

Quantitative *vs.* Semiquantitative Ecosystem Models: Comparing Alternate Representations of an Estuarine Ecosystem

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ABSTRACT

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As the management of marine and coastal resources continues to move toward an ecosystem-based approach, there is a need for tools that can match the scope and complexity of the systems in question. This article contrasts the strengths and weaknesses of two types of models that can be used to understand ecosystem-level changes: Ecopath with Ecosim, a whole-ecosystem trophic-based quantitative model, and a semiquantitative fuzzy cognitive mapping conceptual model developed by local stakeholders. It also compares the modeled results of reducing nutrient loads to a temperate estuary to understand how the different approaches can be best utilized to meet the needs of resource managers. Both models responded to the nutrient load reduction in a similar fashion, despite the differences in data sources, approaches, and methodology. This congruence between the two methods most likely reflects a shared conceptual understanding of the ecosystem between scientists and stakeholders. The largest benefit from the strengths of both models is gained by using them in combination; the fuzzy cognitive mapping model can scope out critical components and interactions to be included in the Ecopath with Ecosim model. The latter model can then be parameterized and “what-if” scenarios run to ascertain the patterns and magnitudes of changes that can be expected.

ADDITIONAL INDEX WORDS: *Ecosystem-based management, fuzzy cognitive mapping, Ecopath with Ecosim, Barnegat Bay.*

INTRODUCTION

As human pressure on the planet’s ecosystems continues to increase, the management paradigms that previously served as a framework for ensuring sustainability have not been able to prevent widespread degradation and losses in ecosystem services (Millennium Ecosystem Assessment, 2005). The perceived failure of these management structures, which typically addressed environmental impacts using a single sector–based approach (Pew Oceans Commission, 2003), has led to a shift toward ecosystem-based management (EBM) (Ecosystem Principals Advisory Panel, 1998; U.S. Commission on Ocean Policy, 2004). EBM is an integrated approach that considers the interaction between ecosystem components and the cumulative effects of a full range of management activities (Rosenberg and McLeod, 2005). This broad definition of EBM describes a gradient of interconnectivity from a focus on multispecies interactions across a range of trophic levels (including some abiotic factors) to a comprehensive view that includes a range of human impacts (Hilborn, 2011).

In the context of the management of marine and coastal resources, a number of quantitative modeling approaches, varying in their complexity and data requirements (Plagányi, 2007), have been developed to evaluate EBM strategies. A suite

of models extend single-species assessment to account for additional interactions, such as predation (e.g., ESAM, Livingston and Methot, 1998). Some models are restricted to a few species (e.g. predators and prey) most likely to have important interactions with the species of interest (e.g., MSVPA, Pope, 1991; MRM, Punt and Butterworth, 1995). Others attempt to capture all trophic levels in the ecosystem as well as important physical forces (e.g., Ecopath with Ecosim, Christensen and Walters, 2004; ATLANTIS, Fulton and Smith, 2004). By incorporating a wide range of important biotic and abiotic variables, multitrophic-level quantitative models are able to replicate historic changes in natural resources of interest. A “fitted” model (one compared with known data) can then be used to provide formal management advice (Fulton, Smith, and Smith, 2007), investigate the broad-scale effects of different management strategies (Christensen, 2013), understand how ecosystem evolution interacts with adaptive management strategies (Coll *et al.*, 2015), and identify research needs by highlighting data gaps or areas of high uncertainty (Christensen and Walters, 2004).

While they are powerful tools, quantitative ecosystem models have large data requirements, which can be an impediment to their use in systems without robust sampling programs (Fulton, Smith, and Johnson, 2003). Furthermore, the models incorporate non-trophic interactions through relationships that may be difficult to quantify at appropriate scales, making the outcomes of the model sensitive to the modeler’s assump-

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tions (Harvey, 2014; Vasslides *et al.*, 2016). The formal structure of model development and underlying complex theories can also discourage the participation of non-modelers, limiting the inclusion of local ecological knowledge and early buy-in by stakeholders, which are crucial to acceptance of management recommendations coming from the model (Raymond *et al.*, 2010).

