1.22]	0.52	[0.24, 1.12]
Landing site region (0 = Mara, 1 = Mwanza)	2.40	[0.86, 6.69]	1.46	[1.13, 1.89]	0.90	[0.72, 1.13]	1.48	[0.95, 2.31]
Driver ID (0 = Awareness, 1 = Climate change)	0.15	[0.05, 0.53]	0.03	[0.01, 0.11]	0.88	[0.62, 1.25]	0.03	[0, 0.26]
Driver ID (0 = Awareness, 1 = Corruption)	0.35	[0.1, 1.28]	0.81	[0.55, 1.2]	0.99	[0.73, 1.35]	0.79	[0.41, 1.52]
Driver ID (0 = Awareness, 1 = Decreased water level)	0.12	[0.04, 0.41]	0.92	[0.61, 1.39]	0.69	[0.47, 1]	0.96	[0.5, 1.86]
Driver ID (0 = Awareness, 1 = Fishing in Breeding grounds)	70160142.68	[0, Inf]	2.11	[1.56, 2.84]	0.96	[0.72, 1.29]	2.40	[1.45, 3.97]
Driver ID (0 = Awareness, 1 = Fishing regulations)	0.49	[0.13, 1.93]	0.96	[0.67, 1.4]	0.96	[0.71, 1.31]	0.79	[0.41, 1.52]
Driver ID (0 = Awareness, 1 = High demand for Nile perch)	0.45	[0.12, 1.71]	0.70	[0.47, 1.06]	0.85	[0.62, 1.17]	0.85	[0.44, 1.63]
Driver ID (0 = Awareness, 1 = Monitoring)	0.80	[0.19, 3.25]	0.32	[0.19, 0.53]	1.34	[1.01, 1.78]	0.39	[0.17, 0.9]
Driver ID (0 = Awareness, 1 = Open access to the lake)	0.50	[0.14, 1.76]	0.86	[0.58, 1.28]	0.87	[0.63, 1.2]	1.22	[0.66, 2.28]
Driver ID (0 = Awareness, 1 = Overfishing)	1.16	[0.29, 4.67]	1.60	[1.16, 2.21]	1.03	[0.77, 1.39]	2.61	[1.57, 4.33]

(*continued on next page*)

Table C1 (*continued*)

	Driver selection		In-strength		Out-Strength		Betweenness	
	Estimates(odds & odds ratio's)	Profile likelihood 95% confidence interval	Estimates (mean & ratio of means)	Profile likelihood 95% confidence interval	Estimates (mean & ratio of means)	Profile likelihood 95% confidence interval	Estimates (mean & ratio of means)	Profile likelihood 95% confidence interval
Driver ID (0 = Awareness, 1 = Overpopulation)	0.35	[0.1, 1.27]	0.19	[0.09, 0.37]	1.18	[0.88, 1.6]	0.22	[0.07, 0.71]
Driver ID (0 = Awareness, 1 = Water pollution)	0.15	[0.04, 0.51]	0.93	[0.61, 1.42]	0.74	[0.51, 1.08]	0.61	[0.27, 1.37]
Driver ID (0 = Awareness, 1 = Poverty)	0.29	[0.08, 1.01]	0.69	[0.44, 1.08]	0.84	[0.6, 1.17]	0.83	[0.41, 1.65]
Driver ID (0 = Awareness, 1 = Use of destructive fishing gear)	3.41	[0.45, 25.52]	1.84	[1.35, 2.5]	1.10	[0.83, 1.46]	2.15	[1.3, 3.54]
Driver ID (0 = Awareness, 1 = Water hyacinth)	0.06	[0.02, 0.2]	0.35	[0.16, 0.77]	0.82	[0.53, 1.27]	0.52	[0.15, 1.86]
Migration status (0 = native, 1 migrated)	0.47	[0.18, 1.18]	0.93	[0.74, 1.16]	1.04	[0.85, 1.28]	0.84	[0.57, 1.23]
Fishing experience (0 < 10 years, 1 > 10 years)	0.64	[0.26, 1.55]	1.00	[0.8, 1.23]	0.98	[0.8, 1.19]	1.06	[0.73, 1.53]
Landing site region (0 = Mara, 1 = Ukerewe)* Driver ID (0 = Awareness, 1 = Climate change)	1.34	[0.31, 5.79]	3.85	[0.57, 26.08]	0.73	[0.4, 1.31]	0.00	[0, Inf]
Landing site region (0 = Mara, 1 = Mwanza)*Drive ID (0 = Awareness, 1 = Climate change)	0.69	[0.2, 2.38]	1.68	[0.48, 5.93]	1.06	[0.74, 1.51]	2.45	[0.29, 20.86]
Landing site region (0 = Mara, 1 = Ukerewe)* Driver ID (0 = Awareness, 1 = Corruption)	2.86	[0.61, 13.38]	1.57	[0.85, 2.9]	1.16	[0.74, 1.83]	1.72	[0.61, 4.87]
Landing site region (0 = Mara, 1 = Mwanza)*Driver ID (0 = Awareness, 1 = Corruption)	0.47	[0.13, 1.73]	0.80	[0.54, 1.19]	1.17	[0.85, 1.6]	0.92	[0.48, 1.77]
Landing site region (0 = Mara, 1 = Ukerewe)* Driver ID (0 = Awareness, 1 = Decreased water level)	1.05	[0.24, 4.57]	0.76	[0.35, 1.63]	0.98	[0.55, 1.74]	0.99	[0.29, 3.4]
Landing site region (0 = Mara, 1 = Mwanza)*Driver ID (0 = Awareness, 1 = Decreased water level)	0.42	[0.12, 1.46]	0.74	[0.5, 1.11]	1.07	[0.74, 1.55]	0.77	[0.4, 1.49]
Landing site region (0 = Mara, 1 = Ukerewe)* Driver ID (0 = Awareness, 1 = Fishing in breeding grounds)	0.00	[0, Inf]	1.81	[1.09, 3]	1.17	[0.76, 1.82]	1.36	[0.57, 3.26]
Landing site region (0 = Mara, 1 = Mwanza)*Driver ID (0 = Awareness, 1 = Fishing in breeding grounds)	0.00	[0, Inf]	0.79	[0.59, 1.07]	1.13	[0.83, 1.52]	0.73	[0.43, 1.21]
Landing site region (0 = Mara, 1 = Ukerewe)* Driver ID (0 = Awareness, 1 = Fishing regulations)	3.56	[0.75, 16.89]	1.30	[0.72, 2.36]	0.97	[0.62, 1.53]	1.65	[0.59, 4.56]
Region (0 = Mara, 1 = Mwanza)*Driver ID (0 = Awareness, 1 = Fishing regulations)	3.24	[0.72, 14.51]	0.74	[0.51, 1.07]	1.06	[0.77, 1.45]	0.71	[0.36, 1.39]
Landing site region (0 = Mara, 1 = Ukerewe)* Driver ID (0 = Awareness, 1 = High demand for Nile Perch)	4.11	[0.84, 20.17]	1.29	[0.66, 2.5]	1.22	[0.78, 1.91]	1.76	[0.61, 5.12]
Landing site region (0 = Mara, 1 = Mwanza)*Driver ID (0 = Awareness, 1 = High demand for Nile Perch)	1.27	[0.32, 5.01]	0.96	[0.63, 1.45]	1.23	[0.89, 1.7]	1.21	[0.62, 2.37]
Landing site region (0 = Mara, 1 = Ukerewe)* Driver ID (0 = Awareness, 1 = Monitoring)	3.56	[0.72, 17.7]	0.56	[0.21, 1.5]	1.24	[0.82, 1.88]	0.54	[0.1, 2.92]

