Coastal Protection and Restoration Authority
450 Laurel Street, Baton Rouge, LA 70804 | coastal@la.gov | www.coastal.la.gov

2017 Coastal Master Plan

Appendix C – Modeling

Attachment C3-20

Ecopath with Ecosim (EwE)

DRAFT

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Prepared by: Kim de Mutsert (George Mason University), Kristy Lewis (George Mason Universeity), Joe Buszowski (Ecopath Research and Development Consortium), Jeroen Steenbeek (Ecopath Research and Development Consortium), Scott Milroy (University of Southern Mississippi)

Coastal Protection Restoration Authority

This document was prepared in support of the 2017 Coastal Master Plan being prepared by the Coastal Protection and Restoration Authority (CPRA). CPRA was established by the Louisiana Legislature in response to Hurricanes Katrina and Rita through Act 8 of the First Extraordinary Session of 2005. Act 8 of the First Extraordinary Session of 2005 expanded the membership, duties and responsibilities of CPRA and charged the new Authority to develop and implement a comprehensive coastal protection plan, consisting of a Master Plan (revised every 5 years) and annual plans. CPRA's mandate is to develop, implement and enforce a comprehensive coastal protection and restoration Master Plan.

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Executive Summary

Unlike the 2012 Coastal Master Plan, the 2017 Coastal Master Plan modeling effort includes a fish and shellfish community modeling approach. A spatially explicit ecosystem model was developed in the Ecopath with Ecosim (EwE) software suite to simulate fish biomass distribution through time and space. EwE is an open source ecosystem modeling software consisting of three modules: Ecopath, Ecosim, and Ecospace. Ecopath is a virtual representation of the food web of an ecosystem, including flows and pools of biomass within this food web. Ecosim then allows for temporal simulations of changes in biomass of groups in the model (which could be species or functional groups) in response to changes in water quality variables (such as nutrient loads and salinity) over time. Lastly, Ecospace allows for spatial and temporal simulations of biomass change of each of the groups in response to spatially and temporally explicit drivers, forcing functions, and habitat characteristics. This feature not only provides information on the spatial distribution of each group in the model, it also improves estimates of total biomass changes of each group over the course of the model run because movement of consumers and spatially explicit habitat characteristics of the system are taken into consideration.

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List of Abbreviations

%RMSE	Percent root mean square error
ASCII	Gridded file representing model in space with corresponding cell values
CASM	Comprehensive Aquatic System Model
CPRA	Coastal Protection and Restoration Authority
CPUE	Catch per unit effort
CV	Coefficient of variation
DO	Dissolved oxygen
EE	Ecotrophic efficiency
EO	Expert opinion
EwE	Ecopath with Ecosim and Ecospace Ecosystem Modeling Software
FIMP	Fishery independent monitoring program
GIS	Geographic information systems
ICM	Integrated compartment model
LDWF	Louisiana Department of Wildlife and Fisheries
LOWESS	Locally weight scatter plot smoothing
MC	Monte Carlo simulations
MRIP	Marine Recreational Information Program
NMFS	National Marine Fisheries Service
NOAA	National Oceanic and Atmospheric Administration
OECL	Oyster environmental capacity layer
PAR	Photosynthetically active radiation
PBIAS	Percent bias
r	Correlation coefficient
r^2	Coefficient of determination
SS	Sum of Squares
TKN	Total Kjeldahl nitrogen
TroSim	Trophic Simulation Model
TSS	Total suspended solids

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1.0 Introduction

A community modeling approach is being used in the 2017 Coastal Master Plan to evaluate effects of individual restoration and protection projects and alternatives (groups of projects) on fish and shellfish communities (hereafter referred to as fish) over fifty years under multiple environmental scenarios (i.e., multiple values of sea level rise, subsidence, precipitation, etc.). To this purpose, a spatially explicit ecosystem model (an Ecospace model) has been developed in the Ecopath with Ecosim software suite. The resulting Fish and Shellfish Community Model will simulate fish biomass distribution through time and space.

A previously prepared document, detailing the strategy for selecting fish modeling approaches for the 2017 Coastal Master Plan(Rose and Sable 2013), suggested that three models may be best suited for this effort: the Comprehensive Aquatic System Model (CASM), the Trophic Simulation Model (TroSim, a pre-proprietary version of CASM), and Ecopath with Ecosim (EwE). Rose and Sable (2013) also concluded that the choice of model depends on the objectives that need to be met by this model. Since the objectives of the Coastal Protection and Restoration Agency (CPRA) are to estimate effects on fish of long-term (20 and 50 year) restoration and protection scenarios, we contend that EwE is the most suitable modeling framework, which is designed to perform best at these decadal simulations (Christensen and Walters 2004). The main strength of CASM and TroSim, as has been shown in previous publications using these methods (Bartell et al. 1999, Fulford et al. 2010) is to simulate short-term (daily) variations within a time frame of 1 or 2 years.

As part of this effort, we have compared EwE with TroSim and justified our model choice. EwE outperformed TroSim during a 10-year simulation by providing the best fit to data and showing the ability to replicate trends through time in the data (Appendix A). Other benefits of EwE over TroSim are detailed in Appendix A and include the ability to simulate fisheries and movement in Ecospace.

In this document, we will describe the modeling approach with which the Fish and Shellfish Community Model is developed, key assumptions of the model and modeling approach, and improvements made to fit the needs of the 2017 Coastal Master Plan. We describe the model developed to support the 2017 Coastal Master Plan, and data used to develop the model. The methods used and results of a sensitivity analysis, and model calibration and validation, including goodness of fit metrics, are presented. We provide output of a preliminary 50-year test run and explain the modifications performed to finalize the model after this test. The model is linked to the suite of models that support the 2017 Coastal Master Plan (the Integrated Compartment Model or ICM – refer to Attachment C3-22 — ICM Integration); details on the linking process including the model code are provided.

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2.0 General Description of Ecopath with Ecosim

Ecopath with Ecosim (EwE) is an open source ecosystem modeling software, originally developed by Polovina (1984) to model trophic interactions and to estimate mean annual biomass on a coral reef ecosystem. Since that time, the model has been greatly improved and is used to model ecosystems worldwide (Christensen and Pauly 1992; Walters et al. 1997; Walters et al. 1999; Walters et al. 2000). While a spatial application was added in 1999 by the name of Ecospace (Walters et al. 2000), the name for the software has remained 'Ecopath with Ecosim', or EwE for short. Since this aspect has been cause for some confusion, it deserves clarification that Ecospace is part of EwE, and has been included in all recent developments regarding this software.

Ecopath is a virtual representation of the foodweb of an ecosystem, including flows and pools of biomass within this foodweb. Ecosim then allows for temporal simulations of changes in biomass of groups in the model (which could be species or species guilds) in response to changes in environmental variables (such as nutrient loads and salinity) and fishing over time. Because of the trophic interactions represented with the initial foodweb, both direct and indirect effects of these drivers and forcing functions are made evident. Lastly, Ecospace allows for spatial and temporal simulations of biomass change of each of the groups in response to spatially and temporally explicit drivers and habitat characteristics. This feature not only provides information on the spatial distribution of each group in the model, it also improves estimates of total biomass changes of each group over the course of the model run because movement of consumers and fishing fleets, and spatially explicit habitat characteristics of the system are taken into consideration.

2.1 Ecopath: Structure and Assumptions

The first step in developing an EwE model is to create a mass-balanced foodweb that is representative of the ecosystem of interest. This virtual 'snapshot' of the ecosystem is the Ecopath model. For each group in the model, three of the following parameters need to be provided in the model interface: the initial biomass (tonnes km-2 yr-1), the production to biomass ratio $\left(\frac{P}{B}\right)$, the consumption to biomass ratio $\left(\frac{Q}{B}\right)$, and the ecotrophic efficiency (EE). Two master equations must be satisfied to correctly parameterize the Ecopath model. The first equation describes the production of each functional group as a set of n linear equations for n groups:

$$\left(\frac{P_i}{B_i}\right) \cdot B_i \cdot EE_i - \sum_{j=1}^{n} B_j \cdot \left(\frac{Q_j}{B_j}\right) \cdot DC_{ji} - Y_i - E_i - BA_i = 0 \qquad (1)$$

where $\left(\frac{P_i}{B_i}\right)$ is the production to biomass ratio for group i, EE_i is the ecotrophic efficiency (the proportion of production used in the system), B_i and B_j are the biomasses of the prey and predators respectively, $\left(\frac{Q_j}{B_j}\right)$ is the consumption to biomass ratio, DC_{ji} is the fraction of prey i in predator j's diet, Y_i is catch rate for the fishery for group i, E_i is the net migration rate, and BA_i is the biomass accumulation for group i.

The Ecopath model assumes conservation of mass over a year. Energy balance within each group is ensured with the second master equation:

Consumption = production + respiration + unassimilated energy (2)

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where production can be described as:

Production = predation mortality + catches + net migration + biomass accumulation + other mortality (3)

More succinctly, production can be described by the following equation:

$$P_i = \sum_j Q_j \cdot DC_{ji} + (F_i + NM_i + BA_i + M0_i) \cdot B_i \quad (4)$$

where P_i is the production of prey group i, Q_j is the consumption of predator j, DC_{ji} is the diet composition contribution of i to j's diet (by weight, not energy), F_i is the instantaneous rate of fishing mortality, NM_i is the net migration rate of prey group i, BA_i is the biomass accumulation rate for i, $M0_i$ is the other mortality rate for i (non-predation, non-fishery), and B_i is the biomass of i.

Species or groups in Ecopath can be divided into multiple life stages. This approach is referred to as the multistanza approach and can include a juvenile and adult for each group, or multiple life stages per group when ontogenetic shifts occur at several instances in the life cycle. Each stanza in Ecopath requires input for the production to biomass ratio $\left(\frac{P_i}{B_i}\right)$, and time (in months) of stanza break, while biomass(B_i), the consumption to biomass ratio$\left(\frac{Q_j}{B_j}\right)$, and von Bertalanffy K values (Bertalanffy 1938) are required for the leading stanza (i.e., the life stage for which the initial biomass is entered) allowing for Ecopath to estimate those parameters for the other life stages based on the von Bertalanffy growth function. K is considered a curvature parameter and suggests how fast a fish will reach the length of an "old fish," otherwise known as L∞ (Sparre and Venema 1998).

In addition to the above-mentioned parameters, a diet matrix must be developed that specifies the diet items of each group and stanza, and the relative proportion of each of these diet items in the diet of each stanza. A consumer can feed proportionally on any prey item ranging from 0 to 1, with a predator's entire diet composition summing to a total of 1. Lastly, fleets must be described if fishing occurs in the model. Fleets are defined here as specific fisheries responsible for biomass removal of the target species by which it is named. Fleets can also be responsible for bycatch of other non-target species and this bycatch can be explicitly modeled in EwE. For each fleet (e.g., brown shrimp fishery) we include the annual catch of each target species in weight per area fished (tonnes km-2), plus discards in tonnes km-2.

In order to move into either the Ecosim or the Ecospace module in EwE, the Ecopath model must achieve mass balance (which means that the Ecopath master equations are solved.) The EwE software enables the balancing process by not allowing higher consumption on a certain prey item than biomass of that prey item present in the system. If a group's EE is > 1 during model parameterization, more biomass than present in the system is being consumed/removed (either by predation mortality or fishing mortality), and the model will not balance. Adjustments to the model will then need to be made to reduce this mortality. While Ecopath usually solves for EE when biomass, P/B and Q/B are provided, it is also possible to have Ecopath solve for any other of these four parameters (biomass, P/B, Q/B, and EE) as long as three parameters are provided.

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2.2 Ecosim: Structure and Assumptions

Applying the initial parameters derived from the first master equation in Ecopath, the Ecosim module of EwE can be invoked. Ecosim re-expresses the system of linear equations from Ecopath as a system of coupled differential equations to predict future outcomes:

$$\frac{dB_i}{dt} = g_i \sum_j C_{ji} - \sum_j C_{ij} + I_i - (M_i + F_i + e_i)B_i \qquad (5)$$

where g_i is the net growth efficiency; I_i is the biomass immigration rate; M_i is the nonpredation mortality rate; F_i is the fishing mortality rate; e_i is the emigration rate; C_{ij} can be considered the "flow" from pool i to pool j organisms as a function of time, and represents the consumption rate of type i biomass pool by type j biomass pool.

Environmental parameters can influence trophic interactions when included as forcing functions, which are used to alter the effective search rate of predators in a way determined by species-specific response curves. The effective rate of search in Ecosim allows predators to spend more (or less) time foraging in arenas where prey are concentrated. To include forcing functions in the model, a dataset with monthly values of the environmental variables of interest is uploaded to the model. These data can be field observations or output of other models. In addition, response curves need to be created that represent the tolerance ranges of each group in the model for the specific environmental variable. Effective search rate of the group will be affected in sub-optimal conditions, which reduces energy derived from food, and thereby reduces the biomass of the affected group. The software provides other options as well to invoke effects of forcing functions in the ecosystem; for example, primary producers can respond to changes in nutrient levels with a multiplier instead of a response curve to simulate increases and decreases in primary production in response to changes in nutrient loading.

2.2.1 Foraging Arena Theory

Within the dynamic components of the EwE modeling framework (Ecosim and Ecospace), each prey group is present in a vulnerable and invulnerable state. This characteristic represents a situation where prey groups seek refuge until they have to expose themselves to forage, at which point they become vulnerable to predation. This a`djustment to predator-prey interactions that introduces prey behavior into the traditional equation of the predator-prey model is termed the Foraging Arena Theory (Walters and Martell 2004). In Ecosim, the rates of consumption can be limited at very small temporal scales, allowing for the flow of prey (v_{ij}) from (behaviorally or locationally) varying states of vulnerability to limit the rates of predation to levels that the traditional Lotka-Volterra mass-action models would not predict. Consumption rates in Ecosim can be described by:

$$Q_{ij}(B_i, B_j) = \frac{a_{ij} v_{ij} B_i B_j}{(v'_{ij} + v_{ij} + a_{ij} B_j)} \qquad (6)$$

where B_i is the biomass of the prey; B_j is the biomass of the predator/consumer; a_{ij} is the rate of effective search for prey i by predator j; v_{ij} and v'_{ij} are the behavioral exchange rates between prey pools, expressed as vulnerable and invulnerable. Equation (6) is based on the concept of the foraging arena theory, which regulates consumption rates by assuming predator-prey interactions take place in restricted arenas where prey vulnerability in terms of predation depends on a prey's need for a particular resource (Ma et al. 2010; Walters et al. 1997). Vulnerability in predator-prey interactions can also be influenced in Ecosim by the

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addition of mediation factors, M_{ij}, which allows for a third organism to affect a predator/prey pair's interaction. The transfer rate v_{ij} values determine whether control within the ecosystem is top-down or bottom-up, where high values indicate top-down control and low values indicate bottom-up control (Christensen and Walters 2004) . Users can 'turn off' this improvement in representation of predator-prey interactions by simply setting vulnerabilities of each prey group to a high value.

2.2.2 Calibration and Validation

An important step in using and applying dynamic ecosystem models is to ensure they can reproduce historical patterns of abundance for further use in policy analysis and future predictions (Shannon et al. 2004). Calibration is an important step in model development and usually involves adjustments to input parameters within a plausible range of solutions. The model parameterization step in Ecopath is the first calibration step a user employs when developing a model in EwE. During this step the model gives warnings if the model is unbalanced, which usually means that more of a certain group is consumed in the model than is present in the ecosystem, thus failing to achieve the assumption of a mass-balanced ecosystem. So, to achieve mass balance, the user adjusts, within plausible ranges, the diet matrix, the $\left(\frac{P}{B}\right)$ or $\left(\frac{Q}{B}\right)$ values, the initial biomass of a group, or perhaps even the number of groups in the model. Once the model is balanced, Ecopath represents an ecosystem in which the energy flow is balanced over a certain time period (usually a year). This feature in Ecopath is a valuable component of the EwE software and is often used in other community model applications (e.g., Atlantis) to ensure that the model is based on a balanced foodweb.

A second important calibration step is the fitting to time series routine in Ecosim. During this routine, model runs are fitted to observed data of a combination of biomass, fishing mortality and/or fishing effort. The routine searches for the lowest Sum of Squares (SS) by adjusting the vulnerabilities of groups to predation and fishing (see Section 2.2.1 for more on vulnerability). Validation of the model can be completed by comparing the final model run to a different set of observed data and noting the SS without fitting the model to this second set of time series.

2.3 Ecospace: Structure and Assumptions

Ecospace is the spatially explicit and time dynamic module of the EwE software package. In this module, the same set of differential equations applied in Ecosim is now applied in every grid cell over a geo-referenced base map (Christensen and Walters 2004; Walters et al. 1997). Consumption rates are still based on the foraging arena theory, as is the case in Ecosim, allowing Ecospace to represent biomass and consumption dynamics over two-dimensional space (Christensen et al. 2008; Walters et al. 1999). While Ecosim runs in each Ecospace grid cell, a portion of the biomass of each group will move to adjacent grid cell in search of better living conditions with dispersal rate *m* in km yr^{-1}. Dispersal rate *m* can be user defined, and is set at a default of 300 km yr^{-1} when no specific dispersal rate is known for a specific group through tagging studies. This base dispersal rate is increased using a multiplier in non-preferred cells/habitat. In addition, vulnerability to predation and/or relative feeding rates outside of preferred habitat conditions can be adjusted using response curves.

Fleets are dynamic in Ecospace as well. The Ecospace model simulates fishing effort relative to the baseline landings in Ecopath; the number of trips in the first year is relative to the landings in the initial conditions for each fleet. Fishing effort is distributed over cells using a gravity model; i.e. effort in any particular cell is a function of biomass of the target species and profitability of

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fishing in that particular cell. Profitability can include factors such as the price per pound and the cost of fishing (e.g., increased distance from port increases the cost of fishing). Fleets in the model can represent recreational fishing effort as well. It has become exceedingly clear that fishing is a very important determinant of fish and shellfish biomass in any ecosystem where fishing occurs (Worm et al. 2009), whether a species is targeted or a portion of the bycatch.

2.3.1 The Habitat Capacity Model

The EwE model calculates the suitability of each model cell for each species based on its environmental conditions (using the various response curves), and then modifies dispersal rates and prey availability. Suitability of cells in EwE is termed habitat capacity, and the tool to determine this per cell the habitat capacity model.

In the habitat capacity model the relative habitat capacity by group and by cell is estimated from a vector of habitat attributes – which can be made to consider any environmental parameter, e.g. dissolved oxygen, salinity or temperature. The habitat capacities can be updated for each time step (in a computationally efficient manner), and can typically be obtained from output from physical or biogeochemical models.

The habitat capacity model modifies spatial dispersion of biomass so as to obtain movements toward preferred cells and avoid dispersing excessive biomass into unsuitable spatial cells with the following equation:

$$\frac{m_{1j}}{m_{2j}} = \frac{C_{rc+1j}}{C_{rcj}} \qquad (7)$$

Where m_j is the user supplied dispersal rate, C_{rcj} the capacity of a cell in row r and column c, and C_{rc+1j} the capacity of a cell one column to the right. For each border between cells, for example between cell (r,c) and cell (r,c+1) to its right, Ecospace assumes instantaneous mixing rates $m_{1j}B_{rcj}$ (where B is biomass) to the right and $m_{2j}B_{rcj}$ to the left. This movement is affected by the habitat capacity of the neighboring cell. Ecospace sets the exit rate to the user supplied dispersal rate for whichever cell has lower capacity (e.g. C_{rcj}, then the user supplied dispersal rate is m_{1j}), then adjusts the exit rate for the cell with higher capacity (e.g. C_{rc+1j}, then the adjusted dispersal rate is m_{2j}) to the user-supplied dispersal rate times the capacity ratio, i.e m_{2j} is set to $m_j C_{rcj}/C_{rc+1j}$. In this way, the exit rate from the cell with higher capacity to the cell with lower capacity is reduced to an extent determined by the difference in capacity between the two cells.

In addition, the habitat capacities are linked to trophic interactions in the foraging arena model so that it impacts the size of the foraging arena in the following manner:

$$V_{ij} = \frac{v_{ij} \times B_i}{2 \times v_{ij} + a_{ij} \times B_j / C_{rcj}} \qquad (8)$$

The predation activity is thereby concentrated in a smaller area when C decreases which in turn impacts the vulnerable prey densities (V) more rapidly if predator density (B_j) increases because of a decrease in the size of the foraging arena. These relationships make spatial patterns of biomass proportional to their habitat capacities.

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2.3.2 Use of GIS in Ecospace

Until recently, a major limitation in Ecospace has been its inability to apply external spatial forcing data into model applications. In the original Ecospace model, environmental driver data had to be hand-sketched in a user interface or directly read into the model using difficult to create GIS raster data. So while there has been a capability of using GIS in Ecospace from its inception, the process was exceedingly difficult and rarely utilized.

Before the EwE software package was completely recoded in Visual Basic .NET, Ecopath and Ecosim models have been successfully linked to other models but the spatial model Ecospace had seen little innovation due to the complexity of data exchange in the model architecture. In 2006, EwE source code was migrated to the .NET programming environment and this transition is one of the primary factors allowing for the development of a new and flexible spatial-temporal data framework to solve the data connectivity shortcomings of Ecospace.

The new spatial-temporal data framework in Ecospace is built with a modular design (Steenbeek et al. 2013). External data integration is divided into three layers: data access, data conversion and data integration (Figure 1). Then, to obtain output GIS datasets, the pathway for data integration is effectively reversed. Once the output data are passed through a conversion process, data are made available to the user and can then be saved to an external location (Figure 2).

Using the Ecospace spatial-temporal framework is straightforward and made specifically for users with limited GIS experience. The first step is to define maps that describe the ecosystem (e.g., bathymetry and relevant environmental parameters) in an Ecospace scenario. Then, users define and time-tag external datasets of time-varying maps for each environmental variable. Then, the environmental driver map in Ecospace and the external datasets are connected, which allows the software to locate and apply the spatial-temporal varying data. Lastly, the model is executed, and external environmental data are integrated into the Ecospace model at monthly time steps.

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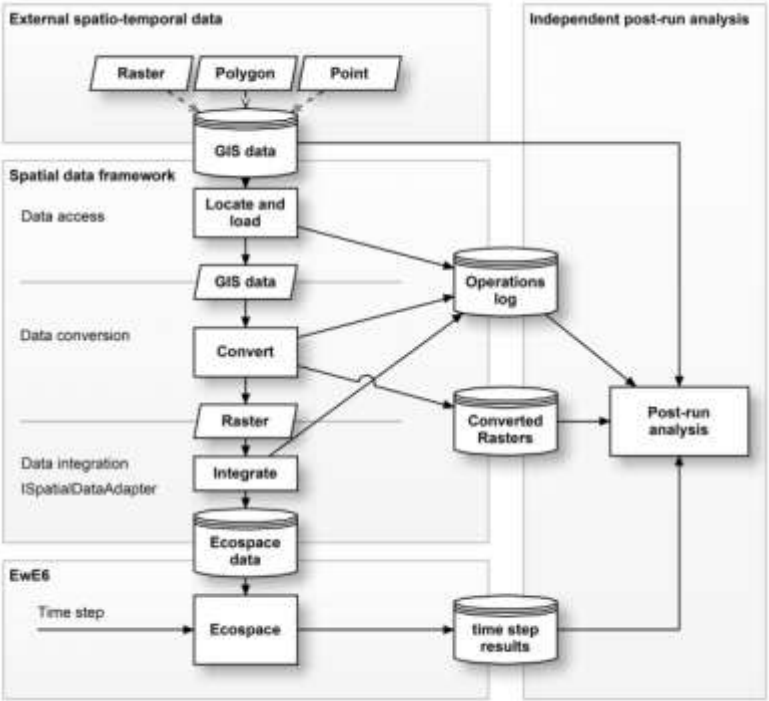

Figure 1: The modular design of the spatial-temporal framework in Ecospace, depicting how external GIS data are integrated into EwE (Steenbeek et al. 2013).

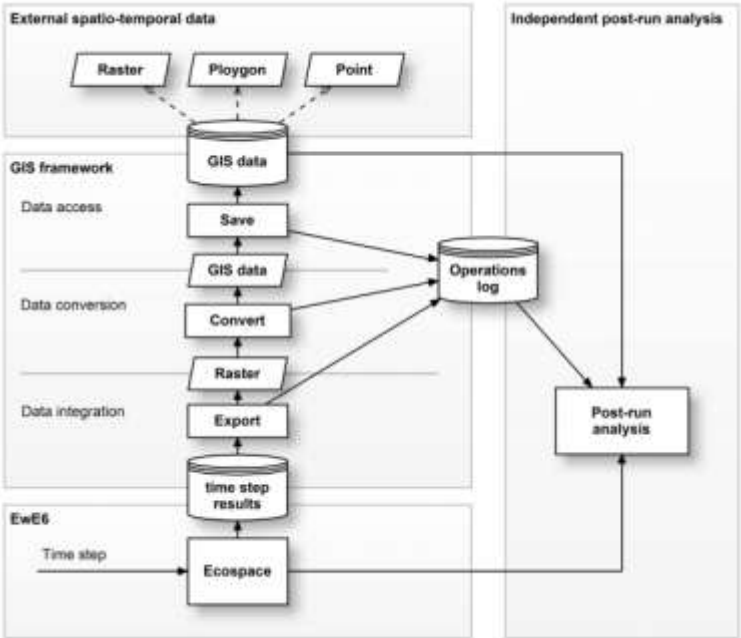

Figure 2: The modular design of the spatial-temporal framework in Ecospace, depicting how external data are output (Steenbeek et al. 2013).

3.0 Development of Master Plan EwE Model

The community model for the 2017 Coastal Master Plan represents the Louisiana coastal zone (Figure 3). During model development, a preliminary Ecopath model was developed based on Louisiana Department of Wildlife and Fisheries (LDWF) field data collected in the Barataria, Breton Sound and Pontchartrain basins; this model is a virtual representation of the ecosystem and represents the year 2000. For coast wide expansion, this model was subsequently calibrated in Ecosim against coast wide observations including coast wide environmental drivers. Finally an Ecospace model was created by developing a basemap of the expanded model area (Figure 3), and including spatially-explict environmental drivers that are based on output from the ICM. This Ecospace model accounts for spatial-temporal changes of water quality parameters and habitat features, and movement of individual fish species and fishing fleets in the model. In this section we describe the model domain, the data preparation, model development, and key assumptions.

3.1 Model Domain

The Fish and Shellfish Community Model domain initially developed for the Barataria, Breton Sound, and Lake Pontchartrain basins, was expanded coast wide to support the 2017 Coastal Master Plan (Figure 3). The model has a resolution of 1 km^2, spans the entire coast of Louisiana, and consists of 56,011 connected active cells. Active cells are cells with water that can be occupied by groups in the model and receive environmental drivers. Nekton and fleets move between cells, while habitat and environmental drivers determine the suitability in each cell.

