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Research article

Fuzzy cognitive mapping in support of integrated ecosystem assessments: Developing a shared conceptual model among stakeholders

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ABSTRACT

Ecosystem-based approaches, including integrated ecosystem assessments, are a popular methodology being used to holistically address management issues in social–ecological systems worldwide. In this study we utilized fuzzy logic cognitive mapping to develop conceptual models of a complex estuarine system among four stakeholder groups. The average number of categories in an individual map was not significantly different among groups, and there were no significant differences between the groups in the average complexity or density indices of the individual maps. When ordered by their complexity scores, eight categories contributed to the top four rankings of the stakeholder groups, with six of the categories shared by at least half of the groups. While non-metric multidimensional scaling (nMDS) analysis displayed a high degree of overlap between the individual models across groups, there was also diversity within each stakeholder group. These findings suggest that while all of the stakeholders interviewed perceive the subject ecosystem as a complex series of social and ecological interconnections, there are a core set of components that are present in most of the groups' models that are crucial in managing the system towards some desired outcome. However, the variability in the connections between these core components and the rest of the categories influences the exact nature of these outcomes. Understanding the reasons behind these differences will be critical to developing a shared conceptual model that will be acceptable to all stakeholder groups and can serve as the basis for an integrated ecosystem assessment.

1. Introduction

It is widely accepted that the sustainable management of natural resources must include consideration of human interactions with the environment, not only from a unidirectional perspective (humans impacting natural systems or vice-versa), but with the understanding that these coupled socio–ecological systems are dynamic and have a variety of two-way interactions and feedbacks (An and Lopez-Carr, 2012; Liu et al. 2007). The realization that the use of natural resources is inextricably interwoven with the social, political, and economic complexities of human systems has led to these management challenges being called "wicked problems" (Xiang, 2013), *i.e.* "problems which are ill-formulated, where the available information is confusing, where there are many clients and decision makers with conflicting values, and where the ramifications in the whole system are thoroughly confusing" (Churchman, 1967). With an ever increasing number of wicked problems recognized in social–ecological systems throughout the globe (Sayer et al. 2013; Jentoft and Chuenpagdee, 2009; Ludwig, 2001) the idea of ecosystem-based management has gained traction, particularly in marine policy in the United States (NOAA, 2006). Ecosystem-based management (EBM) attempts to look at a defined geographic area in a holistic manner, defining management strategies for an entire system rather than individual components (Levin et al. 2009).

To successfully manage resources from an ecosystem-wide perspective it is necessary to gather pertinent information on all of the system components, but by definition the data available in instances of wicked problems are confusing, as no clear patterns are

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readily emergent, or if there are patterns they are often contradictory. One organizing framework to synthesize and analyze large amounts of confusing data to support EBM is the Integrated Ecosystem Assessment, or IEA (Levin et al. 2009). The IEA approach is a series of formal processes during which relevant stakeholder groups (including public representatives, scientists, managers and policy makers) synthesize existing knowledge regarding the ecosystem in question, set ecosystem management objectives, select management options, and then adjust future management actions based on feedback from continuing monitoring. The initial activity in the IEA process is the scoping step, during which stakeholder groups define the ecosystem to be addressed, review existing information, construct a conceptual ecological model that identifies ecosystem attributes of concern and relevant stressors, and develop appropriate management objectives (Levin et al. 2008). Generally, this step is conducted during one or more workshops (Hobbs et al. 2002; McClure and Ruckelshaus, 2007) where participants interact in a facilitated format designed to generate consensus on the ecosystem attributes and management objectives. However, there are concerns with the quality of both the process and the outcome when public participation is included in solving environmental issues (Gray et al. 2014; NRC, 2008). In particular, prior studies have shown that groups tend to converge on majority views, that powerful or influential individuals or groups may attempt to dominate or unduly influence the proceedings, and that quality processes and outcomes, especially those related to consensus building, can be cost prohibitive (NRC, 2008).

In light of the potential problems described above, there is a clear need for a strategy that can combine traditional scientific knowledge with public local context, thereby reducing uncertainty and providing for a diversified and adaptable knowledge base (Raymond et al. 2010; Gray et al., 2014). One methodology to improve stakeholder involvement that has been suggested is Fuzzy Logic Cognitive Maps (FCMs) (Axelrod, 1976). FCM are a simplified way of mathematically modeling a complex system (Özesmi and Özesmi, 2004), and have been used to represent both individual and group knowledge (Papageorgiou and Kontogianni, 2012; Gray et al., 2012). This approach has been applied to processes and decisions in human social systems, the operation of electronic networks, and in the ecological realm to identify the interactions between social systems, biotic, and abiotic factors in lakes (Özesmi and Özesmi, 2003, Hobbs et al. 2002), coal mine environs (Zhang et al. 2013), farming systems (Vanwindekens et al. 2013), fisheries (Gray et al., 2012), and nearshore coastal zones (Meliadou et al. 2012; Kontogianni et al. 2012a), but applications in estuaries or as part of a formal assessment process have been rare.

