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USING ECOSYSTEM MODELS TO UNDERSTAND THE FAUNAL RESPONSE TO
NON-TROPHIC IMPACTS IN AN ESTUARINE ECOSYSTEM

by

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ABSTRACT OF THE DISSERTATION

Using ecosystem models to understand the faunal response to non-trophic impacts in an
estuarine ecosystem

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Ecosystem-based management requires a holistic view of the impacts of management activities, and a number of modelling techniques have been suggested as appropriate for the task at hand. In the first chapter I utilized fuzzy logic cognitive mapping to develop conceptual models of a Barnegat Bay, a lagoonal estuarine system, among four stakeholder groups. These findings suggest that while all of the stakeholders interviewed perceive the subject ecosystem as a complex series of social and ecological interconnections, there is a core set of components that are present in most of the groups' models that are viewed as 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.

In the second chapter I constructed a trophic-based ecosystem model for the same estuary and included mortality associated with a nuclear generating station. Under a scenario where the generating station substantially reduces its water withdrawals, the effect on the biomass of an individual species tended to be small ($<3\%$), and the direction of the change varied by species. However, trophic interactions played an important role in determining the overall change in a species' biomass, as some species directly impacted by the generating station had a reduced biomass in the decommissioning scenario due to increased predation mortality.

In the third and fourth chapters I reviewed the available literature regarding incorporation of eutrophication and other anthropogenic impacts into the trophic-based model. I then reduced nutrient loads within models developed in the previous chapters to understand how they 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 suggests that in data-poor situations local ecological knowledge, collected in a stakeholder-based conceptual modelling framework, can be used to understand the patterns and relative magnitude of changes to an ecosystem that can be expected given proposed management actions. However, a more powerful approach would be to use the two models in combination, maximizing the strengths of each.

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Introduction

Estuaries are highly productive ecosystems that provide a wide range of goods and services, such as disturbance regulation, nutrient cycling, biological control, habitat/refugia, food production, raw material, and recreational opportunities. Worldwide they are estimated to be worth over \$28,000 ha⁻¹yr⁻¹ in 2007 dollars (Costanza et al. 2014). With a mosaic of diverse habitats located within close proximity to each other (fringing wetlands, open waters, submerged aquatic vegetation beds, unvegetated bottoms) estuaries are home to a variety of aquatic organisms, many of which are of commercial or recreational importance (Beck et al. 2001). Within temperate estuaries this includes both resident and transient fish across all life history stages (Able and Fahay 2010). Because of this critical habitat function, fishery production within estuaries is higher than most other marine systems (Pauly and Yanez-Arancibia 1994).

The continued high level of fishery productivity of estuaries is currently threatened, however, by a variety of natural and anthropogenic stressors (Kennish and Paerl 2010). Changes in the long-term trends of storm duration and intensity, drought, storm surge, sea level rise, and flooding, all associated with climate change, affect the physicochemical conditions within estuaries that species have adapted to (Anthony et al. 2009). Additional acute impacts will be felt as human populations continue to swell within the coastal zone (Bricker et al. 2007). Coastal development such as dredging, bulkheading, channel and inlet stabilization, and wetland filling leads to the loss and/or degradation of estuarine habitat. The impact of excessive nutrient loading in estuaries from anthropogenic processes (agricultural runoff, atmospheric deposition, non-point source pollution, *etc.*) has been well documented (Bricker et al. 2007, Conley et al. 2009),

and can lead to hypoxia (Howarth et al. 2011), algal blooms (Kennish et al. 2007), and changes in species composition (Purcell et al. 2007). Power generation stations are often sited in estuaries and other coastal habitats to be near the large volumes of water required as part of the generating process or to cool equipment (Dempsey 1988). Planktonic larvae and juvenile stages of fish and invertebrates are susceptible to injury or mortality associated with impingement on screens or filters located at the entrance to the plant or via entrainment through the plant's pumps and other equipment (Fletcher 1990, Mayhew et al. 2000, Newbold and Iovanna 2007, Barnthouse 2013). The harvest of fish and invertebrates over levels that promote long-term sustainability also has a ripple effect through the foodwebs to which these species belong (Pikitch et al. 2004).

The effects of these multiple stressors across various temporal and spatial scales have complicated the management of fisheries resources in estuarine and coastal systems, which has historically operated on a single species or sector level. The need to consider the effects of the broader environment when managing fisheries (Ecosystem Principles Advisory Panel 1998, Pew Oceans Commission 2003, U.S. Commission on Ocean Policy 2004) led to the concept of ecosystem-based management (EBM), an integrated approach that considers the interaction between ecosystem components and the cumulative impacts of a full range of management activities (Rosenberg and McLeod 2005). This broad definition of EBM thus describes a gradient of interconnectivity, from a focus on multi-species interactions across a range of trophic levels, including some abiotic factors, to a comprehensive view which includes human impacts other than fishing (Hilborn 2011). While this approach is being pursued at several management levels (NOAA 2006), there

are a number of questions and concerns regarding how to best implement such a complex framework (Hilborn 2011, Fletcher et al. 2010, Levin et al. 2009).

One class of tools used to assess the effects of changes in resource management strategies at an ecosystem level are quantitative and qualitative models. From the perspective of an ecosystem approach to fisheries management, a myriad of quantitative models have been developed to support the transition from single species/sector to ecosystem - based management, each with particular strengths and weaknesses (see Plagányi 2007 for a thorough overview). A suite of models extend single-species assessment to take a few additional interactions into account (e.g. Extended Single-species Assessment Models (ESAM) - Livingston and Methot 1998), some are restricted to those species most likely to have important interactions with the species of interest (e.g. Multi Species Virtual Population Assessment (MSVPA) - Pope 1991, Minimum Realistic Models (MRM) - Punt and Butterworth 1995), while others attempt to capture all trophic levels in the ecosystem as well as important physical forces. These include Ecopath with Ecosim (Christensen and Walters 2004) and ATLANTIS (Fulton and Smith 2004).

In addition to the development of quantitative models, the move to EBM has given rise to conceptual, qualitative frameworks that are designed to incorporate complexity and institutional cooperation into decision-making (Levin et al. 2009). Foremost among these is coupled human and natural systems (CHANS), also known as social-ecological systems (SES) (An and Lopez-Carr 2012). This paradigm stresses the integration of human and natural systems with an emphasis on their complexity due to feedbacks, nonlinearities, and other unique properties (Liu et al. 2007). Taking

advantage of the collaboration between the social and ecological realms, this synthetic approach allows us to bring to bear social science modeling techniques for understanding how humans and the environment interact, and how human decisions are made within the context of those interactions (An and Lopez-Carr 2012).

An example useful to the realm of EBM is Fuzzy Cognitive Mapping (FCM), a type of qualitative model that has been used to identify critical ecosystem components as perceived by stakeholders (Özesmi and Özesmi 2004). This dynamic model is a useful tool for understanding how the identified key structures and critical drivers may respond to an ever-changing environment. Because an SES framework can be constructed using various means of stakeholder input, management strategies developed directly from an SES model, or through an SES-influenced quantitative model, should have the added benefit of early stakeholder “buy-in”, which typically leads to greater acceptance of the results of the models and any integrated management plans subsequently generated (NRC 2008).

This dissertation explores how qualitative and quantitative ecosystem models can be used separately, and in conjunction, to understand how non-trophic management activities affect estuarine fauna. In the first chapter, I use a semi-qualitative modelling framework to develop a suite of conceptual models of a complex estuarine ecosystem among four stakeholder groups. I then compare the group’s models via a number of indices to understand where there are commonalities between them that can form the basis for future management actions. This chapter is published in *Journal of Environmental Management* (Vasslides and Jensen 2016).

The second chapter utilizes a quantitative “whole ecosystem” model to predict future changes in the aquatic fauna of an estuarine ecosystem associated with the impending closure of a nuclear generating station. Ecopath with Ecosim is a popular trophic mass balance analysis paired with a dynamic modeling module. Ecopath, the mass balance analysis, was constructed and balanced for the base year of 1981, and the Ecosim dynamic module was fitted to existing data from 1981-2013. A baseline scenario and a closure scenario were extended from 2014 to 2030, and the changes in biomass between the scenarios was examined to determine the mechanisms driving the differences. This chapter is in review at *Estuaries and Coasts* (Vasslides, Townsend, Belton, and Jensen, in review).

My third chapter is a review of how watershed-based management actions can be incorporated into Ecopath with Ecosim (EwE). This chapter focuses on the mechanisms for including the effects of eutrophication, salinity changes, and habitat restoration into EwE, with a goal of providing resource managers with a comparison of the potential mechanisms available to them when developing their own models. This chapter is in review at *Coastal Management* (Vasslides, deMutsert, Christensen, and Townsend, in review).

The final chapter in this dissertation compares the results of the semi-qualitative model to those of the EwE model under comparable nutrient reduction scenarios. The semi-qualitative model developed in Chapter 1 was used to simulate a reduction in nutrients to the system, and the response of the ecosystem was compared to a “status quo” scenario. The mechanisms for including non-trophic impacts into EwE models identified in Chapter 3 were used to modify the EwE model developed in Chapter 2 to

include a reduction in nitrogen loads to the ecosystem, and the change in biomass under the nitrogen reduction scenario was compared to a “status quo” scenario. The behaviors of both models were compared, and the relative strengths and weaknesses of each approach in a management context were evaluated.

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**CHAPTER I: 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, constitute 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 is 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.

Keywords: ecosystem based management; Barnegat Bay; fuzzy logic cognitive mapping; FCM

1.0 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 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). FCMs 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 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 that 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.

2.0 Methodology

2.1 Study Site

The social ecological system we have chosen to study is the Barnegat Bay, a 279 km² lagoonal estuary located in central New Jersey, USA (Figure 1). The surrounding 1,730 km² 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. 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 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 maps for 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 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 which 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 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 minutes to 180 minutes, with the typical session lasting 90 minutes. 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

A number of different methods 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 Figure 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] (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 Figure 1 and a flow diagram of the steps in the data analysis process is provided as Supplemental Figure 2.

3.0 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 Figure 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 ($df=38$, $p=.129$) 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 Figure 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 overlap among managers and NGOs and local residents, and little overlap between NGOs and local residents (Figure 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 (Figure 3b).

The hypothetical scenario model run further elucidated similarities and differences between the conceptual models of the stakeholder groups (Fig 2.4). 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.

4.0 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 includes 84 categories even after aggregation. Jørgensen (1994) theorized that quantitative 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.

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.

5.0 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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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

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 no 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)

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

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				

Figure 1 – Map of Barnegat Bay watershed with New Jersey inset.

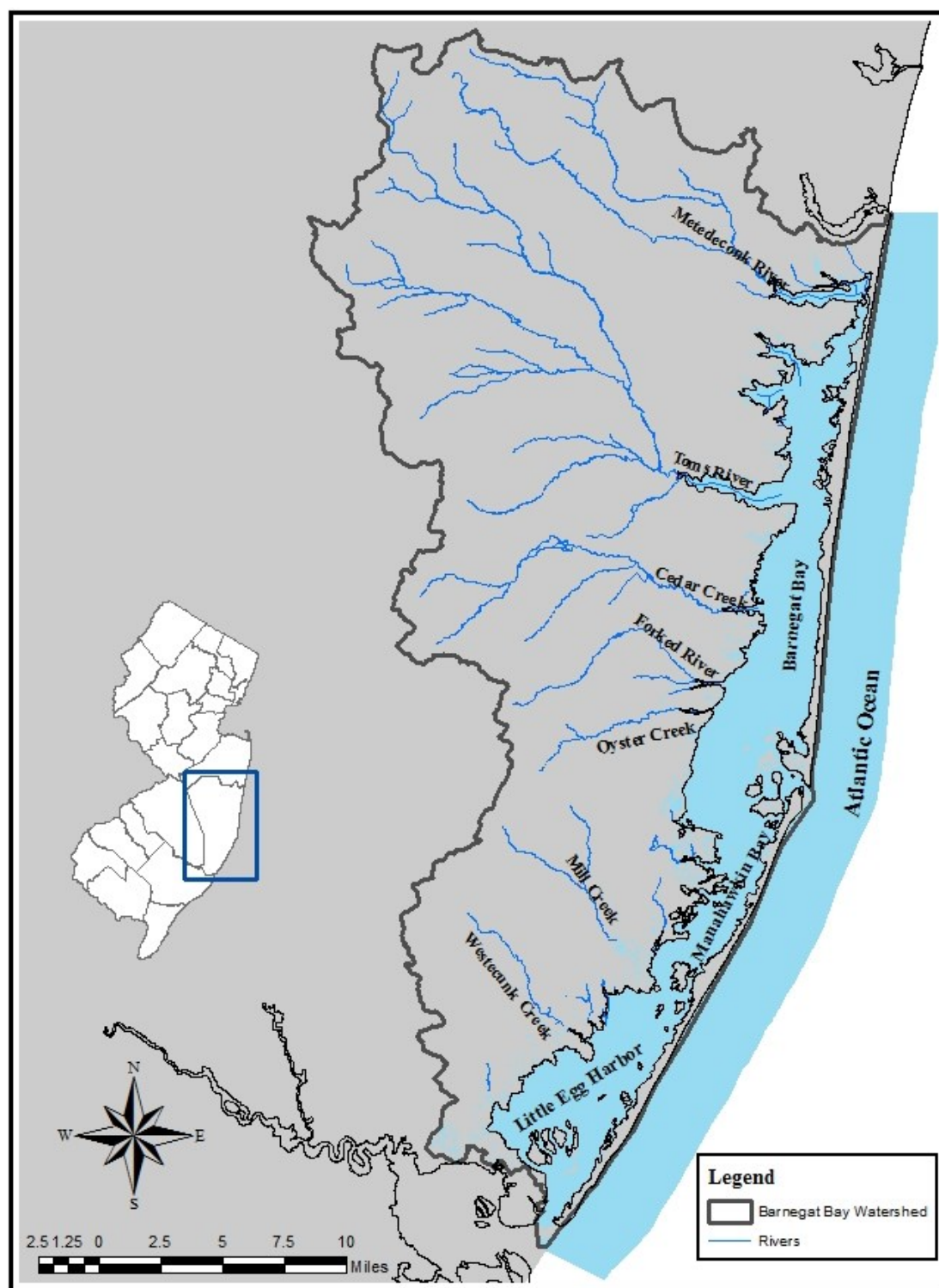


Figure 2 - Subset of the community conceptual model. The twelve nodes with centrality scores greater than 1.0 are shown. Node size is related to centrality score, solid lines are positive interaction strengths, dotted lines are negative interactions strengths.

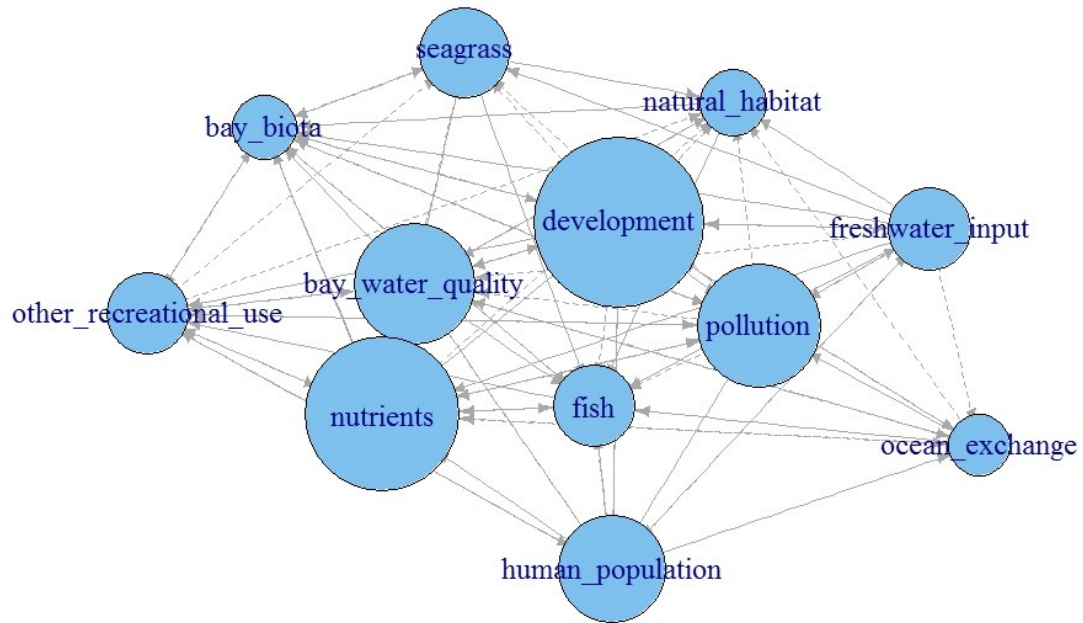


Figure 3 - nMDS plot of the a) individual and b) stakeholder group fuzzy cognitive maps based on centrality scores. Because nMDS is a non-metric procedure, the axes labeled NMDS1 and NMDS2 have no units associated with them. Stress values were 0.279 and 0.169, respectively. Stakeholder groups include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

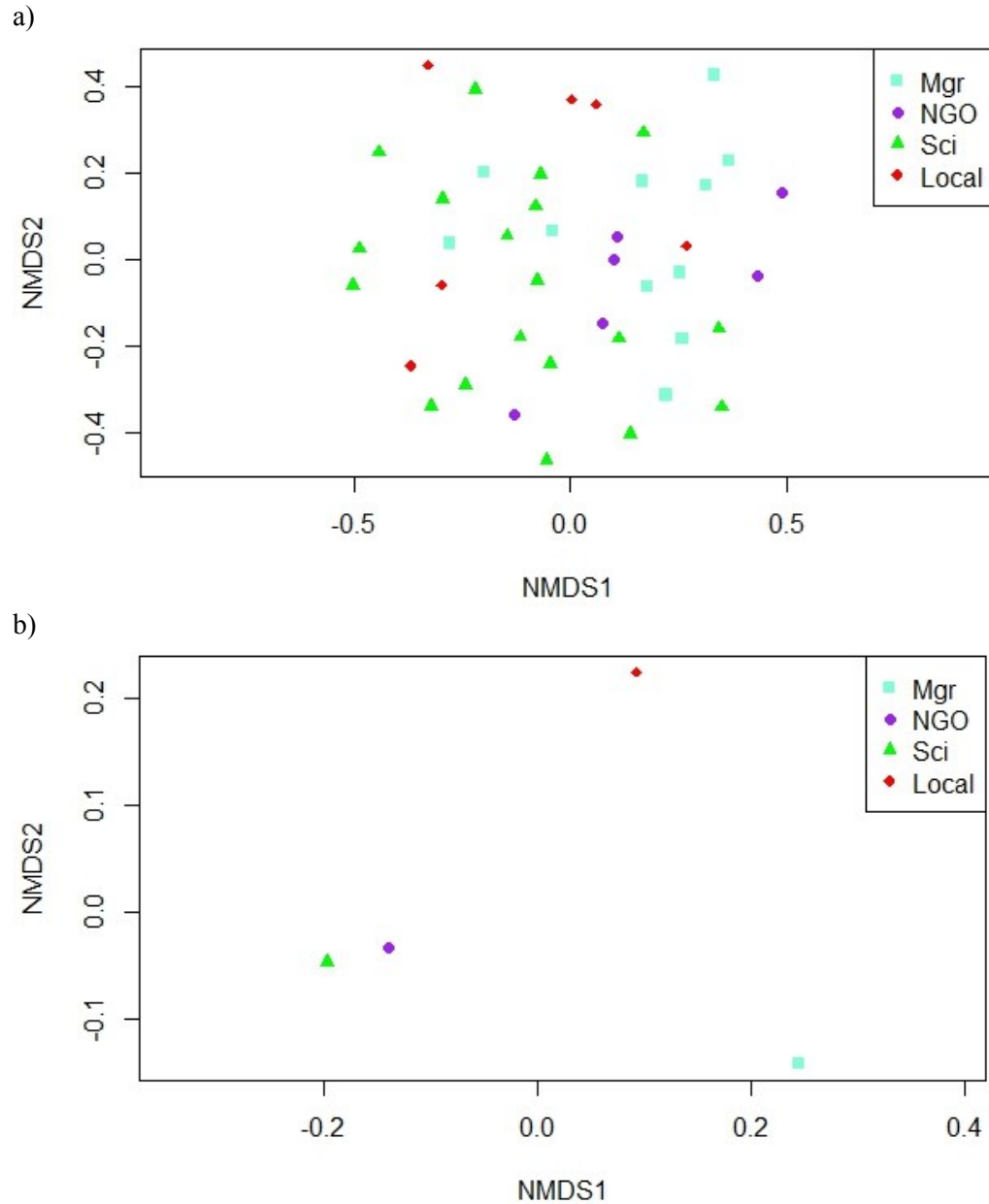
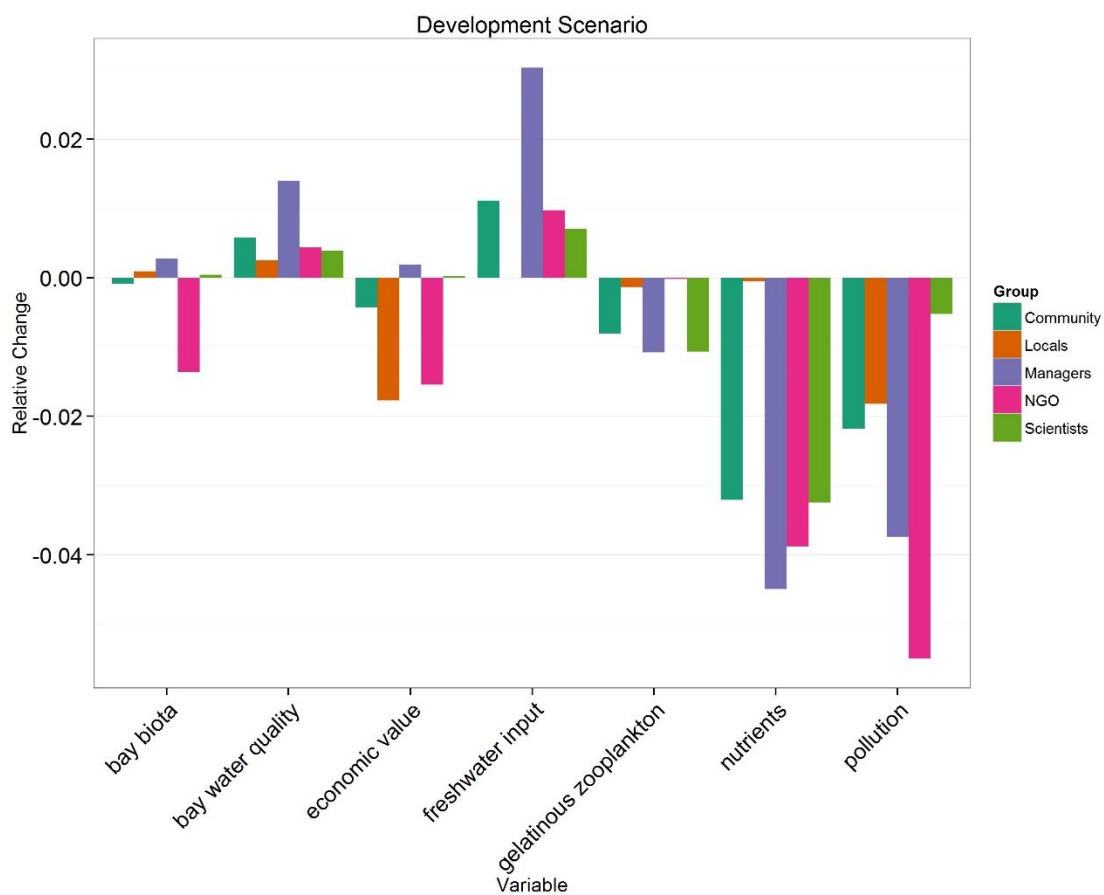


Figure 4 - Results of the scenario model when development was clamped to a low level. Relative change along the y-axis is the difference between the “low development” scenario compared to the initial steady-state solution for a given category. Stakeholder group models were constructed for Local residents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