(continued on next page)

Table C1 (*continued*)

	Driver selection		In-strength		Out-Strength		Betweenness	
	Estimates(odds & odds ratio's)	Profile likelihood 95% confidence interval	Estimates (mean & ratio of means)	Profile likelihood 95% confidence interval	Estimates (mean & ratio of means)	Profile likelihood 95% confidence interval	Estimates (mean & ratio of means)	Profile likelihood 95% confidence interval
Landing site region (0 = Mara, 1 = Mwanza)*Driver ID (0 = Awareness, 1 = Monitoring)	1.50	[0.36, 6.21]	0.69	[0.42, 1.14]	1.32	[0.98, 1.76]	0.67	[0.29, 1.55]
Landing site region (0 = Mara, 1 = Ukerewe)* Driver ID (0 = Awareness, 1 = Open access to the lake)	1.97	[0.45, 8.63]	1.64	[0.87, 3.09]	1.12	[0.69, 1.81]	1.26	[0.43, 3.7]
Landing site region (0 = Mara, 1 = Mwanza)*Driver ID (0 = Awareness, 1 = Open access to the lake)	0.31	[0.09, 1.09]	0.91	[0.6, 1.38]	1.16	[0.82, 1.64]	0.68	[0.35, 1.34]
Landing site region (0 = Mara, 1 = Ukerewe)* Driver ID (0 = Awareness, 1 = Overfishing)	0.90	[0.19, 4.22]	1.49	[0.86, 2.58]	1.19	[0.76, 1.87]	1.20	[0.48, 2.98]
Landing site region (0 = Mara, 1 = Mwanza)*Driver ID (0 = Awareness, 1 = Overfishing)	0.44	[0.11, 1.73]	0.70	[0.5, 0.98]	1.11	[0.81, 1.52]	0.79	[0.46, 1.35]
Landing site region (0 = Mara, 1 = Ukerewe)* Driver ID (0 = Awareness, 1 = Overpopulation)	4.13	[0.84, 20.36]	2.55	[1.03, 6.33]	1.01	[0.65, 1.57]	1.62	[0.33, 8.11]
Landing site region (0 = Mara, 1 = Mwanza)*Driver ID (0 = Awareness, 1 = Overpopulation)	0.62	[0.17, 2.28]	1.44	[0.72, 2.85]	1.17	[0.86, 1.59]	1.11	[0.37, 3.36]
Landing site region (0 = Mara, 1 = Ukerewe)* Driver ID (0 = Awareness, 1 = Water pollution)	1.03	[0.24, 4.53]	0.39	[0.13, 1.21]	0.97	[0.52, 1.81]	0.40	[0.04, 3.59]
Landing site region (0 = Mara, 1 = Mwanza)*Driver ID (0 = Awareness, 1 = Water pollution)	0.37	[0.11, 1.25]	0.76	[0.49, 1.17]	1.21	[0.82, 1.77]	1.11	[0.5, 2.48]
Landing site region (0 = Mara, 1 = Ukerewe)* Driver ID (0 = Awareness, 1 = Poverty)	1.57	[0.37, 6.73]	1.44	[0.67, 3.06]	1.24	[0.75, 2.05]	1.60	[0.47, 5.44]
Landing site region (0 = Mara, 1 = Mwanza)*Driver ID (0 = Awareness, 1 = Poverty)	0.82	[0.24, 2.87]	0.75	[0.47, 1.19]	1.19	[0.84, 1.68]	0.50	[0.23, 1.09]
Landing site region (0 = Mara, 1 = Ukerewe)* Driver ID (0 = Awareness, 1 = Use of destructive fishing gear)	4.95	[0.36, 67.46]	1.30	[0.78, 2.17]	1.06	[0.7, 1.62]	1.11	[0.46, 2.65]
Landing site region (0 = Mara, 1 = Mwanza)*Driver ID (0 = Awareness, 1 = Use of destructive fishing gear)	1.18	[0.14, 9.75]	0.70	[0.51, 0.95]	1.11	[0.83, 1.48]	0.95	[0.57, 1.58]
Landing site region (0 = Mara, 1 = Ukerewe)* Driver ID (0 = Awareness, 1 = Water hyacinth)	2.04	[0.46, 9.12]	0.54	[0.11, 2.59]	0.66	[0.33, 1.33]	0.78	[0.08, 7.61]
Landing site region (0 = Mara, 1 = Mwanza)*Driver ID (0 = Awareness, 1 = Water hyacinth)	0.66	[0.19, 2.28]	0.49	[0.23, 1.02]	0.90	[0.6, 1.37]	0.24	[0.06, 0.92]
Migration status (0 = native, 1 migrated)* Driver ID (0 = Awareness, 1 = Climate change)	1.88	[0.62, 5.75]	2.78	[1.06, 7.33]	0.95	[0.68, 1.31]	2.57	[0.62, 10.63]
Migration status (0 = native, 1 migrated)* Driver ID (0 = Awareness, 1 = Corruption)	4.17	[1.26, 13.75]	1.11	[0.79, 1.56]	0.92	[0.69, 1.23]	1.34	[0.76, 2.35]

(*continued on next page*)

Table C1 (*continued*)