The shift toward EBM has also given rise to a number of qualitative and semiquantitative models that are designed to incorporate complexity and institutional cooperation into decision making (Levin *et al.*, 2009). An example useful to the realm of ecosystem-based management is fuzzy cognitive mapping (FCM; Axelrod, 1976), a framework that has been used to identify critical links between components of aquatic ecosystems using a visual stakeholder-driven approach (Gray *et al.*, 2012; Hobbs *et al.*, 2002; Kontogianni *et al.*, 2012; Meliadou *et al.*, 2012; Özesmi and Özesmi, 2003). FCMs are conceptual models that describe how a system operates on the basis of key system components and their causal relationships as understood by an observer (Kosko, 1991). The components can be tangible aspects of the environment (*e.g.*, a biotic feature such as fish or an abiotic factor such as salinity) or an abstract concept such as aesthetic value. This dynamic model is a useful tool for understanding how the identified key structures and drivers may respond to an ever-changing environment. Because FCM is based on an individual's conceptual understanding of a system, its parameterization is not dependent on the availability of biotic and abiotic data (Özesmi and Özesmi, 2004). The semiquantitative nature of the model is adept at handling traditional and local ecological knowledge, which allows for the inclusion of non-technically trained stakeholders in the process (Gray, Zanre, and Gray, 2014), broadening its appeal for use in management applications (NRC, 2008).

Despite their flexibility, FCMs also have several drawbacks to understanding changes in an ecosystem. Foremost among these is that the dynamic nature of the models is both implicit and vague. For example, the time between a change in one model component and a response in another is not defined. Thus, a model time step must be defined *a priori* and be implicitly considered during model construction (Carvalho, 2013). Additionally, changes to the system are unitless and relative (*i.e.* parameter A increases a great deal compared with parameter B), but the real-world expression of that change is not quantifiable (Özesmi and Özesmi, 2004). FCMs do not incorporate nonmonotonic relationships well (Vasslides and Jensen, 2015), which are often present in ecological systems. Lastly, the completeness and accuracy of FCMs is limited by the understanding of ecosystem components and interactions of the stakeholders who create them.

Both quantitative and semiquantitative models can be used in developing ecosystem-based management approaches to natural resources because they are capable of "what-if" scenario development and predictions. However, these modeling approaches have not heretofore been explicitly compared in the same system. This study develops independent quantitative and semiquantitative models and compares the results of a nutrient reduction scenario run in each, applied to the same estuarine system, Barnegat Bay, New Jersey, to understand how the different approaches can be best utilized to meet the

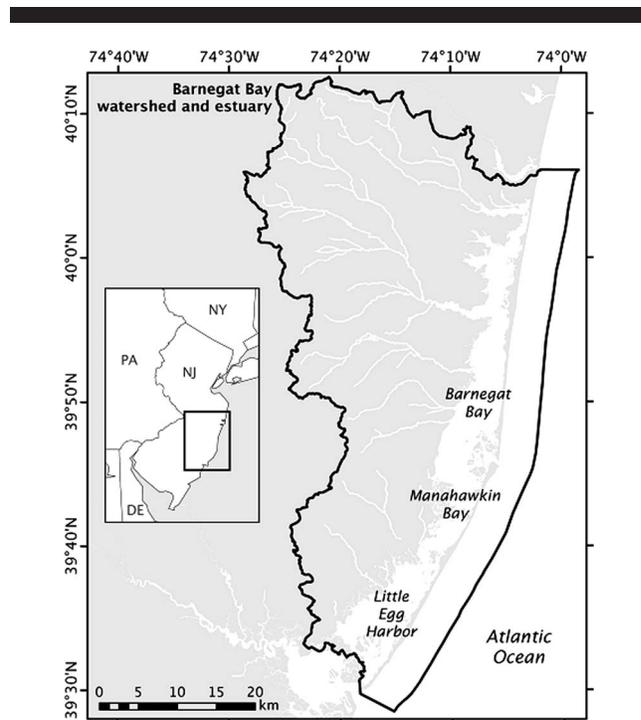


Figure 1. Map of Barnegat Bay estuary and watershed.

needs of EBM. Will the results of the FCM, which is based on stakeholders' perceptions and intuitions, be comparable to the model driven by physical data collection and analysis? If differences between the models appear, are they in components of high confidence in the quantitative model, thus, by implication, not matching stakeholder perceptions about what is occurring in the ecosystem? Alternatively, might the relatively rigid structure of the quantitative model fail to capture important dynamics of the system? More practically, if there are no substantial differences between the models, are FCMs sufficient for at least the initial stages of EBM?

METHODS

Study Area

Barnegat Bay is a temperate lagoonal estuary located in central New Jersey (Figure 1). The estuary stretches nearly 70 km north to south and ranges from 2 to 6 km in width with a total surface area of 279 km², including the tidal portions of its tributaries (Kennish, 2001). The surrounding 1730-km² watershed is home to an estimated 580,000 year-round residents (U.S. Census Bureau, 2012) with a summer population that swells to more than 1 million with the influx of tourists. Land use is a mix of urban and suburban in the northeast and along the barrier islands, grading to more sparsely populated forested areas to the south and west (Kennish, 2001). 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. The blue crab fishery is the main commercial fishery within the bay, although there are still remnants of a historic hard clam fishery that was highly productive in the past (Bricelj, Kraeuter, and Flimlin,