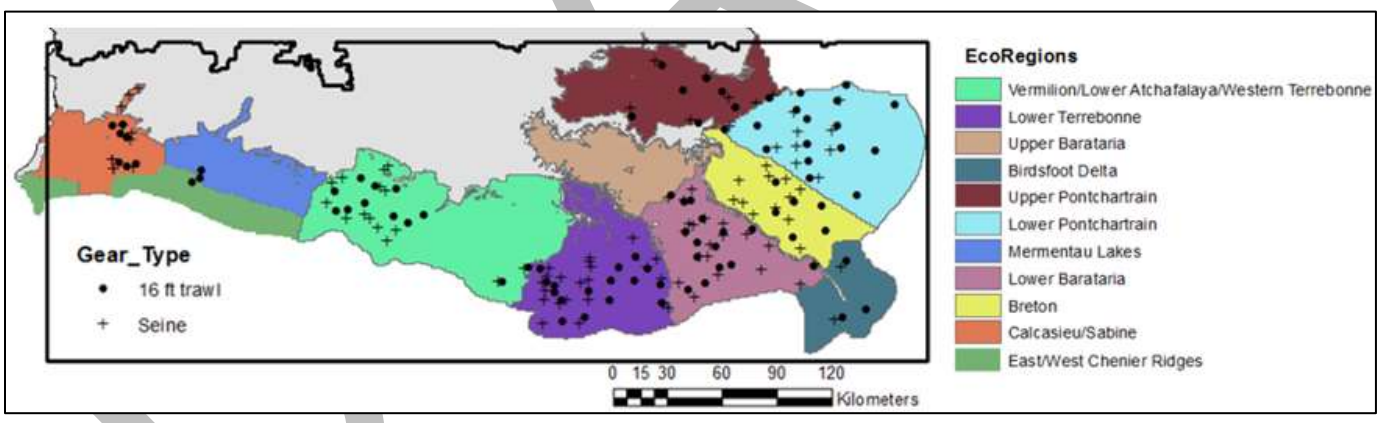

Figure 0-3. The Fish and Shellfish Community Model domain is indicated with the black box. The grey area within the model domain are inactive land cells. Colors indicate the ecoregions within this area that are listed in the legend. Locations of LDWF trawl and seine field collection that are used in model development, calibration, and validation are indicated.

3.2 Biological Data Collection and Preparation

The species included in the EwE model were selected because of their importance in commercial and recreational fisheries, their ecological role, and their overall abundance within the system, in addition to any species specifically requested for inclusion by CPRA (Table 1).

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Biomass data used to develop the Ecopath model and the biomass time series data in Ecosim were derived from data collected by the LDWF Fishery Independent Shrimp/Finfish/Oyster Monitoring Programs. For a detailed description of how fishery independent data were collected, please refer to the Marine Fisheries Division Field Procedures Sample Design and Data Collection Manual (LDWF 2002). When initial biomasses could not be obtained from field data, estimates from stock assessments, other published studies, and/or other ecosystem models from similar systems were used as initial conditions in our model; data sources are listed in Table 1.

The gear types used to calculate intial biomasses and biomass time series were a 4.8 m flat otter trawl and a 15.24 m seine, as recommended by LDWF. For both gear types, all sampling stations located within the spatial extent of the model area were included. The years included in the development of the Ecopath model as well as the Ecosim time series are defined below. Biomass calculations for eastern oysters in both Ecopath and Ecosim were derived from the LDWF Oyster monitoring program, using the square meter gear type.

Biomass estimates for adult or juvenile life stages are used as input parameters in the Ecopath model. To determine whether data collections represent adults or juveniles we created length histograms for each gear type to determine which length/age classes were caught with a particular gear. Then, using literature, we found at what length each species moves from juvenile to adult, and split the age classes at that length. A species that is represented by a juvenile and an adult life stage in the model is part of a multistanza group. For each multistanza group, the initial biomass of only one life stage is entered; biomass of the other is calculated with the von Bertalanffy growth function (von Bertelanffy 1933). Ecopath is also capable of calculating biomass of a group in the model based on production to biomass ratio (P/B), consumption to biomass ratio (Q/B) and ecotrophic efficiency (EE).

Table 1: Groups in the model with species they are based on and source of biomass data.

Group	Scientific Name	Multi-stanza	Data Source
coastal sharks	*Carcharhinus leucas*, and others	yes	Geers 2013
dolphins	*Tursiops truncatus*	no	Waring et al. 2011
sea birds	*Pelecanus occidentailis,* and others	no	Geers 2013
spotted seatrout	*Cynoscion nebulosus*	yes	LDWF FIMP
red drum	*Sciaenops ocellatus*	yes	LDWF FIMP
black drum	*Pogonias cromis*	yes	LDWF FIMP
largemouth bass	*Micropterus salmoides*	yes	LDWF FIMP
Gulf sturgeon	*Acipenser oxyrinchus desotoi*	yes	Kirk 2008
blue catfish	*Ictalurus furcatus*	yes	LDWF FIMP
sea catfish	*Bagre marinus, Ariopsis felis*	yes	LDWF FIMP

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Group	Scientific Name	Multi-stanza	Data Source
Atlantic croaker	*Micropogonias undulatus*	yes	LDWF FIMP
sheepshead	*Archosargus probatocephalus*	yes	LDWF FIMP
southern flounder	*Paralichthys lethostigma*	yes	LDWF FIMP
spot	*Leiostomus xanthurus*	yes	LDWF FIMP
Gulf menhaden	*Brevoortia patronus*	yes	LDWF FIMP
striped mullet	*Mugil cephalus*	yes	LDWF FIMP
sunfish	*Lepomis macrochirus, L. microlophus, L. punctatus*	yes	LDWF FIMP
bay anchovy	*Anchoa mitchilli*	yes	LDWF FIMP
blue crab	*Callinectes sapidus, C. similis*	yes	LDWF FIMP
killifish	*Fundulus spp.*	no	LDWF FIMP
silversides	*Menidia beryllina, Membras martinica*	no	LDWF FIMP
brown shrimp	*Farfantepenaeus aztecus*	yes	LDWF FIMP
white shrimp	*Litopenaeus setiferus*	yes	LDWF FIMP
grass shrimp	*Palaemonetes spp.*	no	De Mutsert 2010/LDWF FIMP
eastern oyster	*Crassostrea virginica*	yes	LDWF Oyster m^2/C. Villaruba
benthic crustaceans	*Rhithropanopeus harrisii*	no	Rozas and Minello 2011/Herman et al. 1999
mollusks		no	Rozas and Minello 2011
zooplankton		no	Walters et al. 2008/Althauser 2003
zoobenthos		no	Rozas and Minello 2011/Herman et al. 1999
phytoplankton		no	R. Lane unpublished data
SAV		no	De Mutsert 2010
benthic algae		no	SEAMAP 2014

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Group	Scientific Name	Multi-stanza	Data Source
detritus		no	Walters et al., 2008

Abundance (number of organisms) and length data are the most consistently reported variables in the LDWF fisheries independent monitoring database. Since EwE requires biomass values in g m-2 yr-1 for initial biomass and time series data, LDWF abundance data per unit effort (CPUE) were converted to g m-2 for each species in the model by using length-weight relationships and estimating the area sampled with each gear. Since LDWF only measures 30-50 organisms per sample in both the trawl and finfish datasets, we determined the proportion of species at length for each sample. The total catch (abundance) per sample (when above the 30-50 organism threshold) was then multiplied by the proportional catch-at-size per sample to determine an estimated catch-at-size for the entire sample. To determine the biomass per sample, abundance (plus length information) was converted to biomass with a length-weight (L-W) regression, $W_i = aTL_i^b$, where a and b are species specific parameters derived from FishBase (www.fishbase.org), TL is length in total length, and i is each species of interest (Table 2). All species' biomasses were then divided by the sampling area of each gear type to determine the gi m-2, where i defines each functional group or species.

Area sampled using the seine was calculated by determining the area of a rectangle created during sampling. The length of the seine net (15.24 m.) represents the short side of the rectangle, while the distance the seine is towed once it is set offshore (30.48 m.) represents the long side of the rectangle:

$$Seine\ Area\ sampled\ (m^2) = (15.24\ x\ 30.48)$$

Area swept using trawl gear was calculated using methods similar to Brown et al. (2013) and Sparre et al. (1998). The area swept equation used in this study was $a = DhX$, where a is the area sampled, D is the distance covered during the tow, h is the length of the headrope, and X is the fraction of the headrope length that is equal to the width of the path.

$$Trawl\ Area\ sampled\ (m^2) = (925.99\ x\ 4.88\ x\ 0.8)$$

Distance (D) was determined by converting 3.0 knots to 1.54 m/s and converting a 10 minute tow time to 600 seconds. Therefore, $D = (1.54\ x\ 600)$ or 925.99 meters covered. Headrope length (h) is 4.88 m and X was determined to be 0.8 in this study since the length of the headrope and the width of the path were similar.

The catch (in biomass) per unit effort of each species is divided by this area value and then in a final adjustment for gear inefficiencies, each biomass value was then adjusted using recommendations from Rozas and Minello (1997).

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Table 2: Length-weight regressions and data sources used to calculate g_i m^{-2}.

Functional Group	Weight-Length Regression	Data Source	Units	
			W	L
Spotted seatrout	$W_{sst} = 1.13\ x\ 10^{-8}\ TL_{sst}^{3.01}$	(Nieland et al. 2002)	g	mm
Red drum*	$W_{rd} = 0.01FL_{rd}^{2.938}$	(Murphy and Taylor 1990)	g	cm
Black drum	$W_{bd} = 1.19\ x\ 10^{-5}TL_{bd}^{3.04}$	(Murphy and Taylor 1989)	g	mm
Largemouth bass*	$W_{lmb} = 0.0296SL_{lmb}^{3.045}$	Fishbase	g	cm
Blue catfish	$W_{bcat} = 0.0185TL_{bcat}^{3.00}$	Fishbase	g	cm
Sea catfish	$W_{scat} = 8.6\ x\ 10^{-6}TL_{scat}^{3.0188}$	(Courtney et al. 2012)	g	cm
Atlantic croaker	$W_{at} = 0.005TL_{at}^{3.148}$	Fishbase	g	cm
Sheepshead*	$W_{sheep} = 0.78SL_{sheep}^{3.045}$	Fishbase	g	cm
Southern flounder	$W_{sf} = 0.0043TL_{sf}^{3.295}$	Fishbase	g	cm
Spot	$W_{spot} = 0.0092TL_{spot}^{3.072}$	Fishbase	g	cm
Gulf menhaden	$W_{gm} = 0.008TL_{gm}^{2.45}$	(De Mutsert 2010)	g	cm
Striped mullet*	$W_{sm} = (2.1\ x\ 10^{-5})x\ (FL\ x\ 25.4)_{sm}^{2.93}$	West et al. 2011	g	cm
Sunfish	$W_{sun} = 0.0218TL_{sun}^{2.96}$	Fishbase	g	cm
Bay anchovy	$W_{ba} = 0.0171TL_{ba}^{2.814}$	Fishbase	g	cm
Blue crab	$W_{bc} = 0.008CW_{bc}^{2.45}$	(GDAR 2013)	g	mm
Brown shrimp	$W_{bs} = 0.006TL_{bs}^{2.938}$	(Fontaine and Neal 1971)	g	cm
White shrimp	$W_{ws} = .003TL_{ws}^{3.247}$	(Fontaine and Neal 1971)	g	cm
Eastern oyster	$W_{oy} = 0.00009TL_{oy}^{2.58}$	(Rose et al. 1989)	g	cm

Species indicated with an asterisk (*) mark the taxa that used FL-TL and SL-TL conversions to calculate these parameters using the data provided. (FL = fork length; TL = total length; SL = standard length).

Estimates of eastern oyster relative abundance are determined annually in June and July by LDWF using the square meter sampling approach (LDWF 2002). To obtain an initial oyster biomass for the entire model area, we calculated one mean biomass using samples collected in the Pontchartrain and Breton Sound basins for the year 1995-2000. Estimates of oyster biomass in

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Barataria Bay were more challenging to obtain because abundance information was only avaliable for the years 2001, 2007, 2008 and 2009. For the missing years, we were provided data from the Davis Pond Freshwater Diversion Monitoring Program through Chuck Villarrubia at the Coastal Protection and Restoration Authority (CPRA). To determine g m^{-2} from the abundance m^{-2} data, we used the L-W relationship described in Table 2. While the LDWF data provide abundance at length data needed for the conversion, the data supplied by CPRA only included abundance for sack oysters, and not length. Therefore, we determined the average length of a sack oyster using the LDWF abundance at length m^{-2} for the years 2001 and 2007-2013. This average length was then applied to the L-W regressions for the abundance of sack oysters provided to us for the missing years.

3.3 Environmental Parameters

Environmental parameters included to drive Ecosim calibration and Ecospace simulations are the spatial and temporal dynamic output from the ICM and include: total kjeldahl nitrogen (TKN), salinity, temperature, and total suspended solids (TSS). Since calibration in Ecosim has no spatial component, the coast wide and monthly averaged ICM output of TKN, salinity, and temperature are used in the calibration process, and no habitat features are included. In the Ecospace model, monthly averaged ICM output of TKN, salinity, and temperature per km2 grid cell is used. In addition, daily averaged output of salinity, temperature, and TSS is used to determine the environmental suitability for oysters in every month by developing Oyster Environmental Capacity Layers (OECLs) based on those daily values (see Section 3.5.4). Habitat features are also included in the Ecospace model and include bathymetry, percent cultch, percent wetland, and percent upland per km2. While bathymetry and percent cultch remain the same during model simulations, percent wetland and percent upland are updated every year based on output from the ICM.

3.4 Fishery Data

Three types of fishery-dependent data were used in our model: commercial landings data, recreational landings data and fishing effort data. Landings used as initial inputs in Ecopath were derived from LDWF Trip Ticket data. While effort was know for the commercial fishery (number of trips per fishery per month), we used recreational landings to create a normalized recreational effort curve, by setting the effort from the start year to 1, and assuming that increased/decreased landings in subsequent years corresponded with increases/decreases in recreational effort. Minimal levels of bycatch or discards from the shrimp fisheries were also included in the model. This input is a qualitative assumption based on our knowledge of the primary sources of bycatch in each fleet. Landings and discards were used as initial inputs in the Ecopath base model to represent biomass removal from the ecosystem via fishing. In addition, time series landings data were used in Ecosim calibration. Fishing effort data were used to drive model dynamics, allowing the model to account for time varying fishing effects on the ecosystem.

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3.5 Ecopath with Ecosim

3.5.1 Ecopath Model Development

The Ecopath model is a virtual representation of the ecosystem, and characterizes the foodweb in the coast wide model area in the year 2000 using mean biomasses calculated from 1995-2000 data collected in the Barataria, Breton Sound, and Lake Pontchartrain basins. Our use of Ecospace (a temporal-spatial ecosystem model) allows us to create one foodweb for the entire model area, while factors driving the dynamic model will determine basin-specific fish biomass and distribution. In other words, our mass-balanced foodweb model (Ecopath) will be affected in both space and time by specific factors unique to each basin. Rather than creating a separate Ecopath model for each basin, we created one unified ecosystem model because the basins are connected, and each basin does not contain its own unique group of species.

Fifty-five groups that represent life stages of species or guilds were defined (Table 8). Major nekton groups were characterized with a juvenile as well as an adult life stage to better represent the ontogenetic changes through a species' life history (Christensen and Walters 2004). The consumer groups considered in this study include zoobenthos, zooplankton, nektonic shrimp and crabs, shellfish, fish, birds, and bottlenose dolphins. The last two groups are included because they are major predators and are needed to complete the foodweb. However, because of data limitations for these groups, their biomass estimates cannot be accepted with high confidence.

Estimates of initial biomass were obtained form the data sources indicated in Table 1, and using calculations described in Section 3.2.2. In addition to initial biomass, consumption to biomass (Q/B) and production to biomass parameters (P/B) were entered for each group. We also defined multistanza groups in the Ecopath model; a multistanza group consists of two or more groups in the model that are linked with a von Bertalanffy growth function; usually the juvenile and the adult of a species. Additional information needed for multistanza groups are the age in months that each life stage starts (i.e., age in month when the juvenile turns into an adult), and the von Bertalanffy k value. The values and sources for each of these parameters are indicated in Table 8.

After basic inputs were entered, a diet matrix was completed. The diet of each group consists of the proportional consumption of some set of other groups in the model, summing to one. While stomach content studies and other literature sources provide a general idea of what the potential prey items for each predator are, the relative proportion of each prey item to the total diet is usually unknown, and is generally determined by the availability of the prey item. Therefore the relative proportion of prey items reported in a stomach content study is not the only possible solution, and this 'snapshot' would be different when repeated at another time or other location. For these reasons, the diet matrix is the first set of parameters in the model that are considered when adjustments need to be made when Ecopath fails to meet the mass-balance assumption.

The diet matrix is a function of the potential prey items of a group and the biomass present of those prey items in the system. To obtain mass-balance, biomasses of certain prey groups for which little information exists can be adjusted; such was the case for the zoobenthos group. In addition, it became clear that additional groups were needed in the model that were currently combined under zoobenthos based on the diet preferences of groups in the model. Therefore the groups benthic crustaceans, mollusks, and grass shrimp were created in addition to

zoobenthos, which now just represent small benthic invertebrates such as amphipods and annelid worms.

In addition to predation, fishery removal plays a role in the mass-balancing process. Fisheries present in the ecosystem were added to the Ecopath model with commercial landings that were derived from the LDWF Trip Ticket data and recreational landings derived from NOAA's MRIP program. The fleets included in the Ecopath model are a fishery for brown shrimp, white shrimp, blue crab, black drum, oysters, menhaden and a recreational fishery (which includes adult spotted seatrout, adult red drum, adult black drum, adult largemouth bass, adult blue catfish, adult southern flounder, adult sheepshead, adult sunfishes, and adult blue crab). Bycatch of fleets was included in the model as well based on estimates from Walters et al. (2008). If these inputs did not meet the mass balance assumption during model balancing procedures (EE's of the group in question too high, while our confidence in trophic interactions and input biomass is high), the landings or discards values were iteratively reduced to meet those assumptions.

3.5.2 Calibration and Sensitivity Analysis in Ecosim

Ecosim simulations were used to calibrate the model and to perform a sensitivity analysis. During model calibration, biomass and landings output of groups in the model were fitted to observed biomass data, landings data and fishing effort, for each group for which such data were available. To ready the model for coast wide simulations in Ecospace, the model was calibrated against averaged observations of coast wide field data collections (see Figure 3 for locations of field collections). Model fitting in Ecosim is accomplished by having the model estimate the vulnerability of a group to predation (v_{ij}) that produces a better fit to the observed data (see Section 2.2.2). To asses the performance of the model, the sum of squared deviations (SS) of the observed logarithmic (log) biomass values was used to determine if these changes in v_{ij} allowed the model to better recreate historical patterns of biomass (Christensen et al. 2008). Model calibration was completed for annual observed data for the 14 year simulation (2000-2013). In this document we show the calibration output of the groups in the model for which we have time series field data (see Section 4.2.2). The available time series, use of these data in the model, and data sources are indicated in Table 3. Environmental drivers used during calibration were based on ICM output as described in Section 3.3. While our calibration period spans 2000-2013, the ICM output we received was from 2006-2013, therefore we repeated 2006 ICM output six times to drive 2000-2005 as well.

Table 3: Use of biological and fishing data to calibrate the EwE model.

Species	Time Series of Data	Data Source	Drive Model	Fit Model
Spotted seatrout	Biomass (g m^{-2}) 2000-2013	LDWF Fisheries Monitoring Data (seine samples)		x
	Total Fishing Effort (number of trips/time period)	Estimated based on recreational catches NOAA MRIP and LDWF	x	
Red drum	Biomass (g m^{-2}) 2000-2013	LDWF Fisheries Monitoring Data (seine samples)		x

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Species	Time Series of Data	Data Source	Drive Model	Fit Model
Atlantic Croaker	Biomass (g m^{-2}) 2000-2013	LDWF Fisheries Monitoring Data (trawl samples)		x
Black drum	Biomass (g m^{-2}) 2000-2013	LDWF Fisheries Monitoring Data (seine samples)		x
	Total Catches (tonnes yr^{-1})	LDWF Trip Ticket Data		x
	Total Fishing Effort (number of trips/time period)	LDWF Trip Ticket Data	x	
Blue crab spp.	Biomass (g m^{-2}) 2000-2013	LDWF Fisheries Monitoring Data (trawl samples)		x
	Total Catches (tonnes yr^{-1})	LDWF Trip Ticket Data		x
	Total Fishing Effort (number of trips/time period)	LDWF Trip Ticket Data	x	
White shrimp	Biomass (g m^{-2}) 2000-2013	LDWF Fisheries Monitoring Data (trawl samples)		x
	Total Catches (tonnes yr^{-1})	LDWF Trip Ticket Data		x
	Total Fishing Effort (number of trips/time period)	LDWF Trip Ticket Data	x	
Brown shrimp	Biomass (g m^{-2}) 2000-2013	LDWF Fisheries Monitoring Data (trawl samples)		x
	Total Catches (tonnes yr^{-1})	LDWF Trip Ticket Data		x
	Total Fishing Effort (number of trips/time period)	LDWF Trip Ticket Data	x	
Gulf menhaden	Biomass (g m^{-2}) 2000-2013	LDWF Fisheries Monitoring Data (trawl samples)		x
	Total Catches (tonnes yr^{-1})			x
Bay anchovy	Biomass (g m^{-2}) 2000-2013	LDWF Fisheries Monitoring Data (trawl samples)		x
Eastern oyster	Biomass (g m^{-2}) 2000-2013	LDWF Fisheries Monitoring Data (square meter samples)		x
	Total Catches (tonnes yr^{-1})	LDWF Trip Ticket Data		x
	Total Fishing Effort (number of trips/time period)	LDWF Trip Ticket Data	x	

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Species	Time Series of Data	Data Source	Drive Model	Fit Model
Largemouth bass	Biomass (g m^{-2}) 2000-2013	LDWF Fisheries Monitoring Data (gillnet samples)		x
Blue catfish	Biomass (g m^{-2}) 2000-2013	LDWF Fisheries Monitoring Data (trawl samples)		x
Sea catfish spp.	Biomass (g m^{-2}) 2000-2013	LDWF Fisheries Monitoring Data (trawl samples)		x
Sheepshead	Biomass (g m^{-2}) 2000-2013	LDWF Fisheries Monitoring Data (trawl samples)		x
Southern flounder	Biomass (g m^{-2}) 2000-2013	LDWF Fisheries Monitoring Data (trawl samples)		x
Spot	Biomass (g m^{-2}) 2000-2013	LDWF Fisheries Monitoring Data (trawl samples)		x
Killifish spp.	Biomass (g m^{-2}) 2000-2013	LDWF Fisheries Monitoring Data (seine samples)		x
Silversides spp.	Biomass (g m^{-2}) 2000-2013	LDWF Fisheries Monitoring Data (seine samples)		x
Grass shrimp spp.	Biomass (g m^{-2}) 2000-2013	LDWF Fisheries Monitoring Data (seine samples)		x
Sunfishes spp.	Biomass (g m^{-2}) 2000-2013	LDWF Fisheries Monitoring Data (seine samples)		x

The following procedures were used to calibrate the model, and were modified from the methods of Shannon (2004), Christensen and Walters (2008), Coll et al. (2008) and Howell et al. (2013):

1) *Balanced model check*. Prior to model fitting, an Ecosim run was invoked with no forcing data or time series data to ensure a balanced model from Ecopath was being utilized (Christensen et al. 2008).
2) *Data input*. All biomass time-series, water quality parameters (TKN, salinity, temperature), and fisheries data were read into the EwE model database. Water quality parameters and fishing effort data were used to drive the model, and biomass and landings data were used to assess the performance of the model by fitting the observed data to the model predicted biomasses.
3) *Baseline model fit*. The relative biomass data were invoked and a baseline goodness-of-fit statistic (SS_i) was calculated in Ecosim following procedures in Christensen and Walters (2004) .
4) *Driver variables invoked*. All combinations of water quality parameters, plus the fishing effort data, were invoked and a model run was completed.

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5) *Vulnerability search*. The Fit-to-Time-Series module was applied by using the Search Groups with Time Series function to search for the values of v_{ij} that would minimize the SS from the SS_i. This was done with all different combinations of water quality parameters. The v_{ij}values were then estimated by the model for the predator-prey interactions for which time series were present in the model.
6) *Evaluation of model outcomes.* The fitted model runs were analyzed by comparing the observed and predicted biomass time series data and landings data and by assessing the decrease in SS.

The SS calculation used in the EwE Fit-to-Time-Series module is a statistical measure of the goodness of fit to currently loaded time series data generated each time Ecosim is run. The SS calculated within the EwE software are based on all data available, and are log-transformed to account for the differences in the absolute values of the different time series in the model. This goodness of fit measure in EwE is a weighted sum of squared deviations (SS) of log biomasses from log predicted biomasses, scaled in the case of relative abundance data by the maximum likelihood estimate of the relative abundance scaling factor q in the equation $y = qB$ (y = relative abundance, B = absolute abundance; equation 5). However, it should be noted that for our purposes, the weighted term has been set to a value of one, and is of no consequence in the internal Ecosim SS calculations.

$$SS = \sum_i^{nts}\left(\sum_t^{nobs_i} w_i \log(o_{it}/p_{it})^2\right) \quad (9)$$

Where nts is the number of time series loaded, $nobs_i$ the number of observations in time series i, w_i is the weight of the time series i, o_{it} is the observed value in time series i at time step t and p_{it} is the Ecosim predicted value for variable i at time step t.

To allow for comparison outside our model, we calculated four more goodness of fit metrics that are not EwE specific after the fit-to-times series procedure was completed. These metrics are percent root mean square error (%RMSE), percent bias (%BIAS), R2 and correlation coefficient. All goodness of fit metrics are presented in a table in Section 4.2.1.

A sensitivity analysis was performed in Ecosim by running 20 Monte Carlo Trials of Ecosim simulations that varied initial biomass of all groups in the model with a coefficient of variation (CV) of 0.1. In other words, we let a Monte Carlo procedure choose a new initial biomass at random twenty times for each group within predefined CV's of 0.1, and ran the model with these new initial biomasses. A CV of 0.1 was chosen to determine whether small changes in initial biomass results in large changes in output biomass, which is the goal of a sensitivity analysis. If the model is indeed sensitive to small changes, the model (or the biomass simulation of one particluar species in the model) is not robust to uncertainty in field data, which most certainly exists. By having the biomass of all species vary at the same time, the potential impact of the changed biomass of other species in the model through trophic interactions are tested with these Monte Carlo trials as well. In this document we show the sensitivity analysis output for the following six species of interest: red drum, spotted seatrout, gulf menhaden, largemouth bass, blue crab and white shrimp. The results shown are from a sensitivity test performed in the calibrated model.

3.5.3 Preparing the Ecospace Module

Ecospace requires a number of spatially explicit data sets, beginning with a 'base map'. The base map is a map of the model area, which typically indicates the coastline, the marine boundary, and the bathymetry. Since the model represents an aquatic foodweb, land cells in the model area become inactive cells, and water cells become active cells. The base map of

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the 2017 Coastal Master Plan Community model is derived from a shapefile with bathymetry information that is used for all models that support the 2017 Coastal Master Plan (see Chapter 3, Attachment C3-27). The model area is shown in Figure 3. The size of the grid cells in this base map is 1 km2. This is the highest resolution for the size of the model domain of any existing Ecospace model, and is purposely designed to account for effects of spatial variability in environmental parameters at this scale. A higher resolution (smaller grid cells) would challenge the Ecospace assumption that all species interaction can occur within a grid cell.

