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Examining Private Landowners' Knowledge Systems for an Invasive Species

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Abstract Shared ecological knowledge about the impacts of biological invasions can facilitate the collective action necessary to achieve desired management outcomes. Since its introduction to an island archipelago in South America, the North American beaver has caused major changes to the ecosystem. We examined landowners' mental models of how beavers impact ecosystem services in riparian areas to understand the potential to implement a large-scale eradication program. We used ethnographic interviews to characterize individual landowners' perceptions about beaver-caused changes to ecosystems and landowners' wellbeing, and examined the degree to which they are shared. While the eradication initiative focuses on ecosystem integrity, landowners considered impacts on provisioning services to be most salient. Landowners did not have a highly shared causal model of beaver impacts, which indicates a diverse knowledge system. This lack of consensus on how beavers impact riparian areas provides some optimism for garnering support for eradication, and also offers insights into challenges with mental modeling methodologies.

Keywords North American beaver *(Castor Canadensis)* · concept mapping · local ecological knowledge · mental models · private lands · network analysis · Tierra del Fuego

Introduction

Addressing large-scale, complex natural resource management challenges requires an integrated understanding of both social and ecological drivers of change. The coordination, mobilization, and communication necessary for successful natural resource management are difficult if not impossible to achieve without knowledge about local social systems (Lövbrand *et al.* 2015). Integrating the social and natural sciences to address complex contemporary problems is a priority among scholars because it leads to more holistic problem solving, and the development of a shared understanding of knowledge systems can make policies and other interventions more effective (Cash *et al.* 2003; Castree *et al.* 2014; Lave *et al.* 2014).

The local ecological knowledge (LEK) framework characterizes place-specific practices and beliefs, and its integration into decision making can increase the effectiveness of ecosystem management. A key function of LEK is to identify shared beliefs that influence cultural norms and thus guide behavior. Understanding LEK can help identify important differences between scientific and local beliefs (Scoones 1999; Olsson

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and Folke 2001) as well as amongst stakeholder groups (e.g., Halbrendt *et al.* 2014). The degree of diversity within a group's knowledge system can also inform management, because greater diversity in beliefs and norms can be a source of flexibility and adaptability in a culture (Dea and Scoones 2003; Ghimire *et al.* 2004; Crona and Bodin 2006).

We examine the structure of LEK in an area where an invasive species is causing major changes to an island ecosystem. Specifically, we focus on the introduction of the North American beaver (*Castor canadensis*) to the Tierra del Fuego Archipelago in southern South America. The beaver was introduced in the 1940s in a failed attempt to initiate a fur trade. By 2008, the two countries that share Tierra del Fuego (TDF), Chile and Argentina, signed a bi-national treaty calling for eradication of beavers from the region citing their detrimental impacts to riparian forests, native biodiversity, infrastructure, and local economies (Parkes *et al.* 2008). Eradication requires the cooperation of over 300 private landowners whose beliefs about how beavers impact their personal wellbeing and surrounding ecosystems vary. Our goal was to characterize the degree to which landowners have a shared understanding of how beavers impact riparian areas to provide insight into policy and management approaches.

We focused on human understanding as a key factor related to invasive species management because differences in perception, logic, and interpretation of environmental problems have been linked to important factors, such as variation in adaptation strategies (Otto-Banaszak *et al.* 2011), conflict among resource user groups (Adams *et al.* 2003), and limits to the implementation of conservation programs (King 2007; King and Peralvo 2010). Differences in how individuals and stakeholder groups construct their own interpretations of external realities (i.e., mental models) influence local patterns of shared knowledge as well as expectations about how environmental systems will react under different policy scenarios. These expectations, in turn, influence preferences about what natural resource policy, if any, should be adopted (Adams *et al.* 2003; Sayer and Campbell 2004; Pahl-Wostl 2006; Biggs *et al.* 2011; Gray *et al.* 2012). Many conservation efforts encounter conflicts related to decision-making, differences in values, public participation processes, and the inherent uncertainty of complex system behavior (Biggs *et al.* 2011). An in-depth understanding of stakeholders' knowledge and beliefs can be used to anticipate and prevent complications, since conflicts often stem from variation in individual stakeholders' knowledge and beliefs.

We examined local landowners' mental models of the ecosystem services of riparian areas, and the perceived impact of the invasive beaver on the provisioning of those services. Our specific objectives were to: (1) identify the ecosystem services produced by riparian areas that are most salient to TDF landowners, (2) characterize landowners' perceptions about how beavers alter ecosystem structure and function as well as the landowners' own wellbeing, and (3) understand the degree and structure of shared perceptions among individual landowners. We used ethnographic interviews to elicit mental models and network analysis to quantify links and degree of shared understanding within these models.

Conceptual Framework

Concerns about the ever-increasing extent and rate of biological invasions are being replaced by more nuanced debates on the feasibility, practicality, and desirability of controlling non-native and invasive species. Some invasive species are powerful agents of ecosystem change, driving extinction of native species. Practitioners have become increasingly effective at eradicating invasive mammals from islands (Carrion *et al.* 2011), and the conservation benefits of their removal are well documented (Jones *et al.* 2016). Yet, debates continue surrounding the generality of invasive species impacts, the inevitability of novel ecosystems, and even the use of non-native species to promote conservation goals (Schlaepfer *et al.* 2012; Vitule *et al.* 2012; Hobbs *et al.* 2014). Whether perceived as good, bad, or neutral, the ecological effect of invasive species is a topic of long-standing interest dating back decades (Elton 1958).