8.0 Supplemental Information

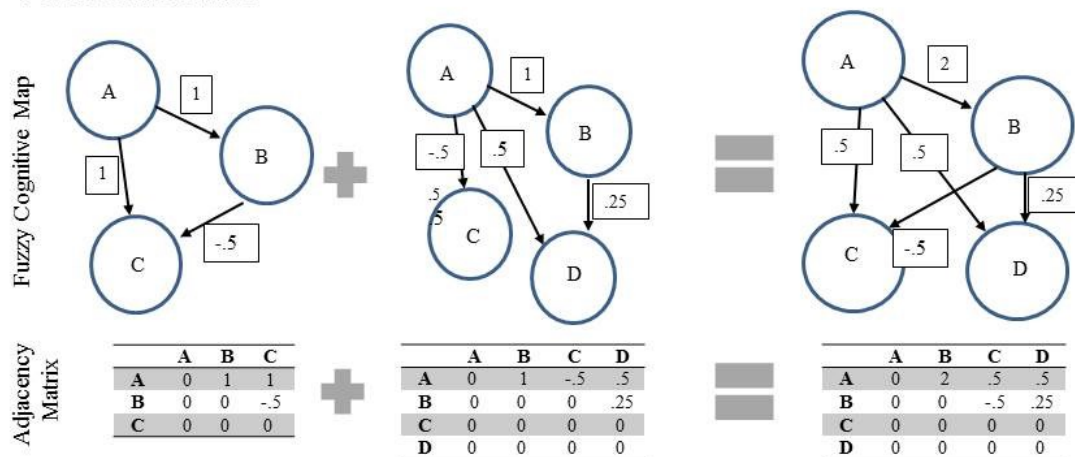
Table S1: Centrality scores by stakeholder group cognitive models. A blank value indicates a category not included in that particular group's model. The Community model is the aggregate of all individual models.					
Category	Scientist	Manager	NGO	Local residents	Community
agriculture	0.34	0.20	0.08		0.22
algal blooms	0.25	0.18	0.54	0.25	0.27
atmospheric deposition	0.43	0.64	1.12		0.43
bay biota	0.61	1.32	2.35	0.71	1.04
bay ecological condition	0.30	1.02	0.50	2.25	0.71
bay salinity	0.99	0.57	1.48	0.38	0.82
bay water quality	1.04	3.27	2.75	1.88	1.96
bay water temperature	0.78	0.80	1.92	0.42	0.71
benthic biota	0.96			0.25	0.47
benthic infauna	0.41				0.19
biochemical/physical processes	0.86		0.17	0.13	0.41
biodiversity	0.12	0.20	0.25		0.11
birds	0.20	0.09	0.54	0.79	0.30
blue crab	0.33	0.34	0.50	0.54	0.39
boating	0.91	0.70	1.04	1.27	0.88
bulkheading/docks	0.57	0.86	0.71	0.71	0.61
climate change	0.59	1.07	1.37		0.71
commercial fishing	0.28	1.10	0.13	0.13	0.44
conservation	0.03	0.77	0.13	0.88	0.29
depth	0.24	0.07	0.50	0.25	0.16
development	1.91	3.93	3.50	3.00	2.75
dissolved oxygen	0.80	0.33	0.79	0.75	0.63
dredging	0.20		0.25	0.25	0.16
economic value	0.37	1.49	0.88	0.50	0.75
ecosystem services		0.68	0.21		0.21
effective management	0.24	0.78	2.16		0.62
elected officials			1.24	0.50	0.25
erosion	0.28	0.18	0.54	0.25	0.27
fish	1.33	1.39	1.54	1.50	1.33
fishing	0.58	1.02	1.75	0.38	0.81
freshwater input	1.13	2.44	2.15	0.13	1.34
freshwater quality	0.33	0.72	1.33	0.75	0.61
freshwater use	0.50	1.07	1.42	0.38	0.71

Table S1: Centrality scores by stakeholder group cognitive models. A blank value indicates a category not included in that particular group's model. The Community model is the aggregate of all individual models.					
Category	Scientist	Manager	NGO	Local residents	Community
gelatinous zooplankton	1.05	0.39	1.33	0.63	0.86
geomorphological processes	0.29	0.47	0.17		0.27
government	0.04	0.60	1.46	0.38	0.34
hard clams	0.38	0.66	0.38	0.50	0.47
harmful algal blooms	0.45	0.32	0.25		0.31
household inputs	0.30	0.39	0.25	1.00	0.42
human population	0.88	3.15	1.50	2.48	1.74
impervious surfaces	0.22	1.09	1.96		0.67
intangible values	0.17	0.86	0.42	0.38	0.38
invasive species	0.18	0.51		0.29	0.25
larval supply	0.50	0.32	0.17		0.33
macroalgae	0.18	0.11	0.46	0.88	0.30
microbial loop	0.41		0.33		0.23
natural habitat	0.99	1.64	1.27	0.38	1.08
NGOs			1.19	0.54	0.25
nutrients	3.10	2.10	4.25	0.63	2.48
ocean exchange	1.31	1.18	1.63	0.25	1.00
OCNGS	0.49	0.66	1.83	0.08	0.60
other crustaceans		0.18		1.13	0.21
other groups		0.36	0.34		0.12
other land use	0.58	0.84	1.33	0.38	0.68
other plankton	0.22		0.54	0.25	0.21
other recreational use	1.25	1.62	1.00	1.88	1.32
oysters	0.16		0.29	0.38	0.17
phytoplankton	1.27	0.40			0.64
policy decisions	0.13	1.50	0.46	0.13	0.47
pollution	1.32	3.03	3.29	1.63	2.00
precipitation	0.16	0.12	0.46		0.17
preserved open space	0.33	1.30	1.04	0.50	0.71
public	0.17	0.41	1.04		0.33
public awareness	0.20	0.91	1.08	1.58	0.68
recreational fishing	0.28	0.68		0.13	0.27
regulations	0.30	0.30	0.63	0.25	0.32
residence time	0.59	0.98	0.58		0.58
resource users	0.04		1.92		0.29
runoff	0.53	0.39	1.17	0.63	0.60
salt marshes	0.59	0.59	0.17	0.38	0.48
scientists			1.33		0.19

Table S1: Centrality scores by stakeholder group cognitive models. A blank value indicates a category not included in that particular group's model. The Community model is the aggregate of all individual models.					
Category	Scientist	Manager	NGO	Local residents	Community
seagrass	1.68	1.00	1.17	1.92	1.46
sediment	0.73	0.34			0.42
sewer systems	0.07	0.08	1.08	0.63	0.26
shellfish	0.70	0.66	0.88	0.71	0.67
stormwater	0.12	0.57	0.13	0.13	0.24
tides	0.33	0.32	0.54		0.27
tourism	0.09	1.23	1.88	0.25	0.67
turbidity	0.93	0.18	0.54	0.50	0.62
vehicles	0.07	0.50	0.67	0.42	0.32
water circulation	0.74	0.30	0.25	0.25	0.41
wetlands	0.04	1.03	0.21		0.32
wind	0.13		0.29	0.13	0.12
zooplankton	0.64	0.16	0.38	0.25	0.42

Figure S1. Conceptual schematic of the FCM combination process and steady state calculation.

FCM Combination



Steady State Calculation

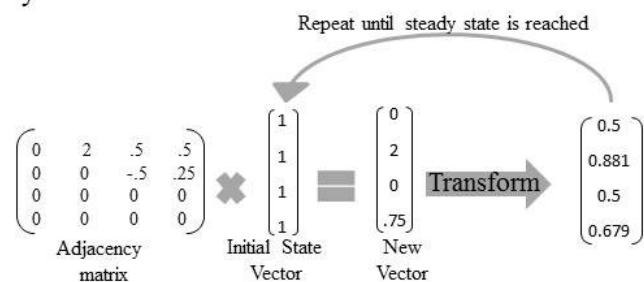


Figure S2. A flow diagram of the data analysis steps.

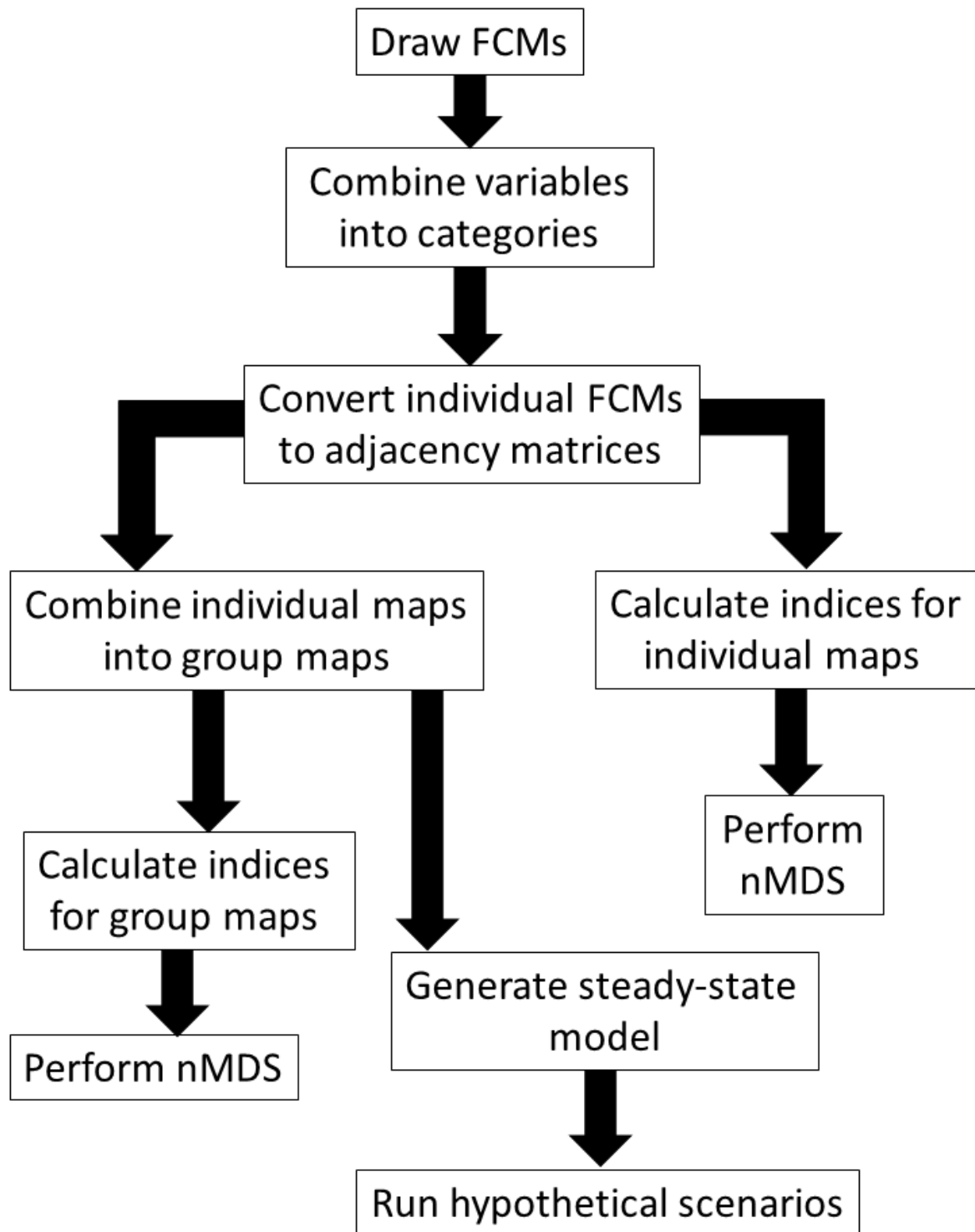
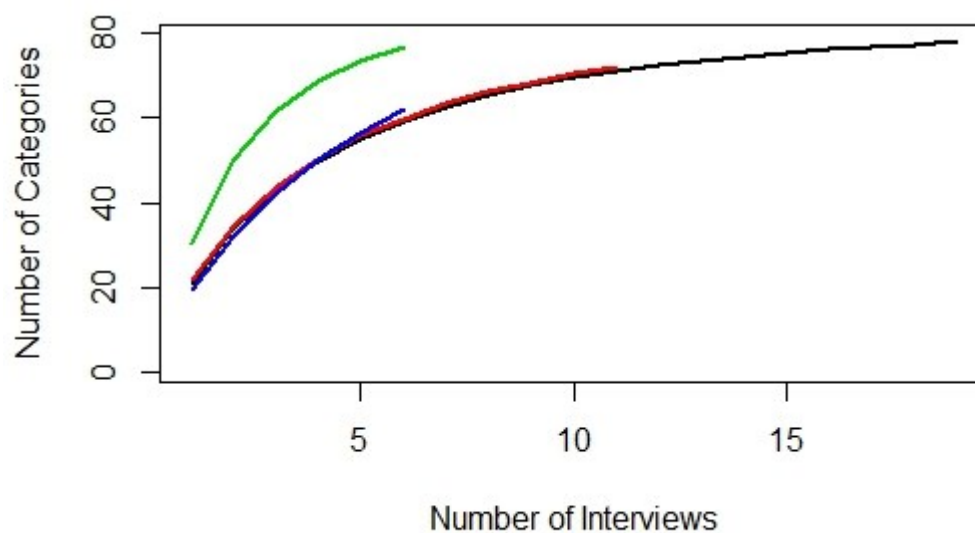


Figure S3. Accumulation curves for the total number of categories versus the number of interviews. The black line is scientists, red is managers, blue is local people, and green is environmental NGOs.



**CHAPTER II: Modeling the effects of power plant decommissioning on an
estuarine food web**

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Abstract: While a number of studies have looked at the impingement and entrainment impacts of power generation facilities on recreationally and commercially important fish species, few have assessed the effects on forage species or the broader aquatic community. Here we constructed a trophic-based ecosystem model for the Barnegat Bay estuary, which is home to the Oyster Creek Nuclear Generating Station. Utilizing this model we developed two scenarios, a baseline scenario for 1981-2030 and a decommissioning scenario where the generating station substantially reduces its water withdrawals beginning in 2020. The effect on the biomass of an individual species tended to be small ($<3\%$), and the direction of the change varied by species. Trophic interactions played an important role in determining the overall change in a species' biomass, as some species directly impacted by the generating station had a reduced biomass in the decommissioning scenario due to increased predation mortality. The differences in results between the static Mixed Trophic Impact analysis and the dynamic simulations analysis highlights the value of dynamic modeling in assessing management strategies.

Keywords: Ecopath with Ecosim, Barnegat Bay, trophic interactions, power generation facility

Introduction

Historically, management of natural resources, particularly in marine systems, has occurred on a species or sector level. This single species approach has had mixed success, with recent analyses suggesting that 28% of the world's major fish resources are overexploited or depleted (FAO, 2009). In response to perceived shortcomings in the single species approach, management agencies began to utilize a multi-species approach in some circumstances, whereby the trophic interactions between a target stock and its prey were taken into account. The assumption was that a reduction in a predator's forage base would lead to reduced productivity of the predator, and thus reduced biomass available to the fishery.

While the multi-species approach accounted for single predator - prey dynamics, it was broadly recognized that fish stocks of interest were impacted by more than this simple interaction; that there was a need to consider the effects of the broader environment when managing fisheries (Ecosystem Principles Advisory Panel 1998, Pew Oceans Commission 2003, U.S. Commission on Ocean Policy 2004). This led to the advancement of the concept of ecosystem-based management (EBM), an integrated approach that considers the interaction between ecosystem components and the cumulative impacts of a full range of management activities (Rosenberg and McLeod 2005). The broad definition of EBM thus describes a gradient of interconnectivity, from

a focus on multi-species interactions across a range of trophic levels, including some abiotic factors, to a comprehensive view which includes human impacts other than fishing (Hilborn 2011).

Aquatic communities are subject to a myriad of anthropogenic influences, both direct and indirect. Indirect human-mediated impacts include increasing water temperatures associated with a warming climate, changes in salinity due to alterations in freshwater flow, and the ripple effects of increasing nutrient loads. In addition to the direct removal through commercial and recreational harvest, power generation can also negatively affect aquatic biota. Power generation stations require large volumes of water as part of the generating process or to cool equipment, and are therefore often located adjacent to waterbodies from which they can withdraw water (Dempsey 1988). In the older open-cycle design, water is withdrawn from a waterbody, utilized within the plant, and then discharged into the same, or nearby waterbody (Kelso and Milburn 1979). During this process planktonic larvae and juvenile stages of fish and invertebrates are susceptible to injury or mortality associated with impingement on screens or filters located at the entrance to the plant or via entrainment through the plant's pumps and other equipment (Fletcher 1990, Mayhew et al. 2000, Newbold and Iovanna 2007, Barnthouse 2013).

While estimates of losses due to impingement and entrainment at power generation stations are often calculated as part of the permitting process, they are typically focused on commercially and recreationally important species, dubbed representative important species (Greenwood 2008, Ehrler et al. 2002, Saila et al. 1997, Heimbuch et al. 2007), with fewer studies of species that serve important ecosystem

roles, such as forage fish (but see Summers 1989)). Thus, while there are calculations of the impacts of power generation on individual species through production-forgone models (Rago 1984, EPRI 2004) adult equivalency models (Goodyear 1978, Ehrler et al. 2002, Saila et al. 1997, Greenwood 2008, there is little understanding of how these removals impact the broader food web, and what these losses mean for species that may not be directly affected by impingement or entrainment. This is of particular interest given the age of many power generating stations within the United States which are transitioning to closed-loop cooling systems or are being decommissioned.

In this study we utilize a widely-used trophic based ecosystem model, Ecopath with Ecosim (Coll  ter et al. 2015), to predict changes to an estuarine food web associated with the upcoming decommissioning of a nuclear generating station. We first develop a balanced static model of the estuary, and then create a dynamic “key run” for the system using 22 years of time-series data. The dynamic model is then extended into the future under a *status quo* scenario and a scenario where water withdrawal volumes associated with the nuclear generating station are substantially reduced during the model run. The results of the two model runs are then compared and discussed.

Methods

Study Area

Barnegat Bay is a temperate lagoonal estuary located in central New Jersey, USA (Figure 1). The estuary stretches nearly 70 km north to south and ranges from 2 -6 km in width for a total surface area of 279 km² including tidal portions of its tributaries (Kennish 2001a). With an average depth of 1.5 meters, it has a volume of approximately

$4.39 \times 10^8 \text{ m}^3$. There are two main sources of tidal exchange: Barnegat Inlet in the center of the estuary and Little Egg Inlet at its southern terminus. A third source of ocean exchange is the manmade Manasquan Canal at the northern end, which connects the bay to the Manasquan River and inlet. The surrounding $1,730 \text{ km}^2$ 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. 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 (Kennish 2001a). 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, though there are still remnants of a historic hard clam fishery that was highly productive in the past (Bricelj et al. 2012). Commercial fishing, once an important source of income for local baymen, is now a minor component of the regional economy (Kennish 2001a). The Barnegat Bay is a popular destination for recreational fishing, crabbing, and clamming. The bay suffers from symptoms of eutrophication, mainly due to nutrient enrichment through non-point source pollution (Bricker et al. 2007).

Located in the central portion of Barnegat Bay between Oyster Creek and Forked River is the Oyster Creek Nuclear Generating Station (OCNGS), the nation's oldest continuously operating nuclear power plant (Figure 1). OCNGS, which commenced operation in 1969, utilizes a once-through cooling system where water is withdrawn from the Forked River and discharged into a canal that flows into Oyster Creek. During normal plant operations approximately 662 million gallons of water per day (MGD) are

withdrawn from Forked River for cooling the main condenser at the facility (CWIS) and an additional 749 MGD are withdrawn from Forked River for diluting the thermal effects of the condenser cooling water (DWIS) (NJDEP 2010). Under an Administrative Consent Order agreed upon between the State of New Jersey and the operators of OCNGS, power generation at the facility will cease no later than December 31, 2019.

Ecosystem model

We developed a trophic model for the Barnegat Bay using the Ecopath with Ecosim 6.4.3 (EwE) software package (Christensen and Pauly 1992, Christensen and Walters 2004). EwE is a well-known program for addressing questions of aquatic ecosystem changes with over 400 trophic mass balance models built for a variety of ecosystems, ranging in size from oceanic basins to small estuaries (Coll  ter et al. 2015), including other estuaries within the mid-Atlantic region of the United States (Christensen et al 2009, Frisk et al. 2011). Ecopath is a trophic mass balance analysis program that parameterizes an initial model using two master equations, one to describe the production term for each group:

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

and one equation for the energy balance for each group:

$$\text{Consumption} = \text{production} + \text{respiration} + \text{unassimilated food}$$

This “base” model provides the foundation for the simulation component of EwE, Ecosim, where a series of coupled differential equations are used to simulate biomass dynamics through time, fitting the model to time-series reference data and forcing functions entered by the user.

Ecopath requires four groups of basic input parameters to be entered into the model for each of the species (or groups) of interest: diet composition, biomass accumulation, net migration, and catch (for fished species). Three of the following four additional input parameters must also be entered: biomass, production/biomass (P/B), consumption/biomass (Q/B), and ecotrophic efficiency, which is the fraction of the production consumed or harvested within the system. The model uses the input data along with algorithms and a routine for matrix inversion to estimate any missing basic parameters so that mass balance is achieved (Christensen et al. 2008). Once the Ecopath model has been balanced the mass-balanced linear equations are then re-expressed as coupled differential equations so that they can be used by the Ecosim module to simulate what happens to the species groups over time (Christensen and Walters, 2004). Model runs are compared with time-series data and the closest fit is chosen to represent the system. Time-series data for model calibration are thus essential for developing and validating an Ecosim model (Christensen et al. 2009). Therefore, time-series data depicting trends in relative and absolute biomass, fishing effort by gear type, fishing and total mortality rates, and catches for as long a period as possible should be viewed as additional data requirements.

Barnegat Bay Ecopath Model

Our model of the Barnegat Bay ecosystem is comprised of 27 biomass groups, including 12 fish species, 5 benthic invertebrate groups, 2 gelatinous zooplankton species, 3 planktonic groups, 2 benthic vegetation groups, 2 shorebird groups, and a detrital pool. A complete description of the sources used to determine the parameter values for each of the biomass groups is available in the Electronic Supplementary Material (ESM) 1, with a summary provided here.

The Ecopath model was developed for 1981, the earliest year for which reliable catch data for many of the fish species is available and shortly after a large research initiative in the central portion of Barnegat Bay was completed (Sugihara et al. 1979). For most of the species/groups P/B and Q/B were taken from published studies of the same species/groups in a different location, which is common in the development of these models as those parameter values are fairly consistent across systems or can be modified based on local conditions (Christensen et al. 2008). Standing biomass estimates specific to Barnegat Bay were only available for bay anchovy (Vougliotis et al. 1987), hard clams (Celestino 2002), and submerged aquatic vegetation (Lathrop et al. 2001). Sea nettle (*Chrysaora quinquecirrha*) biomass for 1981 was estimated by reducing a current biomass estimate by 75% to reflect the apparent scarcity of sea nettles in the bay at that time (Young et al in review). Atlantic croaker (*Micropogonias undulatus*), a common component of contemporary field surveys, was recorded only sporadically in samples collected during the mid and late 1970s (McClain et al. 1976). In order to include this species in the model its biomass was estimated by the software to balance the requirements of its predators and fishery at their earliest recorded values for Barnegat

Bay. Biomass of the remaining groups was modified from literature values or estimated by the software assuming literature derived Ecotrophic Efficiencies. The diet data for most of the fish groups are based on a diet study conducted in the Barnegat Bay by Festa et al. (1978), with the diets of the remaining groups taken from literature values or other models (see ESM 2 for the initial diet matrix). For predatory fish, when stomach contents were listed as “unidentified fish” or as a species not included in the model that percentage of the diet was redistributed amongst the other diet categories in proportion to their prevalence by weight in the identified portion of the diet. As described above, Atlantic croaker were scarce in the Barnegat Bay at the time of the diet study, and were not listed as a prey item for any of the piscivorous fish in the model. We know from studies in other nearby systems that when croaker are present they are a common food source for weakfish, striped bass, and bluefish (Nemerson and Able 1994, Frisk et al. 2006, Christensen et al. 2009). Limited predation on Atlantic croaker was therefore added to the initial diet matrix of the model as it is not possible to add them as a prey item during the simulation procedure (Pinnegar et al. 2014). The levels of predation on croaker are based on the consumption rates found in EwE models of the Delaware Bay (Frisk et al. 2006) and Chesapeake Bay (Christensen et al. 2009). Thus Atlantic croaker biomass in the early years of the model is likely overestimated. The last input required for the Ecopath module is harvest data, which is incorporated as the landings ($\text{t}/\text{km}^2/\text{year}$) for the year in which the model is initiated. The Barnegat Bay model includes gear specific landings for the blue crab fishery provided by the NJ Bureau of Marine Fisheries and species specific landings for other fish and invertebrates, which combines the National Oceanic and Atmospheric Administration’s recreational landings as recorded in

the Marine Recreational Fishing Survey and Marine Recreational Information Program (NOAA 2015a) and commercial landings as recorded by the Fisheries Statistics Division (NOAA 2015b). This large amount of data was reduced through a series of gear and location filters to approximate landings for Barnegat Bay as they are not collected at the estuary level in New Jersey (see ESM 1 for the process). To assess the impacts of the Oyster Creek Nuclear Generating Station (OCNGS) on the biota of Barnegat Bay we treated the power plant as a “fishery” to account for the mortality due to the use of bay water for cooling the power plant (Amergen 2008). Because the mortality caused by OCNGS is not removed from the system as a landing we modeled it as discards that flow into a detrital pool. The landings values included in the model are in Table 1, with details on their derivations found in ESM 3.