Habitat features included in the model are percent wetland, percent upland, percent cultch and bathymetry. Percent wetland is updated every year in the model based on output from the ICM. Bathymetry, percent cultch, and percent upland remain the same over the simulations. Water quality parameters included in the model are TKN, salinity, temperature and TSS.

Previous versions of the EwE software packages made it challenging to incorporate spatial-temporal simulations in Ecospace. Recent innovations using geo-referenced water quality parameter drivers have enabled modelers to input spatially and temporally explicit water quality data, and receive output of spatial responses of organisms to these drivers (Steenbeek et al. 2013). Further improvements to accept spatial data in Ecospace have been described in this document (Section 2.3 and appendix B). To include water quality parameters in the Ecospace model, we created an ASCII file per month for salinity, temperature (°C) and TKN (µg/l) output from the ICM. Since the data were geo-referenced, we were able to convert the spatial information to one value per km2, in such a way that the ASCII files contain one value per grid cell of our model area. During each monthly time-step, a new set of ASCII files was called in by Ecospace to create spatial and temporal dynamic environmental drivers. Fisheries are transferred into Ecospace from Ecopath as explained in Section 2.3.

The groups in the model respond to the water quality parameters and habitat features with trapezoid-shaped group-specific response curves. These environmental parameters coupled to response curves are affecting the groups following the habitat capacity model (Section 2.3.2). A group will only respond to an environmental driver when a response curve is applied, and not all groups respond to each driver in the model. Table 4 lists for each group: the response curves applied to salinity, temperature and percent wetland area; the parameters that define the response curve; and the source of information for the development of the response curve. A depth response curve for benthic crustaceans and adult coastal sharks linked to the bathymetry of the basemap was also used in the model (Figure 4). These were implemented to reduce biomass of benthic crustaceans off the coastal shelf, and to keep adult coastal sharks out of areas that are too shallow for them, while also representing their preference for the coastal shelf (as compared to further offshore). There is no response curve for TKN; instead phytoplankton is driven using the relative TKN values by normalizing the TKN data based on the TKN concentration of year 1 of the FWOA ICM output. In this way, the TKN forcing function causes increases and decreases in phytoplankton biomass relative to the change in TKN as a bottom-up forcing that affects the whole foodweb. Finally, fish were prevented from entering the main stem of the Mississippi River (because no ICM output is generated there) and from utilizing upland areas.

Furthermore, a cultch response curve was used for all three life stages of oysters. Oysters do not respond to the monthly-loaded water quality parameters. Instead, ICM output goes through a separate subroutine that allows oysters to respond to daily values of salinity, temperature and TSS. The monthly Oyster Environmental Capacity Layer (OECL) value calculated from those daily parameters has a 1:1 linear response curve (Figure 4) so that the OECL directly reflects the habitat capacity based on salinity, temperature and TSS. Further details on the development of OECLs are provided in the following section (Section 3.5.4).

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Table 4: Trapezoidal response curve values for salinity, temperature, and percent wetland.

Group name	Salinity					Temperature (°C)					Wetland (%)				
	LB	LT	RT	RB	Source	LB	LT	RT	RB	Source	LB	LT	RT	RB	Source
juvenile sharks	1	10	35	40	A	5	8	30	40	E					
adult sharks	1	10	35	40	A	5	8	30	40	E					
dolphins	0	12	23	-	B	5	8	30	40	E					
sea birds						5	8	30	40	E					
juvenile spotted seatrout	0	5	20	30	C	5	8	30	40	E	-10	25	80	100	H
adult spotted seatrout	0	7.5	20	30	C	5	8	30	40	E					
juvenile red drum	0	5	20	25	C	5	8	30	40	E	-10	25	80	100	H
adult red drum	0	1	15	40	C	1	5	30	40	D					
juvenile black drum	0	2	30	40	D	5	8	30	40	E	-10	25	80	100	H
adult black drum	0	3	30	40	D	5	8	30	40	E					
juvenile largemouth bass	-	0	2	9	C	5	8	30	40	E	20	30	50	85	I
adult largemouth bass	-	0	2	9	C	5	8	30	40	E					
juvenile gulf sturgeon	-	0	20	25	E	5	8	30	40	E					
juvenile blue catfish	-	0	2	7	C	5	8	30	40	E					
adult blue catfish	-	0	2	7	C	5	8	30	40	E					
juvenile sea catfish	0.18	7.9	20.05	40	D	5	8	30	40	E					
adult sea catfish	0.19	3.76	16.84	35	D	5	8	30	40	E					
juvenile southern flounder	0.09	1.09	15.08	37	D	5	8	30	40	E	-10	25	80	100	H
adult southern flounder	0.09	2.33	16.31	30	D	5	8	30	40	E					
juvenile croaker	0	2.72	17.85	43	D	5	8	30	40	E					
adult Atlantic croaker	0	2	35	40	D	5	8	30	40	E					
juvenile sheepshead	0.09	1.1	15	33	D	5	8	30	40	E	-10	25	80	100	H
adult sheepshead	1	5	30	35	D	5	8	30	40	E					
juvenile striped mullet	-	0	20	30	C	5	8	30	40	E	-10	25	80	100	H
adult striped mullet	-	0	15	35	C	5	8	30	40	E					

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Group name	Salinity					Temperature (°C)					Wetland (%)				
	LB	LT	RT	RB	Source	LB	LT	RT	RB	Source	LB	LT	RT	RB	Source
juvenile spot	0	2	30	35	D	5	8	30	40	E	-10	25	80	100	H
adult spot	0.18	4.23	22.25	35	D	5	8	30	40	E					
juvenile sunfishes	-	0	2	7	D	5	8	30	40	E	20	30	50	85	I
adult sunfishes	-	0	2	7	D	5	8	30	40	E	20	30	50	85	I
juvenile bay anchovy	0	1	17	40	C	5	8	30	40	E	-10	25	80	100	H
adult bay anchovy	0	1	17	40	C	5	8	30	40	E					
juvenile menhaden	0	1	10	25	C	5	8	30	40	E	-10	25	80	100	H
adult gulf menhaden	0	5	40	40.01	C	5	8	30	40	E					
killifishes	0	3.72	17.83	32	D	5	8	30	40	E	-10	25	80	100	H
silversides	0	3.13	17.29	33	D	5	8	30	40	E					
juvenile blue crab	0	1	20	35	C	5	8	30	40	E	-10	25	80	100	H
adult blue crab	-7	7	20	35	C	5	8	30	40	E					
juvenile brown shrimp	0	10	25	35	C	5	8	30	40	E	-10	25	80	100	H
adult brown shrimp	0	10	25	35	C	5	8	30	40	E					
juvenile white shrimp	0	5	25	35	C	5	8	30	40	E	-10	25	80	100	H
adult white shrimp	0	5	25	40	C	5	8	30	40	E					
grass shrimp	0	0.01	12.38	31	D	5	8	30	40	C	-10	25	80	100	H
oyster drill	10	15	30	40	F	5	8	30	40	E					
benthic crustaceans	0	5.42	13.21	30	G	5	8	30	40	E					
mollusks						5	8	30	40	E					

Values indicate the left bottom (LB), left top (LT), right top (RT), and right bottom (RB) of a trapezoid in the unit of the parameter. Sources are indicated to the right of each set of values, where A = Heupel and Simpfendorfer 2008; B = Miller and Baltz 2010; C = LDWF expert opinion; D = LDWF FIMP; E = Expert Opinion; F = Garton and Stickle 1980; G = Herman et al. 1999; H = Minello and Rozas 2002; I = Stuber et al. 1982.

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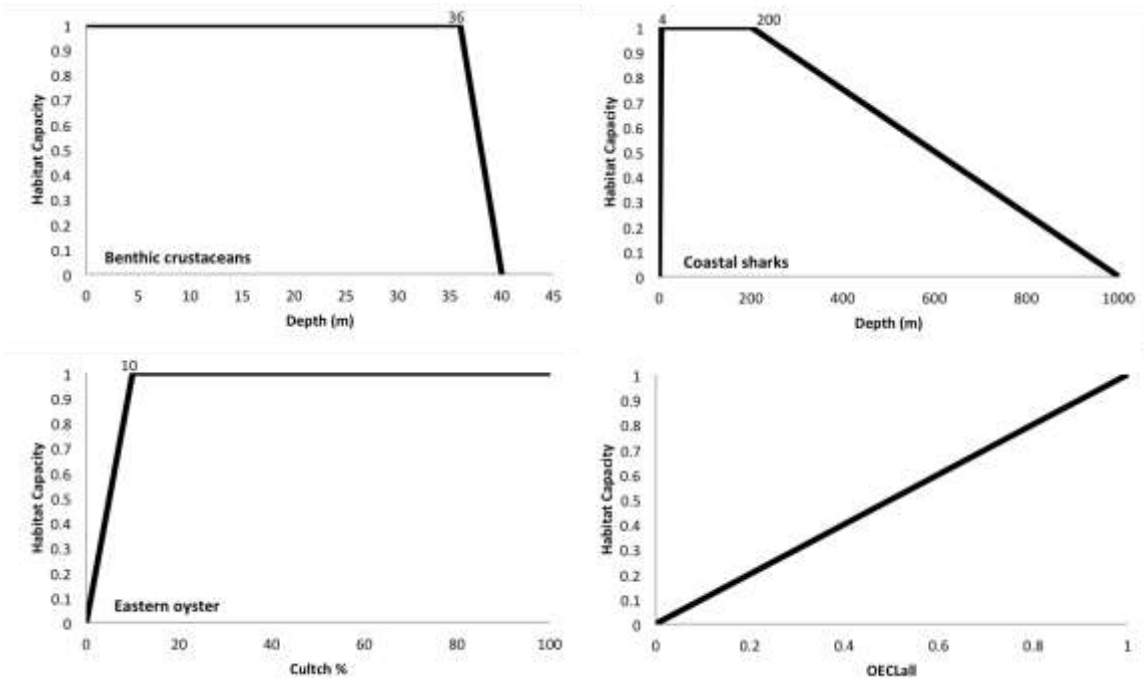

Figure 4: Additional response curves in the model. The response curves regulate the depth distribution of benthic crustaceans (top left) and adult coastal sharks (top right), the habitat requirement of cultch for all three life stages of eastern oyster in the model (bottom left), and incorporates the OECLs into the Ecospace habitat capacity model framework (bottom right).

3.5.4 Oyster Environmental Capacity Layers

Since EwE has a monthly time-step, there was concern that the model may miss short-term (< month) unsuitable conditions for oysters that could have an effect on long-term oyster biomass. To solve this issue, we used 2017 ICM model output of daily salinity, temperature, and TSS to create external Oyster Environmental Capacity Layer (OECLs). An OECL functions similarly to a Habitat Suitability Index (HSI), where environmental parameters are used to define a normalized scale of suitability (0.00 – 1.00; analogous to "% of ideal"), which can then be applied as a damping function (response curve) to mitigate virtually any biological rate.

Since each OECL is normalized to vary on a scale from 0.00 – 1.00, each OECL can be used separately to determine the environmental capacity to support oyster growth (among spat, seed, and sack), based on oyster sensitivities to TSS ($OECL_{TSS}$), salinity ($OECL_{Sal}$), and temperature ($OECL_{Temp}$). For combined effects, the $OECL_{Combined}$ is calculated as the geometric mean of all OECLs included in the analysis:

$$OECL_{Combined} = \left(\prod_{i=1}^{n} OECL_i \right)^{1/n} \qquad (6)$$

Tables 5 through 7 provide a summary of the information available regarding habitat suitability for oysters, specific to the concentration of TSS (mg/l), salinity, and temperature (°C) respectively in productive reef areas.

Table 5: Available information on suitability range of oyster for TSS.

Spat, Seed	**-**	**n.d.**	**100** [c1976, c1983]
	-	**5 - 25** [c2005]	**100** [c2005]
Sack	**-**	**125** [c1983,d1969]	**750** [c1976, c1983]
	-	**5 - 25** [c2005]	**100** [c2005]
	-	**0 - 450** [p2009]	**2,300** [p2009]

Sources: [c1983]Cake (1983); [c1976]Cardwell et al. (1976); [c2005]Cerco and Noel (2005); [d1969]Davis and Hidu (1969); [p2009]Park et al.(2009), n.d. = no data.

Table 6: Available information on suitability range of oyster for salinity.

Spat	**5.0** [h2014, p1995]	**8.0 - 15.0** [h2014, p1995]	**39.0** [h2014, p1995]
Seed	**2.0** [h2014, p1995]	**8.0 - 15.0** [h2014, p1995]	**43.5** [h2014, p1995]
Sack	**2.0** [h2014, p1995]	**14.0 - 30.0** [h2014, p1995]	**43.5** [h2014, p1995]
Seed, Sack	**3.5** [p1994]	**7.5 - n.d.**[p1994]	**n.d.**[p1994]
	5.0 [g1964, g1955, s1971]	**n.d.**[g1964, g1955, s1971]	**40.0** [g1964, g1955, s1971]
	5.0 [b1954,c1983]	**10.0 - 20.0** [b1954,c1983]	**40.0** [b1954,c1983]
	5.5 [b2007]	**15.5 - 25.5** [b2007]	**40.5** [b2007]
	n.d.[e1977]	**10.0 - 30.0** [e1977]	**n.d.** [e1977]
Spat, Seed, Sack	**4.0** [c2005]	**10.0 - n.d.**[c2005]	**n.d.**[c2005]
	5.0 [v2012]	**7.5 - n.d.**[v2012]	**n.d.**[v2012]
	n.d.[h1990]	**15.0 – 30.0** [h1990]	**n.d.**[h1990]

Sources: *[b2007]Barnes et al. (2007); [b1954]Butler (1954); [c1983]Cake (1983); [c2005]Cerco and Noel (2005); [e1977]Eleuterius (1977); [g1964]Galtsoff (1964); [g1955]Gunter and Geyer (1955); [h2014] Attachment C3-12 – Oyster Habitat; [h1990]Hofstetter (1990); [p1995]Patillo et al. (1995); [p1994]Powell et al. (1994); [s1971]Stenzel (1971); [v2012]VanderKooy (2012)*

Table 7: Available information on suitability range of oyster for temperature.

Spat	**20.0** [h2014, s1986]	**25.0 - 30.0** [h2014, s1986]	**n.d.**[h2014, s1986]
Seed	**n.d.**[c1983]	**20.0 - 30.0** [c1983]	**34.0** [c1983]
Sack	**1.0** [h2014, s1986]	**20.0 -30.0** [h2014, s1986]	**49.0** [h2014, s1986]
	5.0 [c1983]	**20.0 - 30.0** [c1983]	**34.0** [c1983]
	1.0 [g1964]	**n.d.**[g1964]	**36.0** [g1964]
Seed, Sack	**10.5** [b2007]	**23.5 - 30.5** [b2007]	**35.5** [b2007]
Spat, Seed, Sack	**8.0** [c2005]	**25.0 - 29.0** [c2005]	**46.0** [c2005]
	n.d.[h1990]	**n.d.**[h1990]	**32.0** [h1990]

Sources: [b2007]Barnes et al. (2007); [c1983]Cake (1983); [c2005]Cerco and Noel (2005); [g1964]Galtsoff (1964); [h2014] Attachment C3-12 – Oyster Habitat; [h1990]Hofstetter (1990); [s1986]Stanley and Sellers (1986)

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In addition to suitability directly related to salinity, we decided to use the salinity response curve to reflect the high incidence of diseases in seed and sack oysters at salinities higher than 15. Based on data from Table 3-3.5, and this information, TSS, salinity, and temperature thresholds were established as shown in Figure 5.

In the Ecospace model, the $OECL_{all}$ calculated every month based on daily data is loaded on a monthly time-step just like an environmental driver. Figure 5 shows the shape of the response curves per parameter that together determine the $OECL_{all}$. The OECLs are directly translated to a habitat capacity layer in Ecospace using a linear response curve (see Section 2.3.1 on the habitat capacity model, and 3.5.3 on response curves in Ecospace).

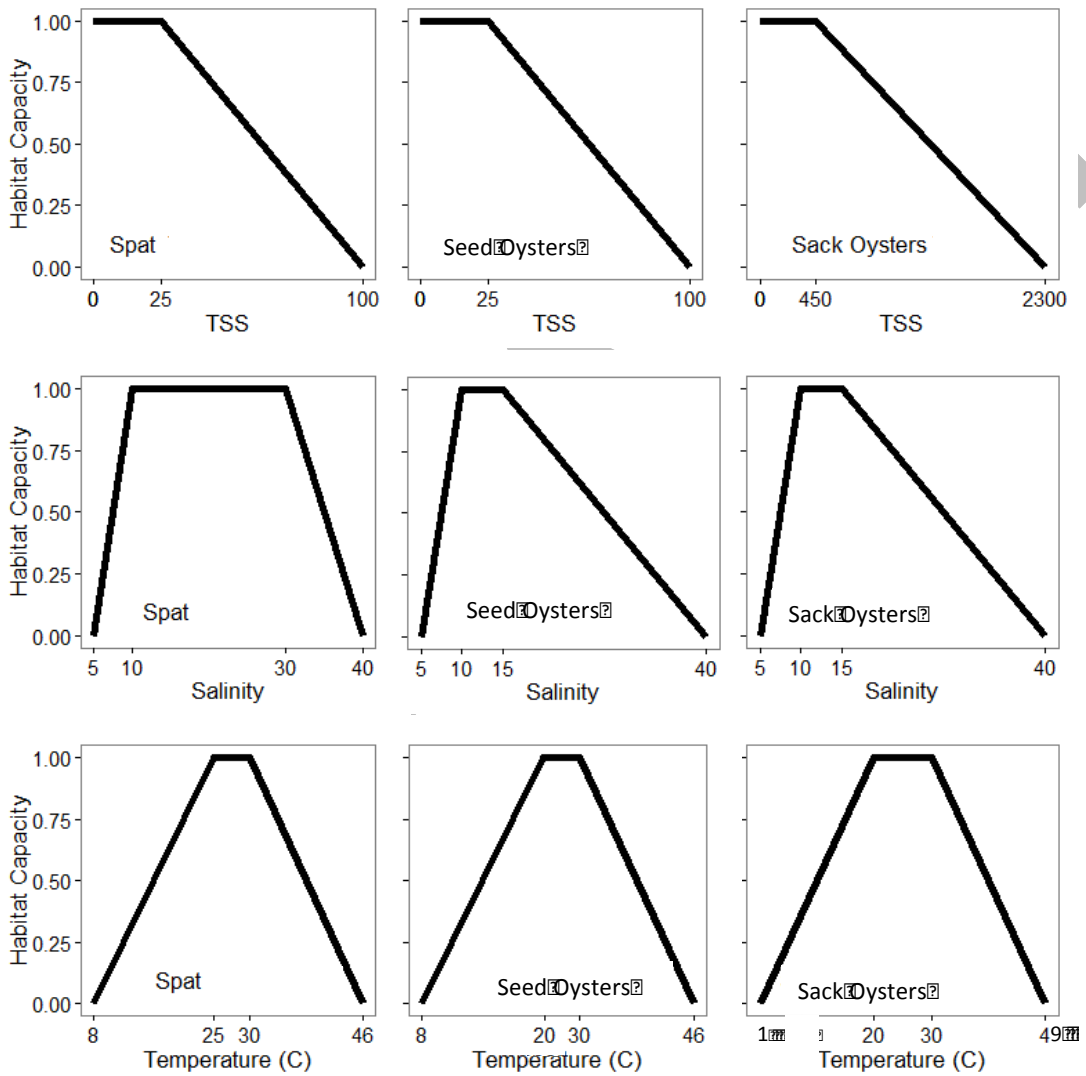

Figure 5: Response curves that form the $OECL_{all}$ for the three life stage of eastern oyster in the model (spat, seed oysters and sack oysters).

3.5.5 Validation

The Fish and Shellfish Community Model is validated in Ecospace with the inclusion of all parameters and features described above. The validation functions as a spot-check in which we

compare model prediction of a specific ecoregion within the coast wide model area (see Figure 3 for ecoregions) to the LDWF FIMP collections within that region only. This re-averaging of a smaller subset of the dataset makes this a different, region-specific time-series that serve as observations to compare the model predictions to (without fitting) as validation. The validation will show if model output resembles region-specific observations, which tests Ecospace-specific features such as movement, inclusion and effect of habitat, and region-specific environmental driver values. We performed model validation in the Lower Barataria and Breton ecoregions (Figure 3), and show output and goodness of fit metrics of five example species in Section 4.2.3.

3.6 Linking the ICM to EWE

The Habitat Capacity Model offers the ability to drive foraging capacity for a species based on the cumulative impacts of physical and/or environmental factors such as depth, salinity and temperature. The Ecospace Spatial Temporal Framework is capable of loading GIS files that are used as spatial-temporal forcing data to drive changes over space and time to the inputs of the Habitat Capacity Model.

To facilitate the linking of EwE into the ICM modeling chain, a console version of EwE was developed that allows EwE to be configured and run from a text command line file. This version of EwE contains all the core computational functionality without the Scientific Interface. This allows multiple instances of EwE to be run at the same time from different inputs, with outputs from each instance of EwE being sent to different output directories. The command line file contains all the required configuration information for the Ecospace Spatial Temporal framework to load physical or environmental GIS input files that are used to drive changes in the Habitat Capacity Model.

The ICM joins models into a chain using the outputs from one model as the input to another. The console version of EwE can be added to this chain by formatting the outputs from various models in the ICM into GIS input files that can be read in via the Ecospace Spatial Temporal Framework. Once the file format conversion is done a new EwE text command line file can be written and EwE can be run on the new input data. The EwE console is currently functional, linked to the ICM, and processes production runs.

3.7 50-year Test Simulation Set-up

To test model performance on a long-term run, a 50-year simulation was performed using preliminary 50 year ICM output of salinity, temperature, TKN, and %wetland for a future without action scenario. The scenario utilized historical records for precipiation and evapotranspiration, an estimate of historic eustatic sea-level rise and subsidence values consistent with the 'moderate' scenario in the 2012 Coastal Master Plan. The purpose of this run is to test model stability and evaluate if change over time in biomass of any of the groups can be considered reasonable. Instead of calculating new OECLs for this 50-year test, the monthly patterns of OECLs of the last year of the calibration run were used to drive oyster biomass during the 50-year simulation. Conversely, the TKN of the first year of the 50 year production run was used for all years of the spin-up period. The 50-year simulation was preceded with a 14 year spin-up period during every run, this spin-up period will be included before each of the subsequent production runs.

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3.8 Key Model Assumptions and Limitations

- The model mass balances over a period of a year.
- The species included in the model together provide a good representation of the food web in Louisiana estuaries.
- The diet of each group consists of species/groups present in the model, and diet switching (i.e. switching to a prey that is not defined as prey for a specific group in the Ecopath model) does not occur.
- Including changes in environmental parameters at a monthly time step will realistically reflect effects of a changing environment on fish (except oyster, see next bullet-point).
- Including changes in salinity, temperature and TSS at a daily time step will realistically reflect effects of those changes on oysters.
- Movement of fish in the Ecospace model is only affected by the suitability of the environment determined by environmental parameters, habitat features, and levels of predation and fishing. Seasonal migration patterns are therefore not reflected in the model, as these movements do not stem from movement away from unsuitable conditions.
- Fleets included are representative of fishing in Louisiana.
- The last know annual pattern of fishing effort for each fishery remains constant over the future simulation time.

4.0 Results

We produced a balanced Ecopath model, which was subsequently calibrated in Ecosim. A sensitivity analysis was performed in Ecosim as well. We moved our tested model into Ecospace where spatial habitat features were added, and coupling to environmental driver datasets occured. We first validated the Ecospace model against 14 years of field data, and then ran the newly developed coast wide Ecospace model for 50 years to test the stability of Ecospace.

4.1 Ecopath

A balanced Ecopath model was achieved with the 55 groups as shown in Table 8. Table 8 shows the input parameters and parmeters calculated by Ecopath during parameterization.

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Table 8: Parameters of the balanced Ecopath model for each group in the model.

P/B=production to biomass ratio, Q/B=consumption to biomass ratio, VBGF K = von Bertalanffy growth function K value, EE = Ecotrophic Efficiency. Parameters calculated by Ecopath are indicated with an *. Data sources are provided in Table 9.