Invasive species can also be viewed as potential change agents that shape societal outcomes (e.g., livelihoods and wellbeing), as well as future human behaviors (Collins *et al.* 2011). From this perspective, the knowledge that underpins human behavior is diverse and dynamic. Learning from and adapting to invasive species occurs as people integrate beliefs about the species' positive and negative impacts into their daily behaviors and cultures (e.g., Pfeiffer and Voeks 2008). People's attitudes toward invasive species are complex and influenced by multiple factors, such as the degree to which they interact with the species, knowledge of ecological history, the degree they value the ecological processes that the species alters, knowledge of other people's behavior, and whether or not they believe the species threatens ecological or human wellbeing. Beliefs about efficacy and morality of invasive species management strategies further complicate the willingness to respond to ecological feedbacks in social-ecological systems. Thus, an individual's mental model of the threat of an invasive species is a function of their cognitive understanding of the relations between causal factors and their effects (Craik 1967; Johnson-Laird 1983).

Given that mental models are the foundation for action, and that shared mental models form the basis of a group's knowledge system, we situate our research within the local ecological knowledge framework. LEK refers to the, "knowledge held by a specific group of people about their local ecosystems...it concerns the interplay among organisms and between organisms and their environment. LEK may be a mix of scientific and practical knowledge; it is site specific and often involves a belief component" (Olsson and Folke 2001:87). Scholarship on LEK has advocated increased incorporation of local knowledge into conservation and natural resource management (Berkes *et al.* 2000; Goldman 2003; Bohensky *et al.* 2013) and has offered new strategies to do so (Anadon *et al.* 2009; Cullen-Unsworth *et al.* 2012; Robinson and Wallington 2012).

In highlighting the character and relevance of shared knowledge systems, much of the scholarship on LEK has used qualitative, descriptive, or participatory methods of data collection and analysis. These have included participatory mapping (Ferguson and Messier 1997; Aswani and Lauer 2006; Robinson and Wallington 2012; Robinson *et al.* 2015) and sampling (Gratani *et al.* 2011), co-research (Cullen-Unsworth *et al.* 2012), semi-structured interviews (Knapp and Fernandez-Gimenez 2009; Peloquin and Berkes 2009; Eyssartier *et al.* 2011; Sundaram *et al.* 2012), focus groups (Gómez-Baggethun *et al.* 2012; Leonard *et al.* 2013), and other qualitative approaches including participant observation, oral histories, and content analysis of archival records. These approaches are especially useful for identifying causal mechanisms and core themes, and for providing thickly descriptive accounts of social characteristics and processes. Opportunities remain, however, to incorporate additional methodologies to examine the structures of, and potential embedded diversity within LEK.

Building structured cognitive maps from qualitative data is one way to approach the analysis of mental models (Jones *et al.* 2011). A cognitive map is comprised of a network of concepts (nodes) and causal relationships (ties) connecting those concepts. The map represents an individual's understanding of cause-effect relationships within a specific topic area or domain (Morgan *et al.* 2002; Breakwell 2004). Cognitive maps can therefore be used to explicitly reveal specific beliefs and patterns of thinking about complex systems (Eden 2004; Jones *et al.* 2011).

Cognitive maps of different individuals can be layered on top of each other to identify areas of overlap that describe collective knowledge. Cognitive maps represent an individual-level assessment, but aggregating them allows them to be scaled-up to characterize group knowledge (Özesmi and Özesmi 2004; Gray *et al.* 2015). Current approaches to investigate LEK use network analysis to examine the mental models' structures and the degree to which they are shared. Further, cognitive mapping, and semi-quantitative approaches in particular, provide a level of analytical standardization that is especially useful for understanding similarities and differences in knowledge structure or function (Borgatti *et al.* 2013; Gray *et al.* 2014). Our research examines mental models of private landowners in Tierra del Fuego to understand patterns of convergence and divergence within LEK regarding the impacts of the invasive beaver.

Methods

Study Area

The Tierra del Fuego (TDF) Archipelago is located at the southern tip of South America, below the Strait of Magellan. The Chilean-Argentine international border bisects Isla Grande, the largest, most populated island of the archipelago, and is the focus of this study. Most island inhabitants (97%) live in urban areas, with the Argentine residents (~150,000) greatly outnumbering Chileans (<7000). The principal economic activities on the Argentine portion of the island are social services, commercial activities (i.e., restaurants, tourism), manufacturing, transportation, construction, fisheries, timber harvesting, real estate, and mining (DGEC 2010), while the Chilean portion relies mostly on oil and gas exploration, and ranching (SDRA 2014). Public land makes up about half of TDF. Families or shareholder groups operate large private ranches throughout the island, and we focused on these landowners. Conservation NGOs, government agencies, and a small number of private forestry companies manage most of the forested areas in southern TDF.

Sampling

The population of interest consisted of individuals serving as the primary decision-maker for at least 300 ha of privately held, non-corporate, titled land on TDF. We limited our analysis to landowners with large properties because many small parcels and plots are unmanaged and because large properties were prioritized in the bi-national beaver eradication plan (Malmierca *et al.* 2011). We excluded properties without surface water (river, stream, lake, pond, wetland, bog, or spring) that could serve as beaver habitat. The unit of analysis was a property's primary decision-maker, typically the landowner.

We obtained and updated publicly available land registry data for private properties in TDF. The final sample frame included 49 landowners in Argentina and 134 in Chile, respectively ($N = 183$). Because landowner experiences may differ across ecological or political contexts, we used a stratified random sampling strategy to include landowners from both Argentina and Chile who owned forested and non-forested land. We overlaid private land ownership boundaries onto the island's biomes using a geographic information system and randomly selected landowners from each country. We selected participants from Chile and Argentina in a ratio roughly proportional to the number of landowners in each country to request interviews. Within each country, we approached sampling by drawing equally from forested and non-forested areas. In reality, however, many landowners owned parcels in both forested and non-forested areas of the island. We chose to interview a maximum of 40 landowners because past mental model studies have approached theoretical saturation (i.e., very few or no new ideas in subsequent interviews) after around 20-30 interviews (Morgan *et al.* 2002; Özesmi and Özesmi 2004).