The initial values for the input parameters were assessed using the PREBAL routine (Link 2010) to identify issues of model structure and data quality prior to balancing. The diagnostics evaluate the parameter’s consistency with general ecological and fishery principals to ensure both theoretical and practical rigor. Each input parameter for each biomass group was also assigned a degree of uncertainty based on the provenance of the data. Taxa specific data collected within Barnegat Bay is given the highest pedigree (lowest uncertainty), followed by species specific sampling from other systems, literature derived values, best professional judgment, and finally parameters estimated by Ecopath. We then balanced the model by changing values for those parameters with the highest degree of uncertainty based on the data pedigree.

Barnegat Bay Ecosim Model

Baseline model

With balancing complete, we then incorporated time-series data to model ecosystem dynamics for the period 1981-2013. Fishery dependent time-series data were used to force changes in the Ecosim module. Because time-series data must be continuous to be used to “drive” the model we used catch time series data for commercial and recreational finfish landings (NOAA 2015a, NOAA 2015b). Another common source of data for ecosystem models are formal stock assessments, which utilize similar time series data for single species management. Unfortunately there are no stock assessments specific to Barnegat Bay. While there is no formal stock assessment for blue crab, the NJ Bureau of Marine Fisheries does collect commercial blue crab landings data by gear and location. This data was used to create gear specific time series, which consisted of the ratio of the landings in a given year to the initial year’s landings, and used to force the model. It should be noted that the NJ blue crab landings data collection in Barnegat Bay began in 1995, so data from 1981-1994 are estimated from NMFS statewide landings based on a regression of the Barnegat Bay data against statewide landings over the same period. The final source of Barnegat Bay specific fishery dependent time series data comes from OCNGS. Because of the nature of OCNGS operations, the cooling and dilution intake structures function nearly continuously, with the only shutdowns associated with temporary, short term maintenance. As such the plant flow has been fairly consistent over the timeframe in question, and therefore the impacts of the plant have been modeled as a steady effort.

Fishery independent time-series were used to assess the model fit. Again, there are limited repeated assessments of biota specific to Barnegat Bay; however to assess the model fit it is not necessary to have records for each year in the time series. Thus we used a combination of fishery independent surveys spanning a variety of timeframes to determine how well our model reflects changes in the ecosystem (see ESM 4 for a complete listing and their derivations). Available data included a Rutgers University Marine Field Station long-term otter trawl survey (1995-2013; Vasslides et al. 2011), hard clam surveys conducted by the NJ Department of Environmental Protection (NJDEP) in 1986/1987, 2001, and 2011 (Celestino 2002, Celestino 2013), and short-term (2011-2013) surveys for benthic infauna, copepods, and microzooplankton. The only consistent time series directly available for primary producers is for submerged aquatic vegetation (SAV). SAV coverage for the bay is available for 1980, 1987, 1999, 2003, and 2009 based on aerial photograph analysis in Lathrop et al. (2001) and Lathrop and Haag (2011). The acreage of seagrass in each year serves as a datapoint of relative abundance, though this method can mask declines in overall biomass due to changes in density or condition. A shorter time series (2008-2013) of relative abundance of phytoplankton bay-wide was estimated from chlorophyll *a* readings taken via aircraft remote sensing.

An additional source of fish time-series data incorporated into the model is an index of biomass generated from the near-shore trawl surveys conducted each fall by the NJDEP. While sampling for this survey occurs along the New Jersey coast adjacent to Barnegat Bay, it provides an estimate of relative biomass in each year for those species that leave the estuary each fall for offshore or southern waters.

An *a priori* determination was made that some of the sampling methods could not be relied upon to provide a reliable time series of relative abundance for select species, and these time series were not used in the model fitting. The vulnerability values for certain groups were also modified from the default value. Vulnerability is a term in the consumption equation for Ecosim that enables the modeler to specify how trophic flows of biomass are controlled (Walters et al. 2000). The model system may be more predator-controlled (top-down) or prey-controlled (bottom-up). The vulnerability term of the consumption equation for a given predator-prey-interaction determines the level of predation mortality for the prey that results from a large increase in predator biomass (Walters and Juanes 1993). A low vulnerability value means that a large increase in predator biomass causes a small change in predation mortality for a given prey group. Conversely a high vulnerability value means that a large increase in predator biomass causes a similarly large change in predation mortality for a given prey group. A high vulnerability value results in a more Lotka-Volterra-like model behavior. Vulnerability values were adjusted for only those groups with a time series of at least 3 years through the automated “fit to time series” algorithm, which seeks to minimize the sum of squares difference between the observed and modeled results. The vulnerability values for sea nettles and Atlantic croaker were both adjusted to reflect the known increases in biomass of those groups within the modeled time period. All other vulnerability values were set at the default value, $v=2$. In practice, adjustments to the vulnerability parameter improves the model fit to data and helps explain some of the variability in the data.

The Monte Carlo approach was used to test for sensitivity of Ecosim's outputs to Ecopath input parameters. Mean, lower limit and upper limit of the distribution used to

draw random values for key input parameters (B, P/B, and Ecotrophic Efficiency) for each group in the model was determined based on the model pedigree. The software made 100 random draws from range of possible input values, determined whether the set of parameters resulted in a balanced model, then ran the Ecosim simulation based on the new randomly selected parameters. The output from the Monte Carlo simulations was plotted (biomass over time for each group) and visually inspected to determine if temporal patterns in group biomasses were consistent or divergent. Consistent patterns suggest that although some underlying uncertainty in the input parameters for the model exists, the conclusions about factors influencing those patterns are robust. As a result point estimates from the model output may have a high level of uncertainty, but relative changes in biomass from comparing the baseline scenario to test scenarios are meaningful.

Oyster Creek Nuclear Generating Station (OCNGS) closure scenario

After the baseline Ecosim scenario was fit to the available time-series data, the model can be extended to make predictions about the future state of the ecosystem under different management strategies. To assess potential ecosystem changes associated with the cessation of power generation at OCNGS by 2020 we developed two scenarios. Under the baseline scenario all of the time series forcing data for 2013 were extended until 2030, including the OCNGS “fishing” effort. Under the OCNGS closure scenario, all of the time series forcing data from 2013 are extended until 2030 except the plant’s fishing effort, which is reduced to 4% of the full operating capacity from 2020-2030.

Ecosystem metrics

The trophic structure of the ecosystem was described using a graphical representation, which documents the flow of energy between individual groups. Within Ecopath, producer groups are assigned a trophic level of 1 while consumers are given a trophic level of $1 + (\text{the weighted average of their prey's trophic level})$ (Christensen et al. 2008). The direct and indirect effects that a small change in biomass of one group (or fishery effort) will have on the biomass of the other groups can be evaluated through the Mixed Trophic Impacts (MTI) analysis, which is based on the approach developed by Ulanowicz and Puccia (1990). We evaluated the MTI of OCNGS at model initialization and again in 2019, the year prior to OCNGS decommissioning.

Results

Barnegat Bay Ecopath Model

The static model shown in Figure 2 represents a balanced model of the trophic connections within Barnegat Bay in 1981 (given the data) with the groups arranged by trophic level. Changes to the initial input parameters in order to balance the model were primarily limited to small adjustments to the diet matrix, particularly for non-fish groups, which tended to be from published studies from different locations. The need to adjust input values was further moderated by the fact that biomass for many of the groups was estimated internally within EwE, which allowed for a greater degree of flexibility. The final parameter values and their pedigrees are given in Table 1.

The MTI analysis (Figure 3) suggests that the direct and indirect impacts of OCNGS are negligible when compared to the effects associated with inter-species trophic

interactions. While OCNGS had both positive (spot) and negative (weakfish, Atlantic croaker) impacts in the initial model year they were an order of magnitude smaller than the impact of the strongest effects calculated for the other groups. In 2019, the year prior to the simulated closure, the relative size of the OCNGS effects remains small. However, OCNGS now has a net positive effect on Atlantic croaker.

Barnegat Bay Ecosim Model

When the time series data are incorporated into the model and the vulnerability values are adjusted to fit the time series, the overall fit of the model prediction to the available data is reasonable, and the model generally behaves as expected. There is variability in how well the predicted biomass trends match the available time-series data among the groups (Figure 4). For winter flounder, summer flounder, Atlantic croaker, and blue crab the overall trends in biomass are captured by the model, but annual fluctuations are not well represented. In contrast, the decline in hard clams that occurred during the early part of the time period is not at all captured in the model.

When we ran 100 Monte-Carlo simulations utilizing the pedigree values set during the Ecopath model construction the current model was the best-fit. For the remainder of the trials the biomass trends were similar, though the relative abundance varied between simulations.

Oyster Creek Nuclear Generating Station closure scenario

The total system biomass summed for 2020-2030 under the baseline scenario was 2637.04 t/km², compared to 2637.45 t/km² for the same timeframe under the OCNGS

closure scenario. While the change in overall biomass was small, the effect on the biomass of individual groups varied, though never by more than 3% (Figure 5). Of the groups directly impacted by OCNGS impingement and entrainment, Atlantic croaker has the greatest response associated with the plant closure, decreasing in biomass by nearly 2.5% compared to the baseline simulation. Weakfish and blue crab both see a greater than 1.5% increase in biomass under this scenario. Changes in biomass to groups not directly impacted by OCNGS were smaller in magnitude, with only striped bass having a change greater than 0.5%.

Discussion

As power generating plants around the world age and are decommissioned or replaced with improved environmentally protective technologies there will be impacts to the aquatic ecosystems that provide cooling water for their operation and receive process water. Here we developed an ecosystem model that describes the changes expected to an estuarine community in response to the decommissioning of a nuclear generating station with a once-through cooling system. While we are not the first to include the effects of a power generating station within an EwE model (Lobry et al. 2008), we are the first to use the Ecosim module to predict how altering a power generating plant's water use will impact the ecosystem as a whole.

Our results indicate that indirect effects mediated through trophic interactions may be more substantive, and of opposite direction, than what would be expected from a single species approach. Atlantic croaker in our system is a prime example. Based solely on the impingement and entrainment impact studies conducted by the plant, one would

expect Atlantic croaker to benefit from the reduced mortality associated with the plant's decommissioning. However, weakfish, which are one of the most important predators of Atlantic croaker are predicted to increase in biomass as result of reduced mortality from the OCNGS. Our model predicts that the net effect on Atlantic croaker biomass in Barnegat Bay will be a slight decline compared to a no-change scenario due to increased predation mortality.

Comparison of the results of the dynamic simulations with the static mass balance model, highlights the value of simulation. The results of the scenario modeling are different from what would be expected given the MTI analysis, particularly for the initial year of the model. The negative impact of OCNGS on Atlantic croaker in the initial model year should translate into additional croaker biomass if the OCNGS effort is reduced, which contradicts the results of the Ecosim scenario. However, the MTI analysis for the year immediately prior to the OCNGS decommissioning suggests a positive impact on croaker associated with the plant operations, which is consistent with the results of the Ecosim scenario. Thus at some point during the modeled timeframe the dominant impact of OCNGS on croaker switched from direct mortality to indirect effects associated with their predators. As noted by Christensen et al. (2008), MTI analysis is not amenable to making predictions of what will happen in the future given changes in interaction terms specifically because changes in abundance may lead to changes in diet composition, and that is not accommodated within this routine. This switching behavior reinforces the desirability of using the Ecosim module to assess the potential indirect effects of non-trophic related activities compared with assumptions of a steady-state system.

The trophic level at which the effects of the power generating station are most visible in our model is higher than those of other models. Lobry et al.'s (2008) results based on MTI analysis suggest that the primary effects of a nuclear generating station in the Gironde estuary of France were on intermediate trophic level (TL) species (TL range: 2.03-3.25). In our study the species impacted by OCNGS ranged in trophic level from 2.93 for blue crab to 3.89 for weakfish. Our higher trophic level impacts are driven by a combination of direct power plant mortality on early life history stages of predators as well as indirect effects through a reduction in biomass of their prey. In comparison, the main upper trophic level species in the Gironde model enter the estuary as juveniles or adults and likely do not experience the same level of power plant related mortality (Lobry et al. 2003). Thus impacts of power generating stations on aquatic biota may be system specific and related to the presence of vulnerable early life stages of predator and prey fishes.

The limited availability of data specific to Barnegat Bay led to compromises in the overall structure of the model. For instance, all of the biomass groups within the model are represented by a single age stanza. For many of the species/groups, this is unimportant as their role in the food web does not depend on life history, *i.e.* phytoplankton, zooplankton, benthic invertebrates, SAV. However, for species for which we wish to investigate management actions or where there may be ontogenic shifts in diet preferences, age-structured stanzas provide increased resolution into the interactions in question. As pointed out above, mortality associated with impingement and entrainment at OCNGS occurs primarily to early life history stages of the taxa within the system, and separating that from juvenile and adult mortality would reduce uncertainty within the

model. Of course, this increased level of resolution requires ever increasing amounts of data to populate the input parameters. The current single stanzas model appears to capture the overall trends in biomass (where available) reasonably well, and is thus useful for investigating questions of ecosystem functioning and exploring scenario development.

It should be noted that the outcomes of management scenarios are only as reliable as the data used to construct them. The OCNGS “fishery” data had to be extensively manipulated (ESM 3) to expand the reported mortality from numbers of individuals to weights, particularly for entrainment losses. The methodology used to determine impingement and entrainment losses and mortality in the Amergen (2008) report were slightly modified from those of earlier studies at OCNGS (EA Engineering 1981), which were the subject of a critical external peer review (Summers et al. 1989). In addition, there was a change in intake protection structures, and thus mortality rates, between the start of our model and the 2008 mortality study. Thus the OCNGS removals used here are a likely conservative estimate.

One of the main benefits of this type of holistic model is the ability to develop and evaluate a number of potential management scenarios from an ecosystem-wide perspective. This approach can lead to some surprising findings, as was seen in the OCNGS decommissioning scenario. Understanding how changes in anthropogenic activities interact with natural process to alter multiple components within an ecosystem will allow resource managers to better assess the impacts of proposed undertakings, and hopefully lead to more resilient and sustainable systems.

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Fig. 1 Map showing the location of the Barnegat Bay estuary system. The location of the Oyster Creek Nuclear Generating Station is denoted by a star

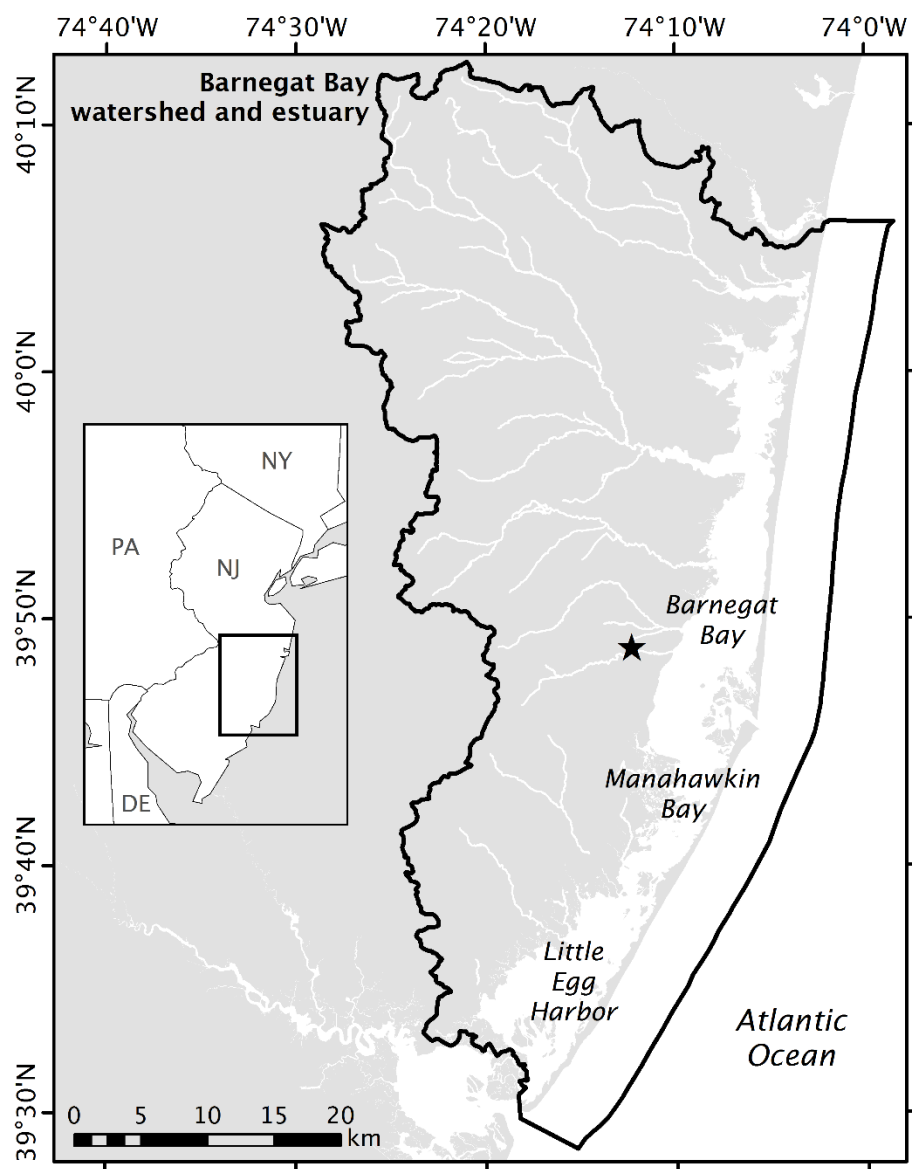


Fig 2 Barnegat Bay Ecosystem Model for 1981. Numbered horizontal lines indicate trophic level. The size of the circle indicates relative biomass, while the lines indicate energy flow from one group to another

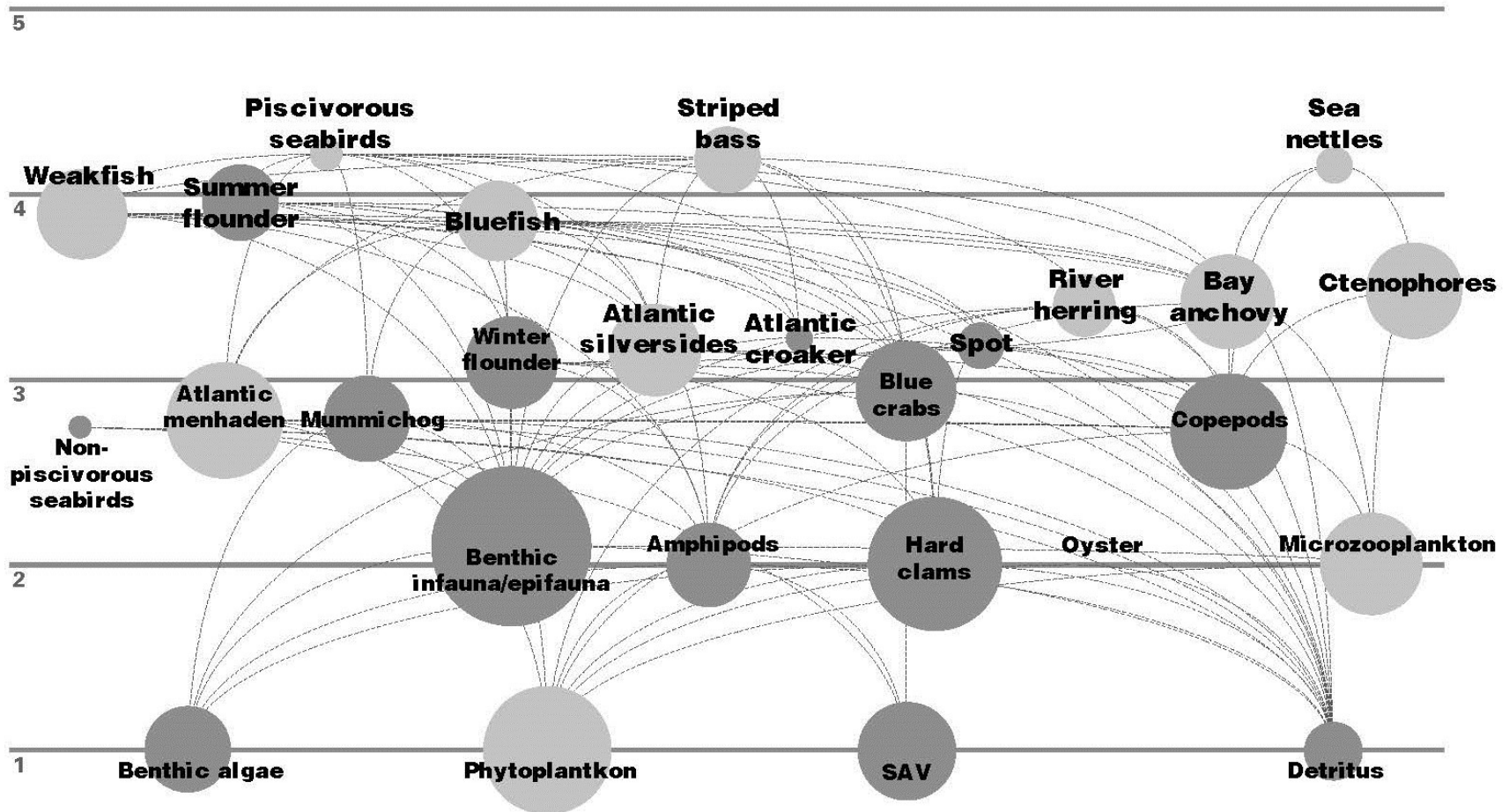


Fig 3 Mixed Trophic Impact (MTI) analysis showing direct and indirect impacts. Red blocks show a positive impact, blue blocks a negative impact. The values are not considered absolute, but are comparable between groups