The FCM approach has several advantages to encourage its use in environmental management (but see Kok, 2009 for general limitations). Recognizing how stakeholders perceive relationships between components and the chains of cause and effect related to anthropogenic perturbations allows for the development of policy prescriptions that can be broadly supported by the community (Kontogianni et al. 2012b). A shared understanding of the important components and processes of the ecosystem in question is also critical if stakeholder groups are to fully “buy-in” to future management decisions (Ogden et al. 2005). The FCM methodology ameliorates many of the challenges associated with integrating the different types of stakeholder knowledge (Gray et al. 2014), and the transparent nature of the model combination allows stakeholders to identify how each groups' model contributes to the overall understanding. We do not expect the different groups' conceptual models to share all of the components; rather we anticipate these differences to be highly informative. Indeed, understanding why these differences occur is likely to help us avoid misunderstandings and disagreements during future phases of the IEA process (Kontogianni et al. 2012b).

In this paper we utilize fuzzy logic cognitive mapping to investigate differences in stakeholders' perceptions of the relationships within an estuarine system and develop a shared conceptual ecosystem model that can serve as the basis for an integrated ecosystem assessment. We begin by constructing stakeholder group conceptual models and then compare their structure and components for similarities and differences. We then combine those models into a shared community conceptual model. The final step is to compare the community model to that of the stakeholder groups to understand how combining the models effects our understanding of the ecosystem.

2. Methodology

2.1. Study site

The social ecological system we have chosen to study is the Barnegat Bay, a 279 km^2 lagoonal estuary located in central New Jersey, USA (Fig. 1). The surrounding 1730 km^2 watershed is home to an estimated 580,000 year round residents (US Census Bureau 2012), with a summer population that swells to over 1 million with the influx of tourists. The physical setting of the watershed is well described by Kennish (2001), but points germane to our study are repeated here. Land use is a mix of urban and suburban uses in the northeast and along the barrier islands, grading to less sparsely populated forested areas to the south and west. Portions of the E.B. Forsythe National Wildlife Refuge and the Pinelands National Reserve are located along the eastern and western sides of the watershed, respectively. There is limited extractive and agricultural land use, and other than minor hard clam and blue crab fisheries, no real commercial fishing. The watershed is considered “highly eutrophic” (Bricker et al. 2007), mainly due to nutrient enrichment through non-point source pollution, and the nation's oldest continuously operating nuclear power plant, Oyster Creek Nuclear Generating Station, is located within the watershed. There is extensive recreational use of the bay's waters for fishing, boating, sailing, and to a lesser degree, bathing.

2.2. Data collection

FCMs are models of a how a system operates based on key components and their causal relationships. The components can be tangible aspects of the environment (a biotic feature such as fish or an abiotic factor such as salinity) or an abstract concept such as aesthetic value. The individual participants identify the components of the system that are important to them, and then link them with weighted, directional arrows. The weighting can range from −1 to +1 (Hobbs et al. 2002; Özesmi and Özesmi, 2004; Gray et al., 2012), and represents the amount of influence (positive or negative), that one component has on another.

To collect FCM from a wide variety of stakeholders with knowledge of the Barnegat Bay ecosystem we contacted the Barnegat Bay Partnership, a US Environmental Protection Agency National Estuary Program, to obtain a list of their management and science committee members, as well as a list of public citizens who have expressed long-term interest in the ecosystem. While the map of an individual stakeholder provides information regarding that particular individual's conception of the important components and linkages within the system, it can be combined with other individuals within the group to produce a more robust picture of the group's understanding of the system (Özesmi and Özesmi, 2004). In addition, all of the individual stakeholder maps can be combined into a single map depicting the collective understanding of the system. To this end, the individuals were divided into four