We contacted landowners from July to December 2014 and conducted in-person interviews that lasted 45-180 min. The first author, who is fluent in both Spanish and English, conducted all interviews. At the end of the interview, each participant received a small token gift of a CD containing reports from previous research projects conducted with the help of rural TDF landowners.

Data Collection and Analysis

Despite a growing interest in cognitive mapping, there is no consensus regarding the most appropriate way to elicit individuals' causal belief systems (Hodgkinson *et al.* 2004; Jones *et al.* 2011; Lynam and Brown 2011). Our approach to eliciting and representing mental models was somewhat novel but grounded in the approach of Morgan *et al.* (2002) and Özesmi and Özesmi (2004). Our process followed four steps: 1) landowners listed ecosystem services provided by their riparian areas, 2) they rank-ordered each item based on perceived importance, 3) they described how riparian areas on their land cause or produce each ecosystem service, and 4) they explained whether and how beavers affect the production of each ecosystem service. Our approach is unique in that we did not constrain participants' answers to a predetermined list of ideas. Many mental models studies ask interview participants to characterize relationships between discrete, predetermined concepts (e.g., Hodgkinson *et al.* 2004; Halbrendt *et al.* 2014). Because of the lack of previous work on invasive species on TDF and in general, we chose an open-ended interview strategy with prompts and probes to maximally capture diverse ideas framed in the participant's perspective (Morgan *et al.* 2002; Bailey 2007; Isaac *et al.* 2009).

Listing Ecosystem Services

Our first objective was to identify ecosystem services provided by riparian areas that are most salient to TDF landowners. The phrase "ecosystem services" is a term that may not be well understood by landowners. Ecosystem services can colloquially be understood as "nature's benefits," and we used the terms "benefits" and "ecosystem services" interchangeably for this research and subsequently in this paper. We first used a free-listing strategy to identify ecosystem services perceived by landowners. In free-listing, interviewees list all of the elements of a domain that they can. We asked them to list "benefits" that water sources (lakes, ponds, rivers, streams, springs, wetlands, bogs) and adjacent land on their property provide (i.e., riparian areas) (Weller and Romney 1988; Quinlan 2005). We then asked them to rank order their list based on importance (1 = most important). After a participant's initial brainstorm and ranking, we introduced prompts designed to encourage them to think about a variety of provisioning, supporting, regulating, and cultural ecosystem services. We used the ranked data to calculate Sutrop's salience (S) for each ecosystem service mentioned (Sutrop 2001):

$$S = F/N(mP)$$

Salience (S) is a function of the frequency with which an ecosystem service was listed, F, divided by the product of the total number of participants included in the analysis, N, and mean position of the ranking, mp, of each ecosystem service:

Cognitive Mapping

We used each participant's list of ecosystem services as a foundation for eliciting and constructing cognitive maps to characterize their perceptions about ways in which beavers cause changes to both ecosystem structure and function that produce the identified services. Our semi-structured interviews started with broad ideas and slowly focused in on more specific concepts (Morgan *et al.* 2002). We first asked participants to describe how riparian areas produce each ecosystem service on their list, including any elements that go into the production process (Fig. 1). We also asked how those elements are related to each other. For instance, although higher water quality increases amount of available drinking water, sedimentation reduces water quality (Fig. 1b). In the second phase, we asked participants to describe if and how beavers affect the production of each benefit. As participants described processes, we further prompted them to explain each idea until no new ideas were produced (Morgan *et al.* 2002). We iteratively validated connections throughout the interview to ensure accuracy.

Data Analysis

To characterize landowners' perceptions about beaver-caused changes to ecosystem structure and function, we proceeded in several steps. First, we transcribed all interviews and constructed cognitive maps by searching interview transcripts for explicit or implicit cause-effect relationship statements using a "cause concept/linkage/effect concept" framework (Özesmi and Özesmi 2004). We used an exploratory approach, coding new concepts as we discovered them, rather than searching for predefined concepts (Carley and Palmquist 1992). The advantage of this approach is that it allows for greater diversity in concepts (Gray *et al.* 2014). We translated concepts from Spanish to English while coding, retaining original language as precisely as possible in order to preserve meaning. We iteratively re-read each transcript to check codes and linkages for meaning. We used the Mental Modeler software package (www.mentalmodeler.org) to draw cognitive

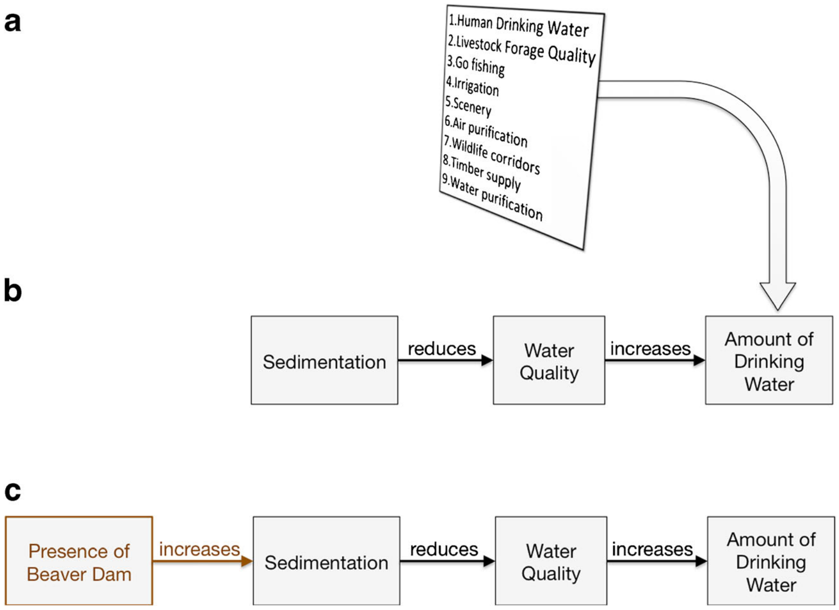


Fig. 1 Simplified mental model illustrating elicitation method: **a**) landowners freelisted the benefits provided by riparian areas, **b**) they identified pairwise relationships describing the production of each benefit, and **c**) they indicated how the presence of beavers affects each benefit

maps as we coded (Gray 2012). After completing each map we exported the corresponding adjacency matrix. Finally, we collapsed synonymous and highly similar nodes to increase interpretability and reduce the chance of artificially inflated diversity (Özesmi and Özesmi 2004; Gray *et al.* 2012; Borgatti *et al.* 2013).