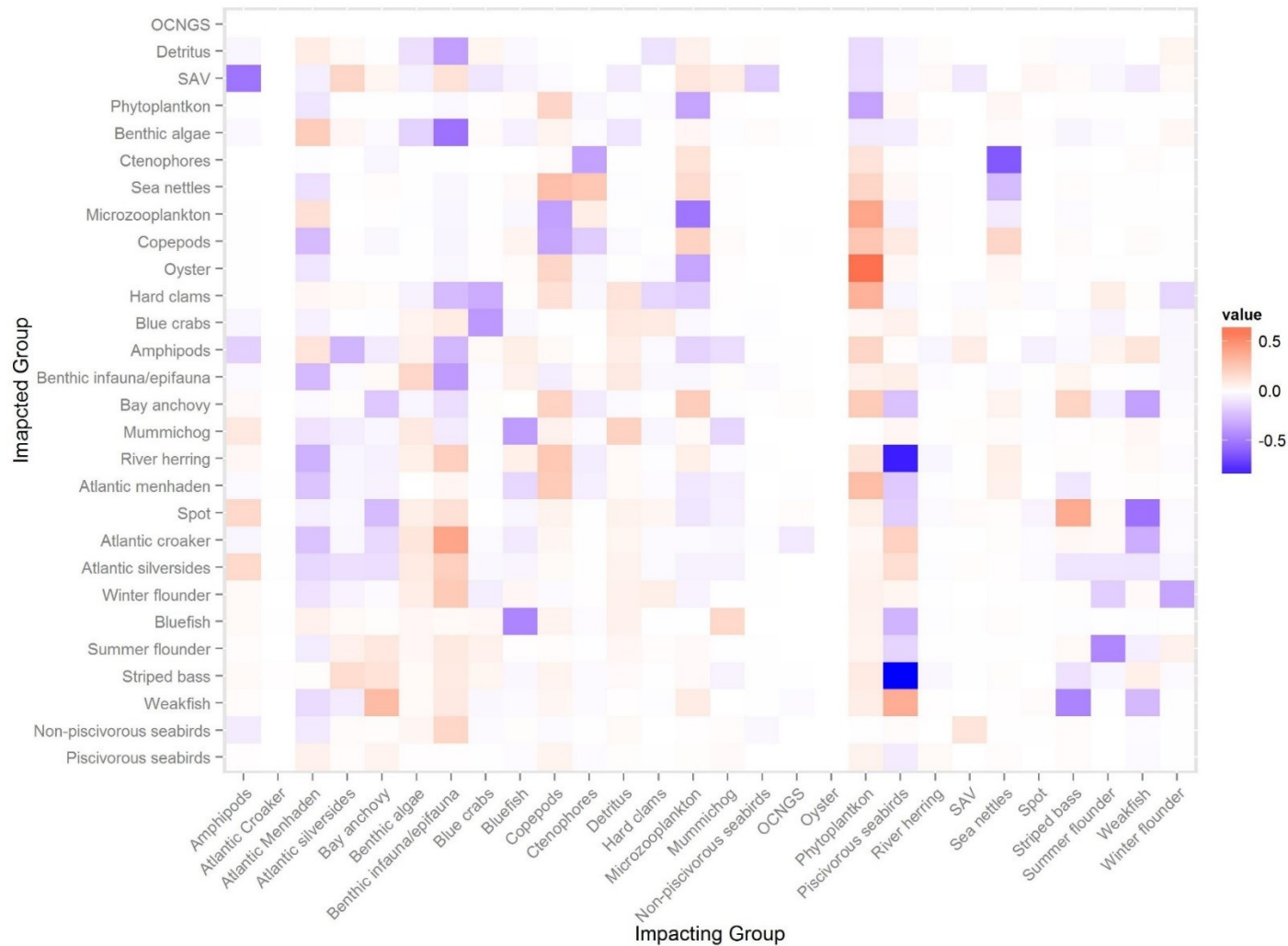


Fig 4 Relative abundance (filled circles) and predicted biomass (lines) for the Ecosim model for Atlantic croaker, blue crab, hard clam, summer flounder, and winter flounder

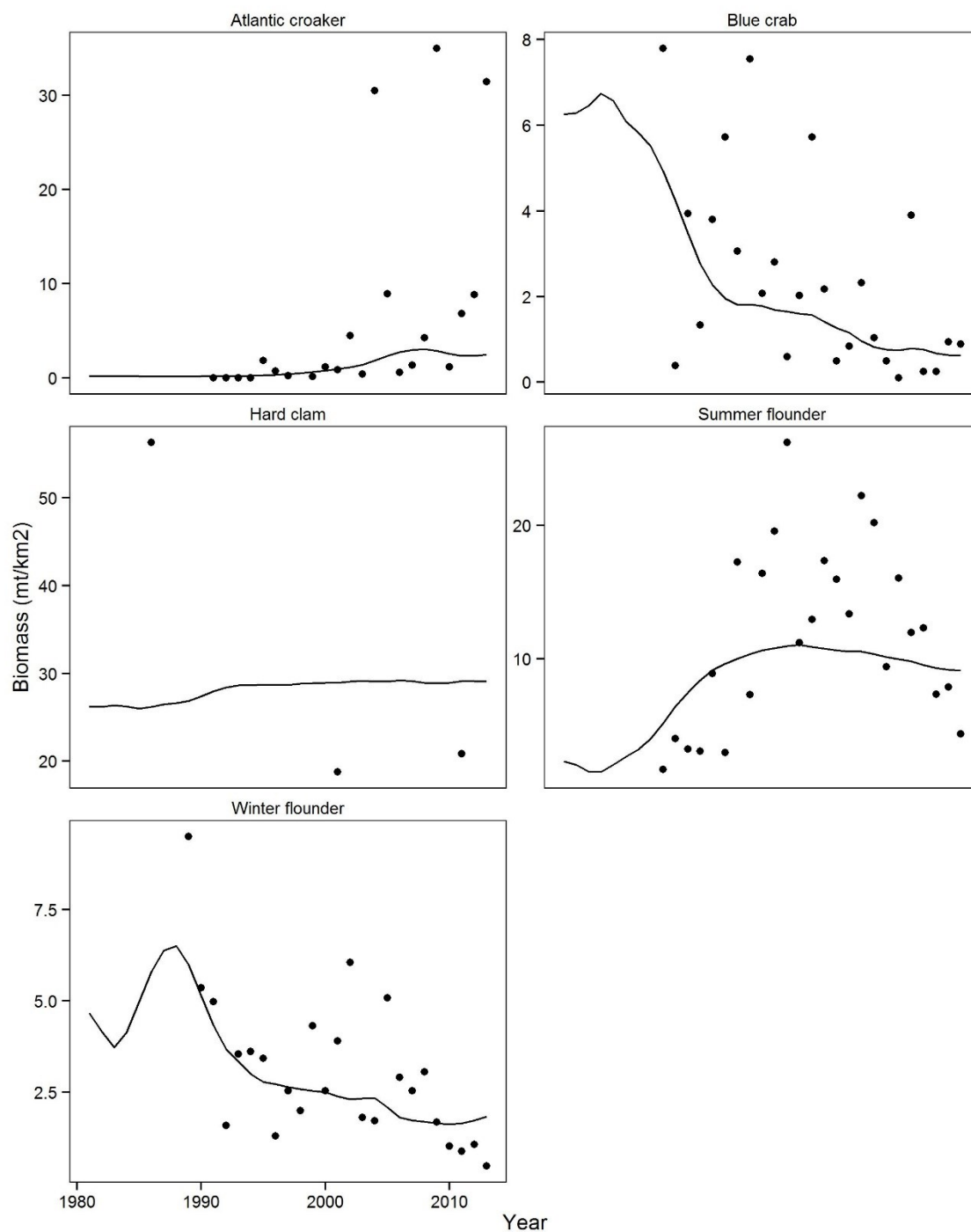


Fig 5 Percent change in biomass between the OCNCS closure simulation and the baseline simulation for 2030

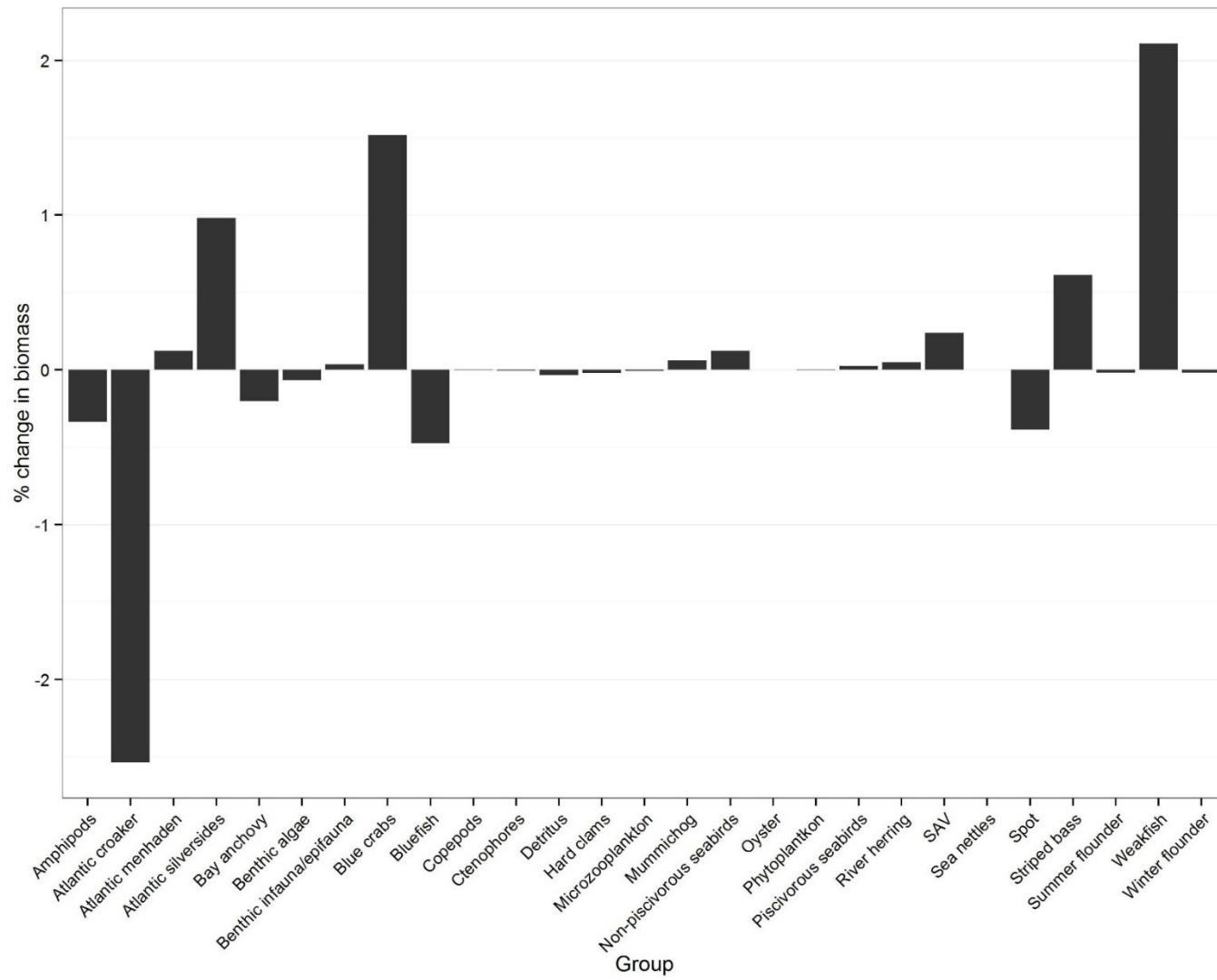


Table 1: Basic input parameters for the Barnegat Bay Ecosystem Model. Catch includes fishery landings and OCNGS discards. Color scale represents the level of confidence in data inputs for Biomass, P/B, Q/B, and EE. Estimated from a variety of sources as described in ESM 1.

<p>Scale</p> <p>Sampling based high precision</p> <p>Sampling based low precision</p> <p>Approximate or indirect method</p> <p>Best Professional Judgement</p> <p>From other model</p> <p>Estimated by Ecopath</p>						
Group name	Trophic Level	Biomass (t/km ²)	P/B (year ⁻¹)	Q/B (year ⁻¹)	Ecotrophic Efficiency	Catch (t/km ²)
Piscivorous seabirds	4.21	0.250	0.163	120	0.0	
Non-piscivorous seabirds	2.73	0.121	0.511	120	0.0	
Weakfish	3.89	3.969	0.26	3	0.95	0.0383
Striped bass	4.19	1.383	0.4	2.4	0.9	0.00001
Summer flounder	3.95	2.300	0.52	2.6	0.95	0.8067
Bluefish	3.85	2.733	0.52	3.1	0.95	0.750021
Winter flounder	3.09	4.661	0.52	3.4	0.95	0.93205
Atlantic silversides	3.15	4.461	0.8	4	0.95	0.0248
Atlantic croaker	3.22	0.179	0.916	4.2	0.9	0.01311
Spot	3.17	0.561	0.9	6.2	0.9	0.00398
Atlantic menhaden	2.77	12.427	0.5	31.42	0.95	0.058616
River herring	3.39	1.180	0.75	8.4	0.95	0.004322
Mummichog	2.78	3.465	1.2	3.65	0.95	0.000001
Bay anchovy	3.41	4.86	3	9.7	0.839	0.0112
Benthic infauna/epifauna	2.10	77.425	2	10	0.9	
Amphipods	2	3.323	3.8	19	0.9	
Blue crab	2.93	6.257	1.21	4	0.95	1.4406
Hard clams	2	26.18	0.5	5.1	0.629	
Oyster	2	0.001	0.63	2	0	
Copepods	2.72	12.485	25	83.33333	0.95	
Microzooplankton	2	6.694	140	350	0.95	
Sea nettles	4.15	0.345	13	20	0	
Ctenophores	3.47	5.29	16.2	35	0.042	
Benthic algae	1	3.533	80		0.899	
Phytoplankton	1	21.273	160		0.95	
SAV	1	5.82	5.11		0.317	
Detritus	1	1			0.132	

ESM 1: Initial parameter values for the 1981 Ecopath model

Fish

Atlantic Croaker

Q/B - Estimates of consumption to biomass ratio was calculated in FishBase (Froese and Pauly, 2004) as 4.2 year^{-1} , assuming an annual temperature of the Barnegat Bay of $T = 15 \text{ }^{\circ}\text{C}$, aspect ratio = 1.32, $W_{inf} = 815.3$, and carnivorous feeding.

P/B - An annual total mortality for the Chesapeake Bay Atlantic croaker stock was estimated to be 55 to 60% per year (Austin et al. 2003). Using the higher end as a conservative mortality estimate yields a $P/B = 0.916 \text{ year}^{-1}$.

Biomass - An EE value of 0.90 was used and EwE estimated the biomass. Croaker were rarely identified in Barnegat Bay by Sugihara et. al (1979) study.

Diet - The diet data is based on the work of Nemerson and Able (1994) in the Delaware Bay.

Atlantic Menhaden

Q/B - A value of 31.42 year^{-1} taken from Palomares and Pauly (1998).

P/B - As there was no commercial fishery for menhaden in Barnegat Bay and only a limited bait fishery, total mortality was set equal to natural mortality, which is estimated at 0.50 year^{-1} (MSVPA-X averaged across all ages and 1982-2008; ASMFC 2011).

Biomass - Biomass was calculated by EwE setting the EE to 0.95.

Diet - Diet data is from Festa et al. (1978).

Atlantic Silverside

Q/B - The consumption ratio for silversides of 4.0 year^{-1} was determined by setting a production/consumption ratio of 0.2 (Christensen et al. 2009).

P/B - Total mortality for littoral forage fish was estimated by local experts at a Chesapeake Bay Ecopath Workshop (Sellner et al. 2001) to be 0.8 year^{-1} and was used here for lack of local data.

Biomass - The biomass for the group was estimated by setting ecotrophic efficiency to 0.95. While baywide biomass was not determined by Voughlitois et al. (1987), they suggested it should be comparable, if not great than what they determined for bay anchovy, given Atlantic silverside was numerically dominant.

Diet - Diet data is from Festa et al. (1978).

Bay Anchovy

Q/B - Assuming habitat temperature of $15 \text{ }^{\circ}\text{C}$, $W_{\infty} = 20 \text{ (g)}$, an aspect ratio of 1.32, and carnivorous diet, the consumption to biomass ratio is calculated by Fishbase to be 9.7 year^{-1} .

P/B - Christensen et al. (2009) used an initial P/B of 3.0 year^{-1} for the Chesapeake Bay model based on a 95% annual mortality rate reported by Luo and

Brandt (1993), while Frisk et al. (2006) estimated a P/B of 2.19 year⁻¹ from catch curve analysis on adults in Delaware Bay. We elected to use the higher rate.

Biomass – Voughlitois et al (1987) estimated biomass for 1976 to range from 0.83 to 4.83 g/m². In the same study the catch per unit effort for 1981 was comparable to that for 1976, and thus the biomass range should be similar. Given the ubiquity of the species within the Barnegat Bay, we chose to use 4.83g/m² for an initial biomass.

Diet - Diet data is from Festa et al. (1978).

Bluefish

Q/B - Assuming habitat temperature of 15 oC, W_{max} = 16,962.1 (g), carnivorous feeding, and an aspect ratio of 2.55, the resulting consumption to biomass ratio is 3.1 year⁻¹.

P/B – Production/biomass was determined as 0.52 year⁻¹ based on an M = 0.25 year⁻¹ (Christensen et al. 2009) and an estimate of F = 0.27 year⁻¹ for 1982 from the NEFSC 41st Stock Assessment Workshop (2005) for Bluefish.

Biomass – Biomass was calculated by EwE setting the EE to 0.95.

Diet – Diet data is from Festa et al. (1978) averaged for all size classes.

Mummichog

Q/B – A Q/B of 3.65 year⁻¹ was used (Pauly 1989).

P/B – We opted to utilize a P/B of 1.2 year⁻¹ as given in Frisk et al. (2006) from “best professional judgement” compared to Valiela 0.287 year⁻¹ (1977 mortality tables) or Christensen et al. (2009) 0.8 year⁻¹.

Biomass- The biomass for the group was estimated by setting ecotrophic efficiency to 0.95

Diet – Diet data is from Festa et al. (1978).

River herring

Q/B – We used a Q/B = 8.4 year⁻¹, which is the average of Pauly (1989; 8.63 at temperature = 10C) and Palomares (1991; 8.23 at temperature= 20C).

P/B - Total mortality for this group was based on the P/B of 0.75 year⁻¹ for alewife in Randall and Minns (2000).

Biomass – Biomass was estimated by EcoPath assuming that the ecotrophic efficiency of these species in the Bay was 0.95.

Diet – Diet data is from Festa et al. (1978).

Spot

Q/B – The consumption biomass ratio was estimated as 6.2 year⁻¹ using the model in Fishbase.org and a habitat temperature of 15 0C, W_∞ = 190g (Piner and Jones, 2004) and an aspect ratio of 1.39 (Christensen et al. 2009).

P/B - Hoenig’s method estimated an M = 0.9 year⁻¹ given a maximum age of 5 (Piner and Jones, 2004). This is consistent with the Z used in the Delaware Bay model (Frisk et al. 2006).

Biomass – Biomass was estimated by EcoPath assuming that the ecotrophic efficiency of this species in the Bay was 0.9.

Diet – Diet data is from Festa et al. (1978).

Striped bass

Q/B - Based on empirical relationship provided by Fishbase.org and assuming an aspect ratio of 2.31 (Christensen et al. 2009), temperature $T = 15^{\circ}\text{C}$, and $W_{\infty} = 46.6 \text{ kg}$, the estimated consumption ratio was 2.4 year^{-1} .

P/B – The 1981 ASMFC FMP suggest an $M=.15$ and an $F=.3$ for the coastwide stock. Given the reduced fishing mortality in the Barnegat Bay, an $F=.25$ is appropriate leading to a P/B of 0.4 year^{-1} . This is equal to the Chesapeake model (Christensen et al. 2009) for resident bass (1-7 years old), though their YOY P/B = 1.8 year^{-1} .

Biomass – The biomass was estimated by EcoPath based on an EE of .90.

Diet – Diet data is from Festa et al. (1978) averaged across all size classes.

Summer Flounder

Q/B- Assuming an aspect ratio of 1.32, $W_{\text{max}} = 12\text{kg}$ (Frisk et al. 2006), carnivorous feeding, and habitat temperature of 15°C , the consumption to biomass ratio is $= 2.6 \text{ year}^{-1}$.

P/B- A P/B = 0.52 year^{-1} was used as was done in the Chesapeake Bay (Christensen et al. 2009) and Delaware Bay (Frisk et al. 2006) models. This value is based on the 2002 NEFSC determination of $M=0.2$ and F ranging between 0.24 and 0.32.

Biomass – The biomass was estimated by EcoPath based on an EE of 0.95.

Diet – Diet data is from Festa et al. (1978).

Weakfish

Q/B - Using Fishbase, consumption to biomass was estimated $= 3.0 \text{ year}^{-1}$, assuming average habitat temperature of 15°C , aspect ratio of 1.32, maximum weight $W_{\infty} = 6,190\text{g}$ (Lowerre-Barbieri et al. 1995) and carnivorous feeding habitats.

P/B – Total mortality of $Z = 0.26 \text{ year}^{-1}$ was estimated using Hoenig's method (1983) assuming a longevity of 17 years (Lowerre-Barbieri et al. 1995). This is in-line with an estimated M of $.25 \text{ year}^{-1}$ as used for stock assessment purposes (Smith et al. 2000). Given the low rate of fishing in Barnegat Bay, Hoenig's estimation of Z seem reasonable.

Biomass – The biomass was estimated by EcoPath based on an EE of .90.

Diet – Diet data is from Festa et al. (1978) averaged across all size classes.

Winter Flounder

Q/B - The estimated consumption ratio of 3.4 year^{-1} was derived using the empirical equation in FishBase (Froese and Pauly, 2004), and was calculated assuming that $T = 15^{\circ}\text{C}$, $W_{\text{inf}} = 3,600 \text{ g}$ (Fishbase), an aspect ratio of 1.32, and a carnivorous diet.

P/B – The 2011 Southern New England/Mid-Atlantic stock assessment (ASMFC 2011b) updated natural mortality (M) to 0.30 year^{-1} for all ages and all years. Fishing mortality for ages 4-6 was determined as 0.61 year^{-1} for 1981. If one assumes only natural mortality for ages 0-3 and then $F+M$ for ages 4-6, total mortality (Z) is 0.52 averaged across all ages.
 Biomass – The biomass was estimated by EcoPath based on an EE of 0.95.
 Diet – Diet data is from Festa et al. (1978).

Piscivorous seabirds

Biomass - The biomass estimate for piscivorous seabirds of $0.25 \text{ t} \cdot \text{km}^{-2}$ is a reduction of the Chesapeake Bay model estimate (Sellner et al. 2001).
 P/B - A total mortality estimate for piscivorous seabirds of 0.163 year^{-1} was based on survival rate values of 85-90% for cormorants and 80-93% for alcids in the northeast Atlantic (ICES, 2000).
 Q/B - The consumption ratio estimate of 120 year^{-1} was from data for the piscivorous seabirds group in Preikshot (2007).
 Diet compositions - The diet composition for piscivorous seabirds was taken from the Chesapeake Bay model (Christensen et al. 2009) and was modified by reducing predation on menhaden and increasing imports based on the large number of migratory seabirds.

Non-Piscivorous seabirds

Biomass - The biomass estimate for non-piscivorous seabirds of $0.121 \text{ t} \cdot \text{km}^{-2}$ was taken from the Chesapeake Bay model and was based on advice provided in a Chesapeake Ecopath Workshop (Sellner et al. 2001).
 P/B - A total mortality estimate for non-piscivorous seabirds of 0.51 year^{-1} was taken from the Chesapeake model and was based on annual mortality rate of 37% for mallard males and 44% females (Anderson 1975).
 Q/B - The consumption ratio estimate of 120 year^{-1} was from data for the non-piscivorous seabirds group in Preikshot (2007).
 Diet compositions - The diet composition for non-piscivorous seabirds was taken from the Chesapeake Bay model (Christensen et al. 2009).

INVERTEBRATES

Blue crab

Biomass – Biomass was estimated by the ecopath software by setting ecotrophic efficiency to 0.95.
 Q/B- The consumption ratio of 4.0 year^{-1} was taken from the Chesapeake Bay model (Christensen et al. 2009).
 P/B – A $P/B = 1.21 \text{ year}^{-1}$ was used based on a stock assessment for Delaware Bay that used a natural mortality of $M = 0.8 \text{ year}^{-1}$ assuming a lifespan of 4 years (Kahn 2003) and fishing mortality on total stock (recruits and post recruits) was $F = 0.41 \text{ year}^{-1}$ (2000-2002).
 Diet – Diet taken from the Chesapeake Bay model (Christensen et al. 2009), averaged across stanzas.