Group Name	Biomass (g/m^2)	P/B	Q/B	Stanza Break (m)	VBGF K	EE
juvenile coastal sharks	0.08443[1]	2.000[1]	17.961[1]			0.00237*
adult coastal sharks	6.87×10^{-7}*	0.510[1]	3.900*	114[2]	0.04[3]	0.28529*
dolphins	0.00229[4]	0.099[5]	30.000[6]			0.00150*
sea birds	0.00747[1]	1.000[5]	17.737[1]			0.20795*
juvenile spotted seatrout	5.94×10^{-5}*	3.700[7]	29.100*			0.03211*
adult spotted seatrout	0.00216[8]	0.700[7]	5.400[7]	12[9]	0.13[3]	0.59981*
juvenile red drum	0.2*	2.200[7]	4.500*		0.46	0.58119*
adult red drum	0.00149*	0.620[7]	1.860[7]	18[7]		0.38302*
juvenile black drum	0.10861[8]	2.000[10]	22.644*			0.86217*
adult black drum	0.00117*	0.500[10]	6.359[11]	48[12]	0.17[3]	0.28568*
juvenile largemouth bass	0.00285*	2.000[10]	9.299*			0.47182*
adult largemouth bass	0.0927[8]	0.600[10]	2.814[13]	12[14]	0.375[14]	0.45428*
juvenile gulf sturgeon	0.00181[8]	2.000[10]	15.076[13]			4.00×10^{-8}*
adult gulf sturgeon	0.00018*	0.150[15]	2.100*	72[16]	0.06[3]	1.03×10^{-9}*
juvenile blue catfish	0.03657[17]	2.000[10]	10.615[3]			0.85266*
adult blue catfish	0.00136*	0.800[6]	3.300*	48[18]	0.15[3]	0.99156*
juvenile sea catfish	0.01752*	2.000[10]	10.800*			0.27738*
adult sea catfish	0.15589[17]	0.800[7]	3.300[3]	12[19]	0.15[3]	0.29629*
juvenile southern	0.00647[17]	2.000[10]	13.307[3]			0.67709*

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Group Name	Biomass (g/m^2)	P/B	Q/B	Stanza Break (m)	VBG F K	EE
flounder						
adult southern flounder	0.00588*	0.417[13]	4.500*	36[20]	0.23[3]	0.73754*
juvenile croaker	0.18945[17]	2.000[10]	20.035			0.62990*
adult Atlantic croaker	1.15804*	1.500[7]	8.023[3]	12[11]	0.35[3]	0.12252*
juvenile sheepshead	0.07633*	2.000[10]	14.648*			0.83142*
adult sheepshead	0.03950[17]	0.417[13]	5.900[3]	36[21]	0.36[3]	0.91292*
juvenile striped mullet	0.37956*	2.400[7]	32.969*			0.22231*
adult striped mullet	1.44273[8]	0.800[7]	12.280[3]	18[22]	0.34[3]	0.12892*
juvenile spot	0.11886*	2.000[10]	15.036*			0.14968*
adult spot	0.09353[17]	1.100[7]	7.200[3]	24[23]	0.43[3]	0.77939*
juvenile sunfishes	0.00039[8]	2.000[10]	16.456*			0.36929*
adult sunfishes	0.00933*	0.800[7]	4.966[13]	12[11]	0.6[11]	0.38825*
juvenile bay anchovy	0.13163*	3.000[6]	39.779*			0.25100*
adult bay anchovy	0.17215[17]	2.530[7]	19.400[3]	12[11]	0.6[3]	0.42962*
juvenile menhaden	0.13834[8]	2.300[7]	19.375[24]			0.04196*
adult gulf menhaden	0.52399[24]	1.900[7]	8.100[3]	12[23]	0.32[3]	0.85674*
killifishes	0.10767[8,25]	2.530[7]	19.400[6]			0.48166*
silversides	0.64814[8,25]	2.300[7]	19.400[6]			0.95181*
juvenile blue crab	0.44348[17]	3.000[10]	17.037*			0.18973*
adult blue crab	0.56326*	2.400[7]	8.500[7]	12[26]	0.7[10]	0.56461*
juvenile brown shrimp	0.14186[17]	4.885[10,6]	66.651[11]			0.07997*
adult brown shrimp	8.92917*	2.400[7]	18.873*	12[10]	1.5[10]	0.04206*

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Group Name	Biomass (g/m^2)	P/B	Q/B	Stanza Break (m)	VBG F K	EE
juvenile white shrimp	0.06321[17]	4.885[10,6]	66.651[11]			0.17948*
adult white shrimp	3.97878*	2.400[7]	18.873*	12[10]	1.5[10]	0.05438*
grass shrimp	0.44643[8,25]	4.500[7]	18.000[7]			0.93491*
oyster spat	0.0053[24]	2.000[10]	40.005[24]			0.02176*
seed oyster	0.18009[24]	1.800[10]	14.651[24]	2[10]		0.63114*
sack oyster	0.10275[27,28]	2.400[10]	10.000[10]	18[10]		0.93698*
oyster drill	0.225[29]	4.500[7]	18.000[7]			0.93975*
benthic crustaceans	4.397[30]	4.500[7]	22.000[7]			0.67958*
mollusks	4.03336[30]	4.500[7]	22.000[7]			0.31789*
Zoobenthos	3.957[13]	4.500[18]	22.000[18]			0.65535*
Zooplankton	4.12400[7,13]	28.772[13]	84.870[13]			0.43242*
Phytoplankton	12.8381[31]	101.7[1,13]				0.31224*
Benthic algae	29.778[32]	3.909				0.79316*
SAV	9.77800[33]	9.014				0.68351*
Detritus	100.00000					0.26793*

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Table 9: Source of parameters in Table 8.

Reference No.	Data Source
1	Geers 2013
2	Waring et al. 2011
3	www.fishbase.org
4	Waring et al. 2011
5	Kirk 2008
6	Expert Opinion (EO)
7	Walters et al. 2008
8	LDWF FIMP Seine
9	Nieland et al. 2002
10	C. Walters, personal communication
11	De Mutsert et al. 2012
12	Murphy and Taylor 1989
13	Althauser 2003
14	Boudreaux 2013
15	Kirk 2008
16	Huff 1975
17	LDWF FIMP Trawl
18	Graham 1999
19	FWRI 2010
20	Reagan Jr and Wingo 1985
21	Beckman et al. 1991
22	Collins 1985
23	Benson 1982
24	von Bertalanffy 1938
25	De Mutsert 2010
26	Guillory et al. 2001
27	LDWF FIMP Oyster Square Meter
28	C. Villaruba unpublished data (Davis Pond Monitoring)
29	M. La Peyre unpublished data
30	Rozas and Minello 2011
31	R. Lane unpublished data
32	SEAMAP 2014
33	De Mutsert et al. 2014

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4.2 Model Tuning and Testing

4.2.1 Sensitivity Analysis

A sensitivity analysis was performed in Ecosim. The results of 20 Monte Carlo (MC) simulations of six example species are shown in Figure 6. Blue catfish (not shown) and red drum (Figure 6) were the most sensitive to small (CV of 0.1) changes in input biomass with variation 6 and 3 times the Ecopath biomass respectively. Other species showed virtually no increased variation over time (e.g., white shrimp), and are thereby not very sensitive to what input biomass is used. Most other species have low variability in output biomass in response to changes in input biomass, and none of the MC runs show biomass collapses and /or exponential increases, which makes this a robust model.

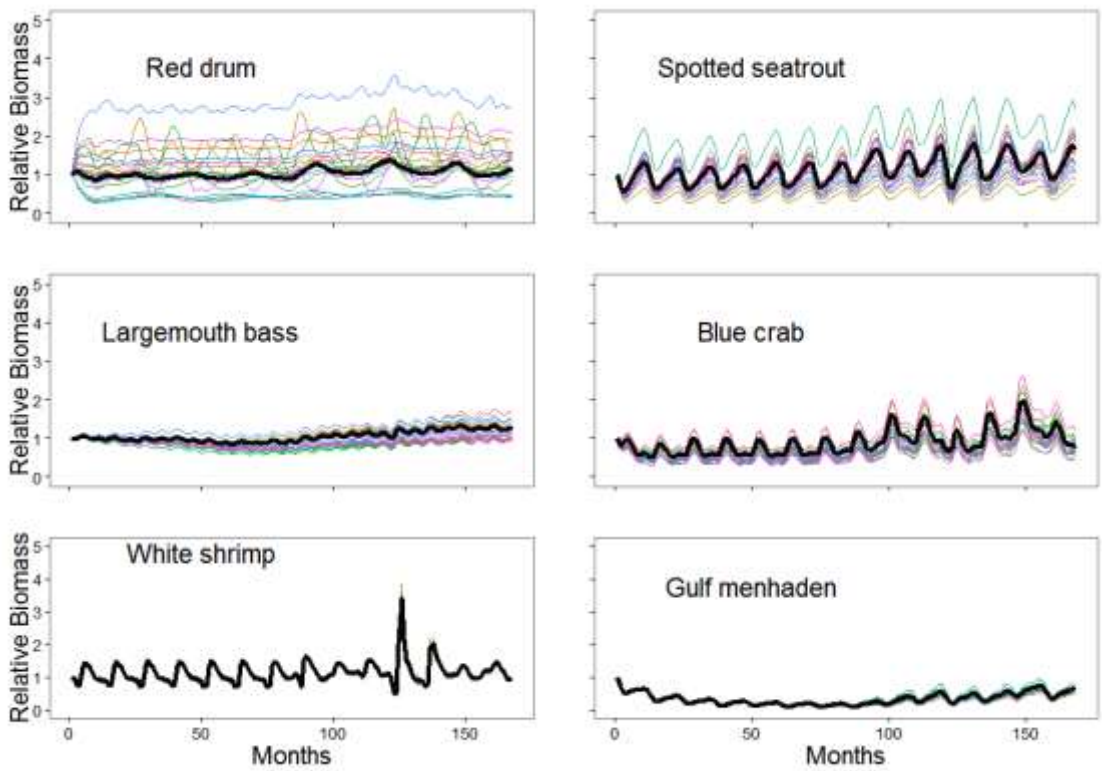

Figure 6: Monte Carlo simulations of the leading stanza of the species CPRA requested to be included in the model. The black line in each plot shows the model run, while the colored lines indicate 20 Monte Carlo Runs. Start biomass of each Monte Carlo Run is randomly picked with CV's of 0.1 around the intial Ecopath biomass. Simulations are run from 2000-2013.

4.2.2 Calibration Results

Calibration was performed in Ecosim from 2000-2013 by fitting the model to coast wide biomass time series (observed values) derived from LDWF FIMP data as explained in Section 3.1.2, as well as fishery landings. Because of the high variability of the survey data, LOWESS curves were

created from the raw data, and those values served as observations. Data on fishing effort (LDWF), nutrient loading (ICM TKN output), and temperature (ICM temperature output) were included as forcing functions (drivers) for the calibration runs. Including salinity and total suspended solids as drivers produced a worse fit as determined by the model-wide sum of squares internal to EwE (equation 5). While salinity is an important driver of fish biomass and distribution in coastal Louisiana, the coast wide averaged salinity does not explain the variability in the model. Salinity will be included in the final Ecospace model following calibration, and will play a role in the biomass distribution of fishes, which is evaluated during model validation. Likewise, TSS will be included in the final Ecospace model for oysters, but only as part of the OECL calculation.

The model fits of catch to landings time series of all fleets in the model, and the model fits to biomass time series for the species for which this information was available are shown in Figure 7 and 8 respectively. Goodness of fit metrics are presented in Table 10 and 11, and can be compared to Table 12, which shows guidelines of what levels are deemed acceptable (derived from Mesehle et al. 2015).

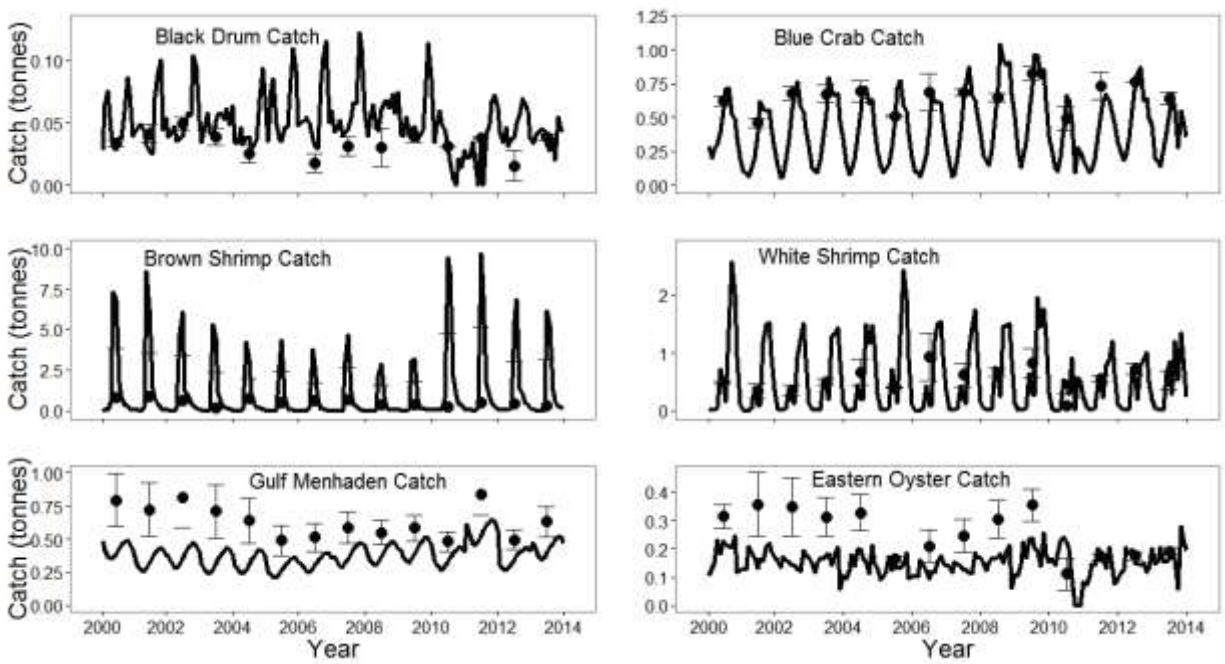

Figure 7: Catch calibration fits to annual landings data in tonnes per year. Error bars indicate the standard error of the observations.

Table 10: Calibration goodness of fit of model output of catch to landings data per fleet.

Group Catch	%RMSE	PBIAS	r^2	r	EwE SS	Confidence estimate
black drum catch	42.00	50.9	0.001	0.03	1.44	High
white shrimp catch	38.00	-4.3	0.13	0.36	4.83	High
blue crab catch	58.00	-35.6	0.44	0.66	0.75	High
oyster catch	81.00	-40	0.41	0.64	2.4	Medium
gulf menhaden catch	71.00	-39.7	0.32	0.57	0.48	Medium
brown shrimp catch	67.00	108.8	0.0004	0.02	24.41	Medium

Goodness of fit metrics calculated for commercial catch in the model include percent root mean square error (%RMSE), percent bias (PBIAS), r^2, correlation coefficient (r), and the EwE specific sum of squares explained in Section 3.5.2. The confidence estimate is made by Kim de Mutsert based on all goodness of fit metrics presented in this table, and knowledge of sensitivity analysis and ecospace results. It and represents the level of confidence in the biomass estimates the model provides for a group.

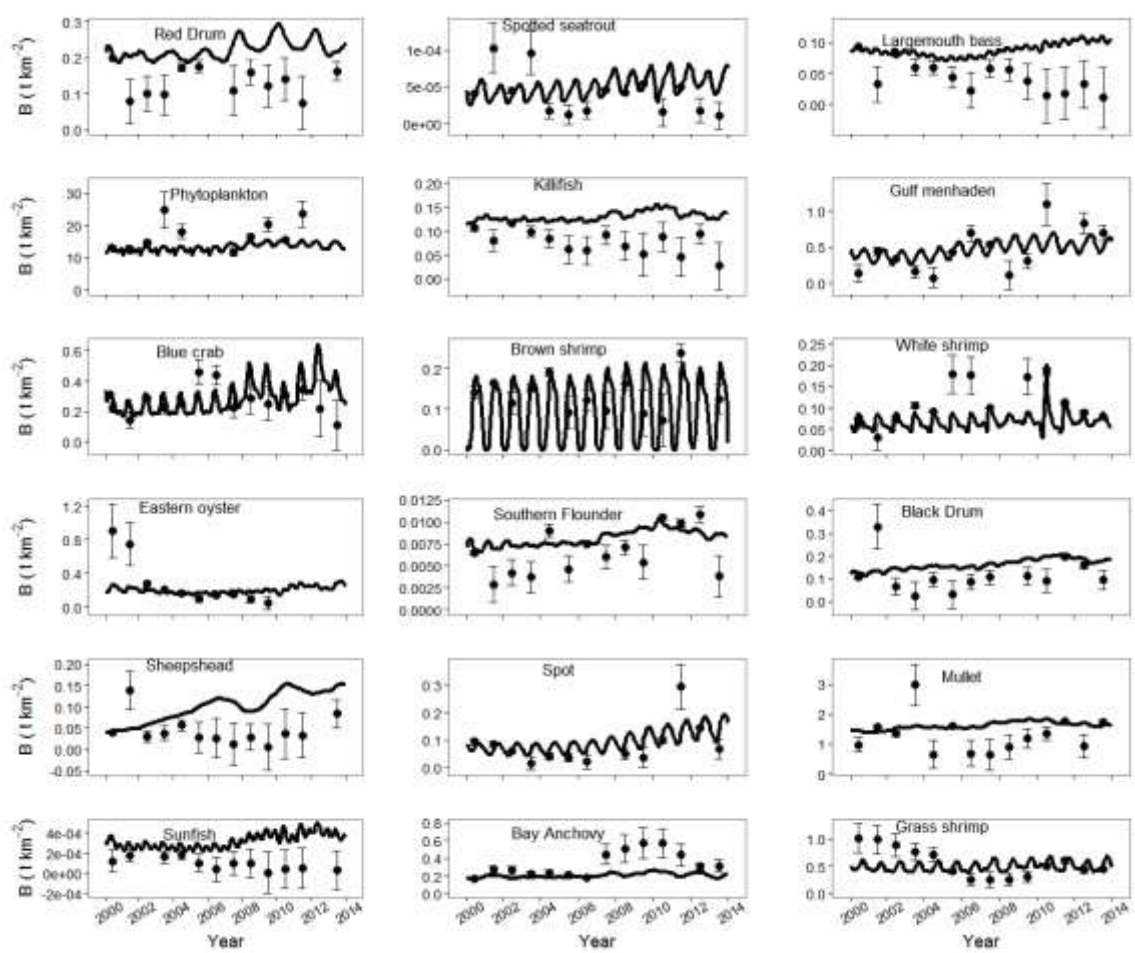

Figure 8: Biomass calibration fits to annual biomass observations. Observations reflect coast wide averages based on collections at stations indicated in Figure 3.

Table 11: Calibration goodness of fit of model output to biomass observations per group.

Group	%RMSE	PBIAS	r^2	r	EwE SS	Confidence Estimate[i]
red drum	45.00	68.00	0.05	0.22	4.77	Medium
spotted seatrout	66.00	23.50	0.11	0.33	8.48	High
largemouth bass	60.00	99.60	0.19	0.44	18.14	Medium
blue catfish	49.00	65.70	0.04	0.20	9.17	Low
Gulf menhaden	53.00	4.00	0.30	0.55	7.10	High
blue crab	45.00	8.70	0.02	0.14	5.70	High
brown shrimp	62.00	-29.60	0.00	0.03	1.73	High
white shrimp	96.00	-40.60	0.20	0.45	3.09	High
eastern oyster	125.00	-12.20	0.02	0.14	6.74	Low
killifish	46.00	69.70	0.07	0.26	6.47	Medium
Atlantic croaker	66.00	-26.40	0.70	0.84	2.28	High
Southern flounder	100.00	24.40	0.30	0.55	3.14	Medium
phytoplankton	45.00	-25.50	0.01	0.10	0.79	High
black drum	56.00	43.40	< 0.01	0.003	9.27	High
sheepshead	79.00	138.90	0.09	0.30	24.17	Low
striped mullet	43.00	22.90	0.01	0.10	3.93	High
sunfish	78.00	238.50	0.55	0.74	39.73	Low
bay anchovy	86.00	-39.20	0.75	0.87	4.42	High
grass shrimp	55.00	-10.80	0.13	0.36	3.70	High

[i]*Goodness of fit metrics calculated for biomass estimates in the model include percent root mean square error (%RMSE), percent bias (PBIAS), r^2, correlation coefficient (r), and the EwE specific sum of squares explained in Section 3.5.2. . The confidence estimate is made by Kim de Mutsert based on all goodness of fit metrics presented in this table, and knowledge of sensitivity analysis and ecospace results. It represents the level of confidence in the biomass estimates the model provides for a group.*

Table 12: Target guidelines for goodness of fit metrics.

Metric	Target[i]
%RMSE	< 60%
r	> 0.1
PBIAS	< 50% for 50% of groups

[i]*Acceptable targets modified from Mesehle et al. (2015) for percent root mean square error (%RMSE), correlation coefficient (r), and percent bias (PBIAS). Note that PBIAS can be a positive or negative number depending on the direction of bias. The targets can be used as guidelines to evaluate the fit of the model.*

Both catch and biomass meet the acceptable target for PBIAS. Fifty percent of the fleets, and 53% of the groups meet the acceptable target for %RMSE, and 67% of the fleets and 90% of species meet the acceptable target for r. Whether a specific group meets a goodness of fit target is dependent on the metric (so a group could have acceptable PBIAS and r but not %RMSE and vice versa). Therefore, it is difficult to pinpoint which specific groups have an unaceptable fit. Furthermore, we included the targets as guidelines, not as a pass or fail test. For practical purposes, we did indicate a confidence level (low, medium, high) of the biomass or

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catch estimates of the groups in Tables 10 and 11 based on the metrics and calibration figures, and our knowledge of the model.

When 50-year simulations are performed, we start the model in 2000 (also because the Ecopath model is representative of 2000), run these 14 years a s a spin-up period, and then continue the run uninterupted into each 50-year production run. We generally recommend showing EwE output on a relative scale, and using the results to compare differences in effects of different projects and/or scenarios, and/or compare each production runs to the output of a future without action. Because of the uncertainty inherent in the predictions of absolute biomass, it is best to evalutae the relative effects (differences in biomass) of projects. In the calibration phase however, showing the model fits to data on an absolute scale gives good insight whether the model simulates biomass on the same order of magnitude.

4.2.3 Validation Results

The Ecospace model was validated in two ecoregions (see Figure 3 for map of regions), Breton and Lower Barataria. Model validation occurred after all habitat features and environmental drivers were inserted, which in addition to the model domain itself includes percent cultch (static), percent upland, percent wetland, TKN, salinity, temperature, and OECLs. We show validation results for five species of interest for which we have adequate data for validation purposes (Figure 9). Observations were based on station collections within the ecoregion that were sampled throughout the validation period. The goodness of fit metrics for the Breton and Lower Barataria ecoregions are provided in Tables 13 and 14 respectively.

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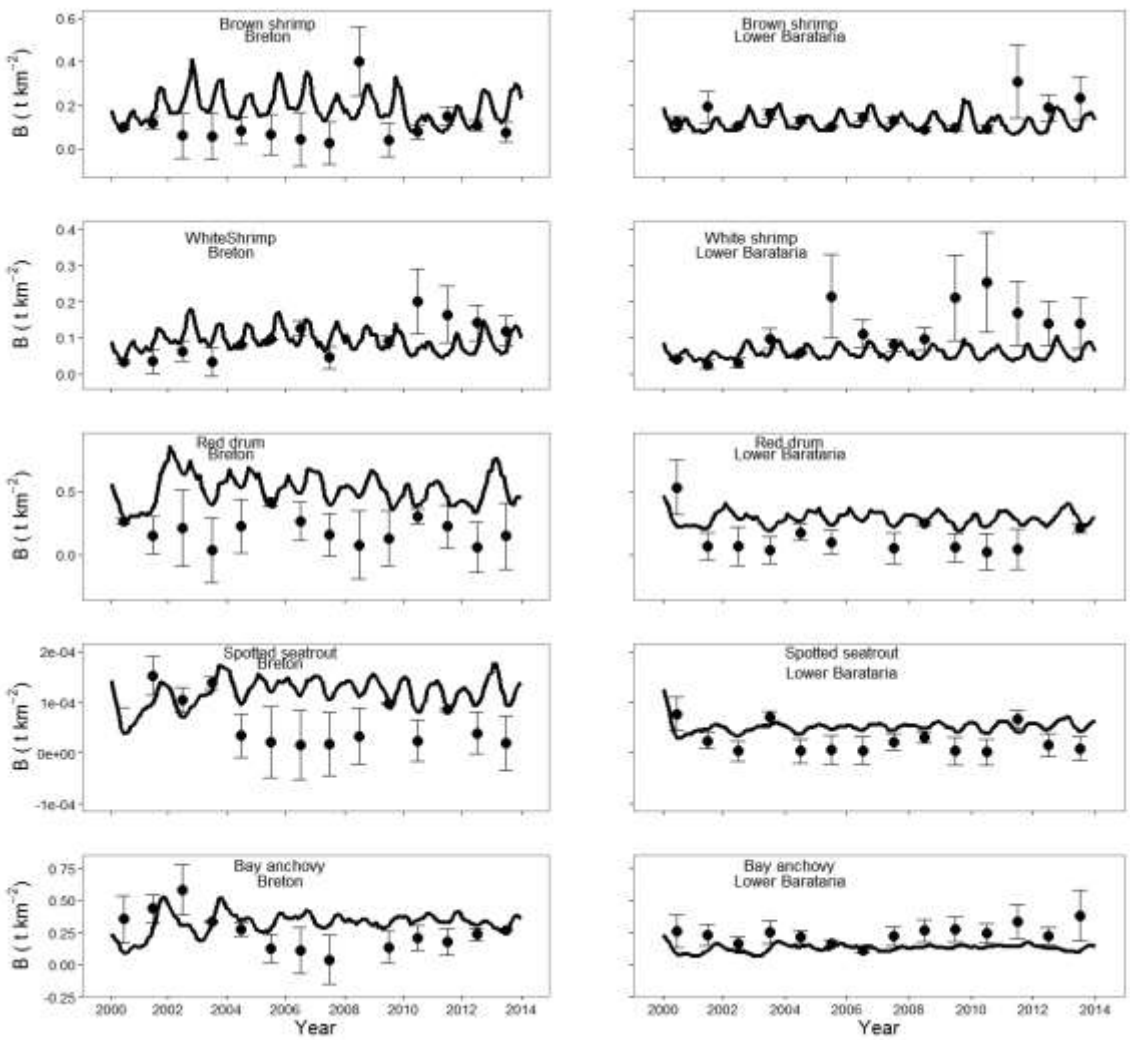

Figure 9: Model validation results in the Breton and Lower Barataria ecoregions of brown shrimp, white shrimp, red drum, spotted seatrout, and bay anchovy. Error bars indicate the standard error of the observations.

Table 13: Goodness of fit of validation of five species in the Breton ecoregion.

Group	# Stations in Breton	%RMSE*	PBIAS	r^2	r^i
red drum	7	67.8	169.9	0.001	0.040
spotted seatrout	7	73.75	67.7	0.46	0.680
brown shrimp	4	71.71	88.1	0.01	0.110
white shrimp	4	23.53	-2.5	0.11	0.332
bay anchovy	7	73.17	28.5	0.076	0.276

[i]Goodness of fit metrics calculated when validating model biomass estimates in the Breton ecoregion include percent root mean square error (%RMSE), percent bias (PBIAS), r^2, and correlation coefficient (r).

Table 14: Goodness of fit of validation of five species in the Lower Barataria ecoregion.

Group	# Stations in Lower Barataria	%RMSE*	%BIAS	r^2	r^i
red drum	**12**	**80.8**	**111.9**	**0.07**	**0.265**
spotted seatrout	**12**	**71.07**	**111.4**	**0.21**	**0.460**
brown shrimp	**10**	**60.8**	**-19.8**	**0.18**	**0.425**
white shrimp	**10**	**152.9**	**-50.3**	**0.074**	**0.270**
bay anchovy	**12**	**99.6**	**-46.1**	**0.036**	**0.19**

[i]Goodness of fit metrics calculated when validating model biomass estimates in the Lower Barataria ecoregion include percent root mean square error (%RMSE), percent bias (PBIAS), r^2, and correlation coefficient (r).

Acceptable targets for goodness of fit metrics are generally less strict for validation than for calibration, since no model fitting occurs in the validation process. Nonetheless, most groups meet or come close to the target guidelines from Table 12. While examples of validation of ecosystem models are hard to find to provide as comparison, these validation results demonstrate a high ability of the model to reproduce observations.

4.2.4 50-year Simulation

Two problems arose and were solved during the 50-year simulation testing. First, blue catfish initially increased exponentially over the 50-year period. The cause for this was that the main predator of adult blue catfish in the model, coastal sharks, became spatially separated from the adult blue catfish due to depth restrictions and differences in salinity preferences. Such a spatial separation of predator and prey does not become apparent in the Ecosim-based calibration. This problem was solved by spreading predation mortality of blue catfish more evenly over multiple groups including dolphins, birds, largemouth bass, and blue catfish (cannibalism), and increasing mortality by recreational fishing, making sure ecotrophic efficiency of blue catfish still did not exceed a value of1.0. While these small adjustments to diet and fishing solved the problem, this may be an indication that the model lacks a large freshwater predator; coastal sharks were the main predator because adult blue catfish are too large to serve as prey for most groups in the model. In a future iteration of this model, the inclusion of alligators as fish predators may be considered. Secondly, the biomass of largemouth bass initially crashed over the 50-year simulation. The very restrictive response curves for salinity and % wetland isolated largemouth bass quickly in small pockets where the populations subsequently crashed. While largemouth bass is indeed stenohaline, the exact response of the species to marsh cover is less well documented. The proposed response curve, which restricts largemouth bass from any area with less than 20% marsh, was deemed too restrictive. The response curve was removed from the adults and only applied to the juveniles, which improved the ability of adult largemouth bass to move between low-salinity areas and avoided the crash.