We then identified and analyzed beliefs about how key salient ecosystem services are produced. We chose to limit our subsequent analyses to the two of the ecosystem services with the highest salience values: human drinking water and forage production for livestock. We built models explicitly representing aggregated knowledge about these two key services. We used UCINET (version 6.547) to aggregate (sum) all individual cognitive maps from landowners who had mentioned human drinking water and forage production (Borgatti *et al.* 2002). We identified pathways that linked beavers to each of the two ecosystem services, extracted models that included only the nodes falling on pathways from beaver to the ecosystem service of interest, and excluded nodes that did not fall on these pathways. Due to computational limitations of the software, the pathways extraction was limited to paths of seven ties or less.

Our final objective was to understand the degree to which landowners share perceptions of how beavers impact livelihoods and wellbeing as well as to examine the structure of those perceptions. We identified shared local knowledge by examining areas of agreement in each aggregated model. Each connecting tie in the forage and drinking water models had an associated "level of agreement;" this is the percentage of landowners in the sample identifying that particular tie in their individual cognitive map. We identified shared knowledge by progressively restricting our aggregated models so as to include only those nodes and ties shared by higher numbers of landowners. This created a series of network images that shows how shared knowledge is a function of level of consensus.

We characterized overall complexity and patterns of shared understandings about the production of each target ecosystem service by analyzing the aggregated maps holistically. Examining cognitive maps using network analysis can reveal patterns of thinking. In addition to the relative complexity of an individual's understanding of a phenomenon, it can reveal whether it is hierarchical (i.e., some ideas have a strong, top-down influence on the others), democratic (i.e., many interconnected ideas), highly central (i.e., connected to other well-connected nodes), or commonly held (Özesmi and Özesmi 2004; Knoke and Yang 2008; Borgatti *et al.* 2013). We examined five whole-network metrics: number of nodes, ties, pathways, density, and hierarchy index. Higher numbers of nodes, ties, density, or pathways indicate more complex beliefs about how the beaver influences an ecosystem service (Eden 2004). Density reflects cohesion in the network and is measured as the number of ties in a model as a proportion of the total possible connections between nodes (Özesmi and Özesmi 2004). Hierarchy indicates the degree to which the aggregated model represents democratic thinking (nodes are evenly interconnected) or hierarchical thinking (some nodes have stronger influence than others) (Özesmi and Özesmi 2004). Democratic thinking is integrative, and suggests that stakeholders perceive more options for intervention in a system, although each intervention might have a lesser overall impact on an outcome than in a hierarchically structured model (Özesmi and Özesmi 2004; Gray *et al.* 2014).

Additional insights about the structure of shared understanding can be gained by examining all possible paths from beaver to ecosystem service and the structural importance of nodes along a path. Nodes that occur on more paths connecting two nodes have greater structural importance in the aggregated cognitive map. We created a "pathway occurrence score" for each node, which represents the percentage of all pathways connecting beavers to a target ecosystem service that pass through the specified node. It indicates which nodes are most pivotal in the overall model. We calculated pathway occurrence (O_c) as:

$$O_C = T_{AB,C} \ /T_{AB}$$

where T_{AB} is the total number of unique pathways connecting an origin node *A* to an endpoint node *B* in a model, and $T_{AB,C}$ is the number of pathways from *A* to *B* that include node *C*. The measure is reported as a proportion. For example, if there are 1000 pathways that connect node A to node B, and 700 of them contain node *C*, $O_C = 700/1000 = 0.70$.

To assess the general overall influence of each concept in the network we calculated Bonacich's power value (beta centrality) for each node as a measure of the "total amount of potential influence a node can have on others via direct and indirect channels" (Rodan 2011; Borgatti *et al.* 2013). This metric measures how extensively and strongly connected a node is to other influential nodes (i.e., being connected to the well-connected). Bonacich power requires a choice of an attenuation factor that defines how strongly to weight the influence of surrounding nodes. Because we found little guidance provided in the literature on selecting the attenuation factor, we used the default value provided by the software.

Finally, we used an integrated approach to identify and characterize key groups of concepts in our aggregated models. Because no single metric provides a complete picture of the structure of the aggregated cognitive map, we used pathway occurrence, beta centrality, and the highest-consensus pathway to conduct a multivariate analysis. We included nodes with high scores for any single node-level metric in a nonmetric multidimensional scaling (NMDS) analysis. This analysis provides a multivariate visual representation of the pattern of similarities between nodes. We then conducted a hierarchical cluster analysis of the NMDS results using Ward's linkage in order to identify groups of nodes that had high in-group similarity and large between-group variation (Kachigan 1991). We qualitatively characterized each cluster of nodes to understand the overall influence of nodes in the aggregated model.

Results

We interviewed 41 of 63 landowners we contacted, including 25 landowners in Chile and 16 in Argentina (raw response rate = 65%). After removing ineligible respondents (e.g., unreachable due to non-working contact information) the adjusted response rate was 66% (AAPOR 2011a, b). Three interviews were unusable in the final analysis and the final usable sample size was 38. Landowner demographics were diverse in our small sample. The typical participant was male (88%), 56 years old (Range = 34 to 79), and managed 16,000 ha on average (Range = 365 to 100,000). Half (50%) of landowners had forestland on their properties. Each mental model elicitation took between 45 and 180 min, which is similar to previous research (Eden *et al.* 1979; Özesmi and Özesmi 2004; Gray *et al.* 2012). We found that the number of new concepts in each interview approached zero in our final interviews, suggesting that our sampling approached theoretical saturation (Morgan *et al.* 2002).