Hard Clams

- Biomass – A value of 26.18 t/km² was used based on a density of 1,309,233 clams per km² (adjusted values for the 1985-1987 surveys, Celestino 2002) and an average mass of 20 g (mean length of 7.46cm, Celestino 2013).
- Q/B - The consumption ratio was estimated to be 5.1 year⁻¹ assuming a P/Q = 0.20.
- P/B - A production/biomass ratio of 0.5 year⁻¹ was used based on the empirical studies of Hibbert (1976).
- Diet – Diet taken from the Chesapeake Bay model (Christensen et al. 2009).

Oyster

- Q/B - The Q/B ratio of 2.0 year⁻¹ was taken from the adult stanza of the Chesapeake Bay Model (Christensen et al. 2009).
- P/B – A 2009 survey of the restored oyster reef at Good Luck Point in Barnegat Bay determined a mean annual mortality of 47%, or an $M=0.63 \text{ year}^{-1}$ (Calvo 2010). As oysters in Barnegat Bay are an unfished resource, $Z=M=.63 \text{ year}^{-1}$.
- Biomass – Based on NJDEP experience there does not appear to be a viable oyster set in Barnegat Bay; the known oyster reef is seeded by the NJDEP. In order to keep oysters in the model for future management considerations the biomass was set to 0.001t/km² to simulate a very small population.
- Diet – Data taken from the Chesapeake model (Christensen et al. 2009).

Sea Nettles

- Q/B – A Q/B of 20 year⁻¹ was taken from the Chesapeake Bay model (Christensen et al. 2009). This value is based on an assumed P/Q of 0.25.
- P/B – As reported by Matishov and Denisov (1999) the daily growth rate for *Aurelia aurita* is estimated as 0.053 at 5 °C to 0.15 at 16.5 °C. Sea nettle medusa are present in the Barnegat Bay during the summer months, when waters are typically warmer than 16.5 °C. As such the P/B for Barnegat Bay was calculated as $(0.15 \times 365)/4 \sim 13 \text{ year}^{-1}$.
- Biomass – In 2012, a baywide survey data from Monmouth University led to an estimate of 24,711 individuals per km² (Ursula Howson, unpublished data). Assuming an average wet weight of 56g per individual, this translates to a biomass of 1.38t/km². Recent work by Young et al. (in review) suggests that sea nettle abundances were at very low levels (unrecorded in contemporary research) until the late 1990's, and did not reach current levels until the mid-2000s. Therefore we estimate that sea nettle biomass was about 1/4th of the current biomass, or 0.345t/km².
- Diet – The sea nettle diet data was taken from the Chesapeake Bay model (Christensen et al. 2009)

Ctenophores

- Q/B - Shushkina et al. (1989) found that ctenophores in their study had growth rates 1.5 to 2 times greater than true jellyfish. Therefore, the Q/B value for

ctenophores was the value for sea nettles multiplied by 1.75, *i.e.* Q/B was 35 year⁻¹.

P/B – Shushkina et al. (1989) found that ctenophores in their study had growth rates 1.5 to 2 times greater than true jellyfish. Ctenophores tend to be present in Barnegat Bay at cooler temperatures than those of sea nettles, therefore the P/B was calculated as 1.75 times the average estimated daily growth rate of *Aurelia aurita* over the course of 3 months

$$(((0.053+0.15)/2)*365)/4*1.75 \sim 16.2 \text{ year}^{-1}$$

Biomass – A biomass of 7.86 t/km² was calculated using bay-wide survey data collected by Monmouth University during 2012 and an average weight of 3.42g per individual (Ursula Howson, unpublished data).

Diet - The ctenophore diet data was taken from the Chesapeake Bay model (Christensen et al. 2009).

Benthic infauna/epifauna (shrimp, worms, non-blue claw crabs)

Q/B – A consumption ration of 5.0 year⁻¹ was estimated by Ecopath after designating a P/Q ratio of 0.2, as taken from the Chesapeake Bay Model (Christensen et al. 2009).

P/B – A P/B of 2.0 year⁻¹ was taken from the Chesapeake Bay model (Christensen et al. 2009).

Biomass – Estimated by Ecopath, based on a group ecotrophic efficiency of 0.9.

Diet – Diet data taken from Chesapeake Bay model (Christensen et al. 2009).

Amphipods

This category consists mainly of the genus *Ampelisca* (*A. abdita* and *A. verrilli*) and *Elasmopus levis* based on the work conducted by Haskin and Ray (1977) and Taghon et al (2013).

Q/B – Ecopath estimated a Q/B = 5.0 year⁻¹ using a P/Q ratio of 0.2, following the Chesapeake Bay model (Christensen et al. 2009).

P/B – A P/B of 3.8 year⁻¹ was used based on the average P/B of *Ampelisca abdita* at 3 locations within Jamaica Bay (Franz and Tanacredi 1992). *A. abdita* was the most common amphipod found in Barnegat Bay sampling in 2012 (Taghon et al. 2013).

Biomass – The biomass of amphipods was estimated by Ecopath using an EE=0.900.

Diet – The diet data for this group is the combination of a *Ampelisca abdita* from Haskin and Ray (1979) and *Elasmopus levis* as described by Christian and Luczkovich (1999).

Copepods (Mesozooplankton)

Q/B – A consumption ration of 83.333 year⁻¹ was estimated by Ecopath after designating a P/Q ratio of 0.3, as taken from the Chesapeake Bay Model (Christensen et al. 2009).

P/B – A mortality rate of 25 year⁻¹ was taken from the Chesapeake Model (Christensen et al. 2009).

Biomass – The software estimated biomass using an ecotrophic efficiency of 0.95.
 Diet – The diet ratio is from the Chesapeake Bay model (Christensen et al. 2009).

Microzooplankton

Q/B – A consumption ration of 350 year⁻¹ was estimated by Ecopath after designating a P/Q ration of 0.4, as taken from the Chesapeake Bay Model (Christensen et al. 2009).
 P/B – A total mortality rate for microzooplankton of 140 year⁻¹ was taken from the Chesapeake Bay model (Christensen et al. 2009).
 Biomass – Biomass was estimated based on an assumed EE of 0.95.
 Diet – The 100% phytoplankton diet follows the Chesapeake Bay model (Christensen et al. 2009).

Phytoplankton

P/B – We elected to use the Chesapeake value of 160 year⁻¹ (Christensen et al. 2009) over the Delaware Bay value of 60 year⁻¹ (Frisk et al. 2006) as the Chesapeake is a highly eutrophic system more similar to the conditions found in Barnegat Bay.
 Biomass – Biomass was estimated by the software assuming an ecotrophic efficiency of 0.95.

Benthic algae

P/B – The Chesapeake model assumed a value of 80 year⁻¹ (Christensen et al. 2009).
 Biomass – Biomass of benthic algae was estimated based on an assumed EE of 0.9.

SAV

P/B – Mortality for *Z. marina* was estimated as $Z = P/B = 5.11 \text{ year}^{-1}$, which was taken from a similar system in Japan (Oshima *et al.*, 1999).
 Biomass – In 1979 there was approximately 8,053 ha of mapped submerged aquatic vegetation (Northern segment: 767, Central segment: 5,126, Southern segment: 2,160) out of the 27,900 hectares of Barnegat Bay (Lathrop et al 2001). The highest recorded annual eelgrass maximum biomass in the southern and central portions of the bay occurred in 2004 and was 219.7 g dry wt /m², while the highest *Ruppia* biomass recorded in the northern segment occurred in 2011 and was 32.8 g dry wt/ m² (Kennish et al. 2014). Expanding the biomass estimates over the 1979 SAV acreage yields a baywide total biomass of 1,625.891t, or 5.82t/km²

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ESM 2: Ecopath Initial Diet Composition

	Piscivorous seabirds	Non-piscivorous	weakfish	striped bass	summer flounder	bluefish	winter flounder	Atlantic silversides	Atlantic croaker	spot	Atlantic menhaden
Piscivorous seabirds											
Non-piscivorous											
weakfish	0.0056			0.2		0.013					
striped bass	0.0166										
summer flounder	0.011										
bluefish	0.02										
winter flounder	0.0058				0.2						
Atlantic silversides	0.017		0.05	0.221	0.132	0.087					
Atlantic croaker			0.005	0.01		0.005					
spot			0.03			0.011					
Atlantic menhaden	0.1			0.206		0.255					
river herring	0.028										
mummichog	0.03					0.36					
bay anchovy	0.07		0.535	0.2	0.273	0.094	0.018				
benthic infauna/epifauna		0.276	0.352	0.06	0.186	0.066	0.742	0.59	0.8	0.509	0.18
amphipods			0.022				0.07	0.244		0.25	
blue crab	0.004		0.006	0.1	0.2	0.103	0.002				
hard clams		0.01		0.003			0.157			0.057	
oysters											
copepods								0.154	0.2	0.18	0.338
Microzooplankton											
sea nettles											
ctenophores											
benthic algae											
phytoplankton											0.421
SAV		0.128									
detritus		0.011			0.009	0.006	0.011	0.012		0.004	0.061
import	0.692	0.575									

	river herring	mummichog	bay anchovy	benthic infauna	amphipods	blue crab	hard clams	oysters	copepods	Micro zoo	sea nettles	ctenophores
Piscivorous												
Non-piscivorous												
weakfish												
striped bass												
summer flounder												
bluefish												
winter flounder												
Atlantic silversides												
Atlantic croaker												
spot												
Atlantic menhaden												
river herring												
mummichog												
bay anchovy											0.054	
benthic infauna	0.435	0.260		0.02	0.02	0.5						
amphipods	0.055	0.170	0.044									
blue crab						0.125						
hard clams						0.175						
oysters												
copepods	0.5	0.19	0.582								0.421	0.666
Microzooplankton			.370	0.08	0.08				0.72			0.334
sea nettles												
ctenophores											0.525	
benthic algae		0.12		0.3	0.3	0.05	0.5					
phytoplankton	0.005			0.4	0.4		0.25	0.99	0.28	1		
SAV						0.05						
detritus	0.005	0.26	0.004	0.2	0.2	0.1	0.25	0.01				

ESM 3: Landing Calculations for the Barnegat Bay Ecopath Model

Directed Fisheries

The National Marine Fisheries Service (NMFS) commercial landings database (NOAA 2015a) is the most comprehensive record of commercial landings available for the time period of interest (1950-2011). However, these data represent landings for all of New Jersey, and are not Barnegat Bay specific. The NMFS landings data used below are a subset of the statewide landings based on gear that could be used within an estuary. Gear types considered usable in the bay include the following: by hand; cast nets; dip nets, common; fyke and hoop nets, fish; hand lines, other; pots and traps, blue crab; and weirs. Because these gear types have been used in the Barnegat Bay as well as other larger estuaries throughout the state (Raritan Bay, Delaware Bay, *etc.*), this subset likely overestimates commercial removals from Barnegat Bay. Where Barnegat Bay specific landings data are available they were used to the maximum extent possible.

Recreational landings for finfish were taken from the NMFS Marine Recreational Fisheries Statistics Survey (MRFSS) and Marine Recreational Information Program (MRIP) for Ocean County, inland waters only (NOAA 2015b). The landings for 1981 were used to initialize the model as that is the earliest year for which data is available.

The source and calculations for each species are described below.

Atlantic croaker – Based on the subset of NMFS commercial landing data, there was no harvest of Atlantic croaker reported in the 1980s. There were no recreational landings of croaker reported for Ocean County.

Atlantic Menhaden – There was no commercial harvest of menhaden recorded in the NMFS landing data for the gear types used in Barnegat Bay in 1980. There were no recreational landings of menhaden reported for Ocean County in the MRFSS database. Menhaden are commonly used as bait in the recreational fishery in Barnegat Bay, therefore an estimated landing of 0.2MT was attributed to the recreational fishery, though this likely underestimates landings.

Blue Crab – In Barnegat Bay the commercial blue crab fishery can be divided into a winter dredge fishery and a pot/trap line fishery in the remainder of the year. Landings data specific to Barnegat Bay were available from the NJDEP for 1995-2013 (NJDEP, personal communication), while statewide landings were available from NMFS for 1980-2011. The NJDEP data was regressed on the NMFS data and the results used to calculate bay specific total landings for 1981-1994. The winter dredge fishery represented approximately 17% of the baywide total (NJDEP data); this ratio was used to estimate the gear specific landings from the total baywide landings of 221 metric tons for 1981. Therefore the winter dredge fishery in 1981 landed an estimated 38.1 metric tons while the pots

and trot lines accounted for an estimated 183.3 metric tons. In 2007 the recreational harvest of blue crab in Barnegat Bay was estimated to be 80% of the total commercial harvest (Macro International Inc. 2008), leading to an estimated recreational harvest of 177.1 metric tons in 1981.

Bluefish – Barnegat Bay specific commercial landings were available for bluefish for 1997 only (Kennish 2001). The bay specific landings represented 21% of the subset landings for that year (NMFS). That ratio was utilized to calculate an estimated Barnegat Bay specific commercial landing of 0.02 metric tons for 1980. In 1981 approximately 209.1 metric tons of bluefish were landed in Ocean County inland waters (MRFSS).

Hard Clam – Hard clams are historically one of the most important commercial fishery resources in Barnegat Bay. However there are no records for commercial or recreational landings of hard clams specific to Barnegat Bay. Based on recommendations of Bureau of Shellfisheries staff and long-time commercial clambers an estimate of 0.39t/km² was developed assuming 40 individuals harvesting 3 bushels per day working 200 days per year, with a bushel weighing approximately 10lbs. There are no estimates of hard clam recreational landings available.

River herring – Alewife and blueback herring have been combined into this single category given the similarities in their life history strategies and propensity to co-migrate. In 1981 there were no commercial landings of either species in the subset landings, and no landings reported for Ocean County's recreational inland fishery. However, there were known fisheries for river herring within the bay associated with bait collection. As such a total landing of 0.1MT was assumed based on the landings in subsequent years and split evenly between the recreational and commercial sectors.

Spot – There were no commercial landings of spot recorded in the subset landing data for the late 1970s through mid-1980s. There were 1.1 metric tons of spot landed in the Ocean County inland recreational fishery in 1981.

Striped Bass – In 1981 there were no commercial landings of striped bass recorded in the subset landing data. There were no landings reported for Ocean County's recreational inland fishery. However, there was a well-documented recreational fishery present at the time, therefore 26 MT was used, which is the average of reported landings from 1981-201.

Summer flounder – Commercial landings of summer flounder approached 0.2 metric tons in 1981 according to the subset NMFS database. There were 224.4 metric tons of summer flounder landed in the Ocean County inland recreational fishery in 1981.

Weakfish – Barnegat Bay specific commercial landings were available for weakfish for 1993 only (Kennish 2001). The bay specific landings represented approximately 5.2% of the gear specific statewide landings for that year (NMFS landing data). That ratio was utilized to calculate an estimated Barnegat Bay specific commercial landing of 0.078 metric tons for 1981. There were 3.29 metric tons of weakfish landings reported for Ocean County’s recreational inland fishery in 1981.

Winter flounder – The NJDEP Bureau of Marine Fisheries estimates a commercial harvest of approximately 10.68 metric tons of winter flounder from Barnegat Bay in 1981. In 1981 there were 247 metric tons of winter flounder landed in the Ocean County inland recreational fishery.

OCNGS

The Oyster Creek Nuclear Generating Station “landings” info can be divided into two categories, impingement/impingeable size losses and entrainment losses. Impingement losses describe those animals that become trapped on the traveling Ristroph screens (9mm mesh) associated with the Circulating Water Intake Structure (CWIS) and are subsequently deposited into a fish return system and into the discharge canal. Impingeable size losses are biota that are large enough to be impinged on the Ristroph screens if they were present at the Dillution Water Intake Structure (DWIS). Entrainment losses are the biota that pass through the CWIS and DWIS structures and pass through the plant and dilution pumps, respectively. The data used to estimate these values were collected as part of periodic relicensing of the facility, and were most recently collected during 2005-2007 and include in the “Characterization of the aquatic resources and impingement and entrainment at Oyster Creek Nuclear Generating Station” September 2008 (Amergen 2008).

Impingement/Impingeable size losses

During 2006-2007 the estimated annual biomass of the young of year (YOY) and older ages of selected fish and crustaceans impinged on the traveling screens at the CWIS was calculated (Appendix A: Detailed Characterization of the aquatic resources and impingement and entrainment at Oyster Creek Nuclear Generating Station, Tables A-7 and A-8). The biomass of each species was then multiplied by the empirically determined impingement mortality rate (Appendix H, Tables H-2 and H-4) to derive a CWIS impingement mortality (kg/yr). The estimated annual biomass of impingeable sized fish and shellfish that were entrained through the DWIS was calculated (Tables A-15 and A-18) and multiplied by the empirically determined mortality rates (Tables H-5 and H-6) to derive a DWIS impingeable size mortality (kg/yr). It should be pointed out that the mortality rates were instantaneous, that is injured individuals were considered “live” at the time of counting, and thus the mortality rates are likely low.

Entrainment losses

Entrainment losses occur when biota are able to avoid or slip through the traveling screens at the CWIS and are carried through the cooling water system or are

taken up by the DWIS. The number of individual fish in each species entrained into either the CWIS (Table A-10) or DWIS (A-20) are broken into 5 size categories; eggs, yolk sac larvae, post-yolk sac larvae, YOY, and YOY+. Blue crabs were divided into adult, juvenile, and megalops (tables A-12 and A-22). For this model the entrainment analysis was limited to post-yolk sac larvae, YOY, and YOY+ fish and megalops stage of blue crab. Biomass for each species/size class was calculated by taking the median or mode length from the CWIS entrainment sampling length frequency histograms (Appendix C: Impingement and entrainment studies at Oyster Creek Generating Station 2005-2007) and searching the literature for the corresponding weight. This weight was multiplied by the annual estimated number of individuals to derive an estimate of annual biomass. The biomass estimate was then multiplied by the appropriate empirically determined mortality rate to derive an estimate of entrainment losses for both the CWIS and DWIS. The latent mortality was calculated as the number of live, healthy entrainable-size specimens collected from the discharges who survived for 24 hours (Appendix F, Sections 2 and 3). The mortality was applied equally across all size classes. Given that this methodology does not take into account individuals that do not survive passage through the system it likely underestimates mortality. The specific values selected for the length, weight, and mortality rate for each species are detailed below.

Adult and juvenile blue crabs were not included in the entrainment analysis as there are a number of discrepancies in the crab data. The CWIS impingement sampling collected crabs in the 8-166mm size range; these specimens should not be able to pass through the Ristroph screen, thus nearly eliminating any entrainment at the CWIS. Further, any crabs of this size should be considered part of the “entrainment of impingeable sizes” DWIS calculations, and to include them in DWIS entrainment would be double counting.

Atlantic croaker –

Post-yolk sac – Lengths ranged from 4-16mm, with a rather uniform distribution between 7-15mm. The ASMFC (2005) stock assessment for larval croaker suggests a mode of 11mm and a weight range of 0.02 – 0.04g. An average weight of 0.03g was used in the analysis.

YOY – The lengths of YOY croaker ranged from 15-72mm, with the distribution skewed heavily to the left. The modal length was 21mm. An average weight of 0.06 grams at 21mm was calculated using the length-weight regression from FishBase.

Mortality – A mortality rate was not determined for croaker. The empirically determined weakfish mortality rate (CWIS 0.8, DWIS 0.75) was used as they are both Sciaenids and share similar characteristics at the larval stage.

Atlantic Menhaden –

Post-yolk sac – Lengths were bimodally distributed from 6 – 33 mm, with the larger mode at 24 mm. Hettler (1976) found an average weight of 0.195 grams at 28mm.

YOY – Lengths were evenly distributed between 27-42mm , with a mean length of 34. Hettler (1976) found an average weight of 0.494 grams at 34mm.

Mortality – A 24 hour mortality rate of 1 was used for the CWIS and 0.72 for the DWIS.

Atlantic silverside –

Post-yolk sac – Lengths were unimodally distributed from 4 – 8 mm, with the mode at 5mm.

YOY – Lengths were evenly distributed between 71-85mm. The silverside should be fully recruited to the Ristroph screen at 72mm, so 71mm was selected. An average weight of 0.2.25 grams at 71mm was calculated using the length-weight regression from FishBase.

YOY+ - Lengths were evenly distributed between 74-102mm, with a mean at 87mm. An average weight of 4.71 grams at 87mm was calculated using the length-weight regression from FishBase.

Mortality – A mortality rate was not determined for silverside. The empirically determined bay anchovy mortality rate (CWIS 0.97, DWIS 0.94) was used as they have similar body shapes and tolerances at the larval stage.

Bay anchovy –

Post-yolk sac – Lengths were unimodally distributed from 3 – 37 mm, with the mode at 8mm. Using the length-weight relationship in Table 5 of Leak and Houde (1987), an 8mm individual is approximately 11 days old, and would have a dry weight of 0.000114g. If larvae are assumed to be 95% water, this would lead to a wet weight of 0.0023

YOY – Lengths were unimodally distributed between 26-69mm , with a modal length of 34. An average weight of 0.32 grams at 34mm was calculated using the length-weight regression from FishBase.

Mortality - A 24 hour mortality rate of 0.97 was used for the CWIS and 0.94 for the DWIS.

Summer flounder –

Post-yolk sac – Lengths were unimodally distributed from 10 – 17 mm, with the mode at 14mm. An average weight of 0.04 grams at 14mm was calculated using the length-weight regression from FishBase.

YOY – Lengths were unimodally distributed between 12-17mm , with a modal length of 14. Given the overlap in lengths with post-yolk sac, it appears the demarcation between classes is based on eye migration. An average weight of 0.04 grams at 14mm was calculated using the length-weight regression from FishBase.

Mortality – A mortality rate was not determined for summer flounder. The empirically determined winter flounder mortality rate (CWIS 0.88, DWIS 0.90) was used as they have similar body shapes and tolerances at the larval stage.

Weakfish –

Post-yolk sac – Lengths were unimodally distributed from 2 – 14 mm, with the mode at 5mm. Using the empirically measured mean dry weight of 0.000171g for 5mm larvae from Duffy and Epifanio (1994) leads to a wet weight of 0.0034 grams assuming 95% water.

YOY – Lengths were evenly distributed between 11-123mm, with a mean length of 36. An average weight of 0.41 grams at 36mm was calculated using the length-weight regression from FishBase.

YOY+ - The only size captured in sampling was 172mm. An average weight of 0.44 grams at 172mm was calculated using the length-weight regression from FishBase.

Mortality - A 24 hour mortality rate of 0.80 was used for the CWIS and 0.75 for the DWIS.

Winter flounder –

Post-yolk sac – Lengths ranged from 2-11mm, with a relatively uniform distribution between 3-6mm. The average length was 5mm. Based on mean larval lengths in Buckley et al. (1991), a 6mm winter flounder is approximately 4 weeks old. Laurence (1975) determined the mean dry weight of a 4 week old winter flounder kept at a similar temperature to be 0.000206g. This leads to a wet weight of 0.00412 grams assuming 95% water.

YOY – Lengths ranged between 6-7mm, with 6mm fish dominating the catch. Given the overlap in lengths with post-yolk sac, it appears the demarcation between classes is based on metamorphosis. Laurence (1975) determined the mean dry weight of a metamorphosed winter flounder to be 0.001243g. This leads to a wet weight of 0.02486 grams assuming 95% water.

Mortality - A 24 hour mortality rate of 0.88 was used for the CWIS and .90 for the DWIS.

Blue Crab –

Megalops – There was no information provided in the OCNGS reports on the length, weight, or mortality of blue crab megalopae with regard to entrainment sampling. Blue crab instar #1 have an average carapace width of 2.5mm, which is sufficiently small enough to pass through the Ristroph screen, and have an estimated average of weight of 0.0033 grams (Newcombe *et al.*, 1949). Mortality was assumed to be similar to that found empirically for *Mysidopsis bigelowi* during the study period of 0.66 and 0.17 for the CWIS and DWIS respectively.