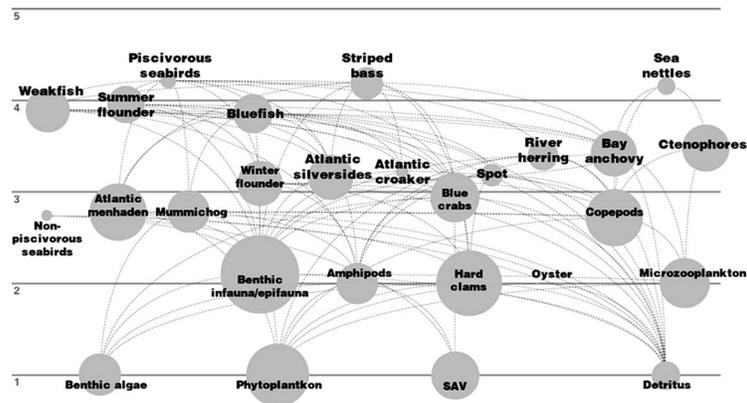


Figure 2. Barnegat Bay ecosystem model for 1981, as developed in Ecopath with Ecosim (EwE). Numbered horizontal lines indicate trophic level, and the area of the circle indicates relative biomass.

2012). Commercial fishing, once an important source of income for local baymen, is now a minor component of the regional economy (Kennish, 2001). Barnegat Bay is a popular destination for recreational fishing, crabbing, boating, and sailing. The bay suffers from symptoms of eutrophication, mainly from nutrient enrichment through non-point source pollution (Bricker *et al.*, 2007).

Ecopath with Ecosim Model

We constructed a trophic ecosystem model of Barnegat Bay utilizing the Ecopath with Ecosim (EwE) software package. Ecopath creates a mass-balanced model of the components and interactions within an ecosystem at a single point in time by trophically linking biomass pools (Christensen and Walters, 2004). Biomass pools can be individual species, ontogenetic stages of a species, or a group of species representing a particular guild. Input parameters required for each biomass pool include diet composition, biomass accumulation, net migration, catch, and three of the following four parameters: biomass (*B*), production/biomass (*P/B*), consumption/biomass (*Q/B*), and ecotrophic efficiency (*EE*), which is the fraction of the production consumed or harvested within the system. These parameters are then used in two master equations. The first equation describes the production term for each group:

$$\text{Production} = \text{catch} + \text{predation} + \text{net migration} + \text{biomass accumulation} + \text{other mortality} \quad (1)$$

The second equation balances the energy flows of a biomass pool:

$$\text{Consumption} = \text{production} + \text{respiration} + \text{unassimilated food} \quad (2)$$

The balanced Ecopath parameters (where within-group production is equal to between-group consumption) are then used to initialize the time-dynamic module called Ecosim. The mass-balanced linear equations are re-expressed as coupled differential equations and are used by the Ecosim module to simulate changes to the biomass pools over time (Christensen and Walters, 2004). Fishing effort or fishing mortality time

series data are used to drive the model, and the resulting changes in biomass are compared with reference time-series data. Parameters primarily associated with predator-prey interactions are adjusted iteratively to fit the model-predicted biomasses to the time-series data with a goodness of fit measure (sum of squares differences) used to compare the model runs.

The Barnegat Bay Ecopath Model (Vasslides *et al.*, 2016) contains 27 distinct biomass groups, including 12 fish species, five benthic invertebrate groups, two gelatinous zooplankton species, three planktonic groups, two benthic vegetation groups, two shorebird groups, and a detrital pool (Figure 2). The model was constructed for 1981, the earliest year for which reliable harvest information for many of the fish groups was available from the National Oceanic and Atmospheric Administration’s Marine Recreational Fishing Survey and Marine Recreational Information Program (NOAA, 2015a) and Fisheries Statistics Divisions (NOAA, 2015b). Data used to parameterize the model were a combination of Barnegat Bay-specific data (fish diets, selected species biomasses and vital rates, harvest), data from similar systems (vital rates, invertebrate diets), and derived values from solving the mass balance equations (biomasses). The PREBAL routine (Link, 2010) was used to identify issues in model structure and data quality associated with the initial input parameter values before balancing the model. The PREBAL diagnostics evaluate the parameter’s consistency with general ecological and fishery principals to ensure both theoretical and practical rigor. Additionally, a “pedigree” was assigned to each input parameter for each biomass group based on the source of the data (and thus the degree of uncertainty associated with it). During model balancing, values for those parameters with the lowest pedigree (highest degree of uncertainty) were changed first.