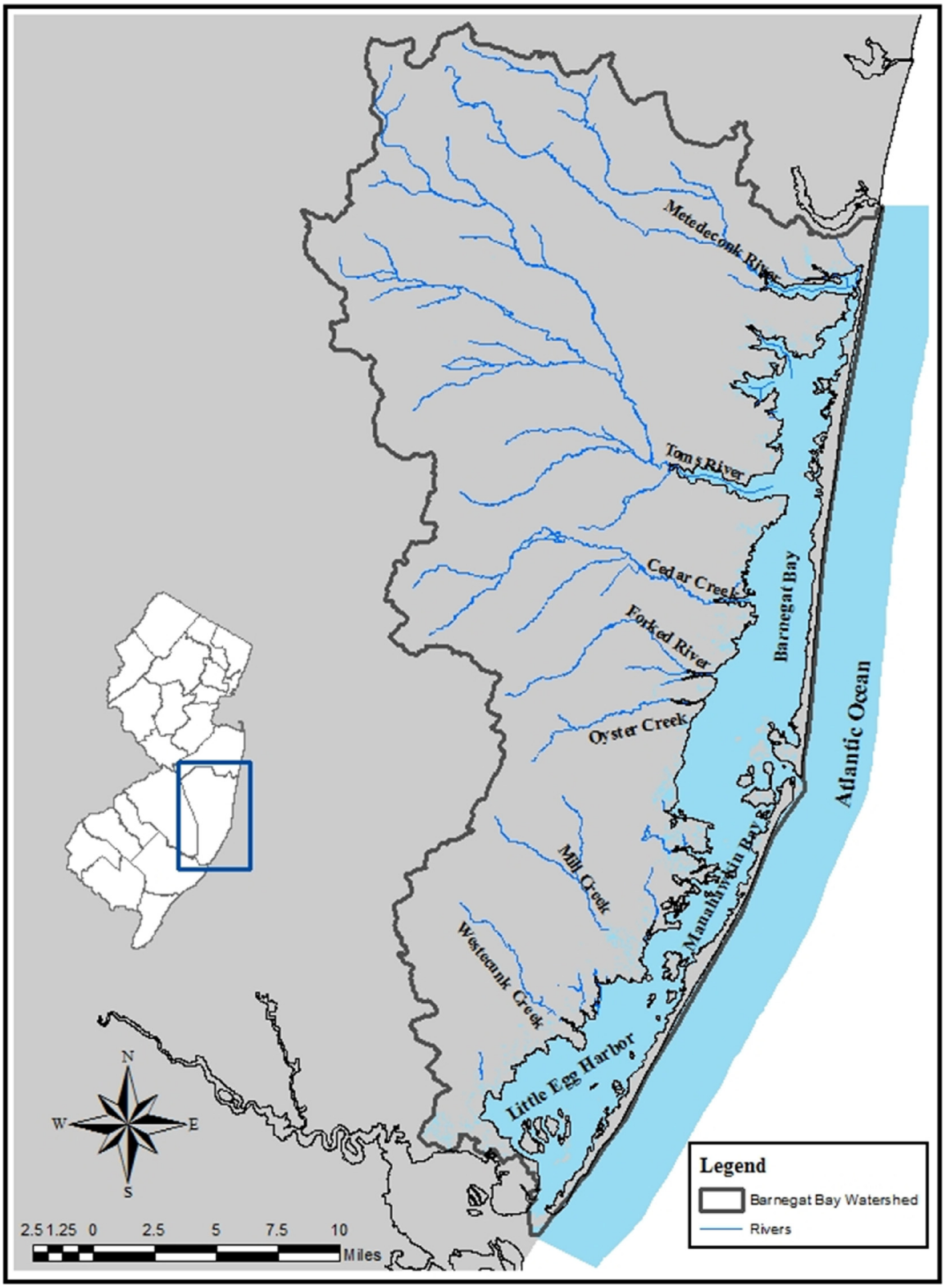

Fig. 1. Map of Barnegat Bay watershed with New Jersey inset.

groups that were determined *a priori*: scientists (n = 19), managers (n = 11), environmental non-governmental organizations (n = 6), and local residents (n = 6) (Table 1). These groups were selected to represent several (though not all) of the major categories of stakeholders present in ongoing efforts to manage and improve the bay's natural resources. The scientist group consisted of individuals from academia, state, and federal institutions who have conducted research within the Barnegat Bay watershed, while managers were from federal, state, county, or local natural resource management agencies who had jurisdiction on some form of activity within the watershed. Environmental non-governmental organizations included local, statewide, and regional groups who are active in watershed protection. The local residents were referred to us by other interviewees, and included commercial fisherman, baymen, and long-term residents with a long-standing interest in the bay.

In accordance with the procedures used in prior studies (Carley and Palmquist, 1992; Özesmi and Özesmi, 2004; Gray et al., 2012) individuals were interviewed separately, and each interview began

Table 1
Information on stakeholders who completed fuzzy cognitive maps on the Barnegat Bay social–ecological system.

Stakeholder group	Maps (N)	People (N)	Occupation/organization/social group
Scientists	19	19	Academic scientists, federal and state agency research scientist
Managers	11	11	Federal, state, county, and local resource managers
Environmental NGOs	6	6	Regional, statewide, and local environmental non-profits
Local people	6	6	Baymen, commercial fisherman, longtime (+40 year) residents

with an overview of the project, a promise of anonymity, and an example of a simple FCM related to an issue outside of the realm of ecology, namely traffic flow. Interviewees were then asked to describe what they considered to be the key components of the Barnegat Bay social–ecological system and how those components relate to one another. They were then asked to score the strength and direction of the relationship using positive or negative; high, medium, or low. The discussion continued until the interviewee was satisfied that the map as drawn accurately depicted their understanding of the system. This ranged anywhere from 45 min to 180 min, with the typical session lasting 90 min. Once mapping was complete, the interviewees were asked which of the components in their maps they would like to see increased and which decreased. The interviews were conducted under an approved human subjects protocol (number: E13-560).