Free-Listing

Respondents listed a total of 61 unique ecosystem services provided by the water and riparian ecosystems found on their lands; and each landowner mentioned between three and 15 services (Appendix 1). The four most salient were provisioning ecosystem services, including: human drinking water (S = 0.30), animal drinking water (S = 0.29), better forage/grass (S = 0.20), and ability to irrigate (S = 0.15). The most salient cultural, supporting, and regulating ecosystem services, respectively, were landscape beauty (S = 0.09), general system health/balance of nature or biodiversity (S = 0.07), and erosion control (S = 0.06).

Mental Model Representations

We identified 934 concepts (i.e., nodes) used by landowners to connect beavers to ecosystem functions and services while coding our interviews and building cognitive maps. To increase interpretability and reduce redundancy, we collapsed those nodes representing highly similar concepts to 471 final nodes (see Santo 2015). A total of 34 landowners listed drinking water as an ecosystem service in their models, and 38 listed forage.

The two aggregated models representing shared perceptions about how beavers influence key ecosystem services (drinking water, forage) were structurally similar in number of nodes, ties, density, and hierarchy index, suggesting a similar overall structure to the mental model network (Table 1; Appendix 2). Density values were nearly equivalent and very low, suggesting that both models exhibited similar levels of complexity and were loosely connected. This indicates that knowledge of beaver-drinking water and beaver-forage connections was not cohesive. Supporting this, low hierarchy index values indicated that landowners exhibited democratic patterns of thinking about both domains (i.e., high integration and interdependence of ideas in the network) (Özesmi and Özesmi 2004), suggesting that they perceived beavers influencing each ecosystem service in diverse and intersecting ways.

Table 1 Network-level analysis metrics for characterizing the structure of two models that show pathways connecting beavers to ecosystem services

Metric	Human Drinking Water Model	Forage Quality Model
Number of nodes	293	297
Number of ties	1802	1793
Density	0.021	0.02
Hierarchy Index	0.0053	0.0049
Number of pathways	192,435	528,388
Sum of weighted pathways	1802	1793

Although the networks were similar across structural measures, the forage model had more than double the number of pathways as the drinking water model (Table 1). We also found considerably more feedback loops and nodes involved in feedback loops in the forage model than in the drinking water model (133,632 paths and 114 nodes versus 41,908 paths and 91 nodes, respectively). Because the number of pathways increases exponentially as the number of nodes increase, a small difference in number of nodes contributes to the large difference in pathways.

We did not find high levels of agreement regarding the process by which beavers were perceived to impact drinking water and forage. The number of nodes remaining on pathways in the drinking water model decreased by 74% as the level of agreement increased from four to five landowners (Fig. 2a). No pathways existed after a threshold level of agreement of nine landowners (26%). Pathway connections between beaver abundance and forage availability also declined abruptly but persisted longer than the drinking water pathways (Fig. 2b). All pathway connections were severed in the forage model when we examined agreement among 11 landowners (34% of the sample).

We found that the pathway nodes had low values of persistence in the models. For the drinking water model, the most persistent nodes were directly linked to either beaver abundance (dam and pond abundance) or the ecosystem service (water availability). The most persistent nodes in the forage model were those reflecting concepts generally related to beaver impacts (i.e., dam, pond abundance, size/intensity of flooding), vegetation growth (i.e., amount of vegetation, use of water for irrigation, and soil moisture), and livestock (i.e., amount of livestock, livestock drinking water). These nodes persisted longer on average in the forage model than in the drinking water model.