4.3 Example Output

To perform a 50-year simulation, preliminary ICM output of a future without action test scenario was provided (scenario properties are described above). In this section we show results of this simulation with line plots that represent coast wide averages, and spatial distribution maps of biomass of a select group of species. The species represented with the example biomass output are the juvenile stages of red drum, spotted seatrout, blue crab, brown shrimp, gulf menhaden, and largemouth bass. Output of all fleets in the model is shown with a histogram depicting the

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catch changes between the start and end of the simulation. The line plots show that the model is stable over the run time. The examples show no significant trends in time over 50 years, though some increased variability is visible in largemouth bass (Figure 10).

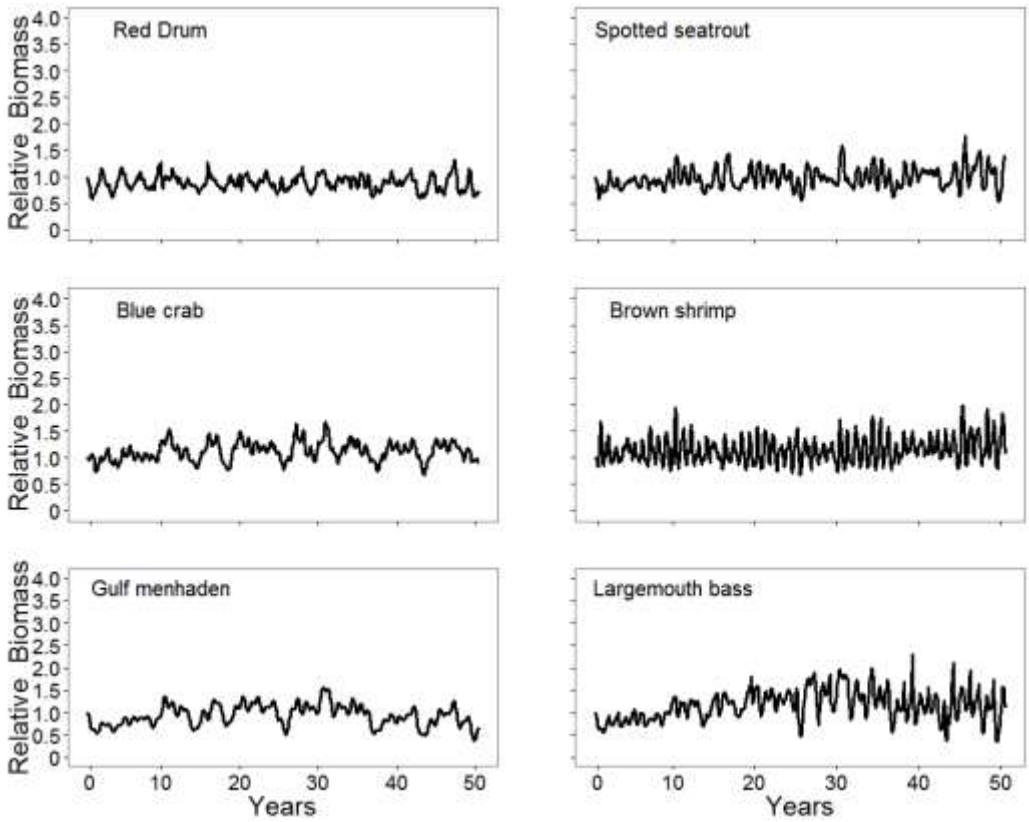

Figure 10: Example output of biomass simulations of six species of interest over 50 years of future without action. All plots depict the juvenile stage of the species. Biomass changes are relative to year 0.

The spatial distribution of each of these species is shown in Figures 11-16. The color scheme in the figures represent the difference from the grid cell average from the start of the model run. To determine change that strictly occurred over time, output of year 25 and year 50 can be compared to output of year 0 in each figure. The effects of environmental drivers, especially salinity and % wetland, are clearly visible in the spatial distribution of each of the species shown in the example output. The subset of species shown in Figures 11-16 contains juveniles, which all have response curves that represent a higher habitat capacity in cells with a higher percentage of wetland (Table 4). This affinity for wetlands is demonstrated by the concentration of biomass in cells with a high percentage of wetland, which shows up in the figures as a red outline of marsh areas. Salinity effects can be seen by examining areas that have low salinity, such as the Atchafalaya basin and the birdfoot delta, which show low biomass of species that prefer higher salinities (such as spotted seatrout), and high biomass of species that prefer low salinities, or are euryhaline (such as blue crab). The overall low biomass in the open Gulf is not salinity driven, but an effect of the lower nutrient levels in the offshore region. Of note is than not any one of these drivers singularly determines the spatial distribution of species; this is determined by the interactive effects of at least salinity, nutrients, temperature, percent wetland, predator-prey interactions, and fishing.

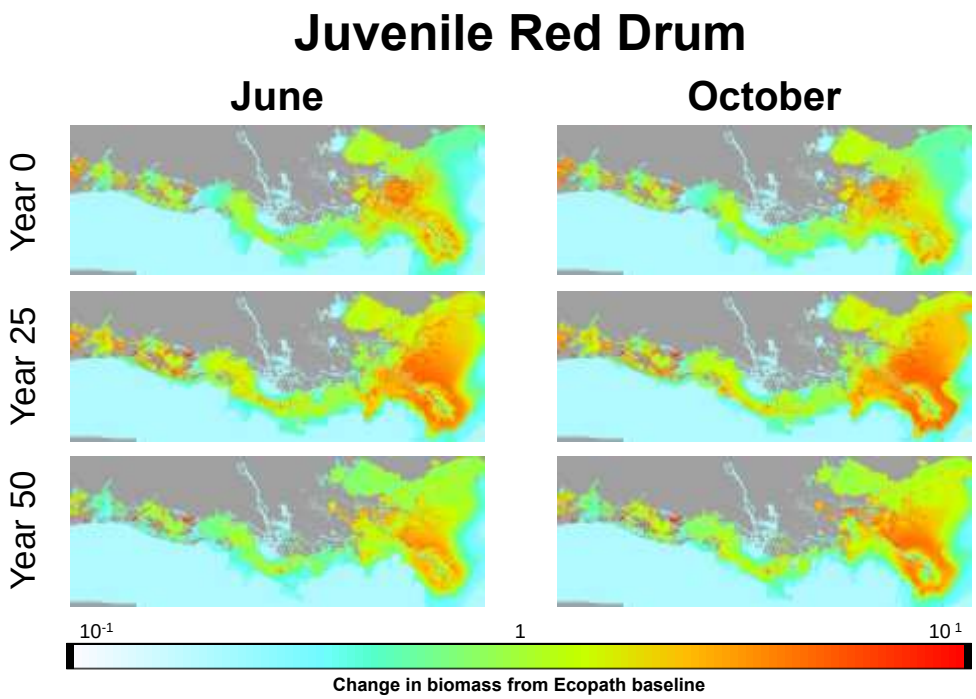

Figure 11: Spatial distribution of juvenile red drum in year 0, 25 and 50 during the months June and October in a 50-year future without action simulation.

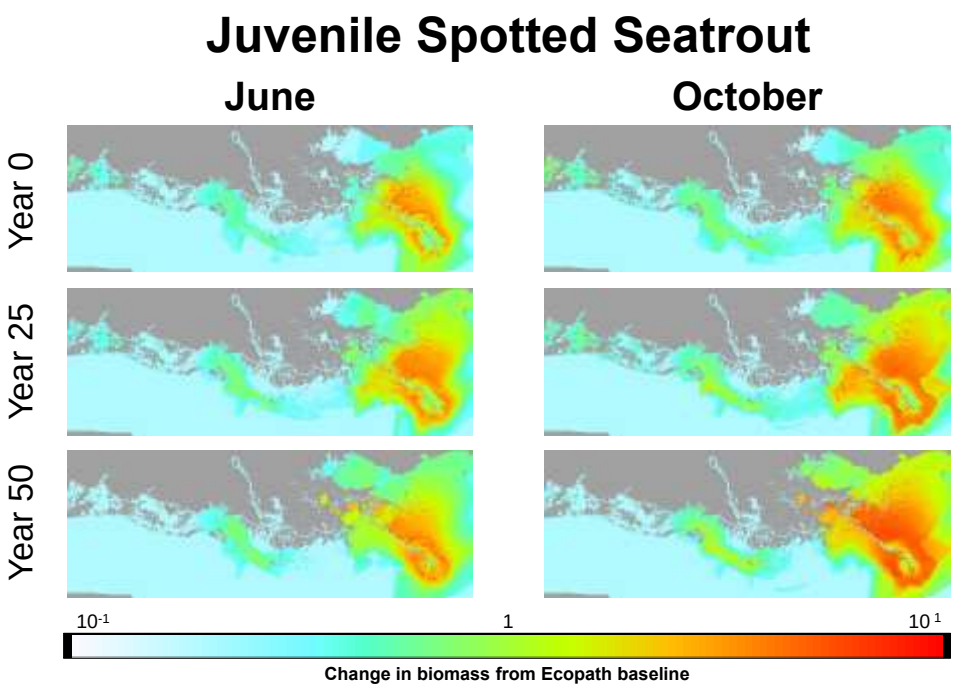

Figure 12: Spatial distribution of juvenile spotted seatrout in year 0, 25 and 50 during the months June and October in a 50-year future without action simulation.

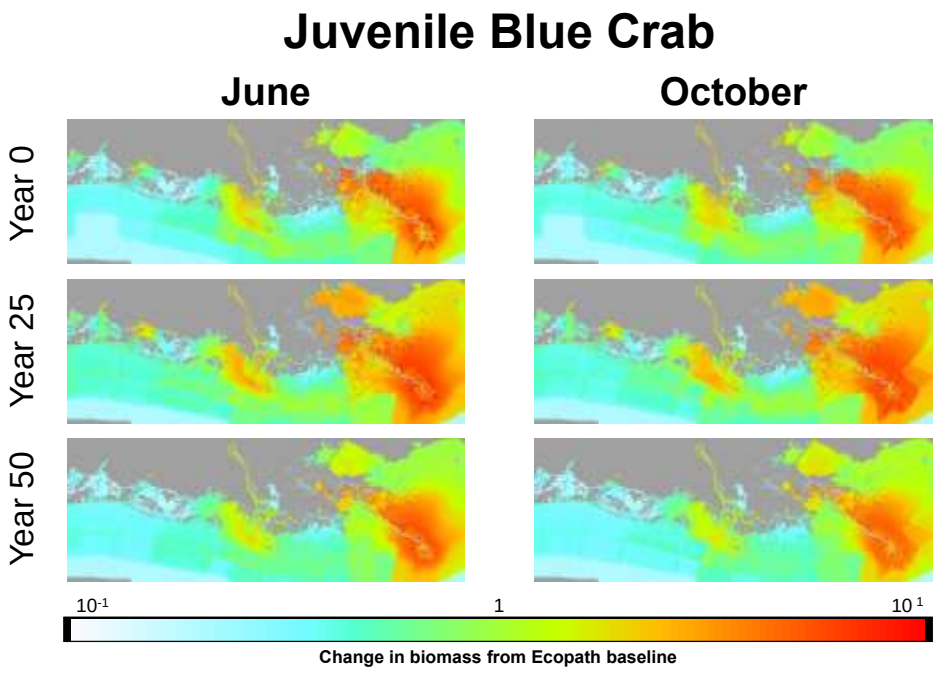

Figure 13: Spatial distribution of juvenile blue crab in year 0, 25 and 50 during the months June and October in a 50-year future without action simulation.

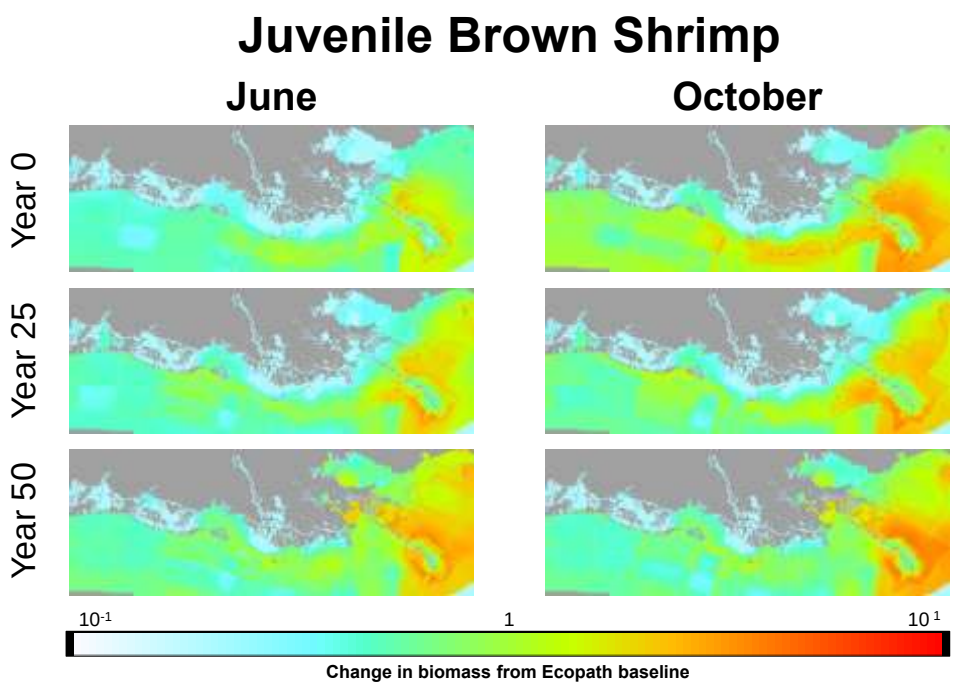

Figure 14: Spatial distribution of juvenile brown shrimp in year 0, 25 and 50 during the months June and October in a 50-year future without action simulation.

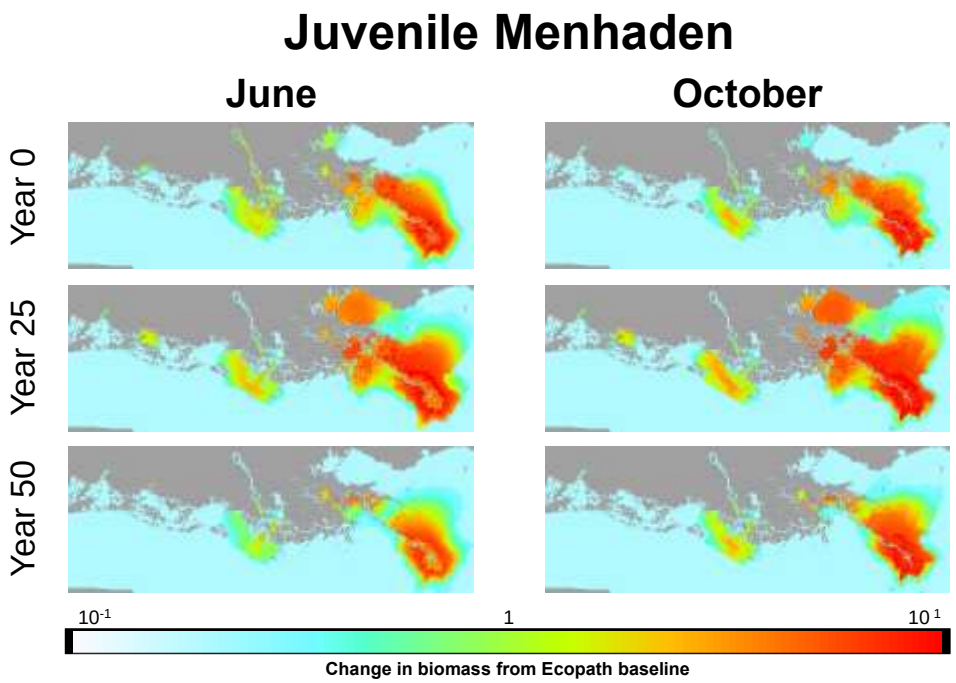

Figure 15: Spatial distribution of juvenile Gulf menhaden in year 0, 25 and 50 during the months June and October in a 50-year future without action simulation.

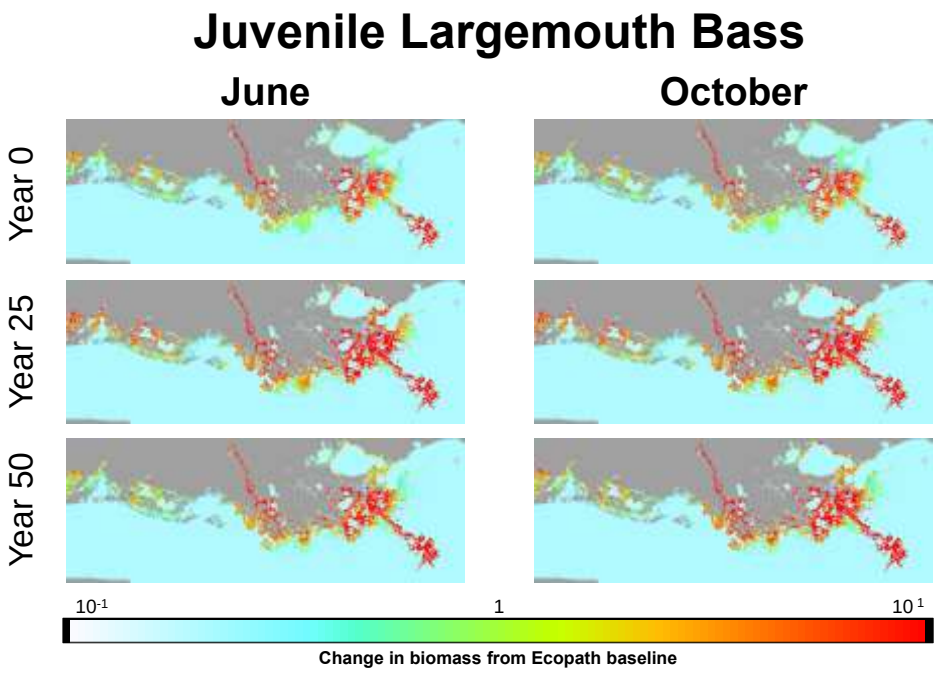

Figure 16: Spatial distribution of juvenile largemouth bass in year 0, 25 and 50 during the months June and October in a 50-year future without action simulation.

The change in catch of fleets in the model is shown in Figure 17. A future without action simulation shows a slight decrease in black drum, Gulf menhaden and eastern oyster catches, a small increase in blue crab, brown shrimp, and white shrimp catch, and a marked increase in recreational harvest. However, we were unable to calibrate and validate the recreational fishery because of a lack of data, and have low confidence in the recreational catch predictions. Conversely, the commercial fisheries calibrated well (see Section 4.2.2), and we have medium to high confidence in the commercial fleets in the model.

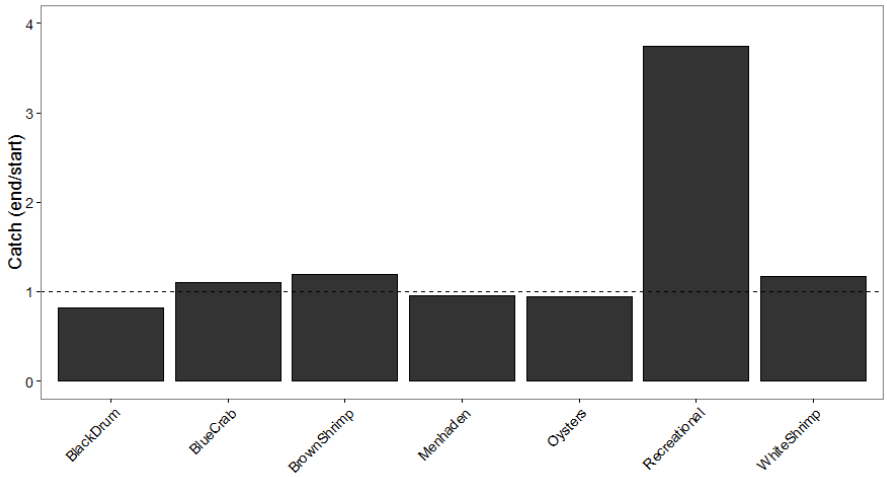

Figure 17: The change in catch of each fleet in the model over a 50-year future without action simulation is shown with an end/over start ratio, where 1 indicates no change.

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5.0 Summary

This document describes the ecosystem model to be used for the community modeling component of the 2017 Coastal Master Plan. Fifty-five groups are simulated in the model, which includes the juvenile and adult life stages of seventeen species requested by CPRA to be included in the model. Using biological field data, fisheries data, and environmental driver output from the ICM, the model was calibrated and validated over 14 years. Significant improvements in the EwE software were made for the development of this model, especially in the Ecospace module. An unlimited number of spatial distribution maps of external drivers such as water quality parameters, habitat features, and biomass data can be read into an Ecospace model at a monthly time-step, significantly improving the capability of Ecospace to perform spatial-temporal simulations of species biomass and fisheries. A TroSim model was initially developed specifically to simulate phytoplankton and oysters, for potential inclusion in the Ecospace model using the above-described feature to force in biomass of these specific groups. Unfortunately the TroSim inclusion did not improve the model, and we recommend going forward with the Ecospace model without TroSim linkage. Instead we developed a sub-routine that creates oyster environmental capacity layers based on daily salinity, temperature and TSS, that is included in the model as an environmental driver on oysters. A 50-year simulation performed in EwE shows model stability throughout the model run, and demonstrates the capability of the ecosystem model to run 50-year simulations as part of the modeling effort to support the 2017 Coastal Master Plan.

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Appendix A. Comparison to TroSim (CASM)

1.0 Introduction

A community modeling approach will be used in the 2017 Coastal Master Plan to evaluate effects of restoration and protection scenarios on fish and shellfish (hereafter referred to as fish). A previously prepared document, detailing the strategy for selecting fish modeling approaches for the 2017 Coastal Master Plan(Rose and Sable 2013), suggested that three models may be best suited for this effort: the Comprehensive Aquatic System Model (CASM), the Trophic Simulation Model (TroSim, a pre-proprietary version of CASM), and Ecopath with Ecosim (EwE). Rose and Sable (2013) also concluded that the choice of model depends on the objectives that need to be met by this model. Since the objectives of the Coastal Protection and Restoration Agency (CPRA) are to estimate effects on fish of long-term (20 and 50 year) restoration and protection scenarios, we contend that EwE is the most suitable modeling framework, which is designed to perform best at these decadal simulations (Christensen and Walters 2004). The main strength of CASM and TroSim, as has been shown in previous publications using these methods (Bartell et al. 1999, Fulford et al. 2010) is to simulate short-term (daily) variations within a time frame of 1 or 2 years. In this report we will compare EwE with TroSim, which is a freely available model built using the same architecture of CASM (a proprietary model), to compare model performance, justify model choice, and demonstrate the models' applicability at different time-steps.

To justify the choice of modeling framework, we provide a comparison of model output from EwE and TroSim for a high trophic level species and a low trophic level species (spotted seatrout and eastern oyster), during a long-term simulation (10 years with annual output), and a short-term simulation (2 years with monthly output). To provide this example output, we adjusted an existing EwE Barataria Bay model (Lewis 2014), and developed a TroSim Barataria Bay model using the parameters from the EwE model to maximize comparability between the two approaches. In Section 2 we describe the methods used to develop these models and to produce the model output presented in Section 3. In Section 3 we present the comparison of model output, in addition to other output from the EwE Barataria Bay model to exemplify other features of the modeling framework, such as sensitivity analysis and simulation of spatial distribution (TroSim is not spatially explicit). In Section 4 we will discuss results and the path forward towards developing the 2017 Coastal Master Plan community model. Note that this document provides example output of a Barataria Bay model, while the community model under development for the 2017 Coastal Master Plan will encompass a larger spatial area, and will include multiple environmental parameters and habitat characteristics provided by other subroutines within the 2017 Coastal Master Plan. This document also describes recent advances in EwE, and new developments in the software specifically designed for this effort. Software adaptations to fit the needs of the 2017 Coastal Master Plan will be a continuous effort throughout the development of the 2017 community model, and model code will be provided upon model completion.

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2.0 Methods

The objective of this report is to justify the choice of a community model for the 2017 Coastal Master Plan and to demonstrate both the strengths and weaknesses of EwE and Trosim, inclusive. We adjusted an existing EwE Barataria Bay model (Lewis 2014) and developed a TroSim Barataria Bay model using the parameters from the EwE model to maximize comparability between the two approaches. These models only cover a limited spatial extent and contain a smaller number of species and environmental drivers than will the 2017 Coastal Master Plan models that are currently under development. Our planned approach for the 2017 Coastal Master Plan community model is to integrate some components of TroSim into EwE in cases where the increased time resolution in TroSim results in better biomass predictions.

2.1 Model Area

The models represent Barataria Bay, a 6280 km2 sub-region of the Barataria-Terrebonne estuary system and member of the National Estuary Program (Nelson et al. 2002). Barataria Bay (Figure 18), isolated from the Mississippi River since the 1940's, gets a majority of its freshwater input from rainfall and includes freshwater, brackish, and marine coastal marshes. The basin is bordered on the west by Bayou Lafourche, an abandoned distributary of the Mississippi River (Conner and Day 1987)and on the east by the main stem of the Mississippi River. In addition to rainfall, the Davis Pond Freshwater Diversion can provide a maximum controlled flow of 28 m3 s-1 freshwater into the upper reaches of the estuary, but the actual flow varies.

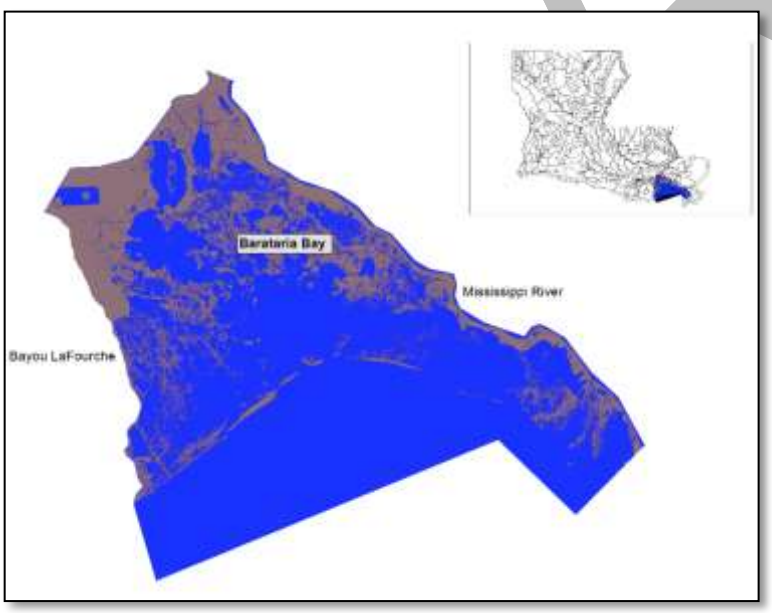

Figure 18: Barataria Bay, LA, USA, bordered on the east by the Mississippi River and on the west by Bayou LaFourche (Couvillion et al. 2011).