2.3. Data analysis

There are a number of different methods that can be used to analyze the data contained within an FCM, many of which are based upon graph theory (Harary et al. 1965; Özesmi and Özesmi, 2004; Kosko, 1991). To better understand the structure of an individual FCM we translated each map into a square adjacency matrix, with all of the variables acting as potential transmitters (influencing other variables) v_i on the vertical axis and the same set of variables acting as receivers (influenced by other variables) v_j on the horizontal axis (see Supplemental Fig. 1 for an example). A list of all individual variables mentioned throughout the process was compiled and redundant variables (plurals, different names for the same species, *etc.*) were eliminated. When two variables represented opposite directions of the same concept (*i.e.* dam construction and dam removal) the more prevalent variable was retained and the other variable was renamed, with the polarity of the interactions reversed, in keeping with accepted practices (Kim and Lee, 1998). The interactions strengths between variables were then scored, with high interactions scored as 0.75, medium as 0.5, and low as 0.25 (Harary et al. 1965).

To more easily understand the components and patterns within an individual FCM it is often helpful to simplify the map by reducing the number of variables (Harary et al. 1965). After all of the maps were completed we listed the full set of variables and identified those most often mentioned. We then subjectively combined less frequently mentioned variables into larger categories based on shared characteristics, a process known as qualitative aggregation. For example, “homes”, “urban development”, “housing”, and “overdevelopment”, were combined, with a number of other similar variables, into a category called “development”.

With the large list of variables reduced into broader categories, the type of categories, and number of each, were identified to provide additional insight into the overall structure of the map and how these categories relate to each other (Bougon et al. 1977; Eden et al. 1992; Harary et al. 1965). Each category was classified as transmitter, receiver, or ordinary (both influenced by and influencing other categories), based on its indegree and/or outdegree (Table 2). Indegree is the cumulative strength of the connections entering the category (sum of the absolute values within a column in the matrix), while outdegree is the cumulative strength of the connections exiting the category (sum of the absolute values within a row in the matrix) (Özesmi and Özesmi, 2004). A transmitter category has positive outdegree and no indegree, a receiver category has no outdegree and a positive indegree, and an ordinary category has positive indegrees and outdegrees (Bougon et al. 1977). Finally, the centrality, or a measure of a category's connectedness to other categories within the map, as well as the overall strength of those connections, was calculated as the sum of the indegree and outdegree values of a given category (Harary et al. 1965).

Indices of complexity and density were also determined for each stakeholder map. The complexity of a map is calculated as the ratio of receiver categories to transmitter categories (R/T). A large number of receiver categories in a map suggests a system where there are multiple outcomes (Eden et al. 1992), while a large number of transmitter categories suggest that a system is hierarchical in nature, and driven by “top down” thinking (Özesmi and Özesmi, 2004). Density describes how well connected categories are within the map, and is determined by dividing the number of connections present by the maximum number of connections possible (Hage and Harary, 1983). A dense map suggests that an interviewee (or stakeholder group) perceives a number of possible pathways to influence a variable in their map (Özesmi and Özesmi, 2004).

In addition to developing indices for each individual map, maps were combined 1) within stakeholder groups to produce four group maps and 2) across all individuals to produce a community map. To combine maps the connection values between two given categories are added, so connections represented in multiple maps are reinforced (provided they have similar signs) while less common connections are not reinforced, but are still included in the map (Özesmi and Özesmi, 2004). To compare connection values across group maps, the summed values are divided by the number of individuals in the group.

Non-metric multidimensional scaling (nMDS) was used to assess the similarities between individual stakeholder maps (R v3.0.2). This technique orders samples by rank similarity along their two most important latent gradients and has an advantage over other ordination techniques in that it has a greater ability to accurately represent complex relations among samples in two-dimensional space (Clarke and Warwick, 2001). The nMDS data were calculated as each category's centrality score for an individual stakeholder and then the Bray Curtis index was used to construct the sample similarity matrix (variable by stakeholder array). The nMDS plot was then visually assessed to identify patterns between stakeholder groupings.

Besides understanding the structure of the stakeholder groups' and community maps, maintaining the initial conditions through time allows us to determine if the model will coalesce around a stable state, go into a limit cycle, or enter into a chaotic pattern (Dickerson and Kosko, 1994). To generate this steady state, the adjacency matrix of the cognitive map is multiplied by an initial steady state vector (a value of 1 for each element of the vector). The resulting vector is then subject to transformation using a logistic expression ($1/(1+e^{-1\times x})$) to bound the results in the interval [0,1]

Table 2
Fuzzy cognitive map indices.

Term	Definition
Indegree	Cumulative strength (absolute value) of the connections entering a category
Outdegree	Cumulative strength (absolute value) of the connections exiting a category
Centrality	Sum of the indegree and outdegree for a given category
Receiver	A category with a positive indegree and no outdegree
Transmitter	A category with a on indegree and a positive outdegree
Ordinary	A category with positive indegree and outdegree
Complexity	The ratio of receiver categories to transmitter categories within a map (R/T)
Density	The number of connections within a map divided by the total connections possible between categories (C/N^2)

(Kosko, 1987). This new vector is then multiplied by the original adjacency matrix and again subject to the logistic function, repeating these steps until an end result is reached.