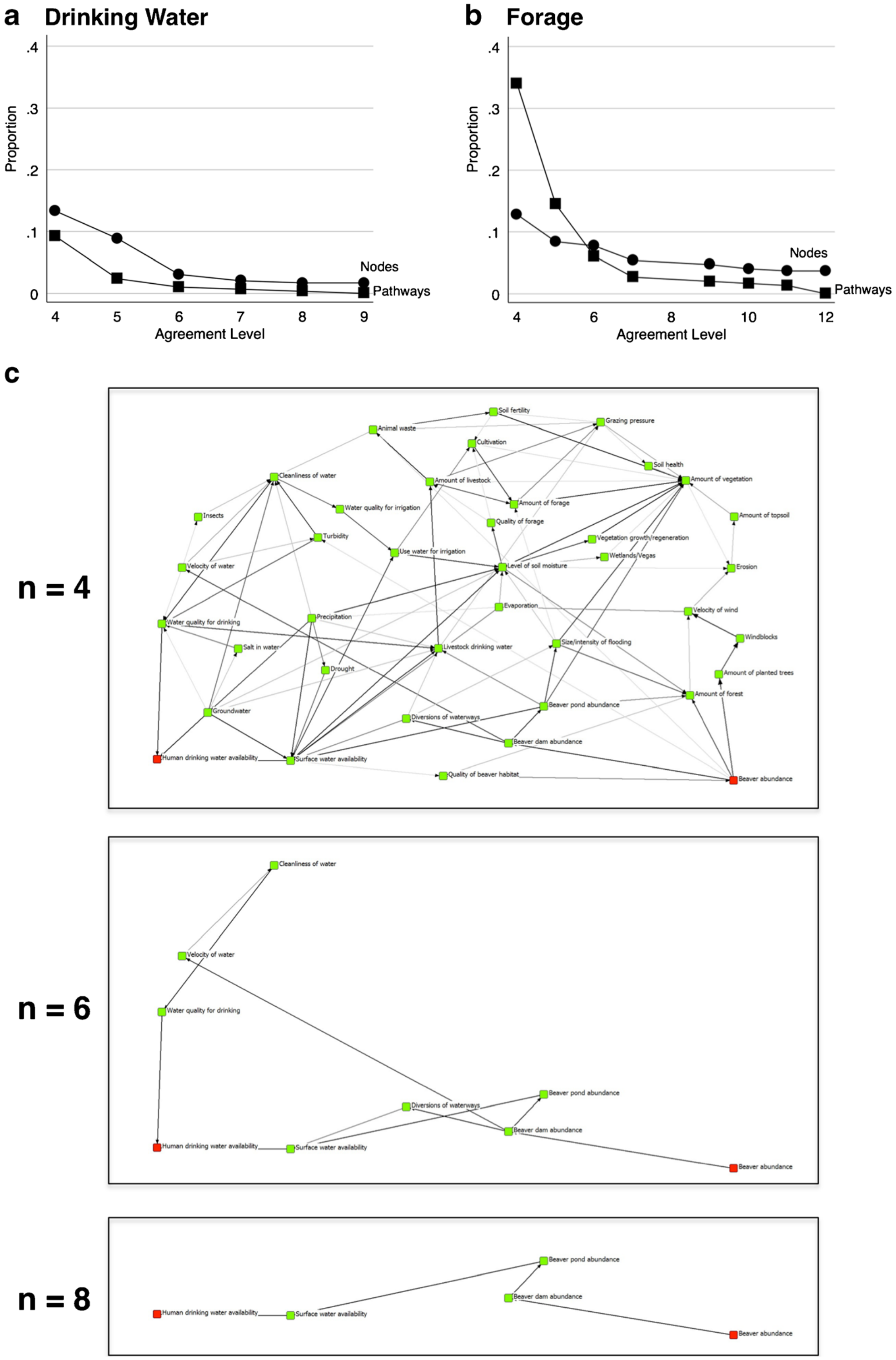
Overall, pathway occurrence values were low (Drinking water M = 0.09, Range: 0.00 to 0.43; Forage M = 0.09, Range: 0.00 to 0.41). These low levels indicate that even the most pivotal nodes in the models were only included in a minority of all possible pathways. Although some nodes did fall on a greater number of pathways than others, none were indispensable in connecting beavers to either ecosystem service because many alternate pathways existed.

Bonacich's power (beta centrality) results indicate a large majority of nodes were not well connected in either model; thus, most nodes were only peripherally connected to the network. However, some nodes were more influential and prominent than others due to their connectedness. Nodes with the greatest power or prominence in the network tended to be those with a direct influence on high persistence nodes. For example, in the drinking water model, *precipitation* had the highest beta centrality despite the fact that it occurred on less than 10% of the pathways. This indicates that although *precipitation* is not a common intermediate node connecting beavers to the ecosystem services, the ideas to which it is connected increase its prominence. Similarly, *precipitation* was highly central in the forage model without occurring on many paths. Other highly central ideas included *surface water availability* as an antecedent to *drinking water availability* and *season*.

Using pathway occurrence, beta centrality, and highest-consensus pathway to conduct a multivariate analysis, we found a three-cluster solution to provide interpretable results for both the drinking water and forage models. The y-axis (dimension 1) in the drinking water model was strongly associated with the persistence metric, with longer-persisting nodes toward the top of the graph (Fig. 3a). The x-axis (dimension 2) was associated with the Bonacich power metric but negatively associated with pathway occurrence. Square-shaped symbols at the top form a cluster (e.g., *beaver dam abundance*, *beaver pond abundance*, and *surface water availability*) representing "gatekeeper" concepts: highly agreed-upon concepts that scored relatively highly on all three metrics of importance. These nodes are proximal to the anchoring concepts of beaver abundance and drinking water availability. Groups two and three represent two unique groups of intermediate concepts. The nodes in group 2 (diamonds in Fig. 3a) tend to facilitate pathway connections between *beaver abundance* and *drinking water*. There is a moderate level of agreement amongst this group and they occur on a higher proportion of pathways. Finally, nodes in group 3 (circles in Fig. 3a) represent external influences. Despite the fact that these external factors (*season*, *air temperature*, and *climate*) are exogenous to the beaver-influenced system and tend to be on a lower proportion of pathways, their higher Bonacich power scores indicate that they are influential.

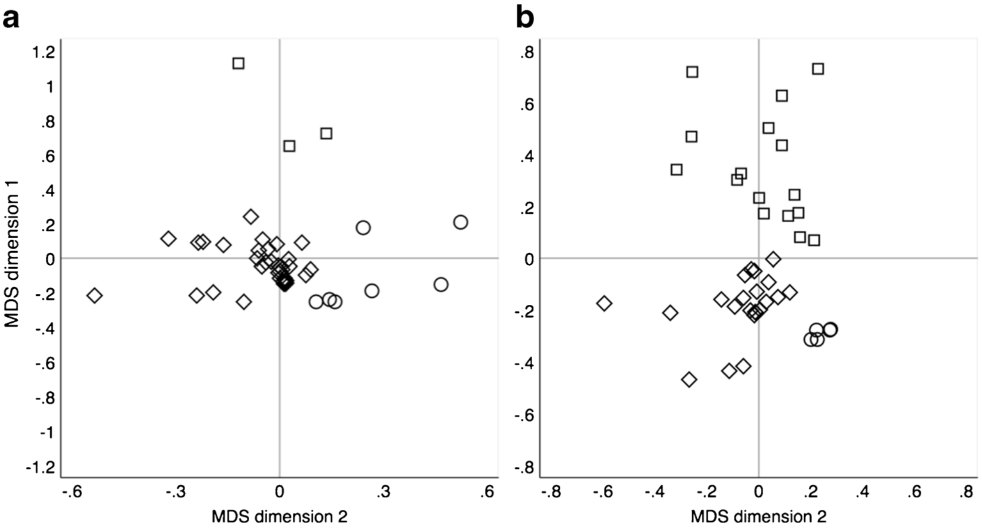
Our three-cluster solution for the forage model similarly identified groups of "gatekeeper" nodes, intermediate nodes (mediating and external influencer concepts), and a group of nodes related to a specialized style of livestock management practiced by a minority of TDF landowners (holistic management concepts). In the forage model, the y-axis (dimension 1)