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2.2 Biological Data

2.2.1 Species Included

The species chosen for this analysis, and included in the EwE model, were selected because of their importance as commercial and recreational fisheries and their overall abundance within the system. The species are spotted seatrout (*Cynoscion nebulosus)*, red drum (*Sciaenops ocellatus)*, black drum (*Pogonias cromis*), brown shrimp (*Farfantepenaeus aztecus),* white shrimp *(Litopenaeus setiferus),* blue crab *(Callinectes sapidus),* Atlantic croaker (*Micropogonias undulatus*), eastern oyster (*Crassostrea virginica*), bay anchovy (*Anchoa mitchilli*), and Gulf menhaden (*Brevoortia patronus)*. While most of these species were in the existing Barataria Bay EwE model (Lewis 2014), eastern oyster and black drum were added to provide oyster model output for EwE-TroSim comparisons. TroSim only simulated adult spotted seatrout and sack (eastern) oysters, and included predation as loss terms. The 2017 Coastal Master Plan model will expand the number of groups to encompass a more holistic representation of the modeled area.

2.2.2 Data Collection and Preparation

Biomass data used to develop the Ecopath model and the biomass time series data in Ecosim were derived from data collected by the Louisiana Department of Wildlife and Fisheries (LDWF) Fishery Independent Shrimp/Finfish/Oyster Monitoring Programs. The finalized Ecopath initial biomass per species, and biomass time series, were subsequently used to initialize the TroSim runs as well. For a detailed description of how fishery independent data were collected, please refer to the Marine Fisheries Division Field Procedures Sample Design and Data Collection Manual (LDWF 2002).

LDWF utilizes different gear types to target certain species. With this information we first calculated the overall catch (combined over years) by gear type to determine which gear provided the highest number of species per sample. We determined the most effective gear type to collect estuarine nekton was a 4.8 m. flat otter trawl or a 229 m. gillnet, because in general, the highest number of species were caught with these gear types (Table 15). While gillnets were most effective at collecting Gulf menhaden, we found a large number of errors within the dataset and therefore opted for another gear type for this particular analysis. We have since rectified these errors and will be using gillnets for biomass estimates for Gulf menhaden in the 2017 Coastal Master Plan. For both trawls and gillnets, all sampling stations located within Barataria Bay were included in biomass calculations.

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Table 15: Total catch (abundance) of nekton species used in the model collected with trawls and gillnets over the period of record (POR). Asterisks (*) indicate which gear type was used for biomass calculations for each species in the model.

	Trawl	Gillnet
Species\POR	**1995-2010**	**1995-2010**
Spotted seatrout	219	10637*
Red drum	200	707*
Atlantic croaker	166956*	2263
Black drum	48	1520*
Blue crab	11555*	3189
White shrimp	53058*	3590
Brown shrimp	103317*	24
Gulf menhaden	3634*	34727
Bay anchovy	372193*	5

Abundance (number or organisms) and length data are the most consistently reported variables in the LDWF fisheries independent monitoring database. Since EwE requires biomass values in g m-2 yr-1 for initial biomass and time series data, LDWF abundance data per unit effort were converted to g m-2 for each species in the model by using L-W relationships and estimating the area sampled with each gear. Since LDWF only measures 30-50 organisms per sample in both the trawl and gillnet datasets, we determined the proportion of species at length for each sample. The total catch (abundance) per sample (when above the 30-50 organism threshold) was then multiplied by the proportional catch-at-size per sample to determine an estimated catch-at-size for the entire sample. To determine the biomass per sample, catch-at-size were converted to catch-at-weight with a length-weight (L-W) regression, $W_i = aTL_i^b$, where a and b are the species specific parameters, TL is length in total length, and i is each species of interest (Table 16). All species' biomasses were then divided by the sampling area of each gear type to determine the gi m-2, where i defines each functional group or species.

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Table 16: Length-weight regressions and data sources used to calculate gi m-2. *Red drum lengths (TL) were converted to FL using a length-length regression $FL = (L_{RD} + 2.394)\ x\ (0.916)$, as the only available parameters were evaluated at FL. **Blue crab were measured using carapace width.

Functional Group	Weight-Length Regression	Data Source	Units	
			W	L
Spotted seatrout	$W_{sst} = 1.13\ x\ 10^{-8}\ TL_{sst}^{3.01}$	(Nieland et al. 2002)	g	mm
Red drum*	$W_{rd} = 0.01FL_{rd}^{2.938}$	(Murphy and Taylor 1990)	g	cm
Atlantic croaker	$W_{at} = .005TL_{at}^{3.148}$	Fishbase	g	cm
Black drum	$W_{bd} = 1.19\ x\ 10^{-5}TL_{bd}^{3.04}$	(Murphy and Taylor 1989)	g	mm
Blue crab**	$W_{bc} = .008CW_{bc}^{2.45}$	(GDAR 2013)	g	mm
White shrimp	$W_{ws} = .003TL_{ws}^{3.247}$	(Fontaine and Neal 1971)	g	cm
Brown shrimp	$W_{bs} = .006TL_{bs}^{2.938}$	(Fontaine and Neal 1971)	g	cm
Gulf menhaden	$W_{gm} = .008TL_{gm}^{2.45}$	(De Mutsert 2010)	g	cm
Bay anchovy	$W_{ba} = .0171TL_{ba}^{2.814}$	Fishbase	g	cm
Eastern oyster	$W_{oy} = .00009TL_{oy}^{2.58}$	(Rose et al. 1989)	g	cm

The species and species groups used in this analysis accounted for over 76% of the total catch in trawl gear samples (6 taxa), and over 20% of the total catch in gillnet samples (3 taxa; Table 17).

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Table 17: Summary of abundance (number of organisms) for the functional groups included in the Ecopath base model for years 1995-2000 for trawl and gillnet gear types. Gear indicates which gear type was used for biomass calculations for each species. Catch per species is the number of a particular species caught over the period of record. Total Catch is the total number of fish and invertebrates caught in all samples. Percent Total Catch is the percentage contribution by number of each species to the total number of organisms caught over all samples.

Functional Group	Gear	Catch per species	Total Catch	Percent Total Catch
Spotted seatrout	gillnet	4731	27101	17.46%
Red drum	gillnet	326	27101	1.20%
Atlantic croaker	trawl	42510	237073	17.93%
Black drum	gillnet	611	27101	2.25%
Blue crab	trawl	4062	237073	1.71%
White shrimp	trawl	8100	237073	3.42%
Brown shrimp	trawl	34441	237073	14.53%
Gulf menhaden	trawl	1166	237073	0.49%
Bay anchovy	trawl	89966	237073	37.95%

Estimates of eastern oyster abundance are determined annually in June and July by LDWF using the square meter sampling approach. When preparing the 2000-2009 model simulations, this information was only available for the years 2001, 2007, 2008 and 2009. For the missing years, we were provided data from the Davis Pond Freshwater Diversion Monitoring Program through Chuck Villarrubia at the Coastal Protection and Restoration Authority. To determine g m^{-2} from the abundance m^{-2} data, we used the L-W relationship described in Table 2.2. While the LDWF data provides abundance at length data needed for the conversion, the data supplied by CPRA only included abundance for sack oysters, and not length. Therefore, we determined the average length of a sack oyster using the LDWF abundance at length m^{-2} for the years 2001 and 2007-2013. This average length was then applied to the L-W regressions for the abundance of sack oysters provided to us for the missing years.

2.2.3 Diet Matrix

The diets of juveniles and adults of each species were determined using stomach content data collected in a Louisiana estuary when available (De Mutsert et al. 2012), published literature, and fishbase (www.fishbase.org). The total biomass of any prey item within a system determines its availability for predation. Ecopath generates an ecotrophic efficiency parameter (EE) that ensures a prey item is being consumed within realistic bounds of its overall biomass. If a stanza group's EE is > 1 during model parameterization, the group is most likely being over-consumed (either by predation mortality or fishing mortality) and the model will not balance. The diet matrix data for that prey item will need to be iteratively adjusted until the model achieves mass-

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balance. After calibrating the diet matrix in EwE during this model parameterization step, it was used in the TroSim model as well.

2.2.4 Environmental Data

The Barataria Bay EwE model developed for this model justification activity included salinity, temperature, and NO2 + NO3 (NOx) as environmental drivers. The time series data for these drivers were obtained from the 2012 Coastal Master Plan output (salinity and temperature) and the USGS database (NO2+NO3; http://toxics.usgs.gov/hypoxia/mississippi/index.html). These data were entered as monthly values over the 10 year period of the model. The TroSim model used the same salinity and temperature drivers, and took the primary productivity predictions from Ecosim instead of simulating its own; this way the nutrient data were in the TroSim model implicitly as well, since driving an Ecosim model with nutrient data affects an Ecosim model from the bottom up starting with primary productivity data. Note that the 2017 master plan models (that are under development) will be set-up to use output from the other 2017 master plan models for these and other environmental drivers.

2.2.5 Fishery Data

Two types of fishery-related data were used in our model: commercial landings data and commercial effort data (number of trips per fishery/month/year). While recreational data are only very sparsely available, we used recreational data collected by NOAA's MRIP (National Oceananic and Atmospheric Administration's Marine Recreational Information Program) program (http://www.st.nmfs.noaa.gov/recreational-fisheries/index) to create a relative effort curve that was adjusted to fit fishing mortality per species using a gaming feature in Ecosim, and recreational fishing information from the 2011 spotted seatrout stock assessment report (West et al. 2011). Landings data were used as initial inputs in the Ecopath base model to represent biomass removal from the ecosystem via fishing and time series landings data were used in Ecosim as a way to assess the fit of model predictions. Fishing effort data were used to drive model dynamics, allowing the model to account for time varying fishing effects on the ecosystem.

Landings used as initial inputs in Ecopath were derived from LDWF Trip Ticket data. If these inputs did not meet the mass balance assumption during model balancing procedures, the landings values were iteratively reduced to meet those assumptions. Low levels of bycatch or discards from the shrimp fisheries were also included in the model. This is a qualitative assumption based on the knowledge of the primary sources of bycatch in each fleet. TroSim uses the same landings as the EwE model as a non-predatory removal term in the model to reflect the amount of biomass removed from the system by fishing.

2.3 Ecopath with Ecosim

2.3.1 Barataria Bay EwE Model

The Ecopath model represents the foodweb in Barataria Bay in the year 2000 using mean biomasses calculated from 1995-2000 data. Twenty-five functional groups (species or species guilds) that represent system and biomass dynamics, were defined (Table 1). Major nekton groups were characterized with a juvenile as well as an adult life stage to better represent the ontogenetic changes through a species' life history (Christensen and Walters 2004). The consumer groups considered in this study include zoobenthos, zooplankton, crustaceans, and

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fish. Values for zoobenthos (which includes the biomass of grass shrimp, *Palaemonetes sp.*) and zooplankton were obtained from the Breton Sound EwE model (De Mutsert et al. 2012) while biomass values for all fish and crustaceans were utilized from local, Barataria Bay specific LDWF fisheries independent data previously discussed. Producer groups (detritus, benthic algae, submerged aquatic vegetation (SAV), and phytoplankton) were also included in the model and were borrowed from the Breton Sound EwE model (De Mutsert et al. 2012)(with the exception of SAV, which was estimated from field data collected by K. de Mutsert).

To test the efficacy of our Activity 1 model, our model was executed using various combination of driving variables. We first created an annual model with fishing and environmental drivers that utilized annual mean biomass time series data. That same model was then executed with no fishing drivers in the model to obtain a better understanding of the influence of fishing pressure on ecosystem dynamics. Next, we created a monthly model with fishing and environmental drivers that utilized monthly mean biomass time series data. Lastly, we executed the monthly model while excluding the influence of fishing on the ecosystem. For the Ecospace model runs, the initial conditions were created from the model runs that used annual mean biomass time series data.

2.3.2 Calibration

To calibrate the model, relative biomass data, landings data, fishing effort, and environmental data were used in the Fit-to-Time Series module of Ecosim. This module was used to find predator-prey interactions that were most sensitive to changes in vulnerability (v_{ij}) from the nekton groups for which time series data were available. The model then estimates v_{ij} values that produce a better fit to the observed data. To assess the fit of the model, the sum of squared deviations (SS) of the observed logarithmic (log) biomass values was used (Christensen et al. 2008). Salinity and temperature (for oysters only) forcing data were applied using procedures from De Mutsert et al. (2012). Fitting was completed for both annual observed data for the 10 year simulation (2000-2009), and for monthly observed data for the two-year simulation (2000-2001). The monthly LDWF field data had a low sample size (1 or 2 units of effort per month per site), which results in very high variability in the monthly observations that do not reflect 'true' changes in population size. To correct for inter-monthly variation, the biomass time series data was fit using the Lowess method, which is a smoothed, non-parametric curve (Cleveland 1979). Table 18 provides an overview of the biological data used in model calibration and how they are used.

The following procedures were used to calibrate the model, modified from methods of Shannon (2004), Christensen and Walters (2008), Coll et al. (2008) and Howell et al. (2013):

7) *Balanced model check*. Prior to model fitting and tuning, an Ecosim run was invoked with no forcing data or time series data to ensure a balanced model from Ecopath was being utilized (Christensen et al. 2008).
8) *Data input*. All biomass time-series, environmental variables, and fisheries data were read into the EwE model database. Environmental variables and fishing effort data were used to drive the model and relative biomass and landings data were used to assess the fit of the model by comparing the observed data with the model predicted biomasses.
9) *Baseline model fit*. The relative biomass data were invoked and a baseline goodness-of-fit statistic (SS_i) was calculated in Ecosim following procedures in Christensen and Walters (2004).
10) *Driver variables invoked*. All environmental and fisheries data were invoked and a model run was completed.

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11) *Vulnerability search*. The Fit-to-Time-Series module was applied by using the Search Groups with Time Series function to search for the values of v_{ij} that would minimize the SS from the SS_i. The v_{ij}values were then estimated by the model for the predator-prey interactions that were deemed most sensitive.
12) *Evaluation of model outcomes.* The fitted model runs were analyzed by comparing the observed and predicted biomass time series data landings data and by assessing the decrease in SS.

A comparison of the SS value is a great way to compare the performance of different models that are fitted to the same observed data. We used the SS to compare TroSim and Ecosim simulations of spotted seatrout and eastern oyster, during a two-year simulation and fitted to monthly data, and a 10-year simulation fitted to annual data. The SS calculated within the EwE software are based on all data available, and is log-transformed to account for the differences in the absolute values of the different time series in the model. The SS for TroSim needs to be calculated per species outside of the modeling framework, and would not be directly comparable to this adjusted SS calculated within EwE. Therefore we calculated the SS for these simulations of interest outside of the EwE framework for Ecosim and Trosim using the following equation:

$$\mathrm{SS} = \Sigma\left(y_{observed} - y_{predicted}\right)^2 \qquad \text{Eq. 2.1}$$

2.3.3 Sensitivity Analysis

A sensitivity analysis was performed with the Barataria Bay EwE model by running 20 Monte Carlo Trials of Ecosim simulations that varied initial biomass of all species in the model with a CV of 0.1. In other words, we let a Monte Carlo procedure choose a new initial biomass at random twenty times for each species within predefined CV's of 0.1, and ran the model with these new initial biomasses. Example output of this sensitivity analysis is shown for spotted seatrout in Section 3.0. By having the biomass of all species vary at the same time, the potential impact of the changed biomass of other species in the model through trophic interactions are tested with these Monte Carlo trials as well. TroSim does not have the option to run a sensitivity analysis within the model package itself, but the option exists to manually perform Monte Carlo trials outside of the model. In this way however, the indirect effects of variation in parameters related to other species on the robustness of the model predictions of a particular species are not tested with the Monte Carlo trials. For this effort a TroSim sensitivity analysis was not performed.

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Table 18: Use of biological data to calibrate the EwE model. TS = Time series, FIMP = Fisheries Independent Monitoring Program.

Species	Time Series of Data	Annual TS	Monthly TS	Data Source	Drive Model	Fit Model
Spotted seatrout	Relative Biomass (g/m^2) 2000-2009	x	x	LDWF FIMP Data (gillnet samples)		x
	Total Fishing Effort (trips/time period)	x		NOAA MRIP Data	x	
	Total Fishing Effort (trips/time period)		x	Estimated in the model	x	
Red drum	Relative Biomass (g/m^2) 2000-2009	x	x	LDWF FIMP Data (gillnet samples)		x
	Total Fishing Effort (trips/time period)	x		NOAA MRIP Data	x	
	Total Fishing Effort (trips/time period)		x	Estimated in the model	x	
Atlantic Croaker	Relative Biomass (g/m^2) 2000-2009	x	x	LDWF FIMP Data (trawl samples)		x
Black drum	Relative Biomass (g/m^2) 2000-2009	x	x	LDWF FIMP Data (gillnet samples)		x
	Total Catches (t/km^2)	x	x	LDWF Trip Ticket Data		x
	Total Fishing Effort (trips/time period)	x	x	LDWF Trip Ticket Data	x	
Blue crab	Relative Biomass (g/m^2) 2000-2009	x	x	LDWF FIMP Data (trawl samples)		x
	Total Catches (t/km^2)	x	x	LDWF Trip Ticket Data		x
	Total Fishing Effort (trips/time period)	x	x	LDWF Trip Ticket Data	x	
White shrimp	Relative Biomass (g/m^2) 2000-2009	x	x	LDWF FIMP Data (trawl samples)		x
	Total Catches (t/km^2)	x	x	LDWF Trip Ticket Data		x
	Total Fishing Effort (trips/time period)	x	x	LDWF Trip Ticket Data	x	
Brown shrimp	Relative Biomass (g/m^2) 2000-2009	x	x	LDWF FIMP Data (trawl samples)		x

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Species	Time Series of Data	Annual TS	Monthly TS	Data Source	Drive Model	Fit Model
	Total Catches (t/km^2)	x	x	LDWF Trip Ticket Data		x
	Total Fishing Effort (trips/time period)	x	x	LDWF Trip Ticket Data	x	
Gulf menhaden	Relative Biomass (g/m^2) 2000-2009	x	x	LDWF FIMP Data (trawl samples)		x
Bay anchovy	Relative Biomass (g/m^2) 2000-2009	x	x	LDWF FIMP Data (trawl samples)		x
Eastern oyster	Relative Biomass (g/m^2) 2000-2009	x		LDWF FIMP Data (square meter samples)		x
	Total Catches (t/km^2)	x	x	LDWF Trip Ticket Data		x
	Total Fishing Effort (trips/time period)	x	x	LDWF Trip Ticket Data	x	

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2.3.4 Preparing the Ecospace Module

A major strength of EwE is the option to develop a spatially explicit community model. While TroSim and CASM will need to imply movement by creating multiple time-dynamic models within a model area, and running these models with different environmental drivers and habitat characteristics within each subsection/polygon, this time-consuming process has become unnecessary in EwE since the development of the Ecospace module. Note that the polygon approach with implied movement can be done with Ecosim as well (De Mutsert et al. 2012). However, even if there are concerns about how movement is simulated in Ecospace (see Section 1.2.7), the best approach would still be to use Ecospace, but simply set m (movement) to 0 m/s. This step allows Ecosim to run in each grid cell of the Ecospace model without movement, creating the same results as the polygon approach but with higher spatial resolution, eliminating the need of running multiple, separate time-dynamic models for each polygon. An analogous spatially-explicit analysis was not conducted in TroSim, and thus the Ecospace component is not part of the model output comparison part of Activity 1. Rather it is meant to provide example output, and justification for the use of Ecospace in the development of the 2017 Coastal master Plan model.

Ecospace requires a number of spatially explicit data sets, beginning with a 'base map'. The base map is a map of the model area, which typically indicates the coastline, and the marine boundary. Since the model represents an aquatic foodweb, land cells in the model area become inactive cells, and water cells become active cells. This base map is typically derived from a shapefile with bathymetry information, but in the case of the Barataria Bay model was derived from Couvillion et al.'s (2011) land-water datasets (Figure 19). Due to the dynamic nature of Louisiana's coastal marshes, the base map year with the least amount of land cells (2010) was chosen for use, as our model can more readily increase the proportion of land in active cells (i.e., add land cells) if needed. The grid cell size in our base map is 754 m x 852 m. This cell size is generally smaller than what has been historically utilized in Ecospace in an attempt to account for both the spatial variation of environmental drivers and the size of the organisms utilizing the ecosystem.

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Figure 19: The Ecospace model base map displaying active water cells (white) and inactive land cells (grey). These data were derived from the 2010 USGS land-water data sets (Couvillion et al. 2011).

Previous versions of the EwE software packages made it challenging to incorporate spatial-temporal simulations in Ecospace. Recent innovations using geo-referenced environmental drivers (i.e., salinity, dissolved oxygen, etc.) have enabled modelers the ability to input spatially and temporally explicit environmental data, and receive output of spatial responses of organisms to these drivers (Steenbeek et al. 2013). To that end, this model incorporated monthly salinity GIS data as a spatial driver in Ecospace. While the Ecospace model is based on the calibrated Ecosim simulations that included temperature and NO_x as well, we are only demonstrating the capability of simulating in Ecospace with spatial-temporal dynamic drivers using salinity. In the to-be-developed 2017 Coastal Master Plan model, each of the drivers will be included in the spatial-temporal framework once we have received that output from the Coastal Master Plan hydrodynamic models. To initialize the Ecospace model, an initial salinity base map was created by calculating the mean salinity in each cell over the initial model year, 2000 (Figure 20).

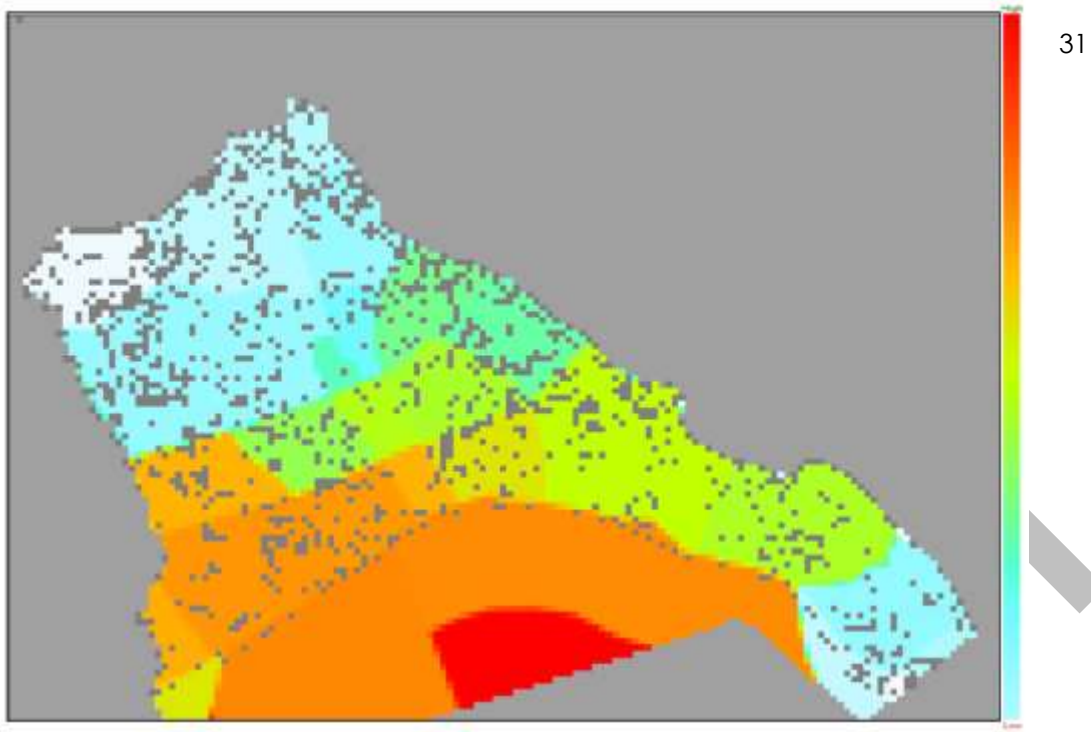

Figure 20: Average salinity in Barataria Bay from the year 2000, used in initializing the Ecospace model runs, warmer colors indicate higher salinity, on a scale from 0-31. Salinity data were obtained from the Louisiana's 2012 Coastal Master Plan model outputs.

2.4 TroSim

TroSim was originally developed by Fultford et al. (2010) using the Comprehensive Aquatic Simulation Model (CASM) framework from Bartell et al. (1999, 2003). Trosim is flexible in that it can be used either as an integrated model within a 3D hydrodynamic model, or it can be used as an autonomous 1D biophysical model which is coupled to the hydrodynamics of a simulation site using daily physical forcings (e.g., water temperature, salinity, daily photosynthetically active radiation (PAR) irradiance). TroSim is a carbon budget model which uses a modular "functional group" approach, where any number of species can be added/removed from the model, grouped by species function, such that the competition parameters and food web connectivities between and among those species may vary, but the fundamental equations defining production, consumption, and growth do not.

For example, the daily change in carbon-specific biomass (*B*, in g C m^{-3}) for any given producer species is calculated as the difference between total daily production of producer species *i* (P_i) and losses due to respiration (r_i), sinking (s_i), non-predatory mortality (m_i) and predation by consumers (Pr_i):

$$\frac{\partial B_i}{\partial t} = B_i \cdot \left(P_{\max} \cdot \left[f_t \cdot g_l \cdot n_d\right]^{1/3} \cdot \left[1 - r_i\right]\right) - m_i - s_i - \mathrm{Pr}_i \qquad \text{Eq. 1.7}$$

where total daily production (P_i) is explicitly calculated as the product of the group-specific maximum production rate (P_{max}) and the geometric mean of control factors for temperature-limitation (f_t), light limitation (g_l), and nutrient limitation (n_d).

Changes in consumer biomass are similarly calculated as the difference between total daily ingestion (I_j) and daily losses due to costs of metabolism (R_j), consumption (SDA_j), waste production (U_j), reproduction (Rp_j), losses due to non-predatory mortality (M_j), and total daily consumption of consumer *j* by other consumers (Pr_j):

$$\frac{\partial B_j}{\partial t} = I_j \cdot \left(1 - \left[SDA_j + U_j\right]\right) - R_j - Rp_j - M_j - \mathrm{Pr}_j \qquad \text{Eq. 1.8}$$

Where daily ingestion (I_j) is based on an estimate of maximum daily consumption (C_{max}) adjusted by a combination of habitat factors, including optimum water temperature, salinity, dissolved oxygen, water velocity, and water depth.

Unlike Ecopath with Ecosim (EwE), which is typically used to provide multi-decadal ecosystem simulations with annual temporal resolution, TroSim is specifically designed to explore aquatic food web dynamics that operate over shorter time-scales and are far more ephemeral (requiring daily time steps).