If the model reaches a steady state outcome, it is then possible to run hypothetical "what-if" scenarios to compare the function of the various models. The hypothetical scenario developed for our simulation was to maintain the category "development" at 0, which is a possible policy prescription, albeit a potentially unpopular one. To do this we utilize the process described above to determine the stable state, but this time the value of the category "development" in the vector is maintained at 0 in each time step. Setting the value of a category of interest in the multiplication vector between 0 and 1 at each time step was referred to as "clamping" by Kosko (1986). The difference between the values of the final vector of the clamped procedure compared to the steady state vector describe the relative change to the conceptual system given the framework provided by each stakeholder group. A conceptual schematics of map aggregation and steady state calculations are provided in Supplemental Fig. 1 and a flow diagram of the steps in the data analysis process is provided as Supplemental Fig. 2.

3. Results

We created fuzzy cognitive maps for 42 individuals from the four targeted stakeholder groups (Table 1). The stakeholders identified 346 unique variables as important to understanding the Barnegat Bay social – ecological system, which were then aggregated into 84 categories for further analysis. Individual maps contained an average of 25 variables, which when aggregated led to an average of approximately 20 categories per map. The average number of categories in an individual map was not significantly different among groups, with the exception of NGOs ($p = 0.02$), who had an average of nearly 30 categories per map (Table 3). An examination of the accumulation curves for the total number of categories versus the number of interviews shows that the managers and scientists were well sampled, while the NGO and local residents' curves had not yet flattened out (Supplemental Fig. 3). Representatives from all of the NGOs active in the watershed at the time of the study were interviewed, limiting the number of samples of available. The pool of potential interviewees who met the criteria for the local resident group was also limited in size. However, the trajectories of these two groups is similar to that of the scientists and managers, suggesting that few new categories would have been added through additional interviews.

There were no significant differences between the groups in the average complexity ($df = 38$, $p = 0.492$) or density ($df = 38$, $p = 0.129$) indices of the individual maps (Table 3). The environmental NGOs and local residents had slightly higher complexity scores (more receiver categories) than the other two groups, while the managers and scientists had slightly higher average densities. The community map, by definition, contained the full suite of categories, but had an order of magnitude more connections than the group maps, leading to a map with the most interconnections between categories, and therefore the highest density. The increased number of interconnections in the community map led to all of the categories being classified as "ordinary" (i.e., both a transmitter and a receiver), with the exception of biodiversity, which was a receiver category. A subset of the community map that includes the categories with centrality scores greater than one, and their interconnections, is shown in Fig. 2. For a complete list of all variables and their centrality scores please see Table S1 in the Supplemental information.

When ordered according to their centrality scores, eight different categories contributed to the top 4 rankings of the stakeholder groups, and six of the categories were shared by at least half of the groups (Table 4). Development had the strongest interactions for managers and local residents and was second only to nutrients for scientists and NGOs. Pollution, bay water quality, seagrass, and human population were also key shared categories, though the strength of the interactions, and their ranking, varied between groups. The outdegree strength for development and human population was at least two times that of the indegree, while pollution and bay water quality had indegrees slightly larger than outdegrees. The direction and magnitude of the strengths for seagrass varied between groups, with local residents giving it a moderately larger outdegree and scientists scoring the indegree twice as high.

There was substantial overlap in nMDS space between the individual cognitive maps of scientists and all other groups, moderate

Table 3
Graph indices by stakeholder group. All values, except for number of maps, are mean and standard deviation.

	Scientists	Managers	Environmental NGOs	Local people	Community
Maps	19	11	6	6	42
Number of categories (N)	20.6 (4.3)	21.2 (5.3)	29.8 (13.4)	19.3 (3.6)	84
Number of transmitter categories (*T*)	5.1 (2.7)	4.4 (2.7)	5.8 (3.3)	4.7 (2.5)	0
Number of receiver categories (*R*)	3.2 (2.8)	2.3 (1.9)	4.5 (2.9)	4.3 (1.8)	1
Number of ordinary categories	12.3 (4.3)	14.5 (4.0)	19.5 (10.8)	10.3 (2.7)	83
Number of connections (C)	38.3 (13.3)	49 (17.8)	64 (40.7)	29.5 (9.3)	1071
C/N	1.9 (0.5)	2.3 (0.6)	2.1 (0.5)	1.5 (0.4)	12.75
Complexity (*R/T*)	0.7 (0.8)	0.6 (0.5)	0.9 (0.5)	1.1 (0.6)	
Density	0.09 (0.03)	0.11 (0.04)	0.08 (0.03)	0.08 (0.02)	0.15