Fig. 2 Pathway robustness measures of nodes and pathways for **a**) drinking water and **b**) forage availability. Panels in **c**) show only the nodes and ties connecting beavers to human drinking water that were shared by *n* = 4, 6, and 8 respondents



again is strongly related to persistence, loosely related to path occurrence, and somewhat related to beta centrality. Cluster 1 (squares in Fig. 3b) reflects nodes similar to those in the drinking water model's gatekeeper nodes (e.g., *beaver dam abundance*, *beaver pond abundance*, and *surface water availability*); however, it includes a greater number of nodes that also exhibited a higher than average persistence. These nodes (e.g., *amount of livestock*, *amount of vegetation*, *soil moisture level*, etc.) have higher agreement and occur on more pathways than other clusters. Cluster 2 (diamonds in Fig. 3b) includes nodes that mediate pathways from beaver abundance to forage (e.g., topsoil, forage quality, soil health) as well as external influences (e.g., climate, season). The third cluster (circles in Fig.) is populated with broad concepts typically

Fig. 3 Nonmetric multidimensional scaling for **a**) drinking water and **b**) forage. □ = Cluster 1, ◊ = Cluster 2, ○ = Cluster 3



identified with holistic livestock management (e.g., naturalness, system health, responsible livestock management, etc.) (see Savory and Butterfield 1998). Holistic management concepts occur on a relatively large number of paths but do not persist as the threshold of agreement is increased.

In sum, the structure of the mental models indicates that the key groups of concepts in the aggregated models are those that are nearest to the origin (i.e., beaver impact) and end point (i.e., ecosystem service) (see Appendix 2). Although there were a number of intermediate concepts, some nodes that were abiotic and exogenous (e.g., air temperature) were indirect influencers in the mental models.

Discussion

Landowner Knowledge Systems

We found that TDF landowners associate a wide variety of provisioning, regulating, supporting and cultural ecosystem services with water and riparian areas. However, they predominantly focus on provisioning services. This emphasis is unsurprising given that landowners depend on material yields for their livelihoods. Lower salience scores for cultural, supporting, and regulating services suggest that landowner mental models focus more on direct material outcomes for livelihoods and may not perceive as strongly the indirect causal connections between nonmaterial and material successes of their land and ranches (Zorondo-Rodríguez 2012). A similar focus on material provisioning services has been found across spatial scales and contexts while doing ecosystem service free-listing activities with rural communities (Rodríguez *et al.* 2006; Campos *et al.* 2012; Zorondo-Rodríguez 2012).

The overall structures of the knowledge systems of drinking water and forage production were similar in many ways, but differed substantially in persistence of nodes and feedbacks. In both models, we found that agreement was largely limited to the beaver's direct impacts (i.e., nodes that diverge from the beaver abundance node) or to factors directly affecting (i.e., that converge on) the ecosystem service of interest. This suggests that landowners perceive beavers' direct activity and some factors directly affecting ecosystem services, but there is little agreement on the exact mechanisms by which beaver activity influences ecosystem services. Further, despite ranking drinking water of higher importance than forage, shared knowledge about how beavers affect drinking water is more limited than knowledge about how they affect forage production. This suggests that landowners may have a more nuanced understanding of the beavers' impacts on forage production than drinking water. Considering that a great majority of landowners depend on forage for their livelihoods, they likely have a more extensive knowledge of ecological processes related to their livelihoods, and may not have such an in-depth understanding of factors contributing to ecosystem services not directly related to their livelihoods.

Our finding that local understandings surrounding beavers in TDF were diverse and divergent are comparable to other studies in the broader mental models literature. Researchers use diverse methods to elicit and analyze mental models (e.g., Lynam and Brown 2011; Papageorgiou 2014), complicating direct comparison between studies. We can, however, describe some commonalities. Stone-Jovicich *et al.* (2011) used consensus analysis to characterize patterns of agreement among mental models of water users in a South African catchment, and found low consensus regarding beliefs about causes and consequences of low river flows, key water users, and priorities for future water use. Abel *et al.* (1998) discovered that variation between individuals' mental models was greater than the differences between models representing group knowledge. Significant individual-level variation in mental models exists across contexts, as we observed in TDF landowners' mental models.

Understanding the structure of TDF landowners' mental models provides insight into the potential for cooperation to eradicate or control beavers. The diversity of local knowledge indicates that landowners are not unified in their understanding of how exactly beavers impact their riparian areas. This may inhibit efforts to gain cooperation as landowners may not all be in agreement. At the same time, scientists and managers can influence mental models that lack cohesion and hierarchy (Eden *et al.* 1979; Eden 2004; Özesmi and Özesmi 2004). Relatively flat cognitive structures indicate that causal links are not well elaborated. This suggests that there may be more opportunities to influence peoples' understanding of particular causal connections because those connections are not highly dependent on prior connections.

Understanding mental models is important as managers seek to frame the conservation issue to maximize cooperation for eradication efforts. Our research indicates that the landowners considered impacts on provisioning services to be most salient. Although public outreach and communication about beavers and the planned eradication in TDF incorporate some direct impacts to landowners, they predominantly focus on the beaver's impacts to the region's biodiversity and ecosystems and suggest that eradication will restore ecological integrity. For example, in the last two years the major newspapers in both Chilean and Argentine TDF have referred to beavers as "the species that devastates native forests," an "ecological disaster," and causing "great damage to the ecosystem" (La Prensa Austral 2013, 2014). The government agencies responsible for coordinating the proposed eradication often distribute similar messages, and describe the beaver with phrases such as, "a global problem that is intimately implicated in the extinction of biodiversity" (e.g., MMA 2014). Furthermore, a primary motive for eradication is to halt forest destruction in TDF and on the South American continent, and thus restore or protect the region's carbon sequestration capacity. The beaver's impacts to biodiversity, ecosystem health, and climate regulation are significant, and messages about these impacts are valuable for increasing awareness of the beaver's impacts. However, because they reflect conservation practitioners' intuitions about which ecosystem service impacts are of greatest concern, rather than an empirical understanding of stakeholder priorities, values, or knowledge, they may not be effective messages to garner the support of key stakeholders for eradication (Van Vugt 2009).