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ESM 4: Time Series data for the 1981-2013 Barnegat Bay Ecosim Model

NMFS finfish, fishery-dependent (Forced catches; -6)

This time series (1981-2013) is a combination of the NMFS commercial landings data subset (as described in the landings calculations – ESM 3) and recreational landings from the MRFSS (1981-2003) and MRIP (2004-2013) surveys.

For summer flounder the 1983 recreational landing of 932MT was 3 times that of the next highest value (1982) and nearly 40 times that of 1984. It was replaced with the average of the 1981-1982 landings.

While there is no large-scale commercial fishery for menhaden in Barnegat Bay, “bunker” are a popular bait fish among recreational fisherman and crabbers. Therefore a steady low harvest rate (0.2mt/yr) was assigned.

If no landings were recorded, or recorded as 0kg, it was entered as 0kg.

NJDEP Blue crab gear specific, fishery dependent (Forced effort by gear type, 3)

Blue crab landing estimates for each fishery in 1981 are described in the landings calculations and were set as a relative effort of 1. The landing values for each fishery from 1995-2013 were then scaled compared to the 1981 estimate. For 1982 to 1994 the total commercial landings were calculated based on a linear regression of the known Barnegat Bay landings against the NMFS statewide landings for 1980 and 1995-2011. The commercial gear specific and recreational landings were then calculated and scaled as previously described.

OCNGS, fishery dependent (Forced effort by gear type; 3)

Because of the nature of OCNGS operations, the cooling and dilution intake structures function as an on/off type activity, with the only shutdowns associated with temporary, short term maintenance. As such the plant flow is fairly consistent, and therefore forced effort is steady.

RUMFS subset, fishery independent (Relative biomass; 0)

These values are relative abundance (CPUE) found through otter trawling at 5 locations in the southern portion of Barnegat Bay from 1997-2011. Data is from the Tuckfile program at the Rutgers University Marine Field Station (Vasslides et al. 2011).

RUMFS all sites, fishery independent (Relative biomass; 0)

These values are relative abundance (CPUE) found through bay-wide otter trawling (47 sites) conducted by RUMFS in 2012 and 2013. The data is from the NJDEP’s WQDE database.

NJ Coast, fishery independent (Relative Biomass; 0)

Since 1989 the NJDEP has conducted a coastal trawl survey five times a year. The data included here are yearly CPUE averaged across all sampling efforts in Stratum 15 and 18, which cover from Belmar to Sea Isle City to a depth of 10m.

Hard clam LEH abundance, fishery independent (Relative biomass; 0)

These values are density (#/ft²) of hard clams in the southern portion (LEH) of the estuary based on stock surveys conducted in 1986 (adjusted values in Celestino 2002), 2001 (Celestino 2002), and 2011 (Celestino 2013).

SAV coverage, fishery independent (Relative biomass; 0)

SAV coverage for the bay is available for 1980, 1987, 1999, 2003, and 2009 based on aerial photograph analysis in Lathrop et al. (2001) and Lathrop and Haag (2011).

Sea nettles, fishery independent (Forced biomass, -1)

Recent work by Young *et al.* (in review) using local ecological knowledge suggests that sea nettle abundances were at very low levels (unrecorded in contemporary research) until the late 1990's, with a large increase occurring around 2007. To simulate this bloom pattern we are forcing a low biomass until the mid-1990s, and then a progressive increase leading to current population estimates in 2007. The population estimate is based on spring/summer/fall sampling using plankton and lift nets conducted as part of the Barnegat Bay Initiative.

Benthic infauna and epifauna, fishery independent (Relative biomass; 0)

Benthic infauna and epifauna abundances were taken from Taghon et al. (2013) and are from samples collected at 100 locations throughout the Barnegat Bay in July of each year. This index represents the average number of individuals found on or near the sediment surface (per 0.04m²) excluding amphipods, blue claw crabs, and hard clams.

Amphipods, fishery independent (Relative biomass; 0)

Benthic infauna and epifauna abundances were taken from Taghon et al. (2013) and are from samples collected at 100 locations throughout the Barnegat Bay in July of each year. This index represents the average number of individuals per 0.04m² belonging to Order Amphipoda.

Copepods, fishery independent (Relative biomass; 0)

This timeseries is based on samples collected from June to November of 2012 and 2013 at 3 locations (northern, central, and southern) within Barnegat Bay using paired 200µm plankton nets. The data are the average yearly CPUE for the major copepod fauna found in Barnegat Bay (n=57).

Microzooplankton, fishery independent (Relative biomass; 0)

This timeseries is based on samples collected from June to November of 2012 and 2013 at 3 locations (northern, central, and southern) within Barnegat Bay using paired 200µm plankton nets. The data are the average yearly CPUE for foraminifera, the only microzooplankton identified.

Phytoplankton, fishery independent (Relative biomass; 0)

The relative abundance of phytoplankton from 2008 to 2013 was estimated from chlorophyll *a* readings taken via aircraft remote sensing collected six days a week from March through October each year.

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CHAPTER III: Using ecosystem models to understand the effects of watershed-based management actions in coastal ecosystems.

Running head: Ecosystem models for understanding human impacts

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Abstract: Resource managers are often tasked with identifying and assessing the potential impacts of management actions on the biotic communities under their care. When the management activities directly impact a single species of interest managers can turn to a variety of models to aid in their understanding of potential changes to that population. But as Ecosystem Based Management becomes more widely accepted managers will have to understand how proposed actions will impact entire biotic communities, through both direct and indirect mechanisms. Thus there is a need for ecosystem models that account for both trophic and non-trophic interactions, and that can be relatively easily used to assess a variety of management scenarios. We reviewed the available literature regarding incorporation of eutrophication and other non-harvest anthropogenic impacts into Ecopath with Ecosim (EwE), one of the more widely used trophic ecosystem modeling frameworks. We found a number of mechanisms of varying complexity have been used to include these stressors in models, providing managers with a suite of options that can be used to complement their existing management options as they seek to understand the impacts of human interactions with the natural environment.

Key Words: EwE, salinity, eutrophication, habitat restoration, ecosystem-based management

Human activities in the watershed and coastal zone can affect a wide variety of living marine resources, so coastal managers need quantitative tools to help understand

and manage the impacts of watershed-based activities on these resources. When human activities only directly influence a single species of interest, such as fishery harvest, a wide range of tools are available to quantify the effects of activities on a single resource. With the advent of Ecosystem-Based Management (EBM) (Fletcher 2002, NMFS 1999, Pitcher et al. 2009) managers need approaches for assessing the impacts of multiple human activities on multiple resources.

Over the past three decades a number of models have been developed to support the move towards ecosystem based fisheries management across the globe (Plagányi 2007). They range in scope and complexity from single species assessments extended to include a limited number of interactions (e.g. Livingston and Methot 1998) to attempts to model the dynamics of complete ecosystems, including biological and physical forces (e.g Christensen and Walters 2004, Fulton and Smith 2004). Each of these model categories has its strengths and weaknesses, and model choice is dictated by the types of questions being asked and the data available to populate the model (Plagányi 2007). Historically, “whole ecosystem” fishery models were used to assess how changes in fishing regimes impact the biomass of aquatic communities, not just targeted species, through time. Given the fisheries focus, changes in fleet sizes or fishing effort are generally specified in these models in a number of ways, allowing for relatively easy adjustments in order to investigate a variety of harvest regimes (Christensen and Walter 2004).

However, trophic interactions between aquatic organisms do not occur in a vacuum; there are physical and environmental aspects of the aquatic environment that mediate these exchanges that need to be accounted for if a model is to represent a “whole

ecosystem”. This is particularly relevant to coastal areas, where human impacts on the ecosystem other than fishing may be a primary concern. As an example, an assessment of 28 estuaries in the United States identified excessive nutrients, physical habitat loss/alteration, and alteration of freshwater flows as key factors in environmental degradation (USEPA 2006). Because estuaries play a vital role in the early life history stages of many commercially and recreationally important fishes (Beck et al. 2001) and provide a suite of additional ecosystem services (Barbier et al. 2011), understanding how these non-trophic anthropogenic stressors can lead to direct and indirect changes in aquatic biotic communities is of critical importance to managing these resources. Thus, there is a need for ecosystem models that account for both trophic and non-trophic interactions and that can be relatively easily used to assess a variety of management scenarios.

Within the suite of ecosystem models developed to address the impacts of fishing on the aquatic environment, several are specifically designed or can be extended to include non-fishing anthropogenic effects on coastal systems (Plagányi 2007). Biogeochemical models (eg. European Regional Seas Ecosystem Model (ERSEM - Baretta, Baretta-Bekker, and Ruardij 1996) and Shallow Seas Ecological Model (SSEM - Sekine et al. 1991)) typically incorporate physical and chemical information to drive phytoplankton and zooplankton dynamics, with less focus on higher trophic levels. While some anthropogenic stressors (changes in temperature, salinity, or nutrients) can be included in these models, the low resolution (or absence) of higher trophic levels limits their usefulness for understanding broader impacts. In contrast, “whole ecosystem models” such as Ecopath with Ecosim (EwE) (Christensen and Walters 2004) and

ATLANTIS (Fulton and Smith 2004) include the higher trophic levels that are generally of interest to resource managers as well as lower trophic levels and primary production, connected via predator-prey interactions. Because these lower trophic levels are more likely to be directly impacted by anthropogenic inputs into the system, accounting for impacts at lower levels will likely translate to additional indirect impacts at higher levels. Both models have the ability to investigate the effects of anthropogenic stressors on the modeled ecosystem, though the means of inclusion vary between the two.

Ecopath is an ecosystem trophic mass balance analysis which is paired with Ecosim, the dynamic modeling aspect, for exploring past and future impacts of fishing and environmental disturbances (Christensen and Walters 2004). Ecospace, the third component of the software package, is used to create a spatially explicit representation of the constructed model (Walters et al. 2010). This modeling suite has the flexibility to be a potentially useful tool for informing coastal resource management (Coll et al. 2015).

Ecopath parameterizes an initial model using two master equations, one to describe the production term for each biological/ecological/trophic group and one for the energy balance for each group (Christensen and Walters 2004). This requires four groups of basic input parameters to be entered into the model for each of the species (or groups) of interest: diet composition, biomass accumulation, net migration, and catch (for fished species). Three of the following four additional input parameters must also be input: biomass, production/biomass (Z), consumption/biomass, and ecotrophic efficiency. The model uses the input data along with algorithms and a routine for matrix inversion to estimate any missing basic parameters so that mass balance is achieved.

Once the base model balances (there is sufficient production to meet consumption and mortality), it is loaded into the Ecosim package, where the temporal dynamics of the model ecosystem can be simulated. Time series reference data can be loaded for a given scenario and each series can be weighted based upon *a priori* estimates of data quality. When run for the timeframe for which external data is available, a statistical measure of goodness of fit to these data is generated (weighted sum of squared deviations). The model can be further tuned to minimize the sum of squared deviations by adjusting settings related to functional response (i.e. predator/prey vulnerability) or through the use of forcing or mediation functions, or both. A forcing function in EwE is defined as a multiplier on an Ecopath base trophic interaction rate, where the multiplier value for each year is the ratio between the value of the variable for the year in question and the base (Ecopath) year. Forcing functions in EwE are applied to a biomass group(s) directly (Christensen et al. 2008), and can influence the effective search rate of predators or alter the area within which vulnerable prey and predators are found. Forcing functions can also alter the rate at which a biomass group moves between vulnerable and invulnerable states, which is based on foraging arena theory (Walters et al. 1997). Forcing functions use factors external to the model to drive consumption and production. In contrast, mediation functions use non-trophic factors internal to the model, i.e., one biological/ecological trophic group's biomass alters the consumption rates of other trophic groups. Mediation functions can be applied to influence a predator's rate of effective search/search efficiency, to change the rate at which a prey group becomes vulnerable to predation, and to change the extent of refugia available (Christensen et al. 2008).

For systems with adequate data on spatial distributions of species and habitat, the Ecospace module of the EwE software can also be applied to ecological issues in the coastal zone. Ecospace uses the time-dynamic algorithms of Ecosim and applies them to spatial grid cells representing different fixed habitat types (e.g., oyster beds, bathymetry, sediment type) in the system and allows species/trophic groups from the Ecosim model to have preferences for different types. This permits alterations to trophic interaction rates based on species habitat affinities and the locations of those habitats. Furthermore, the addition of a habitat capacity model allows for the incorporation of time-varying habitat factors (e.g., temperature, salinity) in the spatial model (Christensen et al. 2014).

The EwE software is a flexible tool that enables the incorporation of non-trophic stressors into ecosystem models. It is a widely used tool - over 400 trophic mass balance models have been built for a variety of ecosystems using the EwE package, ranging in size from oceanic basins to small estuaries (Colléter et al. 2015). EwE has a comprehensive user-friendly interface, that enables a modeler to balance simplicity and complexity, allows for a common framework for making comparisons between systems, and has structured parameterization framework (Butterworth and Plagányi 2004). In addition, recent advances in model development in Ecospace improves its utility for assessing anthropogenic, non-trophic impacts (Christensen et al. 2014). Because of the popularity and versatility of the tool, we chose to evaluate the applicability for EwE to be applied to coastal resource management issues by reviewing the available literature regarding incorporation of coastal zone issues (e.g., eutrophication, habitat alteration, and salinity changes) into Ecopath with Ecosim (EwE) models.

We searched Thompson Reuters Web of Science for published articles using the terms “Ecopath” or “EwE” and “salinity”, “eutrophication”, or “restoration” for articles where the software package was used and the methodology for incorporating one or more of the non-trophic parameters of interest was included. We limited our review to the Ecopath and Ecosim components of the program as those are currently the most frequently used by researchers and managers and had the most well developed approaches. The database of publications found on the Ecopath website (www.ecopath.org) was also reviewed for pertinent articles that may not be included in the Web of Science index. We identified 12 studies in which methods for incorporating the non-trophic effects of interest were explicitly described (Table 1). In the following sections we describe the various methods that have been used for including eutrophication, changing salinity, and habitat restoration in the EwE software, discuss the benefits and drawbacks of these approaches, and highlight a new application for incorporating a broad suite of spatially explicit non-trophic parameters.

Eutrophication

The impact of excessive nutrient loading in lakes, estuaries, and near-shore coastal systems from anthropogenic processes (agricultural runoff, atmospheric deposition, non-point source pollution, *etc.*) is well documented (Bricker et al. 2007, Conley et al. 2009). Increase in nutrient enrichment has been shown to be a primary factor in enhanced primary production, and thus an increase in the rate of supply in organic matter to a system, a process known as eutrophication (Nixon 1995). Eutrophication has been shown to cause numerous negative impacts, including hypoxia

(Howarth et al. 2011), algal blooms (Kennish et al. 2007), and changes in species composition (Purcell, Uye, and Lo 2007).

Two main methods have been utilized to account for the effects of nutrient enrichment in EwE; constructing multiple EwE models each representing a different condition and linking EwE to a separate biogeochemical model. Patrício and Marques (2006) and Baeta et al. (2011) employed the first option, dividing an estuary in Portugal into zones of high, medium, and low eutrophic condition. The individual models constructed for each zone allowed the authors to compare indices of ecosystem condition across the eutrophic gradient using the ecological network analysis tools included in the software (Christensen et al. 2008). A similar multi-comparison method was used by Yu-Chun, Adlerstein, and Rutherford (2014), where an Ecosim model of a Lake Huron was fitted to field collected values, after which temporal simulations were performed under three different levels of phosphorus loading provided by the authors. The ratio of the mean equilibrium biomass during the simulation to the initial Ecopath biomass was used to summarize changes in the food web. The results of the simulations indicated that phosphorus loads were positively correlated with the biomass of most of the groups within the model, and the changes in biomasses (both positive and negative) were consistent with extensive empirical evidence, supporting the utility of this approach.

The second approach used to incorporate the effects of eutrophication into trophic models involves linking EwE models to separate biogeochemical models (BGMs). This can be done through either one-way (information passed up from the biogeochemical to the trophic) or two-way (information passed back and forth) linkages (Figure 1). An example of a one-way linkage is given by Ma et al. (2010) for the Chesapeake Bay. To

understand the impacts of water quality on submerged aquatic vegetation (SAV), and on the commercially and recreationally important blue crab stocks, a water quality model (Cerco and Noel 2004) was indirectly linked to a fisheries ecosystem model constructed in EwE (Christensen et al. 2009). The water quality model was calibrated using historical data, and then rerun under a nutrient reduction management scenario for 1985-1994. The ratio of the two SAV biomass outputs from the water quality model (historic and nutrient reduction) was then used to modify the SAV biomass in the EwE model over the same time period. Mediation functions were then developed to relate the indirect effects of seagrass on blue crab. In this model the effective search rate of blue crab young-of-the-year (YOY) predators and the vulnerability of blue crab YOY to its predators were both reduced as SAV biomass increased. Under the nutrient reduction scenario there was an increase in SAV biomass, which could lower predation rates on blue crab YOY (using SAV to hide from predators) and lead to an increase in blue crab biomass, depending on the strength of the interaction between SAV and adult blue crab predation on YOY.

In contrast to the approach above, Cerco, Tillman, and Hagy (2010) utilized the output values from the same water quality model (Cerco and Noel 2004) as direct inputs into an Ecopath-only model to assess potential management actions in response to eutrophication effects. Rather than model the effects of increased nutrients on a system, this study looked at the potential ramifications of increasing a planktivorous fish's feeding on phytoplankton, which often bloom under eutrophic conditions. Using carbon as a shared "currency" between the models, biological groups present in both models were identified, as were Ecopath input parameters that could be defined by water quality model variables. With the relationships between models established, the rate of predation

on phytoplankton by fish predators within the BGM was increased by 20%. The resulting primary producer biomasses and production rates were then used as inputs in the Ecopath model, and the Ecopath model rebalanced as necessary. Under this scenario, the increase in fish predation on phytoplankton lowered the biomass of all primary producers (including SAV), with no changes needed in the biomasses of higher trophic levels to rebalance the model.

Niiranen et al. (2013) also used a one-way linkage between biogeochemical models and EwE to describe the effects of eutrophication (and climate change) on a Baltic Sea food web. An ensemble of three BGMs were used to simulate the historic changes through time of a number of water chemistry variables, including dissolved oxygen, as well as phytoplankton annual production per biomass rates. These time series were then used in the Ecosim module as forcing functions. In this study, the BGM derived annual average hypoxic area negatively impacted the predator search rate of selected groups and the phytoplankton P/B series derived from the BGM positively impacted phytoplankton P/B in EwE. After calibration using historic data, the BGM and EwE models were run forward (2010-2098) under three nutrient load scenarios (combined with three climate scenarios and two fishing scenarios). With respect to eutrophication, the authors found strong positive indirect responses to increasing nutrient loads between and within trophic levels.

Salinity

The salinity of estuarine ecosystems can be influenced by alterations in freshwater inflow due to anthropogenic activities such as dams and diversions (USEPA 2006), and

sea level rise and precipitation changes related to climate change (Prandle and Lane 2015). The response of a species to changes in salinity will be driven not only by its own salinity optimum and tolerances, but also those of the species with which it shares direct and indirect trophic interactions. Two methods for incorporating the effects of salinity on biotic communities were found in the literature. Similar to modeling eutrophication effects, one relies on the use of multiple Ecopath models and the other incorporates forcing functions into Ecosim simulations.

Prado et al. (2013) utilized multiple models to develop snapshots of different salinity regimes in the Ebro Delta of Spain. In this study, Ecopath models were constructed for two different anthropologically driven salinity regimes (summer lows and winter highs) in three adjacent coastal lagoons that varied in their salinity mean and ranges. The ecological network analysis tools included in the Ecopath software were then used to compare the trophic structure and ecosystem properties across salinity regimes and sites. In this particular system, salinity was shown to be the driving force behind plant standing biomass in each season. The plant biomass, or lack thereof, then affected the consumption of detrital material, the number of energy pathways, and overall ecosystem productivity. Ecosystem productivity has long been noted as playing an important role in determining an ecosystem's complexity and ability to maintain itself through time (Margalef 1963). By comparing the results of the different salinity regimes as they related to key ecosystem indices the authors were able to develop general recommendations regarding target salinity levels for the sustainable restoration of native flora and fauna.

The second methodology used a forcing function within the dynamic modeling portion of the software to simulate expected salinity changes over time that were linked to user specified salinity tolerances for each species/group (de Mutsert, Cowan, and Walters 2012). This study modeled the effects on estuarine aquatic communities of diverting freshwater flows from a main stem river into adjacent estuaries. Monthly mean salinities recorded at three distances from a freshwater source were used to create forcing functions that were representative of three different salinity regimes (low, medium, high). Each species/group was assigned a salinity tolerance range with an optimum and standard deviation based on long-term field measurements. The response curves were then used to modify each species/group's feeding rate within the model, where the maximum feeding rate occurred at the optimum salinity, and feeding rates declined as salinity departed from the optimum. It follows that reduced feeding rates would lead to decreased fitness and reduced biomass. The analysis of the scenarios suggests that as long as a salinity gradient is established, the local distribution of species/groups is altered by the change in flow, but there is no replacement of species from the estuary as a whole.

Habitat modification

As the value of ecosystem services provided by coastal wetlands (Rozas, Caldwell, and Minello 2005), seagrass beds (Waycott et al. 2009), mangroves, and other coastal habitats continue to be realized (Lubchenco and Sutley 2010), resource managers are being tasked with documenting the effects of restoring degraded habitats or the potential benefits of future restoration projects.

The quantification of biomass changes due to habitat restoration is accomplished in EwE through comparisons of multiple scenarios and utilizing the customizable forcing and mediation functions included in the software package. There have been two main approaches to incorporating the effects of habitat restoration into EwE models; one for forecasting the potential effects of future restoration (Rogers and Allen 2012, Plummer et al. 2013), and one for evaluating changes associated with completed efforts (Frisk et al. 2011).

The evaluation of potential restoration activities that involve the removal or planting of vegetation are handled in complementary approaches. For habitat restoration projects that involve the removal of an unwanted species, the proposed reductions in biomass can be accomplished through the use of a “fishery” (tussock sedge a la Rogers and Allen 2012), in which various management options can be modeled as different fishing efforts. Restoration projects that involve an increase in beneficial habitat, such as the replanting of a known amount of seagrass beds, can be modeled as a fixed increase in the amount of biomass of that particular habitat compared to the baseline model (Plummer et al. 2013). In most cases the species being restored (or removed) are not directly consumed within the food web, rather they function in an indirect role that affects predator/prey relationships. As discussed in the Eutrophication section, within EwE these types of indirect effects are handled through the creation of mediation functions. In the tussock sedge example, the mediation functions were set such that increased tussock biomass created refugia for small prey items and reduced their predator’s search efficiency. In the seagrass example, three mediation functions were developed for increases in seagrass biomass. The first increased the rate at which prey

items were vulnerable to juvenile salmon due to prey aggregation, the second increased the amount of refugia for juvenile salmon from the predators, and the third increased the search efficiency of juvenile herring.

Frisk et al. (2011) used a different approach to determine how much production was gained due to salt marsh restoration activities within the Delaware Bay. During a seven-year time period, restoration activities led to a 3% increase in the biomass of salt marshes within their study system, the effects of which were captured in their base model. They then compared this base scenario to one where restoration activities were presumed not to have occurred (the salt marsh biomass was reduced by 3% from the base scenario over the same time period). Instead of using the mediation functions to simulate the indirect effects of salt marsh on trophic interactions, the authors created a forcing function that was applied to the two groups in their model that were marsh dependent (meiofauna and macrofauna). Forcing functions are used to directly relate interactions between two groups; in this case reductions in salt marsh biomass is assumed to lead to direct reductions in marsh macrofaunal or meiofaunal biomass. The differences in annual system biomass between the base and non-restored scenarios can then be compared to see how much production would be forgone if restoration had not occurred.