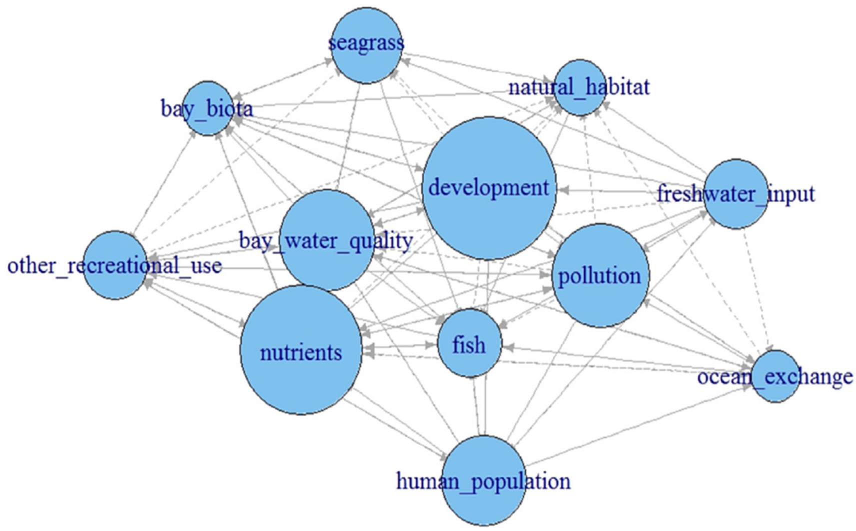

Fig. 2. Subset of the community conceptual model. The twelve nodes with centrality scores greater than 1.0 are shown. Node size is related to centrality score, solid lines are positive interaction strengths, dotted lines are negative interactions strengths.

Table 4
Category centrality scores by stakeholder group. Centrality is the sum of the indegree and outdegree for each category and is an index of its connectedness to other variables within the map. The categories included below represent the top four categories of each stakeholder group.

	Scientists	Managers	Environmental NGOs	Local people	Community
Development	1.91	3.93	3.50	3.0	2.75
Human population		3.15		2.48	
Bay ecological condition				2.25	
Seagrass	1.68			1.92	
Bay water quality		3.27	2.75		1.96
Nutrients	3.10		4.25		2.48
Pollution		3.03	3.29		2.00
Fish	1.33				

overlap among managers and NGOs and local residents, and little overlap between NGOs and local residents (Fig. 3a). The individuals within each stakeholder group were spread along both nMDS axes, indicating that there is a diversity of conceptual models within each group. When viewed as aggregated stakeholder groups, the Scientist and NGO conceptual models are most similar, while the others are quite dissimilar (Fig. 3b).

The hypothetical scenario model run further elucidated similarities and differences between the conceptual models of the stakeholder groups (Fig. 4). When development was clamped to a low level, nutrients and pollution, two of the more central categories in all groups' models, both decreased compared to the steady state models, though the degree of decline varied among groups. The declines in these two categories were driven primarily by the direct linkages participants made between them and development. The increase in bay water quality and decrease in gelatinous zooplankton (primarily identified by participants as the nuisance jellyfish *Chrysaora quinquecirrha*, or stinging sea nettle) across all groups' models appears to be driven by a number of indirect linkages to development. In the case of bay water quality, one potential pathway identified was a decrease in development leading to a decrease in impervious surfaces, which lead to a decrease in runoff, which improved bay water quality. While the prior examples showed concurrence in the effects of low development across the groups' models, they differed in the outcome of the economic value category; the NGOs' and locals' models predicted a decrease in economic value associated with a decrease in development, while the managers' models predicted an increase in economic value.

4. Discussion

4.1. The applicability of FCMs in estuarine environments

Fuzzy cognitive maps have been used to model stakeholder perceptions of causal relationships in social–ecological systems in a variety of settings (Özesmi and Özesmi, 2003; Meliadou et al. 2012; Gray et al., 2012, Kontogianni et al. 2012a; Vanwindekens et al. 2013; Zhang et al. 2013). This study is the first to apply the methodology to an estuarine ecosystem. Estuaries are both an ecosystem in their own right as well as an ecotone between terrestrial and aquatic and between freshwater and the ocean. Thus, we might expect that people's perceptions of estuaries could be more heterogeneous than FCMs of other systems. The complexity of estuaries is reflected in the large number of unique variables mentioned by the stakeholders during the creation of their FCMs. While caution should be used when comparing FCM indices between studies due to potential differences in methodology (Eden et al. 1992), the number of variables recorded in this study exceeds those compiled using similar methods for a large lacustrine system (Özesmi and Özesmi, 2003) and a nearshore coastal region (Meliadou et al. 2012). This level of detail was not driven by a small number of stakeholders in any particular group; the mean number of categories per map, complexity, and density were all similar across groups, suggesting that all of the stakeholders recognize the complexity and multidimensionality of estuaries.