2.4.1 Barataria Bay TroSim Model

The TroSim model developed for Barataria Bay is a derivation of the TroSim model originally developed by Fulford et al. (2010), using the CASM framework from Bartell et al. (1999). Since TroSim and CASM are essentially the same, the comparisons between Ecosim and TroSim can be viewed as a comparison between Ecosim and CASM as well. The goal of Activity 1 was to produce EwE simulation output (as stated), and simply set all TroSim competition parameters equal to those defined in the EwE runs (where direct equivalencies were possible). For Activity 1, only sack oyster and adult spotted seatrout were modeled in TroSim, which were sensitive to salinity as the sole environmental stressor (temperature was included as well, but did not explain any of the variation). The availability of prey for each modeled species was explicitly defined in TroSim, according to EwE simulation output, as initialization data for annual TroSim runs; consumption of available prey and subsequent biomass gains/losses to the oyster and spotted seatrout biomass were simulated autonomously by TroSim. For multi-year simulations, EwE time series output (monthly salinity; prey biomass) was used to define the initial conditions of each new TroSim annual run, but the TroSim-modeled biomass of oysters and spotted seatrout from each previous year were used to initialize the subsequent TroSim annual runs. In this manner, TroSim calculations of the target species' growth dynamics, relative to salinity as the sole environmental stressor, could be directly compared with EwE simulations of the same.

In order to provide the most meaningful comparison between EwE and TroSim, it was necessary to meticulously inventory the competition parameters of the functional groups used in EwE and use the same values for analogous parameters within the TroSim architecture. However, it is important to note that these are two different ecosystem models, each of which uses a different computational schema. As such, it is not always possible to provide an equitable "fix" for parameters and/or forcing functions which are unique to each model. For example, EwE does not explicitly calculate the biomass loss term associated with Specific Dynamic Action (SDA), while TroSim does. The fact that this parameter is not shared among both models makes it impossible to simply set the TroSim SDA parameter equal to an EwE parameter which does not exist. In order to provide a direct comparison between EwE and TroSim output for Activity 1, it

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was necessary to revise the TroSim code to simulate ecosystem function over multiple years (2000-2009) while maintaining a daily time step.

Because of these inequities, it was necessary to carefully review the TroSim code and provide significant revisions (using FTN95) when necessary. These revisions, specific to the demands of Activity 1, included code modifications (to match EwE functions/parameters where possible) specific to:

1. Appropriate functional groups and biomass thereof
2. Daily environmental forcings for 2000-2009 (3650 days)
3. Competition parameters for each functional group species
4. Food web bioenergetics for each functional group species
5. Custom output files for Activity 1 simulations
6. Improved Thornton and Lessem (1978) response curves for temperature-sensitivity
7. Improved Thornton and Lessem (1978) response curves for salinity-sensitivity

In all cases where a direct association could be made between EwE and TroSim variables, the competition parameters of the EwE simulation were used in the tandem TroSim calculations. These comparisons focused on adult (sack) eastern oyster and adult spotted seatrout, with only water temperature and salinity as the environmental drivers (NOx is implicitly included in TroSim as discussed in Section 2.2.4).

Since TroSim is not spatially explicit and does not include its own sensitivity analysis, this document will only show the comparisons with the temporal dynamic fits to time series of EwE on a monthly and on an annual basis. During the development of the actual ecosystem model for the 2017 Coastal Master Plan, where TroSim will be used to provide the oyster output, sensitivity analysis will be performed, and spatial variation will be included by creating oyster biomass output for different polygons within the 2017 model area in a similar fashion as the CASM Barataria Bay model (Rose and Sable 2013). Another important note is that by purposely using EwE parameters to maximize comparability, the TroSim has lost some of its high temporal resolution. For the 2017 Coastal Master Plan we aim to use daily PAR and nutrient levels to calculate phytoplankton biomass instead of using the monthly phytoplankton values from the EwE model. These changes will affect oyster biomass estimates as well.

3.0 Model Output and Comparison

For this document, Ecosim and TroSim model runs of adult spotted seatrout and adult (sack) eastern oyster are compared by fitting all model simulations to observed data and comparing the sum of squares of each fit (with lower SS indicating better fit). To compare both short-term and long-term capabilities, we ran both models 10 years (representing the years 2000-2009) while fitting the runs to annual observations, and 2 years (representing the years 2000 and 2001) while fitting the runs to monthly observations. In Ecosim, two simulations were performed to explicitly show the effect of fishing in the model; one without the effect of fishing, and one with the effect of fishing included in the fit. The TroSim simulation did not take fishing into account. All

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results are shown in relative biomass, which indicates the change in biomass from the initiation of the model.

Fitting to annual observations, the Ecosim simulations of spotted seatrout show a slight improvement in fit when fishing is included (SS: 0.0000195 vs. 0.0000194), but both Ecosim simulations show excellent performance (Figure 21). TroSim shows an exponential increase in spotted seatrout biomass, and the fit is likely to worsen the longer the model runs. One explanation of this poor fit is the fact that there is no fishing in this TroSim model. As a high trophic level species, spotted seatrout is not suffering from a high level of loss by predation in this model, which makes fishing an important factor in controlling their biomass. However, the Ecosim model without fishing shows a much better fit than the TroSim model as well, so other factors influencing trophic dynamics of spotted seatrout are at play here as well. We hypothesize that by running the TroSim model using the exact same parameters as the EwE model to maximize comparability has actually caused problems with TroSim stability, since these are inherently different models. For the 2017 community model, any TroSim simulations will be developed using the conventional methods, which for example include calculating phytoplankton biomass from the light field and nutrient data instead of hard-coding the EwE values into TroSim. While this approach will be more labor intensive and will increase data needs, this will likely produce a better performing TroSim model.

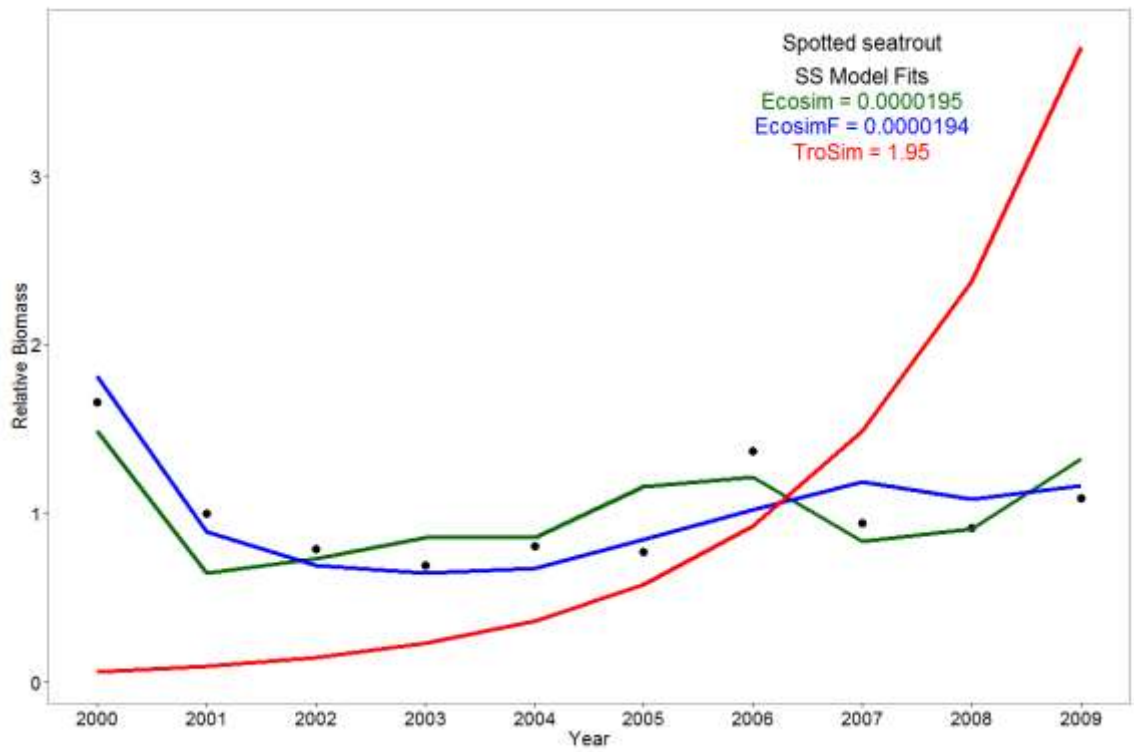

Figure 21: Annual model output of spotted seatrout. Three simulations, Ecosim without effect of fishing, Ecosim with effect of fishing, and TroSim, are compared and fitted to observed data. The Sum of Squares fit of each simulation to observed data is shown in the figure.

A second explanation is that models without the assumption of foraging arena theory are known to display violent oscillations when executed over long time periods (Walters and Martell 2004). These oscillations can result in an early crash of low trophic level species and exponential growth

in high trophic level species. Eventually, when the entire forage base disappears, the high trophic level species will also crash.

The TroSim simulation of eastern oyster supports the second explanation (Figure 22), which shows a crash of eastern oyster biomass in 2003. Because the observed data show relatively low biomass, this results in only a slightly higher (worse) SS for TroSim than for Ecosim (0.38 vs. 0.35 respectively). However the implications of the TroSim results are of course radically different than those of the Ecosim results. TroSim model simulations results could also be explained by successive years of sub-optimal salinities and the fact that the TroSim simulation did not include promotion from spat to sack oysters. To improve the TroSim model, spat to sack oyster promotion will be included for any oyster simulations performed for the 2017 Coastal Master Plan community model.

Ecosim performs reasonably well in its eastern oyster simulations, although the fits were not as good as those for spotted seatrout. This difference is likely an indication that other factors play a role in oyster biomass than the few variables included in this model. The community model for the 2017 Coastal Master Plan will include more environmental variables than just salinity and temperature, habitat features such as presence of cultch, and other stressors (e.g., the oyster drill). It should be noted that including the effects of fishing for oysters in the Ecosim simulation improves the model fit.

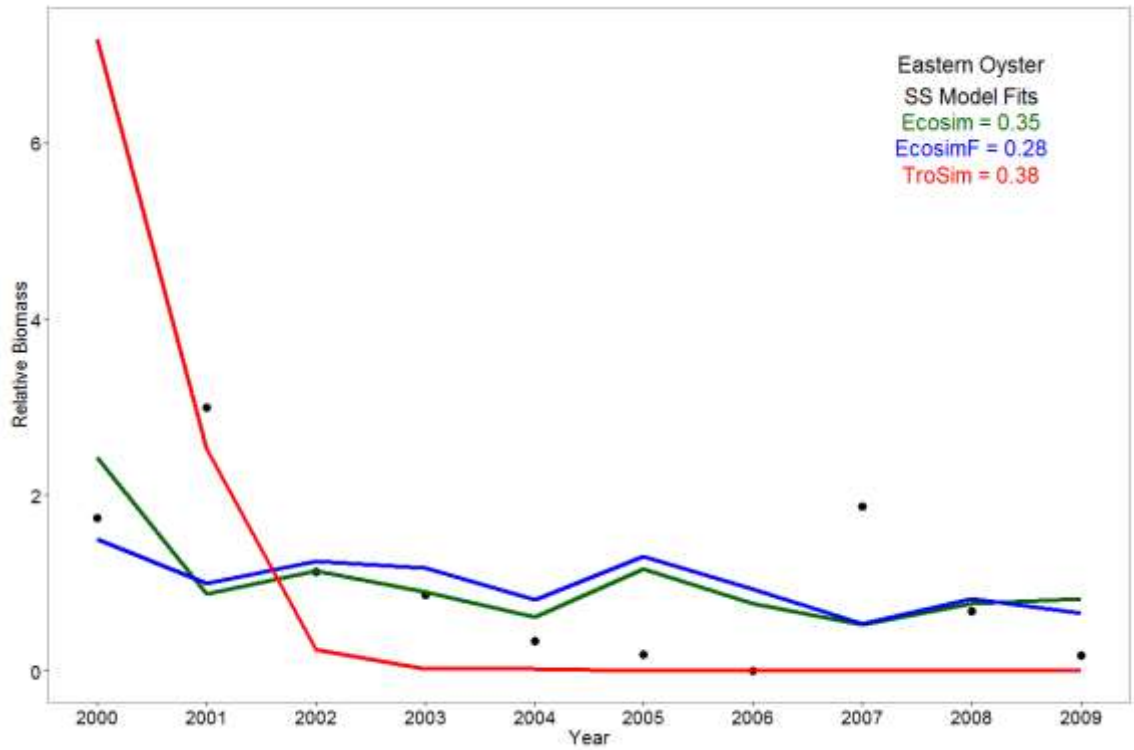

Figure 22: Annual output of eastern oyster. Three simulations, Ecosim without effect of fishing, Ecosim with effect of fishing, and TroSim, are compared and fitted to observed data. The Sum of Squares fit of each simulation to observed data is shown in the figure.

As indicated before, we chose *a priori* to compare two species (spotted seatrout and oysters) with TroSim and Ecosim, since other comparisons would not fit in the timeframe provided for activity 1. With these two comparisons, a high tropic level species and a low trophic level

species are exemplified. In Ecosim, all species biomass is simulated at the same time, and the fitting to time series step is also performed simultaneously for all species for which observed time series data are available. In this way, the calibration of one species immediately affects the fit of other species, especially since the vulnerabilities to predation and fishing are adjusted during this calibration step. Since this output is readily available, we chose to include it as example output in this document as well. The fits to observed data of the other species in the Barataria Bay EwE model are shown in Figure 23. Note that these fits are calculated with the transformed *SS* methods within EwE, and therefore show slightly different values. The same concept applies, however, that lower values indicate better model fits; the values overall are just slightly higher than when calculating SS outside of the model.

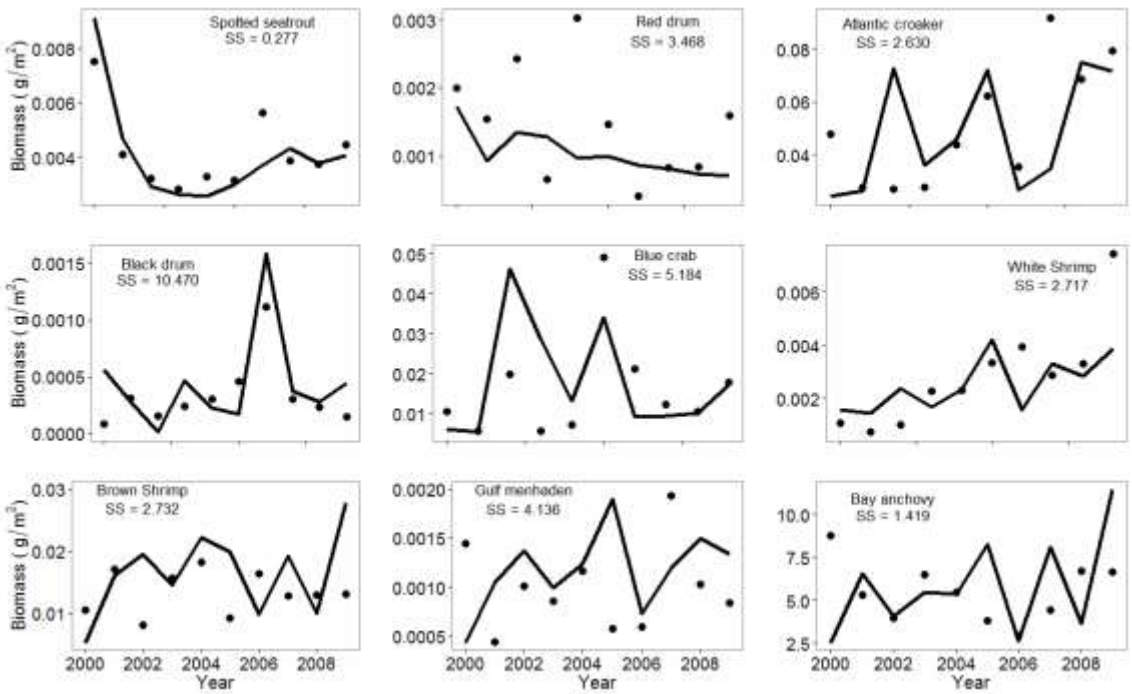

Figure 23: Annual Ecosim model runs compared to observed values. Species are indicated in each panel, values associated with each species represent the sum of squares values between observed data and model runs calculated in Ecosim (EwE compares log biomass to log predicted which results in different SS values than using Equation 2.1).

Next, we compared short-term, monthly fits of TroSim and Ecosim, with the intention to demonstrate the strength of TroSim. For this step, the EwE software had to be altered as explained in Section 1.2.5. As an ecosystem model (as opposed to an individual based model), EwE determines the biomass based on a combination of long-term and short-term events, and is therefore less likely to predict very short-term variations in biomass. An added confounding factor when fitting to monthly observations is the high natural variability in fish collections (observed data), and the low sample size per month of observed data, if available at all. Adjusting a model in such a way that it exactly fits monthly observations based on low sample sizes (1 or 2 units of effort) would result in over-calibration, which does not improve the predictability of the model. In the case of spotted seatrout, we chose to first reduce the high variability of the monthly field data by fitting a Lowess curve to the data (see Section 2.3.2), and then fitting the models to the Lowess curve values (Figure 24). Since we do not have information on monthly spotted seatrout landings (recreational catches) or fishing effort, we made an estimate for spotted seatrout fishing effort to be able to provide an Ecosim simulation with

fishing. Since we do have observed monthly landings for shrimp, we demonstrate our model fit of simulated landings to observed monthly landings for brown shrimp as an example of such a fit when we do have the data in Figure 25. The fit of the model simulations to the Lowess curve of the observed data resulted in a poor fit of the Ecosim run without fishing and a better fit with fishing (Figure 24).

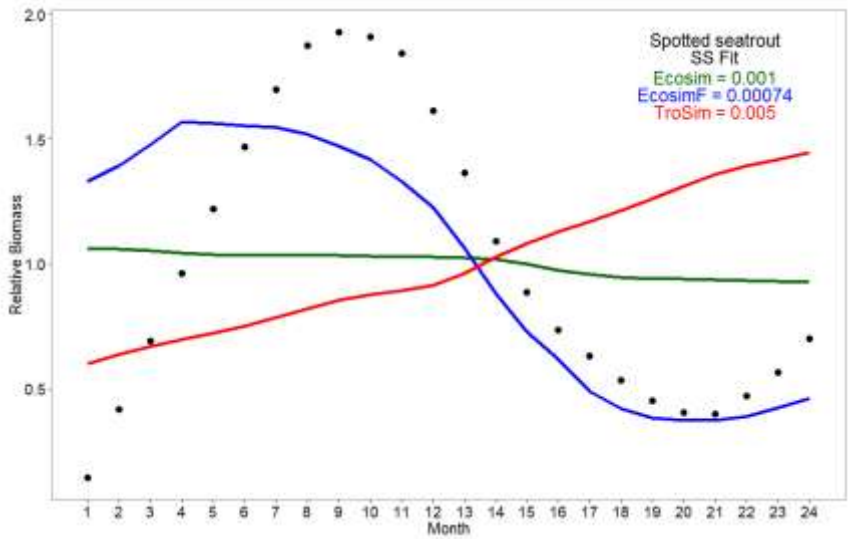

Figure 24: Monthly output of spotted seatrout. The model runs represent two years: 2000 and 2001. Three model simulations, Ecosim without effect of fishing, Ecosim with effect of fishing, and TroSim are compared and fitted to observed data. The Sum of Squares fit of each simulation to observed data is shown in the figure.

Both Ecosim simulations show a better fit than the TroSim simulation. All SS seem relatively low because of the low values included in the SS calculation caused by the small change from initial biomass in spotted seatrout in the first two years after model initiation. Ecosim without fishing does not pick up on the monthly variation in biomass, which is likely due to the fact that the salinity remained suitable for spotted seatrout in each of the months. With the long-term simulation in mind, TroSim seems to be on its way to exponential growth, it is just less obvious when simulating short-term. Ecosim with fishing performs best again during these short-term simulations.

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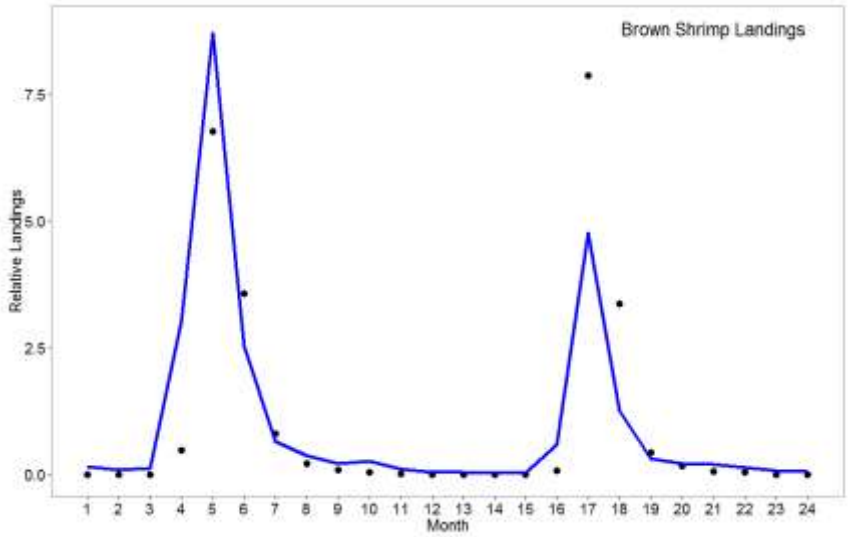

Figure 25: Brown shrimp landings per month for 2000 and 2001. The landings in Ecosim are fitted to the observed landings data.

Eastern oyster model simulations are compared on a monthly basis as well (Figure 26). However, since monthly oyster data are not available, we were unable to compare a fit to observed data as we did for the annual model simulations. The Ecosim simulation and the TroSim simulations actually show a very similar pattern, just at a different amplitude. The inclusion of fishing in Ecosim seems to be smoothing out most annual variability in oyster biomass. While we do not have monthly observations of oyster biomass to determine which model fits best, TroSim seems to better capture the potential increase in relative biomass in oysters that should occur at some point in the year. Ecosim generally performs better when the model estimates of a species are calibrated against observed data. The TroSim simulations most likely diverged from the EwE simulations for a number of reasons. First, the salinity fields in TroSim were outside the bounds for the oyster habitat suitability indices. In other words, the salinity in Barataria Bay was lower than the lower salinity index value for sack oysters, which led to starvation of the oysters in the model. Also, we may have chosen an unrealistic boundary condition, where we assumed that 10% of the initial population would be held as a refuge population within the model. In the multi-year simulations, the 10% refuge was calculated from the previous year's population. So if we start from 100 metric tons km^{-2} in 2000, the refuge would be 10 metric tons km^{-2}. If that's where the population ended up by year's end, the following year would use 10% of 10 metric tons km^{-2}, or 1 metric ton km^{-2} as a refuge. In future runs, we will likely use historical data to determine the "lowest measured population" as a reasonable refuge. Further, in Activity 1 there was no harvest or predation pressure on sack oysters to limit population growth, nor was promotion from seed oyster included to amend population growth. Each of these will establish a more realistic carrying capacity for sack oysters in future simulations; these elements were not included in this TroSim simulation because it was set up to solely simulate the salinity response.

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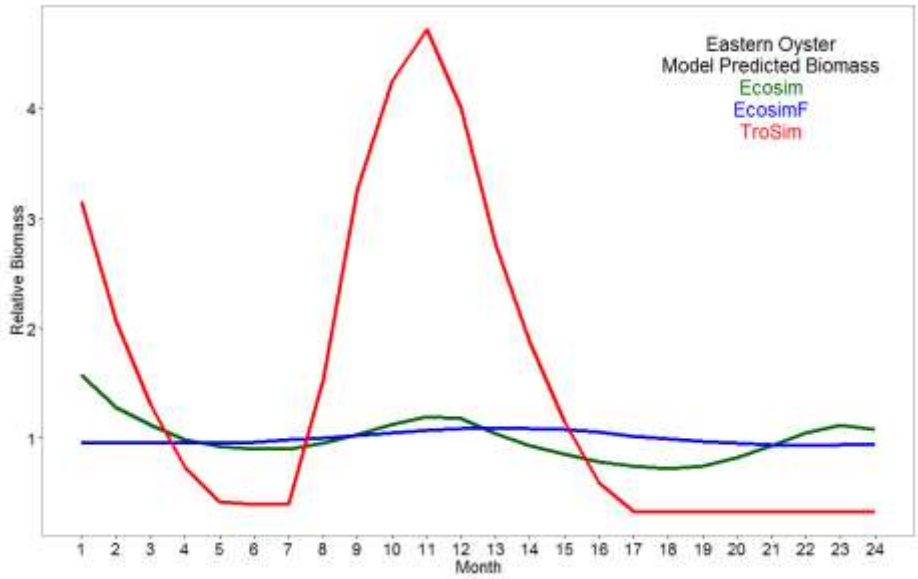

Figure 26: Monthly output of eastern oyster. The model runs represent two years: 2000 and 2001. Three model runs; Ecosim without effect of fishing, Ecosim with effect of fishing, and TroSim are compared. No observed monthly oyster data were available to fit the models.

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To test the sensitivity of the EwE model, we performed Monte Carlo trials for spotted seatrout as explained in Section 2.3.3 and shown in Figure 27. The fact that the model output after a 10-year run shows similar variability as introduced at the initiation of the simulation demonstrates that the EwE model is robust.

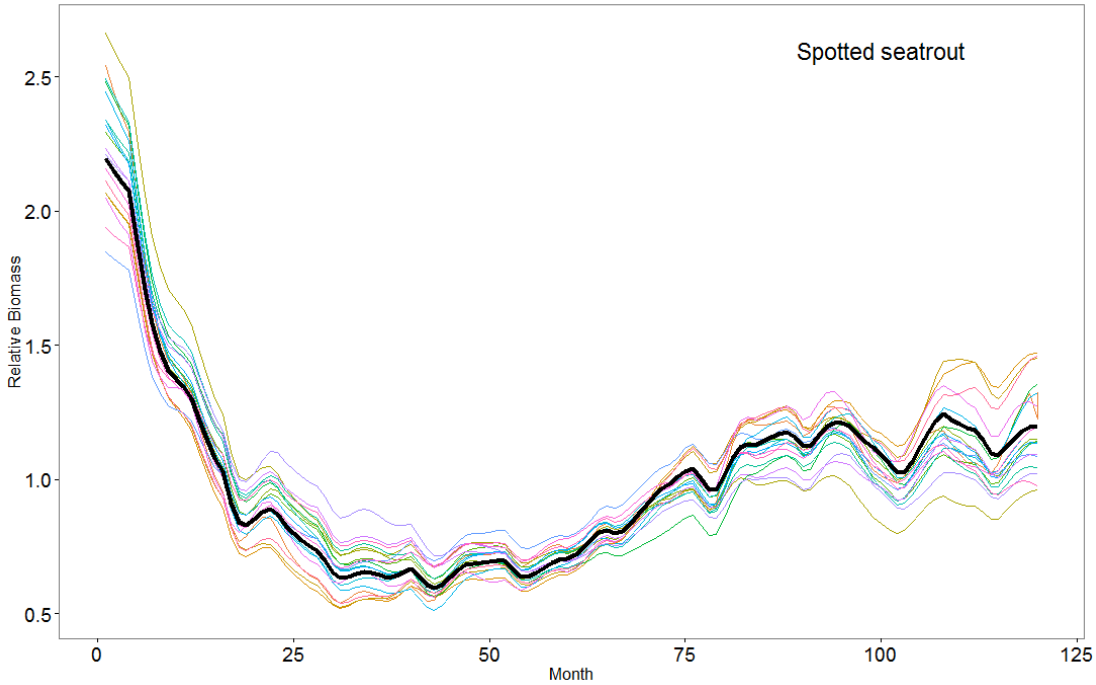

Figure 27: Monte Carlo trials for spotted seatrout biomass of a 10-year simulation. Twenty trials were performed and are indicated with the colored lines; the black line shows the original model run.