	Driver selection		In-strength		Out-Strength		Betweenness	
	Estimates(odds & odds ratio's)	Profile likelihood 95% confidence interval	Estimates (mean & ratio of means)	Profile likelihood 95% confidence interval	Estimates (mean & ratio of means)	Profile likelihood 95% confidence interval	Estimates (mean & ratio of means)	Profile likelihood 95% confidence interval
Migration status (0 = native, 1 migrated)* Driver ID (0 = Awareness, 1 = Decreased water level)	2.87	[0.94, 8.76]	0.99	[0.69, 1.43]	0.99	[0.7, 1.41]	1.26	[0.7, 2.29]
Migration status (0 = native, 1 migrated)* Driver ID (0 = Awareness, 1 = Fishing in breeding grounds)	2.45	[0.41, 14.82]	1.24	[0.95, 1.61]	0.94	[0.71, 1.23]	1.13	[0.72, 1.78]
Migration status (0 = native, 1 migrated)* Driver ID (0 = Awareness, 1 = Fishing regulations)	2.64	[0.69, 10.13]	0.97	[0.7, 1.33]	1.04	[0.79, 1.38]	1.03	[0.58, 1.82]
Migration status (0 = native, 1 migrated)* Driver ID (0 = Awareness, 1 = High demand for Nile perch)	3.27	[0.91, 11.8]	0.98	[0.69, 1.39]	0.91	[0.69, 1.22]	0.93	[0.54, 1.63]
Migration status (0 = native, 1 migrated)* Driver ID (0 = Awareness, 1 = Monitoring)	3.16	[0.84, 11.89]	1.67	[1.07, 2.6]	0.98	[0.76, 1.27]	1.80	[0.85, 3.8]
Migration status (0 = native, 1 migrated)* Driver ID (0 = Awareness, 1 = Open access to the lake)	2.02	[0.66, 6.21]	1.01	[0.7, 1.46]	0.98	[0.71, 1.35]	1.15	[0.62, 2.15]
Migration status (0 = native, 1 migrated)* Driver ID (0 = Awareness, 1 = Overfishing)	2.39	[0.7, 8.11]	1.04	[0.77, 1.39]	0.92	[0.69, 1.23]	1.09	[0.68, 1.74]
Migration status (0 = native, 1 migrated)* Driver ID (0 = Awareness, 1 = Overpopulation)	3.12	[0.93, 10.43]	0.75	[0.44, 1.28]	1.00	[0.76, 1.31]	0.72	[0.28, 1.85]
Migration status (0 = native, 1 migrated)* Driver ID (0 = Awareness, 1 = Water pollution)	1.56	[0.51, 4.73]	1.27	[0.86, 1.88]	0.98	[0.68, 1.39]	1.27	[0.62, 2.57]
Migration status (0 = native, 1 migrated)* Driver ID (0 = Awareness, 1 = Poverty)	1.67	[0.54, 5.18]	1.06	[0.7, 1.61]	0.96	[0.7, 1.3]	1.54	[0.76, 3.13]
Migration status (0 = native, 1 migrated)* Driver ID (0 = Awareness, 1 = Use of destructive fishing gear)	2.77	[0.37, 20.94]	1.05	[0.8, 1.38]	1.03	[0.79, 1.35]	1.13	[0.73, 1.76]
Migration status (0 = native, 1 migrated)* Driver ID (0 = Awareness, 1 = Water hyacinth)	3.11	[1.02, 9.46]	1.08	[0.54, 2.13]	1.00	[0.69, 1.45]	1.12	[0.32, 3.88]
Fishing experience (0 < 10 years, 1 > 10 years)*Driver ID (0 = Awareness, 1 = Climate Change)	1.55	[0.53, 4.5]	1.36	[0.59, 3.14]	1.14	[0.84, 1.56]	1.03	[0.28, 3.81]
Fishing experience (0 < 10 years, 1 > 10 years)*Driver ID (0 = Awareness, 1 = Corruption)	1.57	[0.51, 4.83]	0.97	[0.7, 1.34]	0.99	[0.75, 1.3]	0.94	[0.54, 1.64]
Fishing experience (0 < 10 years, 1 > 10 years)*Driver ID (0 = Awareness, 1 = Decreased water level)	2.97	[1.02, 8.67]	1.24	[0.86, 1.77]	1.18	[0.84, 1.66]	0.85	[0.48, 1.51]
Fishing experience (0 < 10 years, 1 > 10 years)*Driver ID (0 = Awareness, 1 = Fishing in breeding grounds)	0.98	[0.19, 5.02]	0.96	[0.75, 1.24]	1.03	[0.79, 1.34]	0.86	[0.55, 1.32]
Fishing experience (0 < 10 years, 1 > 10 years)*Driver ID (0 = Awareness, 1 = Fishing regulations)	0.96	[0.27, 3.43]	1.11	[0.81, 1.5]	1.12	[0.85, 1.46]	1.06	[0.61, 1.84]

(*continued on next page*)

Table C1 (*continued*)

	Driver selection		In-strength		Out-Strength		Betweenness	
	Estimates(odds & odds ratio's)	Profile likelihood 95% confidence interval	Estimates (mean & ratio of means)	Profile likelihood 95% confidence interval	Estimates (mean & ratio of means)	Profile likelihood 95% confidence interval	Estimates (mean & ratio of means)	Profile likelihood 95% confidence interval
Fishing experience (0 < 10 years, 1 > 10 years)*Driver ID (0 = Awareness, 1 = High demand for Nile perch)	1.18	[0.35, 3.98]	0.83	[0.59, 1.16]	1.09	[0.83, 1.43]	0.72	[0.42, 1.23]
Fishing experience (0 < 10 years, 1 > 10 years)*Driver ID (0 = Awareness, 1 = Monitoring)	0.61	[0.17, 2.23]	0.92	[0.6, 1.42]	0.96	[0.75, 1.23]	0.64	[0.31, 1.33]
Fishing experience (0 < 10 years, 1 > 10 years)*Driver ID (0 = Awareness, 1 = Open access to the lake)	0.66	[0.23, 1.96]	0.81	[0.57, 1.14]	1.00	[0.74, 1.35]	0.66	[0.37, 1.17]
Fishing experience (0 < 10 years, 1 > 10 years)*Driver ID (0 = Awareness, 1 = Overfishing)	0.74	[0.22, 2.41]	0.88	[0.67, 1.17]	0.97	[0.74, 1.28]	0.71	[0.45, 1.11]
Fishing experience (0 < 10 years, 1 > 10 years)*Driver ID (0 = Awareness, 1 = Overpopulation)	1.88	[0.6, 5.9]	0.85	[0.51, 1.4]	0.90	[0.69, 1.17]	0.72	[0.29, 1.8]
Fishing experience (0 < 10 years, 1 > 10 years)*Driver ID (0 = Awareness, 1 = Water pollution)	1.56	[0.54, 4.53]	0.83	[0.56, 1.21]	1.06	[0.75, 1.5]	0.75	[0.37, 1.49]
Fishing experience (0 < 10 years, 1 > 10 years)*Driver ID (0 = Awareness, 1 = Poverty)	0.93	[0.31, 2.75]	0.64	[0.43, 0.95]	1.07	[0.79, 1.43]	0.56	[0.29, 1.1]
Fishing experience (0 < 10 years, 1 > 10 years)*Driver ID (0 = Awareness, 1 = Use of destructive fishing gear)	0.99	[0.14, 6.97]	1.12	[0.86, 1.45]	0.99	[0.77, 1.28]	0.98	[0.64, 1.5]
Fishing experience (0 < 10 years, 1 > 10 years)*Driver ID (0 = Awareness, 1 = Water hyacinth)	1.60	[0.55, 4.68]	0.89	[0.45, 1.76]	1.06	[0.73, 1.54]	0.42	[0.12, 1.48]

Appendix D. Changes in AIC values for each step in model reduction

Table D1

Δ AIC values of each model selection step. This table shows the changes in AIC values in each step of the model selection by computing the difference between the AIC value of the entire model and the AIC value of the smallest term (AIC of full model-AIC of the smallest term in the model = change in AIC value through model selection). In parentheses is the order of omission of each term.