A potential downside to this is the resulting intricacy of the overall community model, which still includes 84 categories after aggregation. Jørgensen (1994) theorized that quantitative

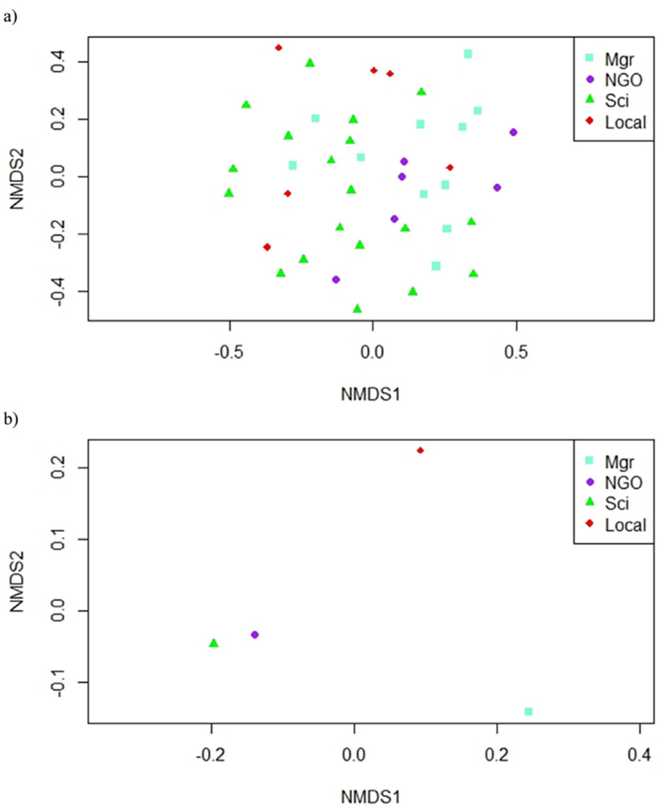

Fig. 3. nMDS plot of the a) individual and b) stakeholder group fuzzy cognitive maps based on centrality scores. Because nMDS is a non-metric procedure, the axes labeled NMDS1 and NMDS2 have no units associated with them. Stress values were 0.279 and 0.169, respectively. Stakeholder groups include Managers (Mgr), Environmental non-governmental organizations (NGO), Scientists (Sci), and Local residents (Local).

ecological models have a bell-shaped curve in regard to performance verses complexity, and others have suggested that cognitive maps are most easily interpreted when the number of variables ranges from the low teens (Buede and Ferrell, 1993) to 30 (Özesmi and Özesmi, 2004). Due to its semi-quantitative nature it is difficult to determine how close a FCM approximates the realities of the social–ecological system. However, the models developed here reach a stable state during the scenario analysis in less than 10 iterations and generally follow well established ecological theory, providing additional support for the validity of the findings.

While fuzzy cognitive mapping is robust enough to handle the large number of variables associated with a complex ecosystem, the applicability of this technique is constrained by how well (or poorly) it handles non-monotonic responses (Carvalho, 2013). This is particularly true for temperate estuaries, where long gradients in environmental factors like temperature and salinity can lead to dome-shaped response curves. Many of the interviewees attempted to side-step this issue by framing the response in terms of what they anticipated the departure from the current range of the condition would be. For example, interviewees said that increased temperature would lead to an increase in the abundance of a given biota (through some physiological or habitat mediated mechanism) up to some degree, after which increasing temperatures would lead to decreases in abundance. They then posited that it would be unlikely that temperatures in the estuary would ever exceed the inflection point, and thus the overall response is positive. This solution is similar to that previously identified by Hobbs et al. (2002) in their construction of an FCM for Lake Erie. Differences in an individual's interpretation on how best to address non-monotonic responses likely led to conflicting causal relationships when aggregating FCMs for the community map. Thus the response of some categories to changes in the scenario model is dampened, though based on notes taken during the interview process it would be limited to a few biotic components and the strength of the interactions tended to be low.

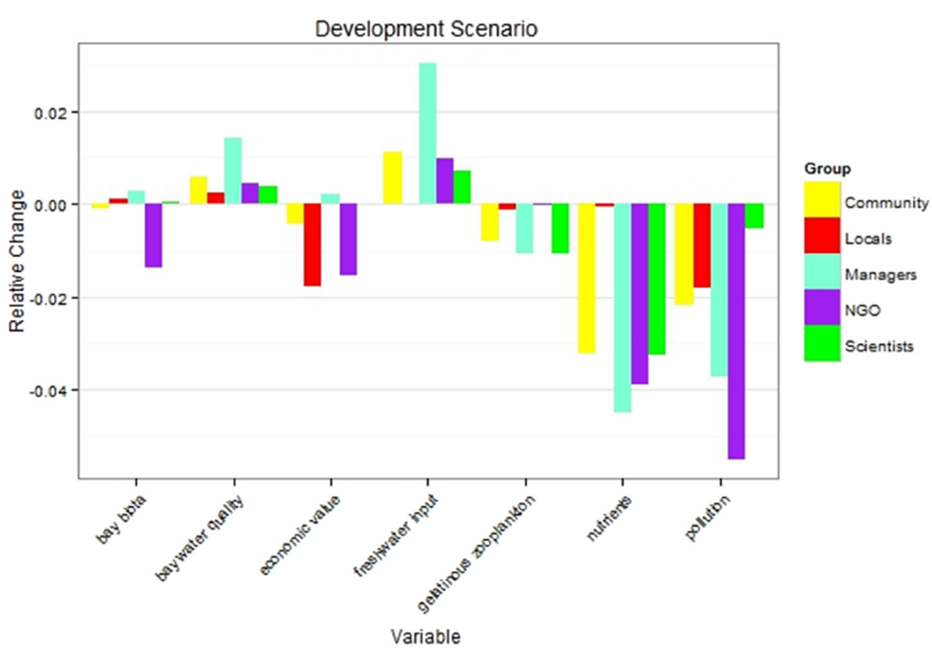

Fig. 4. Results of the scenario model when development was clamped to a low level. Relative change along the y-axis is the difference between the "low development" scenario compared to the initial steady-state solution for a given category. Stakeholder group models were constructed for Local residents (Local), Managers (Mgr), Environmental non-governmental organizations (NGO), Scientists (Sci), and an aggregate of all cognitive maps (Community).