Once the Ecopath model was balanced, recreational and commercial fisheries time-series catch data were used to drive the model, and fishery-independent catch data, primarily from research surveys, were used to assess the model fit (Vasslides *et al.*, 2016). The parameters influencing predator-prey interac-

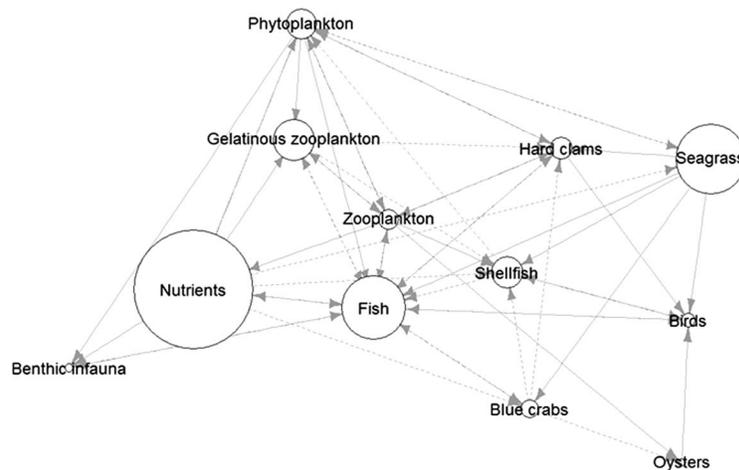


Figure 3. A subset of the fuzzy cognitive map community model for Barnegat Bay showing the groups included in the EwE model and the connections between them. Node size is related to centrality score (*i.e.* importance), solid lines are positive relationships, and dotted lines are negative relationships. The centrality score is the sum of the absolute value of all the weights entering or exiting a component.

tions in the model were adjusted for only those groups with time-series data of at least 3 years in length. In practice, adjustments to these parameters improve the model fit to data and help explain some of the variability in the data. Details of the EwE model setup, parameterization, and fitting to the species time-series data can be found in Vasslides *et al.* (2016).

Fuzzy Cognitive Model

A community-based conceptual model of the Barnegat Bay that used information gathered during interviews of 42 local stakeholders, including scientists, managers, environmental NGOs, and local residents was developed (Vasslides and Jensen, 2015). To construct an FCM, the individual participants were asked to identify the components of the Barnegat Bay social-ecological system (*i.e.* biotic features, abiotic features, or abstract concepts) that they believed were important to the function of the ecosystem and link these components with weighted, directional arrows (Papageorgiou and Kontogianni, 2012). The weighting represents the direction (positive or negative) and the strength of influence that one component has on another and can range from -1 to $+1$ (Gray, Zanre, and Gray, 2014). The individual maps were translated into square adjacency matrices (see Vasslides and Jensen, 2015, for an example), and the number of components was reduced by subjectively combining less frequently mentioned components into larger categories based on shared characteristics (Harary, Norman, and Cartwright, 1965). The final step was to combine the individual matrices into a community conceptual model through matrix algebra, whereby each component-by-component interaction in the community model is the sum of the weights for that interaction provided by all interviewees divided by the total number of interviewees. The community conceptual model contained 84 components connected through 1071 linkages. Figure 3 shows a subset of the FCM community model for Barnegat Bay with the groups included in the EwE model.

Nutrient Change Scenarios

For systems experiencing the negative effects of eutrophication, one of the main restoration efforts is typically the reduction of nutrient loads reaching the ecosystem. The potential effects of this strategy on the biotic community of Barnegat Bay, as represented in the EwE and FCM models were compared, and two scenarios were constructed for both the EwE and FCM models: a no-change scenario, in which the nutrient level remains at the 2013 value through the duration of the simulation, and a scenario with 40% reduction in nutrients from the 2013 value beginning in 2014.

To develop the scenarios in EwE, the fitted Ecosim model was extended beyond the current timeframe to make predictions about the future state of the ecosystem under both the no-change and reduced nutrient loading strategies. Changes in nutrient loading can be incorporated in Ecosim through a nutrient loading forcing function (Christensen *et al.*, 2008). Like other forcing functions in Ecosim, this function specifies the change in the relative concentration of nutrients through time, and the shape of the function is specified by the user. The total nutrients are partitioned between primary producer biomass (in the case of this model: phytoplankton, benthic algae, and submerged aquatic vegetation [SAV]) and the pool of free nutrients in the environment. The primary production rates for each group are linked to the free nutrient concentrations via Michaelis-Menten uptake relationships, wherein the P/B value for a group increases with increases in the available nutrient concentration up to a maximum value for that group (P/B_{max}). The P/B_{max} value sets the sensitivity of the primary producer group to nutrient levels, with a higher P/B_{max} value causing greater sensitivity to changes in nutrient concentration. The base proportion of free nutrients (N_f) can be used to increase the strength of nutrient limitation, with lower values causing greater competition among the primary producer groups.