	Driver selection	In-strength	Out-strength	Betweenness
AIC value of full model	2768.4	7485.9	6818.2	6872.1
Driver ID*Migration status	2768.4–2751.4 = 17 (1)	7485.9–7476.4 = 9.5 (1)	6776.3–6751.5 = 24.8 (2)	6841.1–6822.5 = 18.6 (2)
Driver ID *Fishing experience	2751.40–2741.5 = 9.9 (2)	7476.4–7468.3 = 8.1 (2)	6751.5–6730.5 = 21 (3)	6822.5–6805.6 = 16.9 (3)
Driver ID*Landing site region	2741.5–2731.7 = 9.8 (3)	7468.3–7466.4 = 1.9 (3)	6818.2–6776.3 = 41.9 (1)	6872.1–6841.1 = 31 (1)
Migration status	2731.7–2729.9 = 1.8 (4)	7466.4–7464.6 = 1.8 (4)	6728.5–6726.7 = 1.8 (5)	6805.6–6804 = 1.6 (4)
Fishing experience	2729.9–2729.4 = 0.5 (5)	7464.6–7464.1 = 0.5 (5)	6730.5–6728.5 = 2 (4)	
AIC value of final model	2729.4	6869.9	6726.7	6804.0

Appendix E. Regression estimates of the final model

Table E1
Regression estimates of the final model after stepwise model selection for landing site region, Driver ID and fishing experience predicting driver selection, in-strength, out-strength and betweenness of the drivers in the mental models.

	Driver selection		In-strength		Out-strength		Betweenness	
	Estimates (odds & odds ratio's)	Profile likelihood 95% confidence interval	Estimates (-mean & ratio of means)	Profile likelihood 95% confidence interval	Estimates (-mean & ratio of means)	Profile likelihood 95% confidence interval	Estimates (g -mean & ratio of means)	Profile likelihood 95% confidence interval
Intercept	4.92	[3.03, 7.99]	2.37	[2.02, 2.78]	2.70	[2.43, 3]	1.97	[1.56, 2.5]
Landing site region (0 = Mara, 1 = Ukerewe)	0.59	[0.36, 0.94]	0.81	[0.69, 0.94]	0.95	[0.87, 1.03]	0.65	[0.51, 0.84]
Landing site region (0 = Mara, 1 = Mwanza)	1.53	[1.06, 2.22]	1.13	[1.03, 1.25]	1.03	[0.97, 1.09]	1.22	[1.03, 1.44]
Driver ID (0 = Awareness, 1 = Climate change)	0.25	[0.15, 0.42]	0.07	[0.04, 0.13]	0.94	[0.8, 1.09]	0.10	[0.05, 0.19]
Driver ID (0 = Awareness, 1 = Corruption)	0.74	[0.43, 1.27]	0.70	[0.56, 0.88]	1.06	[0.92, 1.21]	0.87	[0.66, 1.14]
Driver ID (0 = Awareness, 1 = Decreased water level)	0.25	[0.15, 0.42]	0.87	[0.7, 1.1]	0.79	[0.68, 0.93]	0.83	[0.62, 1.09]
Driver ID (0 = Awareness, 1 = Fishing in Breeding grounds)	3.94	[1.88, 8.25]	1.90	[1.6, 2.26]	1.04	[0.92, 1.19]	1.93	[1.56, 2.4]
Driver ID (0 = Awareness, 1 = Fishing regulations)	1.42	[0.79, 2.56]	0.79	[0.64, 0.98]	1.07	[0.94, 1.23]	0.69	[0.52, 0.9]
Driver ID (0 = Awareness, 1 = High demand for Nile perch)	1.24	[0.7, 2.19]	0.58	[0.46, 0.73]	1.00	[0.88, 1.15]	0.82	[0.63, 1.07]
Driver ID (0 = Awareness, 1 = Monitoring)	1.42	[0.79, 2.56]	0.20	[0.15, 0.29]	1.58	[1.4, 1.79]	0.30	[0.21, 0.43]
Driver ID (0 = Awareness, 1 = Open access to the lake)	0.35	[0.21, 0.58]	0.74	[0.59, 0.94]	0.95	[0.82, 1.11]	0.85	[0.64, 1.13]
Driver ID (0 = Awareness, 1 = Overfishing)	0.92	[0.53, 1.6]	1.28	[1.06, 1.55]	1.07	[0.93, 1.22]	1.94	[1.55, 2.43]
Driver ID (0 = Awareness, 1 = Overpopulation)	0.89	[0.51, 1.54]	0.12	[0.08, 0.19]	1.22	[1.07, 1.39]	0.18	[0.11, 0.28]
Driver ID (0 = Awareness, 1 = Water pollution)	0.15	[0.09, 0.26]	0.70	[0.54, 0.92]	0.84	[0.71, 1]	0.60	[0.43, 0.85]
Driver ID (0 = Awareness, 1 = Poverty)	0.37	[0.22, 0.61]	0.41	[0.3, 0.54]	0.97	[0.84, 1.12]	0.50	[0.36, 0.7]
Driver ID (0 = Awareness, 1 = Use of destructive fishing gear)	7.62	[3.05, 19.02]	1.59	[1.33, 1.9]	1.19	[1.05, 1.35]	2.14	[1.73, 2.65]
Driver ID (0 = Awareness, 1 = Water hyacinth)	0.12	[0.07, 0.2]	0.17	[0.1, 0.27]	0.76	[0.64, 0.92]	0.15	[0.08, 0.28]
Fishing experience (0 < 10 years, 1 > 10 years)							0.88	[0.76, 1.02]

Appendix F. Figures of aggregate mental models for each landing site region

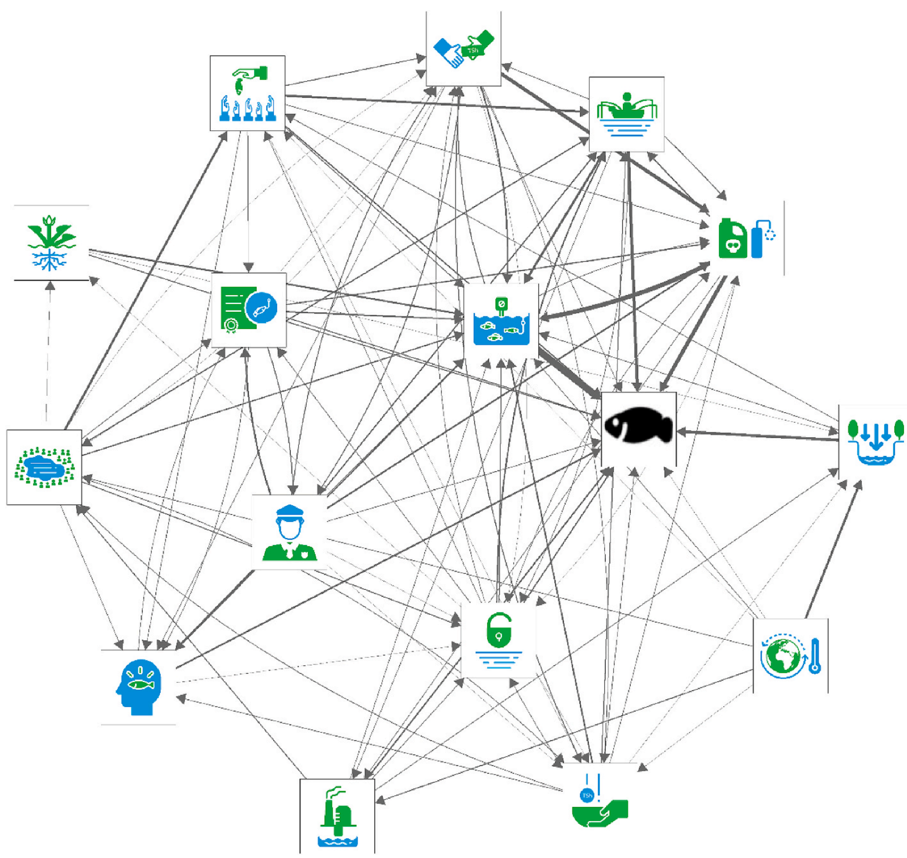


Fig. F1. The aggregated mental model of the Ukerewe sample. Arrow width indicates the sum of the weights of the connections of the individual mental models (thicker arrows indicate stronger connections). The nodes' locations in this figure were determined by the algorithm by Fruchterman and Reingold (1991) that optimises the display of the connections, and does not accurately reflect the nodes' centrality.