4.2. Similarities and differences in stakeholder cognitive models

To develop a comprehensive management plan for complex systems a shared understanding of the components among the stakeholders is a prerequisite (Ogden et al. 2005). The findings of this study suggest that while all of the stakeholders interviewed perceive the Barnegat Bay ecosystem as a complex series of social and ecological interconnections and shared common structural elements, there are differences in the components and linkages of their aggregated conceptual models which influence the final state of the system. There is a core set of components that are present in most of the stakeholder groups' FCMs and have high centrality scores; the stakeholder groups all agree that these components are crucial in managing the system towards some desired outcome. However, the number and strength of linkages between these key components and the rest of the social–ecological system varies, such that the FCMs of two stakeholder groups can have opposite outcomes. This was seen in the scenario modeling, where low levels of development through time led to an increase in the economic value of the bay in the Manager's FCM and a decrease in economic value in the NGO and Local models.

One potential reason for the opposing results in the group models may be the primary focus of the groups themselves, including their conception of the relevant "social" dimensions of the system. The individuals comprising the Manager group are tasked with regulating the use of the biological resources of the estuary (fish, crabs, clams, birds), and in their maps a decrease in development yields an increase in biomass and a concomitant increase in economic value through commercial harvest or other recreational opportunities. In contrast, the environmental NGOs often take a broadly anthropocentric view of the social–ecological interactions of the estuary, and their maps contained social and political actors that were not mentioned by others. These social concepts (taxes, land price) often had strongly positive relationships between development and economic value.

While the aggregated community map incorporates multiple perspectives, and thus should be a more complete representation of the system (Gray et al., 2012), being able to articulate where, and why, stakeholder groups may have similar or diverging views on important causal relationships will be critical to developing the consensus approach needed to plan appropriate management actions for protection and restoration. A starting point for understanding the convergences or divergences is seen in the arrangement of the group maps in the nMDS, which suggests that the scientists and NGOs place similar importance on a broad variety of categories. This stands in contrast with the managers and local residents, who do not share similar centrality scores among categories. Thus one would expect, and should plan for, the additional effort that will be required to bring these two groups to consensus.

4.3. Further FCM benefits

By combining the individual models into stakeholder group models and into a shared community model we were able to combine the knowledge of both traditional and non-traditional experts, reducing uncertainty and filling in data gaps (Papageorgiou and Kontogianni, 2012). However, gaps in our knowledge and uncertainty about the interaction between components may still exist. Opposite interactions (positive versus negative) between two components shared across groups' conceptual models may reflect differences of opinion or perspective but also may point to areas where the understanding of the relationships between concepts is incomplete, such as the effects of climate change on biodiversity and species invasions, and changes to the bay's water quality associated with changes in freshwater input. The identification of these knowledge gaps through FMCs combined with the management objectives developed during the initial stages of the integrated ecosystem assessment will allow for a prioritization of future research and funding needs. These divergences may also indicate subjects where more recent scientific findings have not yet been widely incorporated by those outside specific fields of study (*i.e.* saltmarsh–nutrient interactions, biochemical and physical induced changes in nutrient loads, the pathway and flow of nutrients around the bay) and therefore where additional education/outreach may be warranted.

Additionally, the community map can assist in the selection of variables for monitoring once a course of actions has been agreed upon. Given a modeled scenario, or suite of scenarios, the components along the causal chain can be identified, eliminating potential indicators that are not responsive to the management efforts proposed, or do not meet the criteria for informative indicators (Rice and Rochet, 2005). This is particularly important in an age of shrinking research budgets and results-focused management at resource agencies.

5. Conclusion

We have shown that Fuzzy Cognitive Mapping can be a useful tool for organizing the intricate connections between social and ecological concepts within a highly complex ecosystem, and when applied across stakeholder groups can elucidate not only those mechanisms for which there is a shared understanding, but also highlight where additional resources should be focused to gain the greatest insights into system operation. While subject to limitations associated with the semi-quantitative nature of the approach and the representation of non-monotonic response variables, FCMs can nevertheless serve as a basis from which the initial steps of an Integrated Ecosystem Assessment can proceed. In particular, the individual interview procedure utilized herein avoids some of the pitfalls associated with group participation in the scoping process and provides a clear scaffolding upon which potential management and policy scenarios can be evaluated.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.jenvman.2015.10.038.

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