Discussion

When considering how best to incorporate non-trophic impacts into whole ecosystem models, the choice of a particular methodology will often depend on the data available and the desired output. The comparison of multiple static Ecopath models is warranted if time series data is not available or if models of different ecosystem states are

temporally or spatially distinct. The Ecosystem Network Analysis plug-in (ENA) tools can then be used to compare indices between states. When time series data is available to either fit or force the model, utilizing the dynamic Ecosim module is the best course. Multiple scenarios that start from the same base model can be evaluated, and recent improvements to the EwE software allow users to run the ENA tools by time step for Ecosim runs. By incorporating direct effects external to the model (forcing functions) and indirect effects internal to the model (mediation functions) through Ecosim, the EwE package is able to explore a broad suite of anthropogenic impacts to coastal ecosystems, extending the utility of this software for researchers and resource managers. The potential effects of climate change, habitat modifications, watershed development, and other coastal stressors on aquatic ecosystems can be investigated, with the goal of offering strategic advice for management.

The method(s) selected to include biogeochemical concerns into trophic models also requires careful consideration. The studies discussed in the previous sections consisted of one-way, off-line linkages. Under this relatively straightforward coupling scheme, however, there are temporal and spatial mismatches between the models that must be accounted for (Libralato and Solidaro 2009). BGMs typically have time-steps that operate on the order of hours or days with spatially detailed 3-D resolution, whereas EwE models represent a single 2-D area and have monthly time-steps. Thus BGM outputs must be spatially and temporally aggregated before they can be utilized as an EwE input, a task which has been successfully accomplished in all of the examples described above. An alternative modular approach has been suggested by Libralato and Solidaro (2009), where a trophic model and a BGM of the same system are run

separately, with the outputs of the BGM model used to constrain the trajectory of the trophic model. While this approach moves the trophic model closer to a true “end-to-end” model, it requires the re-parameterization of the trophic model to include components of the BGM domain (nutrient pools and fluxes) and can cause some tools in the EwE software to provide inaccurate estimates, especially those based on trophic level calculations (Libralato and Solidaro 2009). A move towards a more fully integrated approach, where the models exchange information directly in real time, is currently underway and has shown a number of promising results (Coll et al. 2015).

While we have highlighted two methods for assessing the impacts of salinity on food webs using the EwE software, it is likely that the use of the forcing function linked to salinity (or temperature, O₂, pH, etc.) tolerances will gain favor as the routine for entering the optima and tolerance ranges is now a standard part of the software package. This methodology allows for the evaluation of both the direct effects of salinity changes on fitness as well as indirect effects through trophic interactions. Given concerns over warming waters associated with climate change and already observed shifts in oceanic species distributions (Nye et al. 2009, Pinsky et al. 2013) these features are likely to become an important part of a resource manager’s toolkit.

One of the features shared across the methodologies for incorporating non-trophic parameters is the use of forcing and/or mediation functions and response curves to relate the parameter of interest to some aspect of foraging capacity. These functions can be empirically defined, such as the relationship between optimum salinity and feeding rate (de Mutsert, Cowan, and Walters 2012), or they can be hypothetical, like the effects of eelgrass on predator-prey relationship (Plummer et al. 2013). Mediation functions by

their very nature are difficult to quantify through field or laboratory experiments and often have to be estimated (Harvey 2014). The shape and initial state of the function play a role in how the model responds, with a series of simulations suggesting that in the absence of knowledge to the contrary a hyperbolic curve may be the most conservative approach (Harvey 2014).

A recent development in the Ecospace module of the EwE software package is the development of a habitat foraging capacity model, which provides users the ability to spatially drive the foraging capacity of species using a variety of physical, environmental, and oceanographic factors (Christensen et al. 2014). By utilizing geographic information systems (GIS) technology, the output from water quality models, biogeochemical models, or other spatial or temporal varying data can be converted into a spatial-temporal format that can be brought into Ecospace (Figure 2, Steenbeek et al. 2013). An environmental preference function related to each factor can be developed for each species/group in the trophic model, which are then used to define the amount of preferred habitat (Christensen et al. 2014). The amount of preferred habitat available is then used to drive foraging interactions, with the amount of available habitat, and thus foraging interactions, potentially varying at each time step. While some degree of data aggregation may still be necessary, the ability to vary non-trophic factors on a biologically relevant spatial and temporal scale commensurate with trophic interactions increases the usefulness of these models for managers. An application of this new habitat foraging capacity model was part of an assessment of potential environmental impacts associated with the proposed expansion of the Port of Metro Vancouver (Port of Metro Vancouver 2015). Of course increasing the spatial resolution of the trophic model and incorporating environmental

factors requires the user to assume knowledge of how different habitats structure predator-prey interactions.

Conclusion

As management of natural resources evolves from single species to whole ecosystem considerations the models being used must have the ability to incorporate biological, physical, and environmental factors. Eutrophication, changes in salinity, and habitat alterations have been incorporated into a popular trophic model (EwE) through the comparison of multiple Ecopath models, by one-way indirect linkages between biogeochemical models and Ecosim accompanied by forcing and mediation functions, via new routines built into the EwE software, and through a recently developed spatial-temporal framework and habitat capacity model. The variety of approaches discussed here provides managers with a suite of options that can be used to complement their existing models as they seek to understand the impacts of human interactions with the natural environment.

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Table 1: Published models that include methods for incorporating non-trophic effects into Ecopath with Ecosim and Ecospace models.

Citation	Parameter of interest	Location	Method
Patrício and Marques 2006	Eutrophication	Mondego estuary, Portugal	Multiple model states
Libralato and Solidoro 2009	Eutrophication	Venice Lagoon, Italy	Modular modelling
Ma et al. 2010	Eutrophication	Chesapeake Bay, USA	Linked models
Cerco, Tillman, and Hagy 2010	Eutrophication	Chesapeake Bay, USA	Linked models
Baeta et al. 2011	Eutrophication	Mondego estuary, Portugal	Multiple model states
Niiranen et al. 2013	Eutrophication	Baltic Sea	Linked models, forcing functions
Yu-Chun, Adlerstein, and Rutherford 2014	Eutrophication	Saginaw Bay, USA	Multiple scenarios
de Mutsert, Cowan, and Walters 2012	Salinity	Louisiana estuary, USA	Forcing functions
Prado et al. 2013	Salinity	Ebro Delta, Spain	Multiple model states
Frisk et al. 2011	Habitat restoration	Delaware Bay, USA	Multiple scenarios, forcing functions
Rogers and Allen 2012	Habitat restoration	Florida Lake, USA	Multiple scenarios, mediation functions
Plummer et al. 2013	Habitat restoration	Puget Sound, USA	Multiple scenarios, mediation functions

Figure 1- Conceptual schematic of one and two-way linkages between Ecopath with Ecosim (EwE) and biogeochemical models.

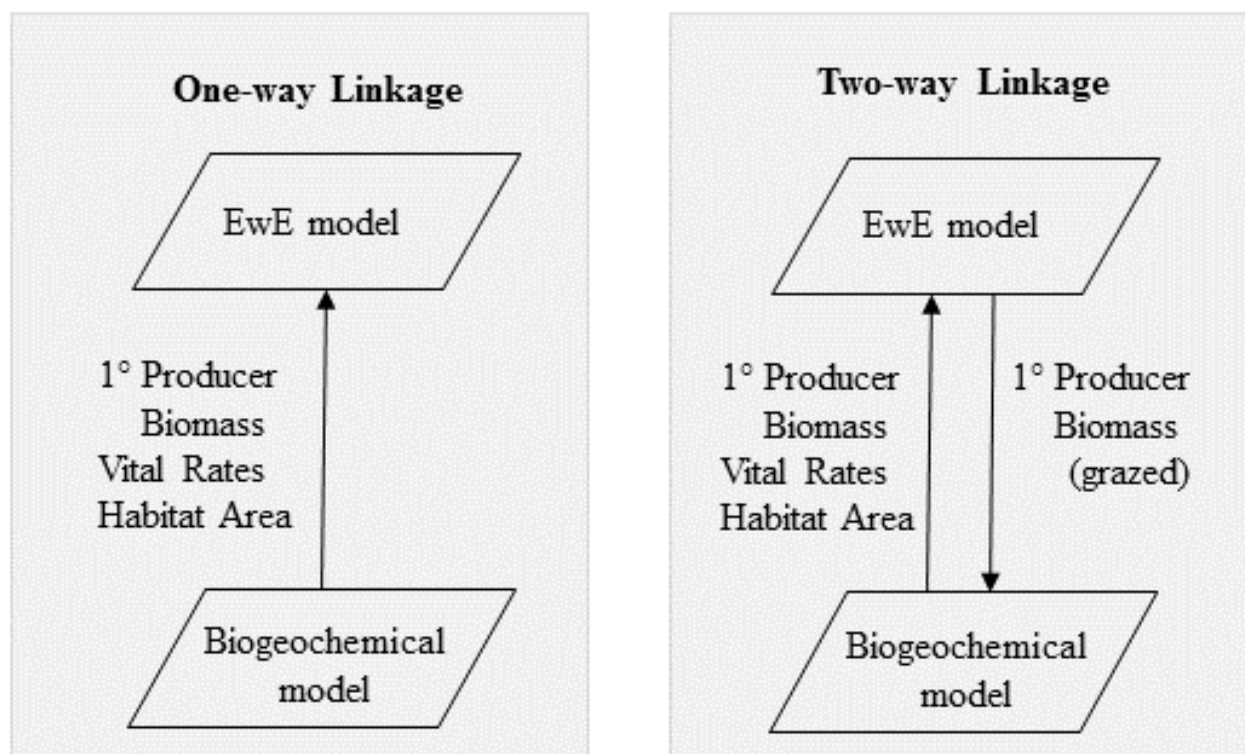
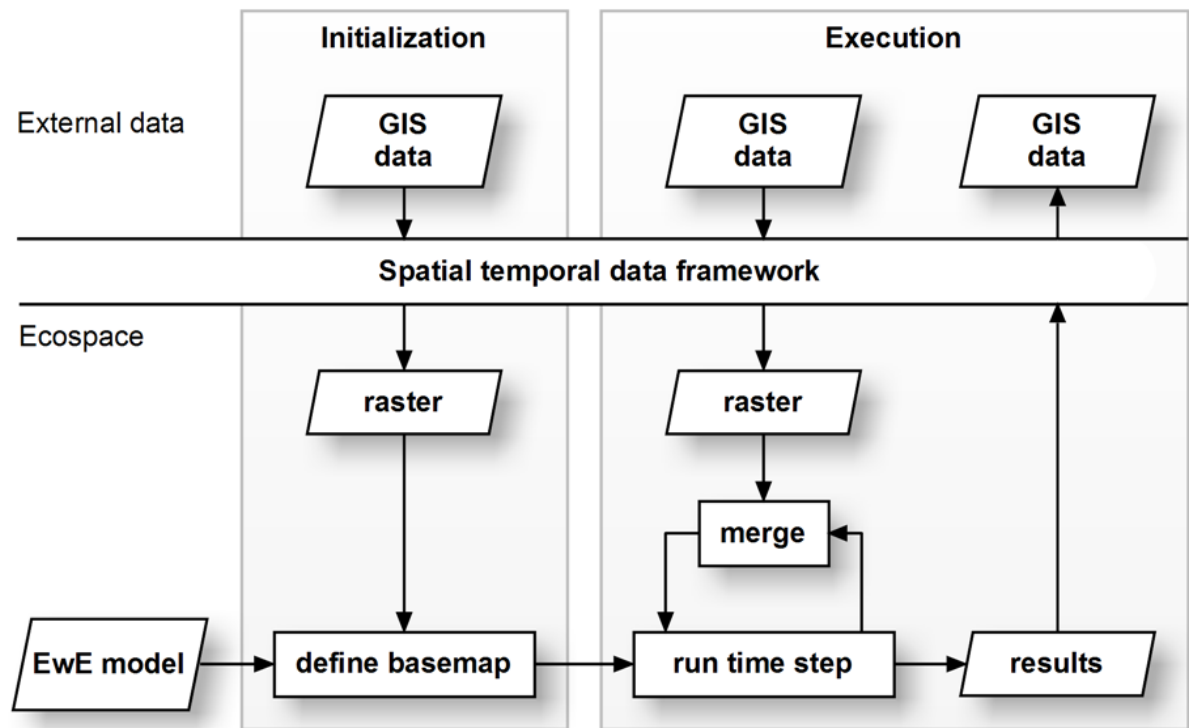


Figure 2 - Conceptual overview of the spatial-temporal data framework, which provides external GIS data to Ecospace model initialization and at runtime, and provides Ecospace results in spatial data formats when the model executes. Courtesy of Jeroen Steenbeek.



**CHAPTER IV: Quantitative vs. semi-quantitative ecosystem models comparing
alternative representations of an estuarine ecosystem**

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Abstract: As the management of marine and coastal resources continues to move towards an ecosystem-based management approach, there is a need for tools that can match the scope and complexity of the systems in question. Herein we review 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 semi-quantitative Fuzzy Cognitive Mapping conceptual model developed through interviews with local stakeholders. We also compared 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 differences in data sources, approaches, and methodology. To gain the largest benefit from the strengths of both models we recommend using them in combination, using the Fuzzy Cognitive Mapping model to scope out critical components and interactions to be included in the Ecopath with Ecosim model. That model can then be parameterized and “what-if” scenarios run to ascertain the patterns and magnitudes of changes that can be expected.

Keywords: 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 (MA 2005). The failure of these management structures, which typically addressed environmental impacts using a single sector-based approach (Pew Oceans Commission 2003), has led to the development of a new management regime: 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 impacts 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 multi-species 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 known as Minimum Realistic Models (MRM - Punt and Butterworth 1995) extend single-species assessment to include those species most likely to have important interactions with the species of interest (e.g. Extended Single-species Assessment Models (ESAM - Livingston and Methot 1998) and Multi-species Virtual Population Analysis (MSVPA - Pope 1991)), while 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, multi-trophic level quantitative models are able to replicate historic changes in natural resources of interest. A “fitted” model can then be used to provide formal management advice (Fulton et al. 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 high data requirements, which can be an impediment to their use in systems without robust sampling programs (Fulton et al. 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 assumptions (Chapter 3, Harvey 2014). 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 towards EBM has also given rise to a number of qualitative and semi-quantitative 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 (Özesmi and Özesmi 2003, Hobbs

et al 2002, Gray *et al* 2012, Meliadou *et al.* 2012, Kontogianni *et al.* 2012a). FCMs are conceptual models that describe how a system operates based on 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 an FCM is based upon an individual's conceptual understanding of a system, its parameterization is not dependent upon the availability of biotic and abiotic data (Özesmi and Özesmi 2004). The semi-quantitative 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 *et al.* 2014), broadening its appeal for use in management applications (NRC 2008).

Despite their flexibility, there are several drawbacks to using an FCM to understand 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 unit-less and relative, *i.e.* parameter A increases a great deal compared to parameter B, but the real-world expression of that change is not quantifiable (Özesmi and Özesmi 2004). Lastly, FCMs do not incorporate non-monotonic relationships well (Vasslides and Jensen 2015), and these are often present in ecological systems.

Both quantitative and semi-quantitative models can be used in developing ecosystem-based management approaches to natural resources as they are capable of “what-if” scenario development and predictions. However, these modeling approaches have not heretofore been explicitly compared in the same system. In this study, we compared the results of a nutrient reduction scenario run in each model applied to the same estuarine system, Barnegat Bay, New Jersey, to understand how the different approaches can be best utilized to meet the needs of EBM. Will the results of the FCM, which is based on stakeholder’s perceptions and intuitions, be comparable to the model driven by scientific data collection and analysis? If differences between the models appear, are they in components where we have a great deal of confidence in the quantitative model, and thus, by implication, stakeholder perceptions do not match 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?

Methodology

Study area

Barnegat Bay is a temperate lagoonal estuary located in central New Jersey, USA (Figure 1). The estuary stretches nearly 70 km north to south and ranges from 2-6 km in width with a total surface area of 279 km² including the tidal portions of its tributaries (Kennish 2001). The surrounding 1,730 km² 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. Land use is a mix of urban and suburban uses 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, though there are still remnants of a historic hard clam fishery that was highly productive in the past (Bricelj *et al.* 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 due to 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 utilized in two master equations. The first equation describes the production term for each group:

$$\textit{Production} = \textit{catch} + \textit{predation} + \textit{net migration} + \textit{biomass accumulation} + \textit{other mortality}$$

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

$$\textit{Consumption} = \textit{production} + \textit{respiration} + \textit{unassimilated food}$$

The balanced Ecopath parameters 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 to reference time-series data. Parameters primarily associated with predator-prey interactions are adjusted iteratively to fit the model to the data with a goodness of fit measure (sum of squares differences) used to compare the model runs.

The Barnegat Bay Ecopath Model (Chapter 2) contains 27 distinct biomass groups including 12 fish species, 5 benthic invertebrate groups, 2 gelatinous zooplankton species, 3 planktonic groups, 2 benthic vegetation groups, 2 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). We utilized the PREBAL routine (Link 2010) to identify issues in model structure and data quality associated with the initial input parameter values prior to balancing the model. 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 the model balancing routine, we changed the values for those parameters with the lowest pedigree (highest degree of uncertainty) first.

Once the Ecopath model was balanced recreational and commercial fisheries time-series catch data were used to drive the model, and fishery-independent data, primarily research surveys, were used to assess the model fit (Chapter 2). The parameters influencing predator-prey interactions in the model (Walters et al. 2007) were adjusted for only those groups with time series data of at least 3 years in length. In practice, adjustments to these parameters improves the model fit to data and helps explain some of the variability in the data.

Fuzzy Cognitive Model

We developed a community-based conceptual model of the Barnegat Bay utilizing information gathered during interviews of 42 local stakeholders, including

scientists, managers, environmental NGOs, and local residents (Vasslides and Jensen 2016). 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 amount of influence (positive or negative) that one component has on another, and can range from -1 to +1 (Gray *et al.* 2014). The individual maps were translated into square adjacency matrices, and the number of components were reduced by subjectively combining less frequently mentioned components into larger categories based on shared characteristics (Harary *et al.* 1965). The final step was to combine the individual matrices into a community conceptual model through matrix addition. The community conceptual model contained 84 components connected through 1071 linkages (Figure 3).

Scenario modeling

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

To develop the scenarios in EwE we began with the fitted Ecosim model and extended it 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, where the P/B value for a group increases with the increases in the available nutrient concentration up to a maximum P/B 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.

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. 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 1981-1988 set at the 1989 value and 2012-2013 set at the 2011 value for lack of other data (Figure 4a). For the baseline scenario the 2013 nutrient values were maintained through the remainder 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.

In addition to the nutrient forcing function we developed a forcing function for SAV based on the relationship between seagrass above-ground biomass and loading of total nitrogen found in Kennish et al. (2014). When applied throughout the simulation period, seagrass biomass fluctuated inversely to total nitrogen load, with the 2013 biomass greater than the initial (1981) biomass, a result we know to be inaccurate (Kennish et al. 2014). In order to maintain the known decrease in SAV biomass during the 1981-2013 timeframe, yet capture the anticipated increase in SAV associated with a reduction in nutrients, we combined the new SAV forcing function with the SAV forcing function from the fitted model run. The forcing function developed for the fitted model was used prior to 2014 and the empirical relationship was applied from 2014 forward (Figure 4b).

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 the final biomass of each group between the nutrient reduction scenario and the baseline scenario was calculated to ascertain the effects of reducing the nutrient load.

To determine the effects of nutrient reductions within the FCM model, we first calculated 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 resulting vector was then subject to transformation using a logistic expression ($1/(1 + e^{-1 \times x})$) to bound the results in the interval [0,1]. 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 (Kosko 1987). We simulated a reduction in nutrients 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. The percent change between the values of the final vector in the nutrient reduction scenario compared to the final baseline vector describes the relative change to the conceptual system given the framework provided by the community map.

For the purposes of inter-model comparisons we focused 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 (*i.e.* fish) are fairly generic and contain multiple EwE biomass groups while 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 non-harvested species (ribbed and blue mussels) (Table 1).

Results

While there were differences in the responses of some individual groups to a reduction in nutrient load between the EwE and FCM models of the Barnegat Bay ecosystem, key components of each model generally respond in similar fashion. In the EwE model, submerged aquatic vegetation (SAV) had the largest positive response in biomass (2600%) to a reduction in nutrient loading, while non-piscivorous seabirds (191%), blue crab (90%), and amphipods (53%) all increased in biomass as well (Figure 5). All other groups had modest declines in biomass (<20%) with the exception of Atlantic croaker (90%) and Atlantic menhaden (57%), which both had slightly larger reductions.

In the FCM model, seagrass had the largest positive response (0.25%) to the nutrient reduction scenario, followed by shellfish (0.06%), blue crab (0.03%), and fish (0.01%) (Figure 6). Phytoplankton (0.17%), gelatinous zooplankton (0.04%), and benthic infauna (0.02%) all had negative responses to nutrient reductions in the FCM model.

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 (Moore et al 1996, Moore and Wetzel 2000, McGlathery et al 2007). In the FCM model, stakeholders indicated that seagrass is negatively 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) is undifferentiated. That the models both predicted similar results through different mechanisms validates the inclusion of the forcing factor in the EwE model as well as its general shape.

The differences between the models' results appear to be mainly driven by how they handle non-trophic interactions rather than by any direct differences in how they characterize the same trophic interactions. 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 et al. 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 due to their associations with seagrass beds, while 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, though this is driven solely by trophic interactions. While adding a mediation function that reduces a

blue crab predators' hunting effectiveness with an increase in seagrass biomass could be used to model this non-trophic effect of SAV on blue crab (Ma et al 2010), the development and use of mediation functions in EwE requires careful consideration as they are often difficult to define (Harvey 2014).

The differences in the form of the models' inputs and outputs present some challenges in comparing the results. The biomass groups in our EwE model are more taxa specific as compared to 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, though not all of those 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 taxa 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 in t/km^2 , while 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 the 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 losers” in a given scenario) the patterns and relative magnitude of changes may often be sufficient.

Conclusion

The similarity in results between the FCM model, which is based on stakeholder’s perceptions, and those of the EwE model, driven by scientific data collection, in this study 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. A 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 non-trophic interactions of importance that would require the development of mediation functions. Once an EwE model is developed, the results of scenario runs in the two models can be compared, as done here. Examining differences in model outcomes can illuminate future research needs as well as education and outreach priorities.

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Table 1: Relationship between biomass groups and components in the EwE and FCM models.	
Biomass group (EwE)	Component (FCM)
Piscivorous seabirds	Birds
Non-piscivorous 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
Oyster	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	-

Figure 1: Map of the Barnegat Bay estuary and watershed.