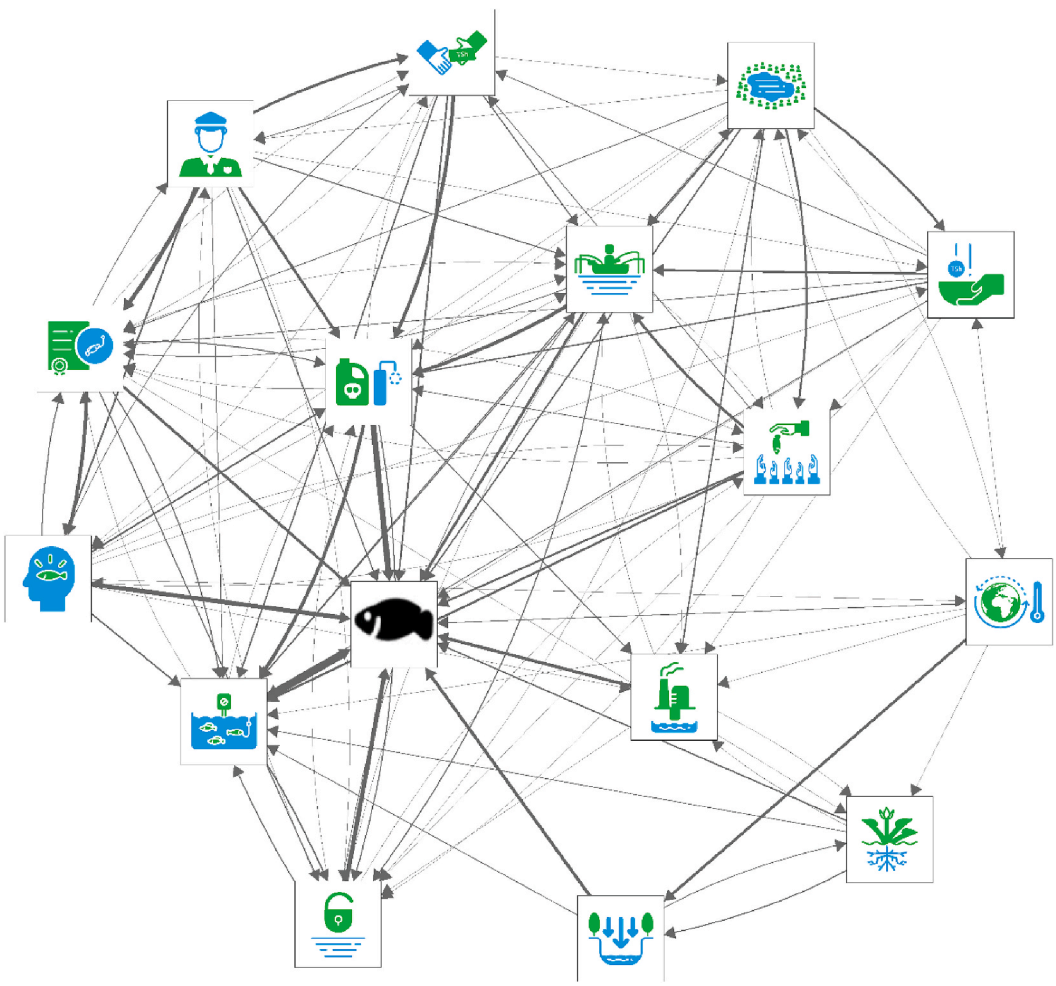


Fig. F2. The aggregated mental model of the Mara sample. Arrow width indicates the sum of the weights of the connections of the individual mental models (thicker arrows indicate stronger connections). The nodes' locations in this figure were determined by the algorithm by Fruchterman and Reingold (1991) that optimises the display of the connections, and does not accurately reflect the nodes' centrality.