Mental Model Approaches to Understand Knowledge Systems

Mental models have been used for a variety of purposes, represented in variable ways, and used in a variety of contexts (e.g., Shepardson *et al.* 2007; Isaac *et al.* 2009; Thomas and Palmer 2015). No standard methodological approach is employed across studies or fields. Our approach differs from other studies in that it was not comparative and did not employ an expert model. We used an unconstrained method of free-listing and exploration of individuals' cause-and-effect beliefs about a complex phenomenon because we were interested in an emic approach that gives voice to landowners without making assumptions about their knowledge systems. While our data collection process adhered to a qualitative epistemology, our data analysis integrated structured coding and quantitative, descriptive metrics from network analysis.

These methodological tradeoffs are significant and merit discussion. On one hand, the network approach cleanly demonstrates explicit pathways in a mental model. This method generates highly detailed data on cause-and-effect beliefs and may thus be particularly suitable for answering some research questions. It also allows for direct comparison and compilation of multiple participants' knowledge systems. On the other hand, the method can produce large and unwieldy datasets when a simpler approach may suffice to answer a number of research questions. Merging elements from both qualitative and quantitative epistemologies increases the complexity of collecting and analyzing the data, and further consideration is needed to understand ways to bridge paradigms.

Further, a network approach risks simplifying nuanced beliefs or amplifying trivial distinctions, especially when concepts are combined in order to simplify analysis and interpretation. For example, landowners may consider trash, parasites, bacteria, algae, decomposing leaves, or toxins in water as "water pollution." In building a mental model, the researcher would have to choose which (if any) of these codes to combine into a single "water pollution" code. Collapsing codes will simplify interpretation and perhaps increase the ability to claim that knowledge is shared; however, there are clear differences between each of these types of water pollution and their implications for human and ecological health. We chose to retain detail in our models, recognizing that collapsing the nodes could obfuscate important differences between them, or even result in pathways that are no longer meaningful or interpretable. Many of these coding dilemmas parallel complications in purely qualitative approaches; however, the risk of obfuscating meaning is particularly high in this method given the explicit linkages between concepts and the temptation to simplify models to increase interpretability. This is an area of research that the broad mental models literature could explore by evaluating similarities and differences in insights drawn from purely ethnographic work compared to hybrid approaches to understanding knowledge systems.

Finally, we found that the current network analysis literature focuses on whole-network or node-specific measures;

there is little guidance for analyzing the pathways that connect nodes within cognitive maps or networks. In mental model research, pathways may be of key interest. Developing metrics that are specific to understanding the causal pathways between a specific origin and destination within a model could benefit this field. We created two simple metrics to understand knowledge pathways, but further metrics should be developed.

Conclusions

Overall, this mental models elicitation and analysis approach contributes to a growing body of literature about how mental models can be used to understand and characterize knowledge systems (Carley and Palmquist 1992; Jones *et al.* 2011; Lynam and Brown 2011; Papageorgiou 2014; Gray *et al.* 2015). We draw four key conclusions from the low levels of consensus observed in our forage and drinking water models.

First, TDF landowners may not share a singular "local knowledge" about how beavers affect key ecosystem services. There were myriad unique pathways connecting beavers to forage and drinking water in our aggregated models, and the number of nodes and ties in the network rapidly declined as we incrementally increased the threshold level of agreement for persisting in the model. Thus, we conclude that beliefs about exactly how beavers affect forage and drinking water are individualistic, diverse, and idiosyncratic, rather than widely shared.

Second, low consensus suggests that the beaver invasion may not be a highly relevant issue for a considerable number of landowners (see also Santo *et al.* 2015). The highest-consensus pathways in our forage and drinking water models were intuitive and relatively direct. Yet, they dissociated at less than 40% agreement. This suggests that landowners do perceive beavers and beaver activity, but they do not necessarily perceive them as a threat to important ecosystem services. Motivating participation in beaver control efforts may thus require the use of externally-motivating strategies, like financial or social rewards for participation.

Third, a lack of consensus may reflect an interaction of the relative recentness of beaver invasion combined with a lack of perceived threat to ecosystem services. Around 20 beavers were introduced in 1946, but they did not fully spread throughout the island until the 1990s. In many areas, just one to two generations of island residents have directly experienced beavers and their impacts to property. Given that beaver impacts are not seen as a direct threat to livelihoods, two generations may not be sufficient to develop common knowledge across time and space about how beavers alter the provisioning of ecosystem services.

Finally, we recognize a potential limitation in our study because our methodology was designed to gather highly detailed information about people's belief systems and may thus accentuate lack of agreement. We recognize that common themes in our data could be interpreted as "local knowledge" if the data were analyzed using qualitative methods. Additional research is needed to understand how variable methodologies differentially reveal shared knowledge. A key methodological issue with network analysis is to understand at what level to aggregate codes. For example, in our mental models, beavers may possibly affect both the *amount* as well as the *quality* of available forage. Some researchers may reduce the codes to a single broad concept of "forage" whereas others prefer to retain information about the means by which forage is impacted. This latter approach we employed may be preferable, as in our case, when exploring opportunities for finding human-centered solutions that enhance cooperation and collective action (e.g., Santo *et al.* 2015; Sorice and Donlan 2015).

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