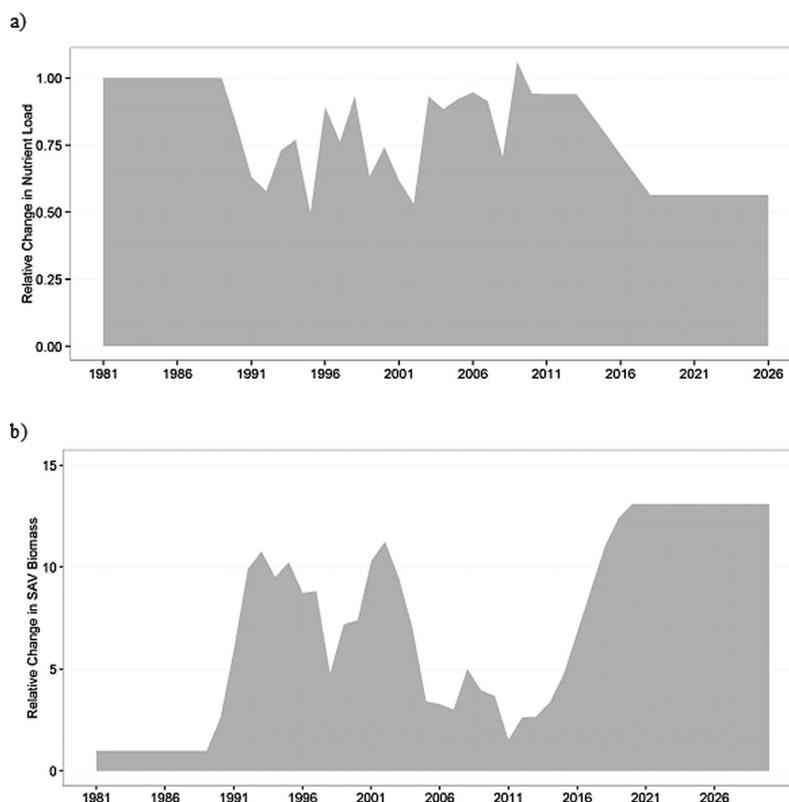


Figure 4. The forcing functions developed for the EwE nutrient reduction scenario. (a) Nitrogen load through time relative to the initial value, with a 40% reduction in loading after 2013. (b) Relative change in seagrass biomass through time compared with the initial value based on the relationship between seagrass total biomass and loading of total nitrogen in Barnegat Bay (as shown in the Appendix).

The P/B_{\max} values for each of the primary producer groups were estimated from available Ecopath-Ecosim models of other coastal systems. Specifically, P/B_{\max} values were estimated as the ratio of the highest P/B value for that group observed in any Ecopath-Ecosim model to the actual P/B value used in this model. The P/B_{\max} values were 1.5625, 1.76, and 2.0 for phytoplankton, SAV, and benthic algae, respectively. The base proportion of free nutrients (N_f) was kept at its default value of 1.0, which assumes that all nutrients not bound in biomass are freely available for uptake by primary producers.

We created a nutrient forcing function using total nitrogen loads for Barnegat Bay for 1989–2011 (Baker *et al.*, 2014), with total nitrogen loads from 1981 to 1988 set at the 1989 value and 2012 to 2013 set at the 2011 value, for lack of other data (Figure 4a). For the baseline scenario, the 2013 nutrient values were maintained for all subsequent years of the simulation. Under the nutrient reduction scenario, the 40% decrease in nutrient loading occurred linearly from 2014 to 2018, and the target nutrient loading level obtained in 2018 was maintained for the remainder of the simulation (Figure 4a).

A forcing function (Figure 4b) was also developed for SAV in the Ecosim module based on the relationship between seagrass total biomass (aboveground and belowground biomass) and loading of total nitrogen in Barnegat Bay (Appendix Figure A1). A linear regression model was fit to data on seagrass total

biomass for 2004–06 and 2008–11 (Kennish and Fertig, 2012; Kennish, Fertig, and Lathrop, 2014) and the total nitrogen loads previously described (Baker *et al.*, 2014). The 3-year moving average of total nitrogen provided the best fit ($R^2=0.37$, $p=0.15$), which is reasonable given that seagrass belowground biomass in temperate estuaries can be persistent across years and thus influenced on longer time scales. Although this relationship is not statistically significant at commonly used values of alpha, the limited available data show a clear indication of declining seagrass biomass with increasing total N (Figure A1), a pattern with widespread support in the literature (Hauxwell, Cebrian, and Valiela, 2003, Latimer and Rego, 2010; Short, Burdick, and Kaldy, 1995).