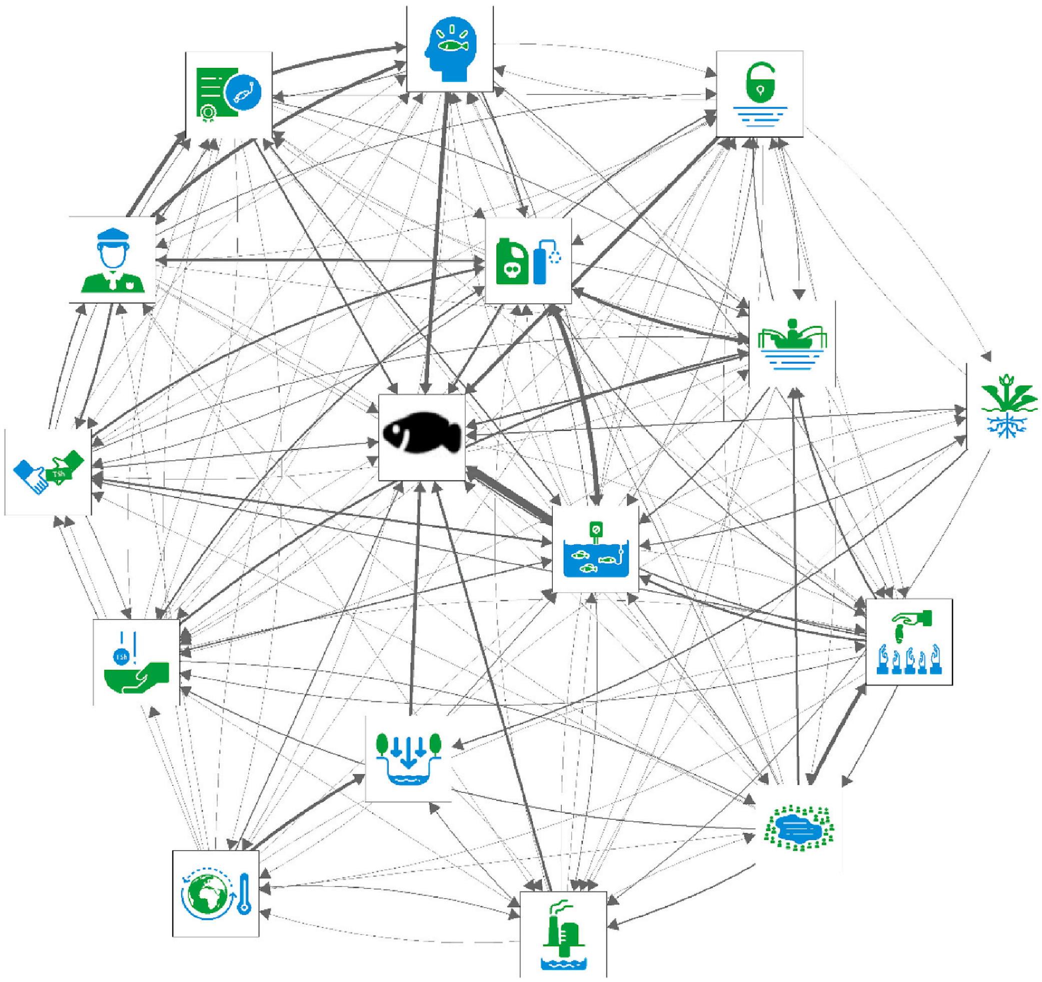


Fig. F3. The aggregated mental model of the Mwanza sample. Arrow width indicates the sum of the weights of the connections of the individual mental models (thicker arrows indicate stronger connections). The nodes' locations in this figure were determined by the algorithm by Fruchterman and Reingold (1991) that optimises the display of the connections, and does not accurately reflect the nodes' centrality.

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, 3*(3), 191–199. https://doi.org/10.1038/s41893-019-0467-z

Atran, S., Medin, D., Ross, N., Lynch, E., Vapnarsky, V., Ek', E. U., Coley, J., Timura, C., & Baran, M. (2002). Folkecology, cultural epidemiology, and the spirit of the commons. *Current Anthropology, 43*(3), 421–450. https://doi.org/10.1086/339528

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory.* Prentice Hall.

Bardenhagen, C. J., Howard, P. H., & Gray, S. A. (2020). Farmer mental models of biological pest control: Associations with adoption of conservation practices in blueberry and cherry orchards. *Frontiers in Sustainable Food Systems, 4*, 1–11. https://doi.org/10.3389/fsufs.2020.00054

Bender, A. (2020). What is causal cognition? *Frontiers in Psychology, 11*, 1–6. https://doi.org/10.3389/fpsyg.2020.00003

Bertolas, R. J. (1998). Cross-cultural environmental perception of wilderness. *The Professional Geographer, 50*(1), 98–111. https://doi.org/10.1111/0033-0124.00107

Biggs, D., Abel, N., Knight, A. T., Leitch, A., Langston, A., & Ban, N. C. (2011). The implementation crisis in conservation planning: Could 'mental models' help? *Conservation Letters, 4*(3), 169–183. https://doi.org/10.1111/j.1755-263X.2011.00170.x

Böhm, G., Doran, R., & Pfister, H.-R. (2018). Laypeople's affective images of energy transition pathways. *Frontiers in Psychology, 9*, 1904. https://doi.org/10.3389/fpsyg.2018.01904

Böhm, G., Doran, R., Rødeseike, A., & Pfister, H.-R. (2019). Pathways to energy transition: A faceted taxonomy. *International Studies of Management & Organization, 49*(3), 303–319. https://doi.org/10.1080/00208825.2019.1623981

Böhm, G., & Pfister, H. R. (2001). Mental representation of global environmental risks. *Research in Social Problems and Public Policy, 9*, 1–30.

Bostrom, A. (2017). Mental models and risk perceptions related to climate change. In *Oxford research encyclopedia of climate science* (pp. 1–31). http://climatescience.oxfordre.com/view/10.1093/acrefore/9780190228620.001.0001/acrefore-9780190228620-e-303.

Bostrom, A., O'Connor, R. E., Böhm, G., Hanss, D., Bodi, O., Ekström, F., Halder, P., Jeschke, S., Mack, B., Qu, M., Rosentrater, L., Sandve, A., & Sælensminde, I. (2012). Causal thinking and support for climate change policies: International survey findings. *Global Environmental Change, 22*(1), 210–222. https://doi.org/10.1016/j.gloenvcha.2011.09.012

Brandes, U. (2001). A faster algorithm for betweenness centrality. *Journal of Mathematical Sociology, 25*(2), 163–177. https://doi.org/10.1080/0022250X.2001.9990249

van den Broek, K. L. (2018). Illuminating divergence in perceptions in natural resource management: A case for the investigation of the heterogeneity in mental models. *Journal of Dynamic Decision Making, 4*, 1–5. https://doi.org/10.11588/jddm.2018.1.51316

van den Broek, K. L. (2019). Stakeholders' perceptions of the socio-economic and environmental challenges at Lake Victoria. *Lakes and Reservoirs: Research and Management, 24*(3), 239–245. https://doi.org/10.1111/lre.12275

van den Broek, K., Bolderdijk, J. W., & Steg, L. (2017). Individual differences in values determine the relative persuasiveness of biospheric, economic and combined appeals. *Journal of Environmental Psychology, 53*, 145–156. https://doi.org/10.1016/j.jenvp.2017.07.009

van den Broek, K. L., Klein, S. A., Luomba, J., & Fischer, H. (2021). Introducing M-tool: A standardised and inclusive mental model mapping tool. *System Dynamics Review, 37* (4), 346–355. https://doi.org/10.1002/sdr.1698

van den Broek, K. L., Luomba, J., van den Broek, J., & Fischer, H. (2021). Evaluating the application of the Mental model mapping tool (M-Tool). *Frontiers in Psychology, 12*, Article 761882. https://doi.org/10.3389/fpsyg.2021.761882

Bruine de Bruin, W., & Bostrom, A. (2013). Assessing what to address in science communication. In *Proceedings of the national academy of sciences* (pp. 14062–14068). https://doi.org/10.1073/pnas.1212729110, 110(Supplement_3).

Burnham, K., & Anderson, D. (2002). *Model selection and multimodel inference (second).* Springer-Verlag.

Calori, R., Johnson, G., & Sarnin, P. (1994). Ceos' cognitive maps and the scope of the organization. *Strategic Management Journal, 15*(6), 437–457. https://doi.org/10.1002/smj.4250150603

Carter, K., Cushing, K., Savers, D., Stein, P., & Berliner, D. (1988). Expert-novice differences in perceiving and processing visual classroom information. *Journal of Teacher Education, 39*(3), 25–31. https://doi.org/10.1177/002248718803900306

Chitamwebwa, D., Amanyi, J. K., Ayungi, J. K., Abbongo, H. N., Golla, A. O., & Juok, J. O. (2009). The present status of the hook fishery and its impact on the fish stocks of Lake Victoria. *African Journal of Tropical Hydrobiology and Fisheries, 82*, 78–82.