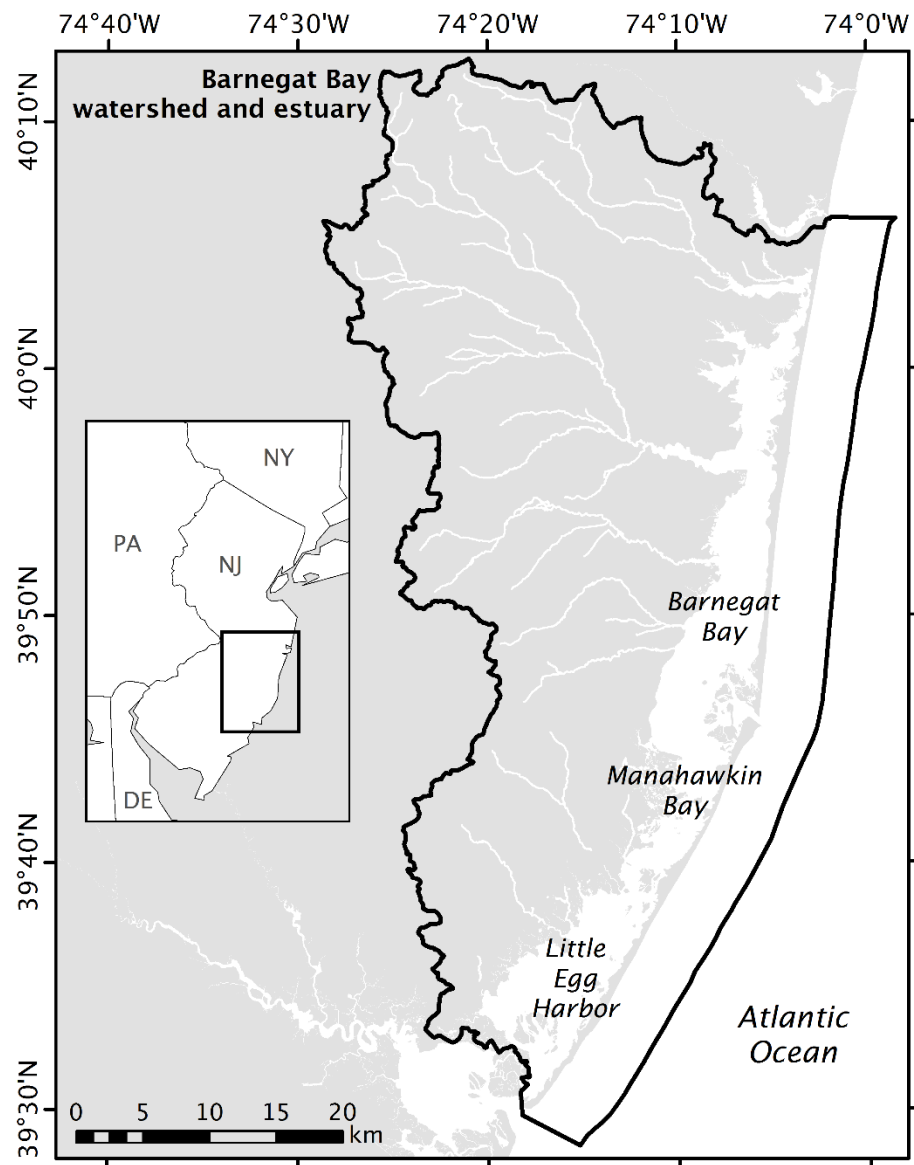


Figure 2: Barnegat Bay Ecosystem Model for 1981 as developed in Ecopath with Ecosim (EwE). Numbered horizontal lines indicate trophic level and the size of the circle indicates relative biomass.

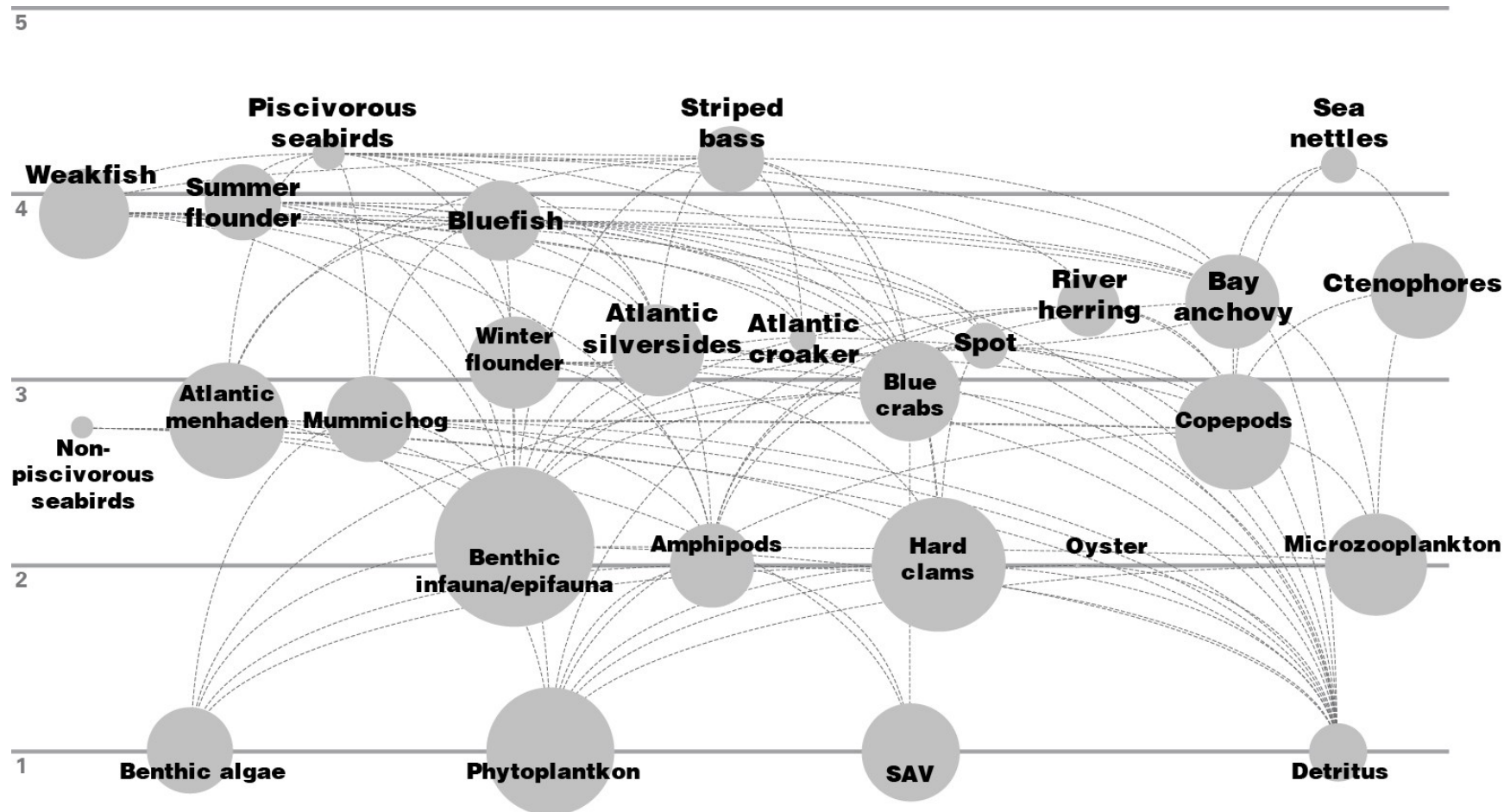


Figure 3: A subset of the Fuzzy Cognitive Map community model for the Barnegat Bay that includes the corresponding components of the Barnegat Bay Ecosystem Model. Node size is related to centrality score (importance), solid lines are positive interactions, and dotted lines are negative interactions.

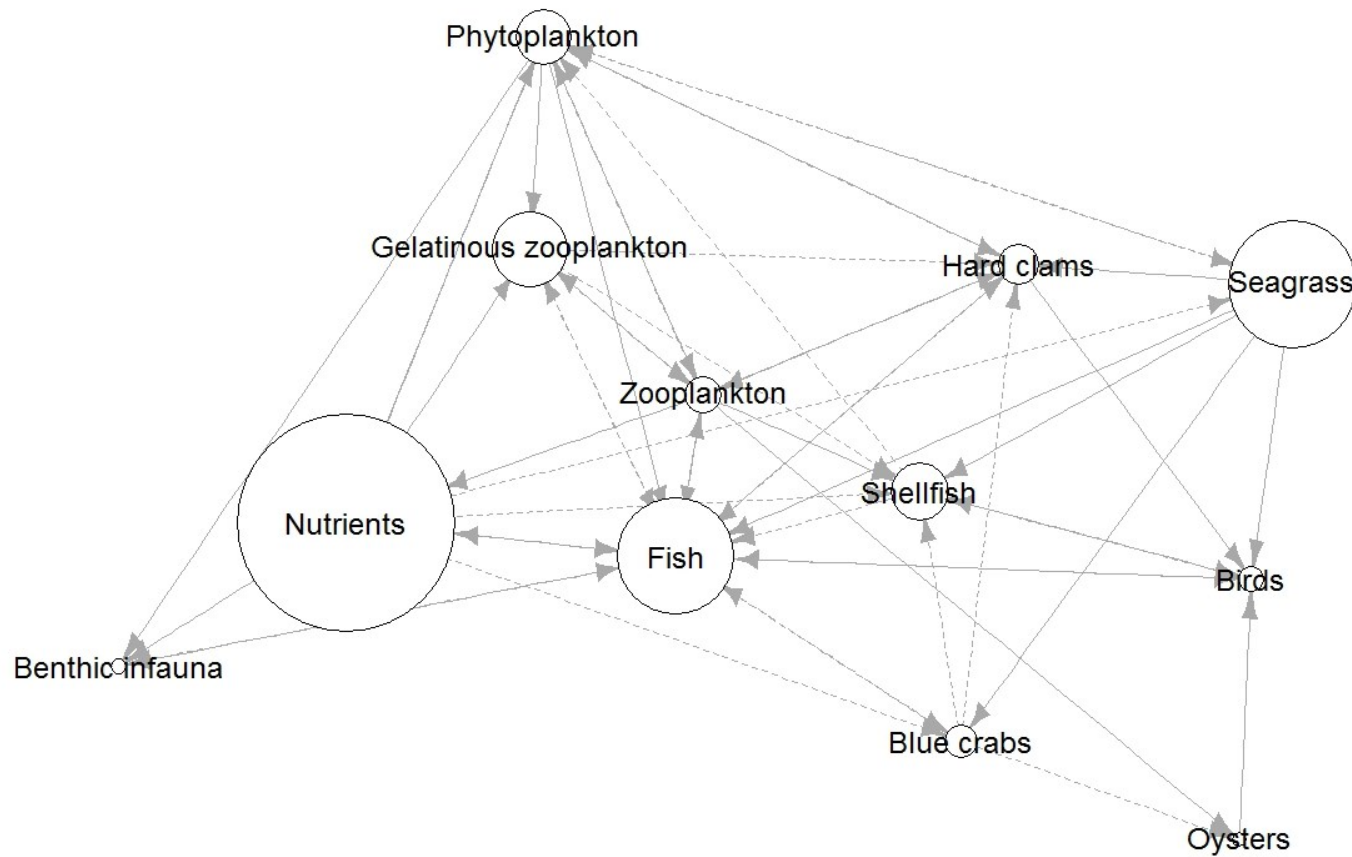
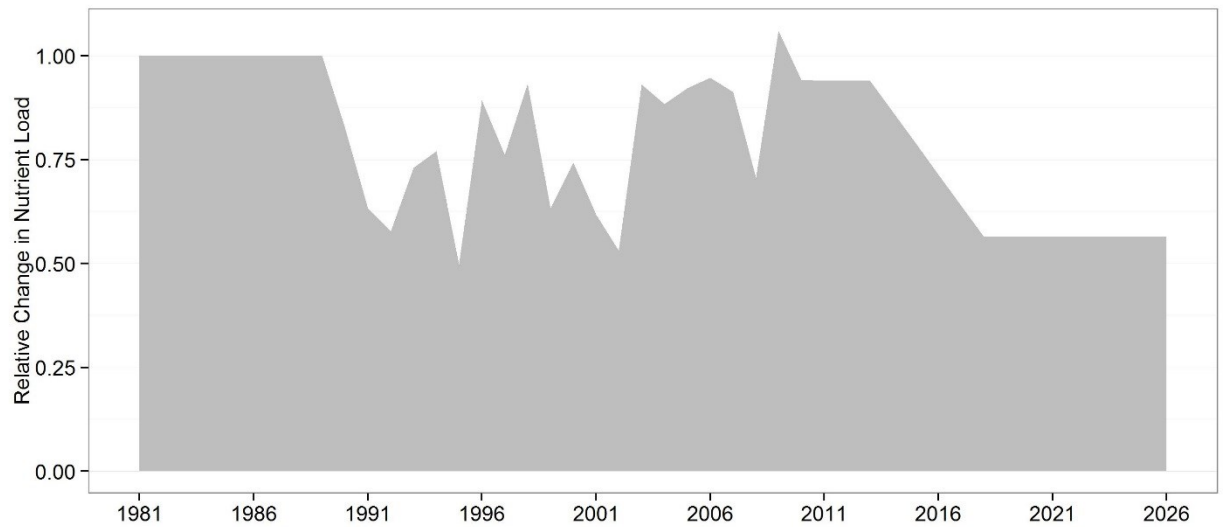


Figure 4: The forcing functions developed for the EwE nutrient reduction scenario; a) a 40% reduction in nitrogen loading after 2013, and b) seagrass biomass.

a)



b)

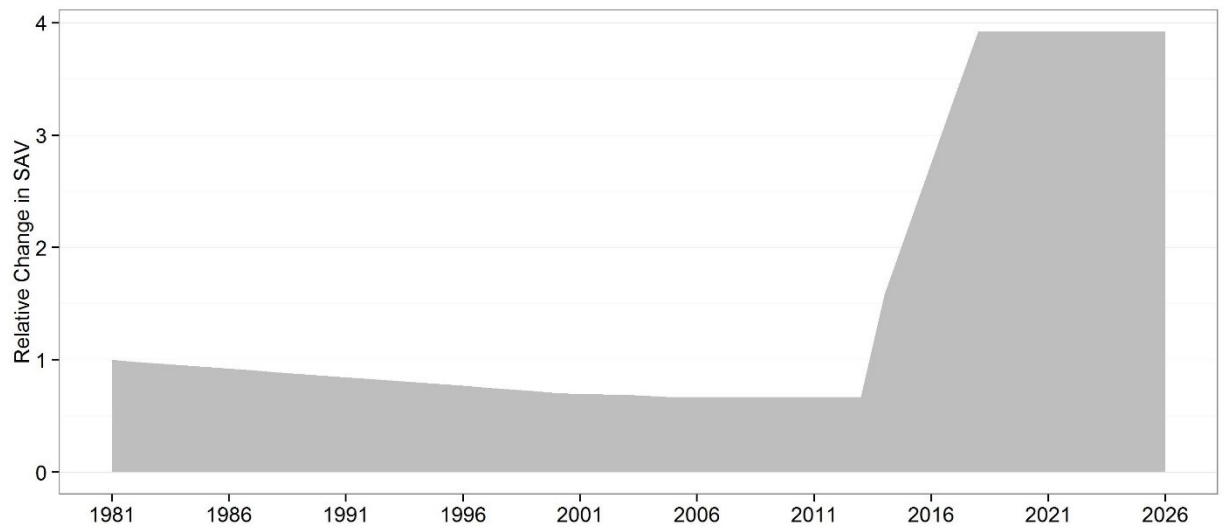


Figure 5: Percent change in biomass for each group in the Barnegat Bay EwE model compared to the baseline scenario for a 40% reduction in nutrient load.

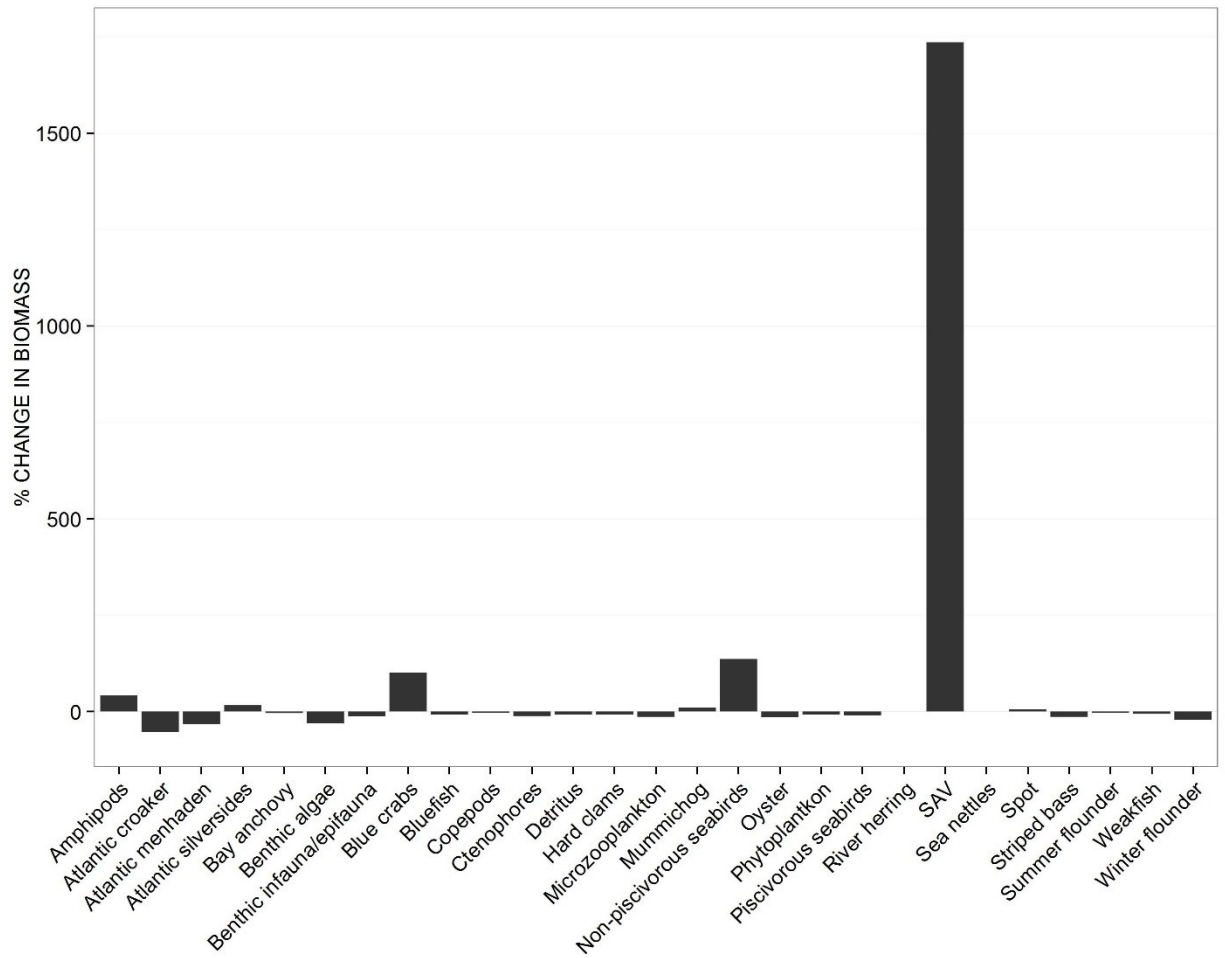
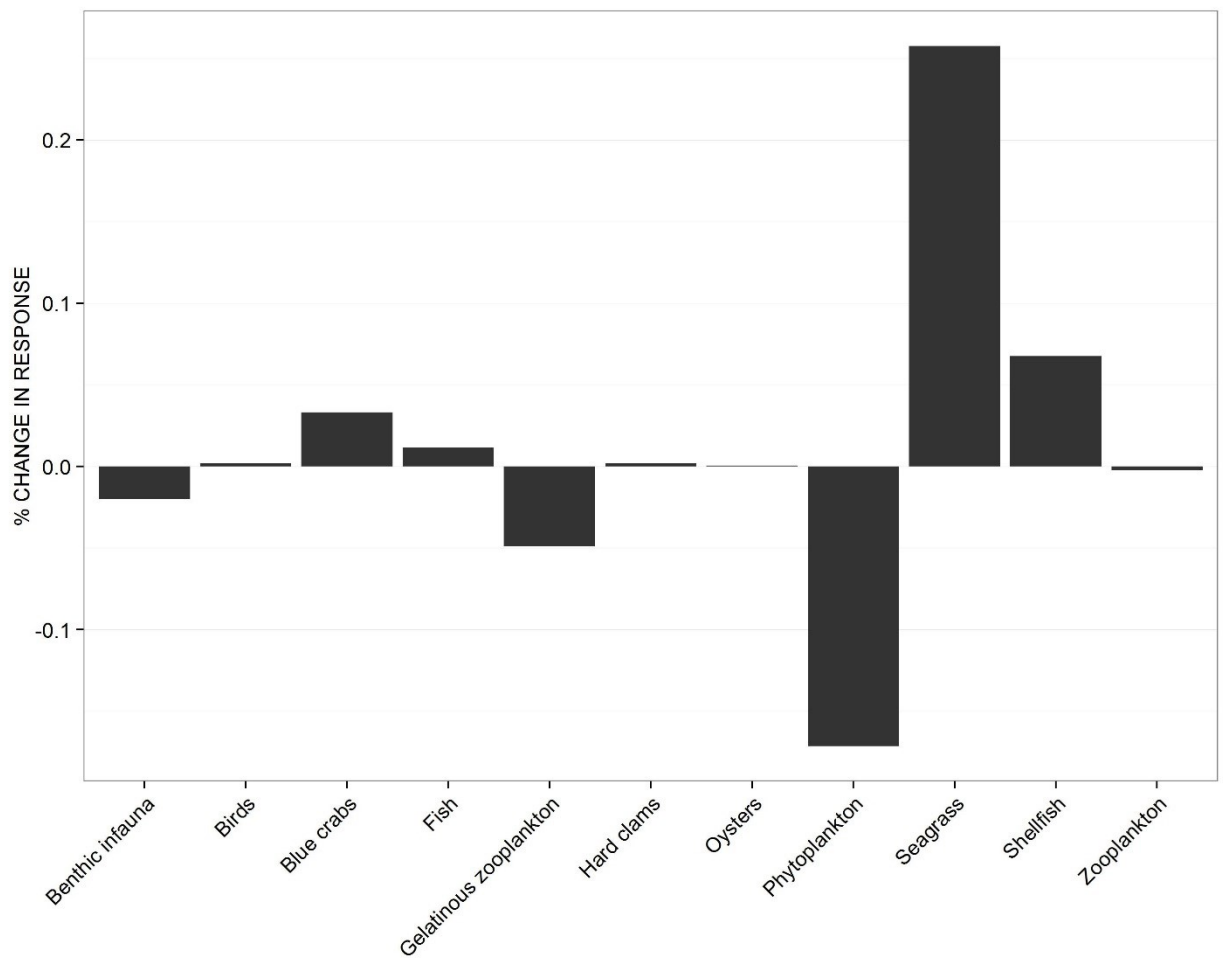


Figure 6: Response of the Barnegat Bay FCM community model to a reduction in nutrient load as compared to the baseline scenario.



CONCLUSION

As human populations in coastal zones throughout the world continue to grow and place increase pressure on these ecosystems, resource managers will have to develop novel paradigms and tools to support a variety of uses. These new approaches will have to integrate human and natural systems if we are to understand how humans and the environment interact, and how human decisions are made within the context of those interactions. The work presented in this dissertation focuses on how two different, but potentially compatible, modelling techniques can be used to support an ecosystem-based approach to managing estuarine resources.

Semi-quantitative Fuzzy Cognitive Mapping conceptual models can provide valuable insight into how ecosystem functioning is perceived by stakeholders involved in the management process. Despite the differences in the way they have accumulated their knowledge of the estuarine ecosystem, different stakeholder groups (scientists, managers, NGOs, locals) shared an understanding of the important components of this social-ecological system. However, the connections between these key components and the rest of the system varied depending upon the particular interests of the group. From an ecosystem-based management perspective, understanding where the interests of stakeholder groups align provides a starting point for building consensus, which is critical in obtaining buy-in for management actions. Conversely, seeing where the models diverge provides insight into the mindset of stakeholder groups and offers a focal area for future research or education efforts.

By evaluating a management scenario utilizing a quantitative, trophic-based “whole ecosystem” model we have shown that indirect effects can have a large, and

potentially unanticipated, impact on the outcome of management activities. The results of the modeled scenario provided further evidence of the importance of indirect effects mediated through trophic interactions; effects which would not be seen in the single-species models traditionally used in resource management. In fact, for some groups in our model the cumulative impacts of the indirect trophic effects was larger, and in the opposite direction, of the direct impacts of the management activity. Thus management actions need to take a holistic, ecosystem-wide view of their impacts or they may not meet their stated goals, and in fact may prove to be counterproductive.

Semi-quantitative models can provide similar responses in magnitude and direction to those of quantitative models when evaluating potential management actions, and therefore can be useful in situations where research-derived data is limited. In data-poor situations local ecological knowledge, collected in a stakeholder-based conceptual modelling framework, can be used to understand the patterns and relative magnitude of changes to an ecosystem that can be expected given proposed management actions. The two modelling techniques can also be used in a collaborative approach, where the strengths of each model is maximized.