Both the baseline and nutrient reduction simulations were extended past 2018 by the number of iterations it took for the FCM model to reach a stable state. The percent change in final biomass of each group between the nutrient reduction scenario and the baseline scenario was calculated to determine the effects of reducing the nutrient load.

Within the FCM model, the first step to ascertaining the effects of nutrient reductions was to calculate the values of each component of the community map under the no-change scenario. To generate these values, the adjacency matrix of the community map was multiplied by an initial steady-state vector (a value of 1 for each element of the vector). The

Table 1. Relationship between biomass groups and components in the EwE and FCM models.

Biomass Group (EwE)	Component (FCM)
Piscivorous seabirds	Birds
Nonpiscivorous seabirds	Birds
Weakfish	Fish
Striped bass	Fish
Summer flounder	Fish
Bluefish	Fish
Winter flounder	Fish
Atlantic silversides	Fish
Atlantic croaker	Fish
Spot	Fish
Atlantic menhaden	Fish
River herring	Fish
Mummichog	Fish
Bay anchovy	Fish
Benthic infauna/epifauna	Benthic infauna
Amphipods	Benthic infauna
Blue crab	Blue crab
Hard clams	Hard clams
Oysters	Oyster
	Shellfish (other than hard clams and oysters)
Copepods	Zooplankton
Microzooplankton	Zooplankton
Sea nettles	Gelatinous zooplankton
Ctenophores	Gelatinous zooplankton
Benthic algae	—
Phytoplankton	Phytoplankton
SAV	Seagrass
Detritus	—

resulting vector was then subject to transformation using a logistic expression $[1/(1 + e^{-1x})]$ to bound the results in the interval $[0,1]$ (Kosko, 1987). This new vector was then multiplied by the original adjacency matrix and again subject to the logistic function, repeating these steps until the values reach a steady state, where there is no change between the two most recent vectors (Özesmi, and Özesmi, 2003). A reduction in nutrients was simulated through the same process, but this time the value of the “nutrients” component in the vector was maintained at 0.6 in each time step. Because the stakeholders created direct connections between the nutrient and seagrass components within the FCM, a function was not needed to link the two, similar to the approach in the EwE model. The percent change between the values of the final vector in the nutrient reduction scenario compared with the final baseline vector describes the relative change to the conceptual system given the framework provided by the community map.

For the purposes of intermodel comparisons, the focus was on the responses of those biotic components (FCM) or biomass groups (EwE) that are shared between the models. Because of the nature of the FCM process, some components (e.g., fish and birds) are fairly generic and contain multiple EwE biomass groups, whereas other components are species specific and match directly between models. All EwE biomass groups are represented in the FCM, with the exception of benthic algae and detritus, and all of the biotic FCM components are in the EwE model, although a generic shellfish group is used in the FCM model and includes nonharvested species (ribbed and blue mussels) (Table 1).

Table 2. The average relative magnitude and direction of response to the nutrient reduction scenario for the FCM components and aggregated EwE groups. A large relative change (top third of responses) is indicated by +++/---, medium relative change (middle third) by ++/--, and small relative change (bottom third) by +/--. See Table 1 for a list of how the EwE biomass groups were aggregated.

Aggregate Group/Component	EwE Response	FCM Response
Birds	++	+
Fish	+	++
Benthic infauna	--	--
Blue crab	+++	++
Hard clams	---	+
Oysters	-	+
Shellfish (other than hard clam and oyster)		+++
Zooplankton	--	--
Gelatinous zooplankton	--	---
Benthic algae	-	
Phytoplankton	---	---
SAV/seagrass	+++	+++
Detritus	--	

RESULTS

Where there was close alignment between the EwE and FCM groups (e.g., SAV, blue crab, phytoplankton), the models responded to reductions in nutrient loads in a similar fashion. When the FCM group was composed of several EwE biomass groups (e.g., fish), the direction and relative magnitude of the FCM response was generally similar to that of the weighted average of the EwE responses (Table 2). In the FCM model, seagrass had the largest positive response to the nutrient reduction scenario as measured by the percent change from the baseline scenario (0.25), followed by shellfish (0.06), blue crab (0.03), and fish (0.01) (Figure 5). Phytoplankton (0.17), gelatinous zooplankton (0.04), and benthic infauna (0.02) all had negative responses to nutrient reductions in the FCM model.