Craik, K. J. W. (1943). *The nature of explanation*. Cambridge: University Press.

de Ridde Ridder, D. T. D, van den Boom, L. A. T. P., Kroese, F. M., Moors, E. H. M., & van den Broek, K. L. (2022). How do people understand the spread of COVID-19 infections? Mapping mental models of factors contributing to the pandemic. *Psychology & Health*, 1–20. https://doi.org/10.1080/08870446.2022.2129054

DeChurch, L. A., & Mesmer-Magnus, J. R. (2010). The cognitive underpinnings of effective teamwork: A meta-analysis. *Journal of Applied Psychology, 95*(1), 32–53. https://doi.org/10.1037/a0017328

Denzau, A. T., & North, D. C. (1994). Shared mental models: Ideologies and institutions. In A. Lupia, M. D. McCubbins, & S. L. Popkin (Eds.), *Elements of reason: Cognition, choice, and the bounds of rationality*. Cambridge University Press.

Doran, R., Böhm, G., & Hanss, D. (2018). Using card sorting to explore the mental representation of energy transition pathways among laypeople. *Frontiers in Psychology, 9*, 2322. https://doi.org/10.3389/fpsyg.2018.02322

Downing, A. S., Van Nes, E. H., Balirwa, J. S., Beuving, J., Bwathondi, P., Chapman, L. J., Cornelissen, I. J. M., Cowx, I. G., Goudswaard, K. P. C., Hecky, R. E., Janse, J. H., Janssen, A. B. G., Kaufman, L., Kishe-Machumu, M. A., Kolding, J., Ligtvoet, W., Mbabazi, D., Medard, M., Mkumbo, O. C., … Mooij, W. M. (2014). Coupled human and natural system dynamics as key to the sustainability of Lake Victoria's Ecosystem services. *Ecology and Society, 19*(4), 31. https://doi.org/10.5751/ES-06965-190431

Dutt, V., & Gonzalez, C. (2012). Decisions from experience reduce misconceptions about climate change. *Journal of Environmental Psychology, 32*(1), 19–29. https://doi.org/10.1016/j.jenvp.2011.10.003

Fruchterman, T. M. J., & Reingold, E. M. (1991). Graph drawing by force-directed placement. *Software: Practice and Experience, 21*(11), 1129–1164. https://doi.org/10.1002/spe.4380211102

Goldberg, M. H., Gustafson, A., & van der Linden, S. (2020). Leveraging social science to generate lasting engagement with climate change solutions. *One Earth, 3*(3), 314–324. https://doi.org/10.1016/j.oneear.2020.08.011

Güss, C. D., & Robinson, B. (2014). Predicted causality in decision making: The role of culture. *Frontiers in Psychology, 5*(479). https://doi.org/10.3389/fpsyg.2014.00479

Hardin, G. (1968). The tragedy of the commons. *Science, 162*(3859), 1243–1248. http://www.jstor.org/stable/1724745.

Hastie, T., Tibshirani, R., & Friedman, J. (2017). Model assessment and selection. In *The elements of statistical learning: Data mining, inference, and prediction* (second, pp. 219–257). Springer.

Henly-Shepard, S., Gray, S. A., & Cox, L. J. (2015). The use of participatory modeling to promote social learning and facilitate community disaster planning. *Environmental Science & Policy, 45*, 109–122. https://doi.org/10.1016/j.envsci.2014.10.004

Hevey, D. (2018). Network analysis: A brief overview and tutorial. *Health Psychology and Behavioral Medicine, 6*(1), 301–328. https://doi.org/10.1080/21642850.2018.1521283

Hmelo-Silver, C. E., Marathe, S., & Liu, L. (2007). Fish swim, rocks sit, and lungs breathe: Expert-novice understanding of complex systems. *The Journal of the Learning Sciences, 16*(3), 307–331. https://doi.org/10.1080/10508400701413401

Hobbs, B. F., Ludsin, S. A., Knight, R. L., Ryan, P. A., Ciborowski, J. J. H., & Ciborowski, J. A. N. J. H. (2016). Fuzzy cognitive mapping as a tool to define management objectives for complex ecosystems. *Ecological Applications, 12*(5), 1548–1565.

Hoffman, M., Lubell, M., & Hillis, V. (2014). Linking knowledge and action through mental models of sustainable agriculture. *Proceedings of the National Academy of Sciences of the United States of America, 111*(36), 13016–13021. https://doi.org/10.1073/pnas.1400435111

Holmgren, M., Kabanshi, A., Langeborg, L., Barthel, S., Colding, J., Eriksson, O., & Sörqvist, P. (2019). Deceptive sustainability: Cognitive bias in people's judgment of the benefits of CO2 emission cuts. *Journal of Environmental Psychology, 64*, 48–55. https://doi.org/10.1016/j.jenvp.2019.05.005

Jaques, E. (1986). The development of intellectual capability: A discussion of stratified systems theory. *The Journal of Applied Behavioral Science, 22*(4), 361–383.

Johnson-Laird, P. N. (1983). *Mental models: Towards a cognitive science of language, inference, and consciousness*. Harvard University Press.

Johnson-Laird, P. N. (1989). Mental models. In M. I. Posner (Ed.), *Foundations of cognitive science* (pp. 467–499). Cambridge: MIT Press.

Johnson-Laird, P. N. (2010). Mental models and human reasoning. In *Proceedings of the national academy of sciences, 107* pp. 18243–18250). https://doi.org/10.1073/pnas.1012933107 (43).

Jones, N. A., Ross, H., Lynam, T., Perez, P., & Leitch, A. (2011). Mental models: An interdisciplinary synthesis of theory and methods. *Ecology and Society, 16*(1), 46-46.

Kaplan, S., & Kaplan, R. (2009). Creating a larger role for environmental psychology: The Reasonable Person Model as an integrative framework. *Journal of Environmental Psychology, 29*(3), 329–339. https://doi.org/10.1016/j.jenvp.2008.10.005

Karon, J. M., & Wejnert, C. (2012). Statistical methods for the analysis of time-location sampling data. *Journal of Urban Health, 89*(3), 565–586. https://doi.org/10.1007/s11524-012-9676-8

Kempton, W. (1986). Two theories of home heat control. *Cognitive Science, 10*(1), 75–90. https://doi.org/10.1207/s15516709cog1001_3

Klein, S. A., van den Broek, K. L., Luomba, J., Onyango, H. O., Mbilingi, B., & Akumu, J. (2021). How knowledge acquisition shapes system understanding in small-scale fisheries. *Current Research in Ecological and Social Psychology, 2*, Article 100018. https://doi.org/10.1016/j.cresp.2021.100018

Krebs, V. (2000). The social life of routers. *Internet Protocol Journal, 3*(4), 14–25.

Levy, M. A., Lubell, M. N., & McRoberts, N. (2018). The structure of mental models of sustainable agriculture. *Nature Sustainability, 1*(8), 413–420. https://doi.org/10.1038/s41893-018-0116-y

Lezak, S. B., & Thibodeau, P. H. (2016). Systems thinking and environmental concern. *Journal of Environmental Psychology, 46*, 143–153. https://doi.org/10.1016/j.jenvp.2016.04.005

Luomba, J. (2013). Role of beach management units in implementing fisheries policy: A case study of two BMUs in Lake Victoria, Tanzania. In *IIFET 2014 conference proceedings*. Brisbane, Australia: IIFET 2014.