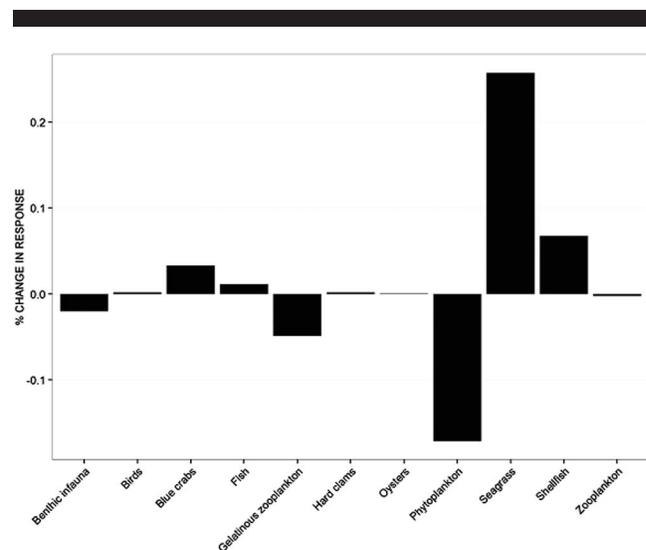


Figure 5. Response of the Barnegat Bay FCM community model to a reduction in nutrient load compared with the baseline scenario.

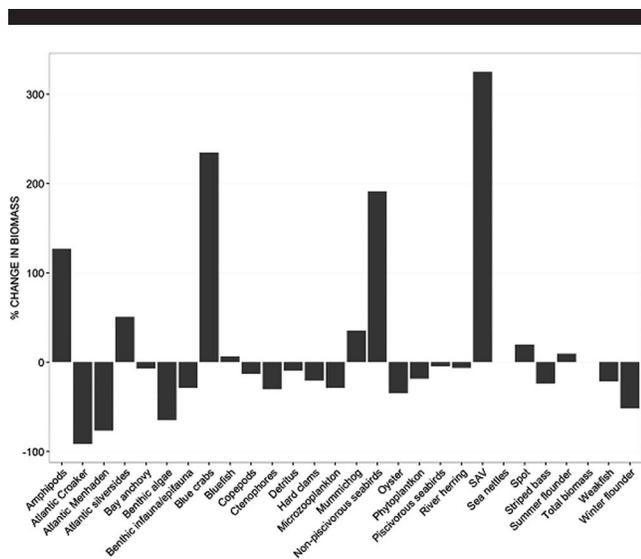


Figure 6. Percent change in biomass for each group in the Barnegat Bay EwE model compared with the baseline scenario for a 40% reduction in nutrient load.

In the EwE model, a reduction in nutrient loading (and the associated response mediated through the SAV forcing function) led to a greater than 100% increase in biomass of SAV, blue crab, nonpiscivorous seabirds, and amphipods (Figure 6). An additional five fish species had biomass increases in response to a reduction in nutrient loading, ranging from 6% to 50%. The remaining groups had declines in biomass, with Atlantic croaker (-91%), Atlantic menhaden (-76%), benthic algae (-65%), and winter flounder (-52%) showing the largest reductions.

DISCUSSION

Despite the differences in data sources, approaches, and methodology, the two models have similar responses to a nutrient reduction scenario for many of the shared components. In both models, seagrass/SAV had an overwhelmingly positive response to the nutrient reduction scenario, which is a well-documented effect in other eutrophic estuaries (McGlathery, Sundback, and Anderson, 2007; Moore, Neckles, and Orth, 1996; Moore and Wetzel, 2000). In the FCM model, stakeholders indicated that seagrass is adversely affected by increases in phytoplankton, which is driven by increased nutrients (Figure 2). However, the stakeholders also created a direct negative link between nutrients and seagrass, suggesting an alternative, undefined pathway. This construction is mirrored in the SAV forcing function applied in the EwE model (Figure 4a), where the known cumulative effects of nutrient enrichment on seagrasses (shading due to phytoplankton and macroalgal blooms and increased epiphyte loading) are undifferentiated.

In the EwE model, the response of SAV to changes in nutrient loads is driven mainly by the forcing function developed on the basis of observed SAV responses to nitrogen load fluctuations seen within this estuary. The negative effects of high nutrient loads on SAV is supported by both

theory and data from this estuary, as well as others. However, as demonstrated by the fit of the regression used to develop the forcing function, the empirical data available for Barnegat Bay are far from clear about the strength of this relationship.

The differences between the models' results appear to be driven mainly by how they handle nontrophic interactions rather than by any direct differences in how they characterize the same trophic interaction. For example, the FCM model includes a positive interaction between seagrass and the fish, blue crab, and hard clam components from a beneficial habitat standpoint (Heck, Hays, and Orth, 2003; Jackson *et al.*, 2001; Tanner, 2005). In this EwE model, interactions between biomass groups and SAV are limited to consumption of seagrass directly or through the detrital pathway. As seagrass increases in both models, fish, blue crabs, and hard clams in the FCM model respond positively because of their associations with seagrass beds, whereas in the EwE model, hard clam biomass declines, as does the biomass for most fish species, despite the known nursery benefits of seagrass habitat. Blue crab biomass in the EwE model does increase, although this is driven solely by trophic interactions. Although adding a mediation function that reduces blue crab predators' hunting effectiveness with an increase in seagrass biomass could be used to model this nontrophic effect of SAV on blue crab (Ma *et al.*, 2010), the development and use of mediation functions in EwE requires careful consideration because there is often a lack of empirical data from which to estimate the parameters of the mediation function (Harvey, 2014).