Mailu, a M. (2001). Preliminary assessment of the cocial, economic and environmental impacts of Water Hyacinth in Lake Victoria basin and status of control. *Biological and Integrated Control of Water Hyacinth, Eichhornia Crassipes, 102*, 130–139.

Mathevet, R., Etienne, M., Lynam, T., & Calvet, C. (2011). Water management in the Camargue Biosphere Reserve: Insights from comparative mental model analysis. *Ecology and Society, 16*, 43. https://doi.org/10.5751/ES-04007-160143

McCullagh, P., & Nelder, J. A. (2019). *Generalized linear models* (2nd ed.). Routledge. https://doi.org/10.1201/9780203753736

Mohammed, S., Hamilton, K., Sánchez-Manzanares, M., & Rico, R. (2017). Team mental models and situation awareness. In *The Wiley Blackwell handbook of the psychology of team working and collaborative processes* (pp. 369–392). Wiley Blackwell.

Molina, F. G. J. (2016). Intergenerational transmission of local knowledge towards river flooding risk reduction and adaptation: The experience of Dagupan City, Philippines. In M. A. Miller, & M. Douglass (Eds.), *Disaster governance in urbanising asia*. Springer Singapore. https://doi.org/10.1007/978-981-287-649-2_8, 145-176.

Morgan, M. G., Fischhoff, B., Bostrom, A., & Atman, C. J. (2002). *Risk communication: A mental models approach*. Cambridge University Press.

Msuku, B. S., Mrosso, H. D. J., & Nsinda, P. E. (2011). A critical look at the current gillnet regulations meant to protect the Nile Perch stocks in Lake Victoria. *Aquatic Ecosystem Health and Management, 14*(3), 252–259. https://doi.org/10.1080/14634988.2011.604567

Newell, B. R., McDonald, R. I., Brewer, M., & Hayes, B. K. (2014). The psychology of environmental decisions. *Annual Review of Environment and Resources, 39*(1), 443–467. https://doi.org/10.1146/annurev-environ-010713-094623

Newman, M. E. J. (2010). *Networks: An introduction*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780199206650.001.0001

Njiru, M., Kazungu, J., Ngugi, C. C., Gichuki, J., & Muhoozi, L. (2008). An overview of the current status of Lake Victoria fishery: Opportunities, challenges and management strategies. *Lakes and Reservoirs: Research and Management, 13*(1), 1–12. https://doi.org/10.1111/j.1440-1770.2007.00358.x

Njiru, J., Knaap, M., Kundu, R., & Nyamweya, C. (2018). Lake Victoria fisheries: Outlook and management. *Lakes & Reservoirs: Science, Policy and Management for Sustainable Use, 23*(2), 152–162. https://doi.org/10.1111/lre.12220

Norström, A. V., Cvitanovic, C., Löf, M. F., West, S., Wyborn, C., Balvanera, P., Bednarek, A. T., Bennett, E. M., Biggs, R., Bremond, A. D., Campbell, B. M., Canadell, J. G., Carpenter, S. R., Folke, C., Fulton, E. A., Gaffney, O., Gelcich, S., Jouffray, J., Leach, M., … Österblom, H. (2020). Principles for knowledge co-production in sustainability research. *Nature Sustainability, 3*, 182–190. https://doi.org/10.1038/s41893-019-0448-2

Onyango, P. O. (2014). *Reforming fisheries management: A case study of co-management in Lake Victoria, Tanzania [unpublished M. Sc. Thesis]*. Norwegian College of Fisheries Science.

Onyango, P. O., Salehe, M., & Mrosso, H. D. J. (2006). *A report on socio-economic baseline survey of fishing communities in Lake Victoria, Tanzania* (pp. 1–75). Lake Victoria Fisheries Organization.

Ostrom, E. (1990). Governing the commons. *The Evolution of Institutions for Collective Action, 302*. https://doi.org/10.1017/CBO9780511807763

Özesmi, U., & Özesmi, S. L. (2004). Ecological models based on people's knowledge: A multi-step fuzzy cognitive mapping approach. *Ecological Modelling, 176*(1–2), 43–64. https://doi.org/10.1016/j.ecolmodel.2003.10.027

IPCC. (2022). Climate change 2022: Impacts, adaptation, and vulnerability. In H. O. Pörtner, D. C. Roberts, M. Tignor, E. S. Poloczanska, K. Mintenbeck, A. Alegría, M. Craig, S. Langsdorf, V. Löschke, A. Okem, & B. Rama (Eds.), *Contribution of working group II to the sixth assessment report of the intergovernmental Panel on climate change*. Cambridge University Press (in press).

Richter, I., Roberts, B. R., Sailley, S. F., Sullivan, E., Cheung, V. V., Eales, J., Fortnam, M., Jontila, J. B., Maharja, C., Nguyen, T. H., Pahl, S., Praptiwi, R. A., Sugardjito, J., Sumeldan, J. D. C., Syazwan, W. M., Then, A. Y., & Austen, M. C. (2022). Building bridges between natural and social science disciplines: A standardized methodology to combine data on ecosystem quality trends. *Philosophical Transactions of the Royal Society B: Biological Sciences, 377*(1854), Article 20210487. https://doi.org/10.1098/rstb.2021.0487

Royston, P. (2007). Profile likelihood for estimation and confidence intervals. *STATA Journal: Promoting Communications on Statistics and Stata, 7*(3), 376–387. https://doi.org/10.1177/1536867X0700700305

Stier, A. C., Samhouri, J. F., Gray, S., Martone, R. G., Mach, M. E., Halpern, B. S., Kappel, C. V., Scarborough, C., & Levin, P. S. (2017). Integrating expert perceptions into food web conservation and management. *Conservation Letters, 10*(1), 67–76. https://doi.org/10.1111/conl.12245

Tanaka, J. W., & Taylor, M. (1991). Object categories and expertise: Is the basic level in the eye of the beholder? *Cognitive Psychology, 23*(3), 457–482. https://doi.org/10.1016/0010-0285(91)90016-H

Tanzanian National Bureau of Statistics. (2013). *Population and housing census 2012: Population distribution by administrative areas*. https://www.nbs.go.tz/index.php/en/census-surveys/population-and-housing-census/162-2012-phcpopulation-distribution-by-administrative-areas.

Trafton, J. G., Marshall, S., Mintz, F., & Trickett, S. B. (2002). Extracting explicit and implict information from complex visualizations. In M. Hegarty, B. Meyer, & N. H. Narayanan (Eds.), *Diagrammatic representation and inference* (pp. 206–220). Springer Berlin Heidelberg.

Uitdewilligen, S., Waller, M. J., Roe, R. A., & Bollen, P. (2021). The effects of team mental model complexity on team information search and performance trajectories. *Group & Organization Management*. https://doi.org/10.1177/10596011211023219, 105960112110232.

Wood, M. D., Bostrom, A., Bridges, T., & Linkov, I. (2012). Cognitive mapping tools: Review and risk management needs. *Risk Analysis, 32*(8), 1333–1348. https://doi.org/10.1111/j.1539-6924.2011.01767.x

Zweig, K. A. (2016). *Network analysis literacy*. Springer.