The ability of FCMs to handle nonmonotonic responses appropriately can limit their applicability in certain settings (Carvalho, 2013). This constraint is of concern in temperate estuarine settings where long gradients in environmental factors, like temperature and salinity, can produce domed-shaped response curves. During the interview process of this study, respondents recognized this constraint and tended to describe the response based on what they thought the likely range of the change would be (Vasslides and Jensen, 2015). As an example, an interviewee might state that an increase in water temperature (from the current condition) would lead to an increase in abundance of a particular biotic group, up to some temperature, after which abundance would decline. However, the interviewee felt that water temperature in the estuary would be unlikely to reach that inflection point, and thus the overall relationship is positive.

The differences in the form of the models' inputs and outputs present some challenges in comparing the results. The biomass groups in the EwE model are more taxon specific compared with the general categories in the FCM model. Because the FCM model was designed to understand the Barnegat Bay social-ecological system as a whole, the stakeholders identified 346 unique variables that were subsequently aggregated into 84 categories for further analysis (Vasslides and Jensen, 2015). A number of specific fish taxa were mentioned, although not as many as present in the EwE model. Because all of the fish biomass groups responded to the nutrient reduction scenario in a similar manner (decrease in biomass) the comparison to the

broader FCM category was still valid. Alternative methods of generating FCMs, such as providing a set list of components to stakeholders (Radomski and Goeman, 1996) or having stakeholders develop their component list in a group setting (Hobbs *et al.*, 2002), may allow for more taxon-specific comparisons.

The unit of measure is also different between the FCM and EwE models, which presents a challenge to direct comparisons between the model results. The EwE model measures biomass for each group (t/km^2), whereas the FCM model utilizes a unitless expression of component size. In both models it is possible to calculate the percent change in the value of the group/component under the nutrient scenario to a baseline (no-change) scenario. This allows for comparison of the patterns in the relative and directional response between models, but not in the absolute value of the response. For informing EBM actions at a broad scale (*e.g.*, understanding which species are the “winners” and which the “losers” in a given scenario), the patterns and relative magnitude of changes may often be sufficient.

CONCLUSIONS

The similarity in results in this study between the FCM model, which is based on stakeholders’ perceptions, and those of the EwE model, driven by empirical data and empirically constrained assumptions, suggests that they can both be useful in advancing ecosystem-based management practices. For ecosystems in which limited research-derived data or funding is available, a stakeholder-based FCM modeling approach can be used to understand the patterns and relative magnitude of changes that can be expected given proposed management actions. A more powerful approach would be to use the two model types in tandem. An FCM model could first be developed, scoping out critical components and interactions to be included in an EwE model. The FCM model could also be used to identify nontrophic interactions of importance that would require the development of mediation functions (*e.g.*, SAV as habitat differentially mediating species-specific foraging functions). Once an EwE model is developed, the results of scenario runs in the two models can be compared, as done here. If there are differences between the model results, and stakeholders have more confidence in the EwE model formulation and outcomes, it suggests that education and outreach may be priorities. Conversely, higher confidence in the FCM results can illuminate future research needs.

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APPENDIX

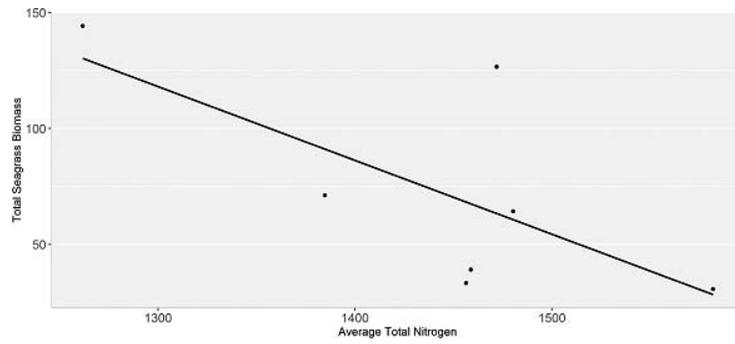


Figure A1. A linear regression model fit to data on seagrass total biomass for 2004–06 and 2008–11 and a three-year moving average of total nitrogen loads for Barnegat Bay.