As our next step, we moved the calibrated EwE model into Ecospace. To be able to demonstrate an example Ecospace model simulation in which fish respond to spatially explicit environmental variables, we inserted the salinity output from the 2012 Coastal Master Plan representing 2000-2009 into Ecospace (per Ecospace grid cell, per month). Ecospace provides us with the spatial distribution of each species in the model (spotted seatrout shown as an example; Figure 28) as well as the total biomass of each species in the model area at the end of the model run compared to the start (Table 19).

The model is responsive to the salinity distribution in the model area as well as trophic interactions and fishing. For the 2017 Coastal Master Plan, the model area will be expanded and more environmental variables and habitat features included.

Table 19: Start (BiomassS) and end (BiomassE) biomass of each group in the Barataria Bay Ecospace model after a simulation run from 2000-2010. The columns percent change and end biomass/start biomass (E/S) indicate the amount of change in biomass over the 10-year model run.

Group name	$Biomass_S$	$Biomass_E$	Percent Change	Biomass (E/S)
Juv. spotted seatrout	0.0031	0.0032	3.86%	1.04
Adult spotted seatrout	0.0077	0.0075	-2.95%	0.97
Juvenile red drum	0.0003	0.0019	459.21%	5.59
Adult red drum	0.0019	0.0010	-47.66%	0.52
Juv. Atlantic croaker	0.0473	0.0542	14.50%	1.15
Adult Atlantic croaker	0.1612	0.2079	28.99%	1.29
Juvenile black drum	0.0030	0.0011	-62.79%	0.37
Adult black drum	0.0082	0.0077	-5.08%	0.95
Juvenile blue crab	0.0392	0.0555	41.86%	1.42
Adult blue crab	0.0307	0.0413	34.66%	1.35
Juvenile white shrimp	0.0074	0.0042	-43.92%	0.56
Adult white shrimp	0.0111	0.0268	140.63%	2.41
Juvenile brown shrimp	0.0173	0.0242	39.65%	1.40
Adult brown shrimp	0.0293	0.0331	13.02%	1.13
Juv. Gulf menhaden	0.0011	0.0019	63.41%	1.63
Adult Gulf menhaden	0.0024	0.0040	70.02%	1.70
Oyster spat	0.4353	0.3954	-9.17%	0.91
Adult eastern oyster	0.2835	0.2666	-5.94%	0.94
Bay anchovy	0.0977	0.1343	37.49%	1.37
Zooplankton	0.6118	0.6270	2.49%	1.02
Zoobenthos	3.2417	3.2526	0.33%	1.00
Phytoplankton	1.9541	1.9753	1.08%	1.01
SAV	5.2521	5.2966	0.85%	1.01
Benthic algae	12.8764	12.8162	-0.47%	1.00
Detritus	3.9959	4.0407	1.12%	1.01

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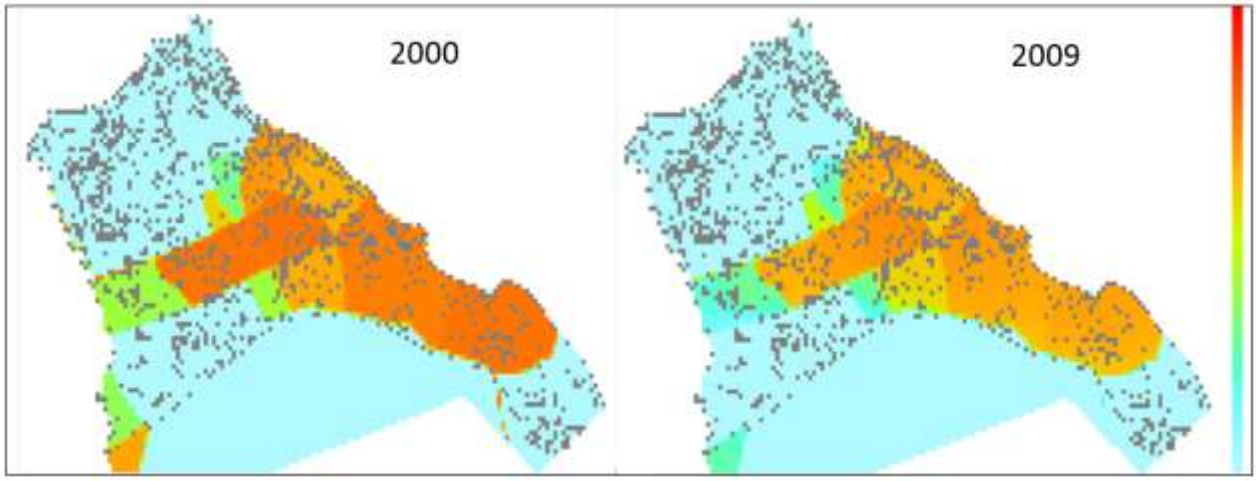

Figure 28: Spatial distribution of adult spotted seatrout after a 10-year simulation in Ecospace. Figures represent the distribution of relative biomass, where warm colors indicate more biomass. Spotted seatrout is again highlighted as an example; the model provides maps for each of the species in the model simultaneously.

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4.0 Discussion and Relevance to 2017 Coastal Master Plan

In this document we explained the functioning of EwE and TroSim, and provided example model output and comparison of both models. Since TroSim is based on the same modeling framework as CASM, with the same capabilities and limitations, our EwE/TroSim comparison can be viewed as an EwE/CASM comparison as well. Other factors that are important to consider in addition to how well models fit to observed data, is how user-friendly, time-consuming, and flexible both applications are. Table 20 provides a summarized comparison of the capabilities of EwE and TroSim/CASM.

Current simulations show that Ecosim outperforms TroSim, especially when running long-term simulations. The poor performance of TroSim may be partially due to the rigorous attempt to work with the exact same parameters as are used and/or calculated in EwE, to maximize comparability for this assignment. For this reason, it is difficult to conclude that TroSim is unsuitable and incapable of providing reliable results. We therefore still consider TroSim an important component for the oyster simulations in the 2017 Coastal Master Plan community model, and more time will be invested to create a stable TroSim model with its own parameters. We will also endeavor to refine the model using daily environmental data (see Table 20) and higher temporal resolution oyster field data if available.

Our recommendation for the 2017 Coastal Master Plan Ecological Modeling is to capitalize on the strengths of both models while keeping the objectives of CPRA in mind. These objectives are to determine effects of fish and shellfish of 20- and 50-year restoration scenarios. Additional objectives are to have a model ready for this purpose in fall 2014, and to have this model represent the entire Louisiana coastal area. These objectives provide considerable strains on the TroSim framework, due to length of the model run, the timeframe of the deliverable, and the fact that the environmental conditions in the model area are not uniform. The implication of this last point for TroSim is that, since it is not a spatially explicit model, a time-dynamic model needs to be created for a large number of subsections (polygons) within the model area, and that each of those time-dynamic models need to be run separately with a different set of environmental conditions. The spatial resolution will depend on the size of the polygons, but it is unlikely that the resolution can be as high as the 1 km^2 grid proposed for the 2017 Ecospace model. In additions, these multiple time-dynamic models will not be able to simulate movement or any other interaction between the polygons.

We initially planned to include TroSim as a subroutine to model oysters in the EwE model, but were unsuccessful in this approach, and successfully used Oyster Environmental Capacity Layers to model effects of daily environmental drivers on oysters instead.

While the EwE framework can now provide monthly biomass output of all groups in addition to annual output, we will focus on annual output of the community modeling effort for the 2017 coastal master plan. By demonstrating both monthly and annual EwE output in this document, we have shown that the annual output is more reliable, especially when we do not have enough empirical data at a monthly resolution for monthly calibration purposes. More importantly, as stated in Rose and Sable (2013), the choice of what model and model output to use largely depends on the objectives for which the model will be used. The objective of CPRA for the 2017 community model is to simulate fish and shellfish response to 20 - and 50-year restoration scenarios. Additionally, CPRA aims to simulate a very high number of restoration projects, on a spatial scale that includes the entire Louisiana coastal area, and aims to have this ready within the next year. The model needs to be calibrated and validated for all groups in the model (when data are available), and information needs to be presented on the sensitivity

(reliability) of the model output. EwE is currently the best available modeling framework with which such objectives can be met.

Table 20: Model attributes of EwE and TroSim/CASM compared. * When any of these parameters are not available, TroSim can still run by including a monthly value ~30 times, and/or by taking predictions of e.g., phytoplankton biomass from Ecosim. It will then however lose its daily resolution (i.e., does not provide more information than what a monthly time step would provide).

Model attribute	EwE (includes Ecopath, Ecosim and Ecospace)	TroSim/CASM
Time step	Monthly	Daily
Calibration	Model parameterization and fitting output to time series	None within the model framework
Fit to time series	Monthly and annually, simultaneously for all groups	Not within the model framework
Performs best when	Simulating annual biomass on decadal time scales	Simulating daily biomass within one year, multi-year simulations possible but time-consuming due to needed reconfigurations of the model per year
Sensitivity analysis	Monte Carlo analysis; option to vary initial biomass, production to biomass ratio, ecotrophic efficiency, and biomass accumulation within user-selected confidence intervals.	None within the model framework
Validation options	Determines SS fit between model run and validation time series without fitting the model to these time series	None within the model framework
Spatially explicit	Yes; movement of all groups and fleets in the model is simulated	No: to imply a spatial component, multiple temporal models need to be developed representing a subset of the spatial area by including a different set of environmental variables specific to that subset
Spatial resolution	0.8 km^2 for Barataria Bay model; 1 km^2 planned for 2017 Coastal Master Plan model	Not spatially explicit; size of polygons will determine spatial resolution. Resolution unlikely as high as one polygon per km^2
Flexibility	Can quickly incorporate changes in output from other models and/or observed data	Reconfiguration of model needed to incorporate a new set of data (environmental or observed time series), potentially delaying response time to simulating a different set of conditions

Model attribute	EwE (includes Ecopath, Ecosim and Ecospace)	TroSim/CASM
Environmental data needs	Monthly data per spatial grid cell of environmental variables of interest. Note: none are needed to initiate the model	Daily values of*: Average Water Column Temp (^{0}C); Epi/Hypolimnion Water Temp (^{0}C) Epi/Hypolimnion DIN Conc (mg/L); Epi/Hypolimnion DIP Conc (mg/L) Epi/Hypolimnion DIS Conc (mg/L); Epi/Hypolimnion TSS Conc (mg/L) Epi/Hypolimnion POC Conc (mg/L); Epi/Hypolimnion Salinity (PSU) Surface Light (PAR) Intensity (Ein/m^2/day); Depth @ Station (m) Current Speed (m/s); Wind Speed (m/s)
Fishing	Included in simulations; landings can be included as non-predatory mortality, fishing effort or fishing mortality can be included to drive model dynamics. Fishing becomes spatially explicit in Ecospace with moving fleets/ recreational effort.	Landings can be included as a non-predatory mortality term, but model cannot be driven by fishing effort or fishing mortality, and does not have a spatial component.
Programming language	Visual Basic .NET	Fortran
Option to couple to other models	Yes	Yes

Appendix B. Improvements to EwE software

While EwE is freeware and periodically new releases are placed on the internet (www.ecopath.org), advanced features are included in the software that specifically serve the purpose of this project. The improvements described below already start from an advanced version, of which the features are described in the main part of this document. All model code of this advanced version is delivered and described in Appendix B.

1.0 Working with Regions in Ecospace

The Ecospace module of the EwE software applies the ecological dynamics of a marine food web across a grid of cells. Ecospace offers the possibility to save .csv files with results averaged across designated clusters of cells. These clusters are referred to as regions.

The latest release of the EwE software contains the ability to produce results for regions for each time step and write annual averaged Ecospace results for these regions.

1.1 Changes to EwE

The following changes have been made to the EwE software to satisfy the region export requirement:

The Ecospace region export logic was extended to calculate average biomasses and catches per functional group over one year periods for all modeled cells in each user-defined region. Here only modeled cells are considered; excluded cells and depth 0 cells (which indicate cells without ecosystem dynamics) are not considered in the calculations.

The Ecospace region file writing logic was extended to produce, for each functional group, one .csv file with annual averages of biomass and catch for that group. The file contains entries for each Ecospace year with averaged biomass and catch.

The Ecospace user interface where regions are defined contained a bug that prohibited generation of regions from habitat maps. This bug was fixed.

1.2 Using the new developments

Users can define the number of regions from the "Edit Regions" form, found in the Ecospace menu, where they can set a maximum number of regions that Ecospace can use, or define regions from either MPA or habitat cells (Figure 29).

In the Ecospace maps interface users can now allocate cells to the number of regions set previously. The regular map import features can be used to import region maps. Figure 30 shows the Ecospace map with three example regions.

Users can enable Ecospace to automatically save results by region in the Ecospace parameters interface (Figure 31). This saving will occur at the end of an Ecospace run. Two .csv files are produced: one file with averages per region (and averages for the remaining cells) for every time step, and one file with averages per region (and averages for the remaining cells) over

each year that the Ecospace model was executed for. The EwE status panel provides information that results per region have been saved, and to what physical location (Figure 32).

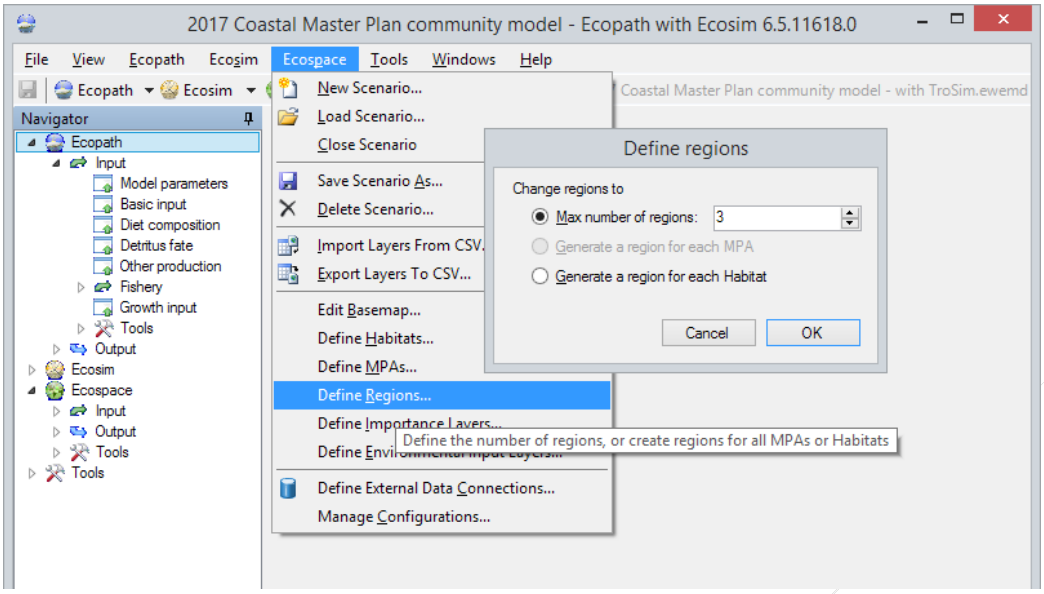

Figure 29: Activating the "Edit Regions" interface from the Ecospace menu.

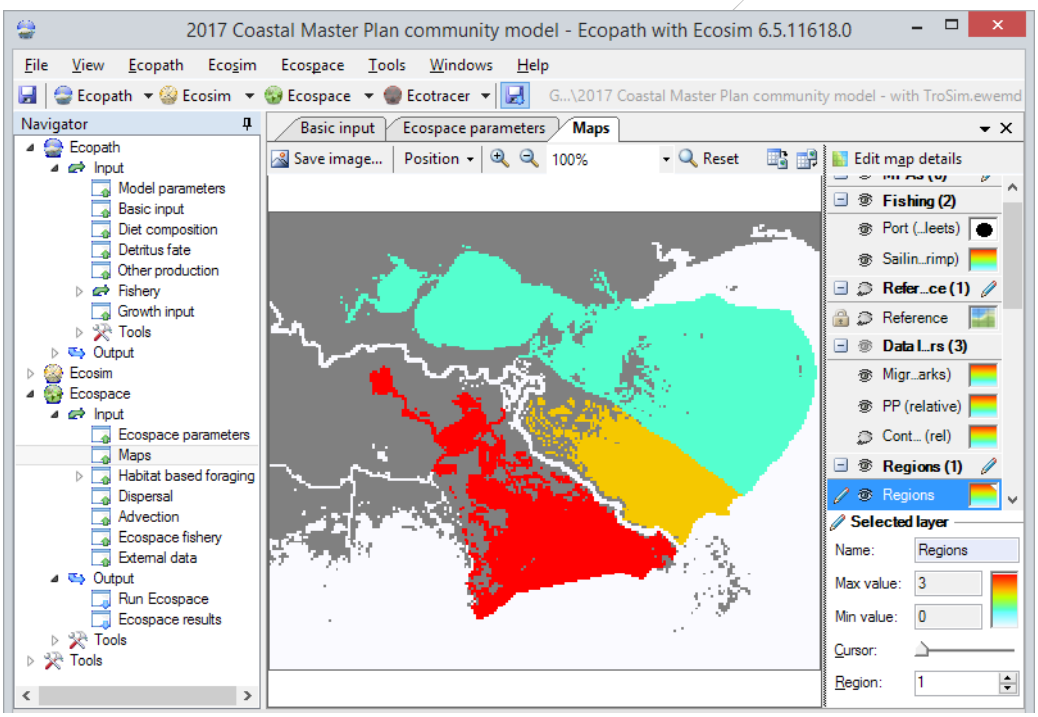

Figure 30: The Ecospace map interface showing three regions.

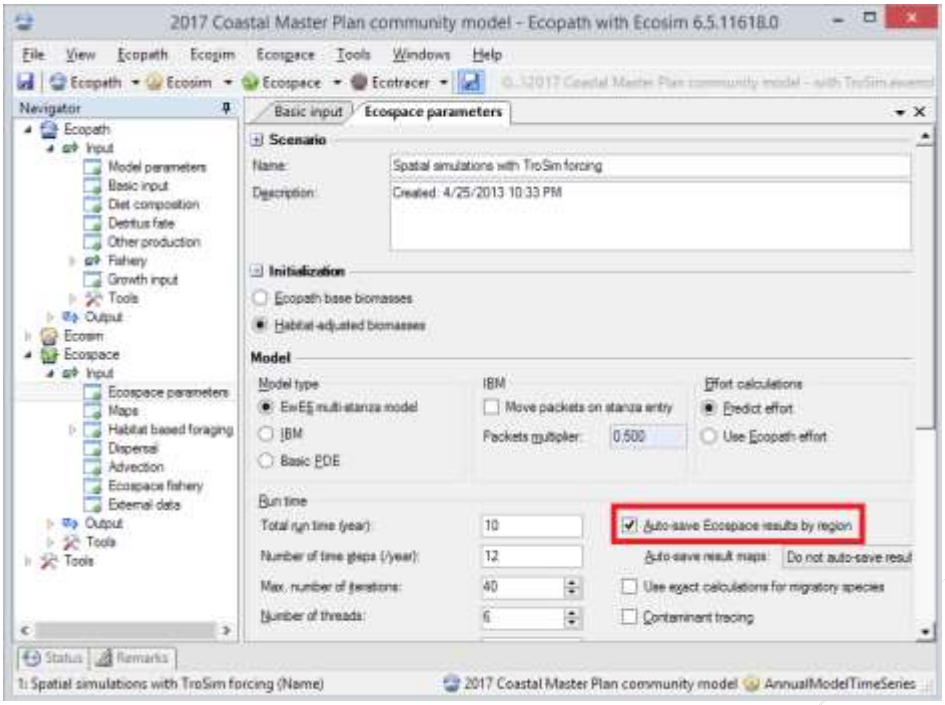

Figure 31: Enabling Ecospace to save results by region.

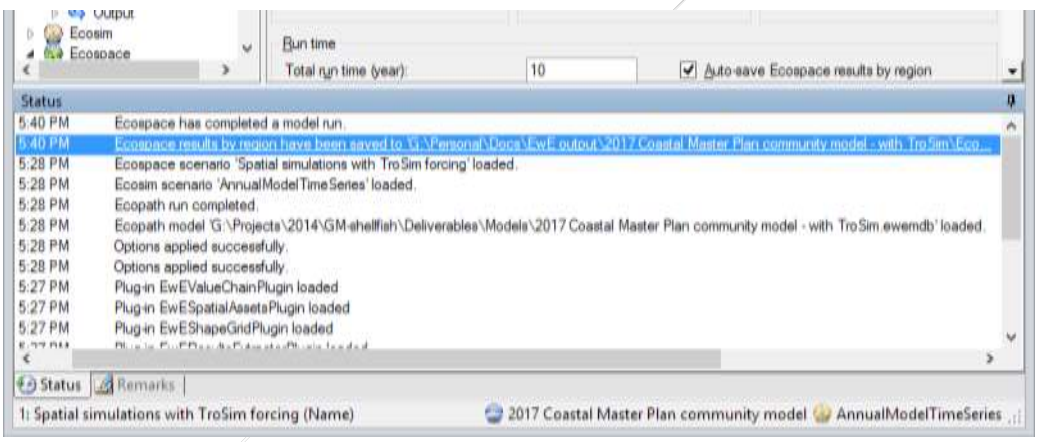

Figure 32: The EwE status panel informing the user that regional averages have been saved.

2.0 Auto-saving Maps in Ecospace

Ecospace offers the ability to save maps to geo-spatial explicit files for further processing and display in GIS (Geographic Information Software). However, users may want to use Ecospace maps for their publications even if GIS software is not available. The Ecospace model already contained the possibility to save its maps to images whenever Ecospace is paused or a run has completed, but saving maps for specific groups at specific execution time steps is difficult to accomplish. A better solution was needed.

In response, the ability to save maps was added to the Ecospace auto-save system that already supports automatic saving of ASCII and .csv files. In the "Run Ecospace" user interface users can enable the option to save map images, and optionally provide a comma-separated list of time steps to save images for (Figure 33).

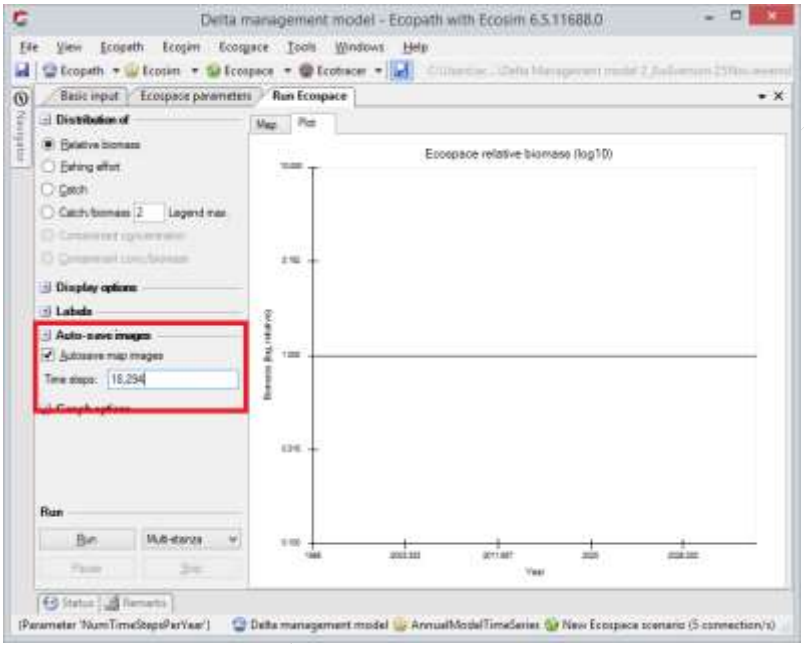

Figure 33: The EwE "Run Ecospace" interface, where auto-saving of map images can be enabled. Here, maps will be saved for Ecospace time steps 18 and 294.

When the "Autosave map images" setting is enabled in this interface, Ecospace will write images adhering to the group/fleet visibility and selected output variable settings in the "Run Ecospace" interface. The image is automatically sized to 10x10 pixels for every cell, with a pixel density of 220 dots per inch (DPI). By default a map image is saved for every Ecospace time step, but users can specify a one-based, comma-separated list of time step numbers to only save map images for.

Note that the current implementation does not allow users to control the final image dimensions other than via changing the number of rows and columns of the Ecospace base map. The default pixel density setting of 220 DPI can be customized by modifying the 'OutputDPI' value in the EwE6.settings file.

Every map image will be accompanied by two extra files: (i) a world file for the image that provides geo-referencing information for the PNG image; and (ii) a legend file for the image.

3.0 Using Spatial-temporal Data in Ecospace

Several improvements have been made to the EwE software to improve the workflow of configuring and applying external spatial temporal datasets to an Ecospace scenario.

3.1 Working with a Large Number of Environmental Response Functions

The Delta Management Ecosystem model required over 120 environmental response functions for driving species distributions in Ecospace (Figure 34). Parameterizing the functional responses to environmental drivers was hindered by this large number of response functions, and significant amounts of time were lost trying to locate desired function. A simple addition to the EwE user interface was needed to assist users finding response functions.

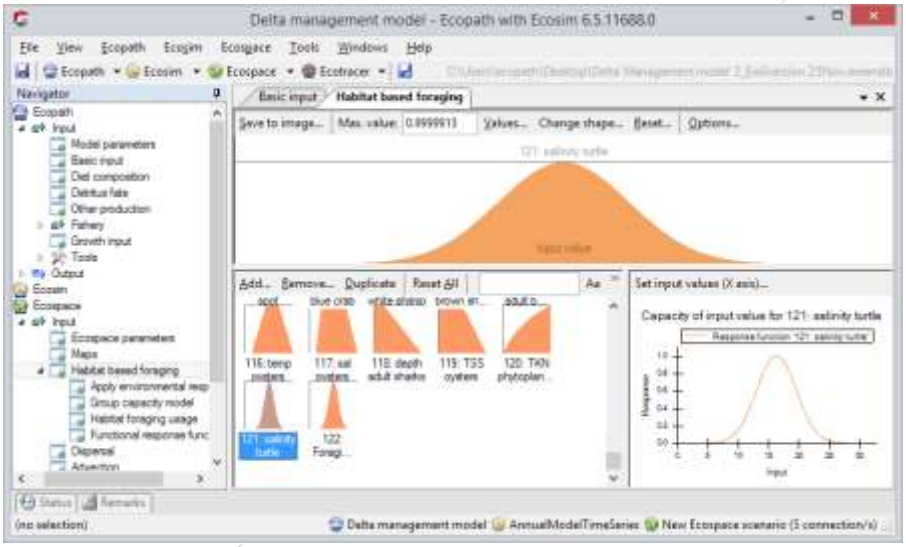

Figure 34: A large number of environmental response functions in the EwE habitat capacity user interface.

As a solution, a name filter was added to the user interface, where response curves are filtered if the name matches the character pattern that users can enter (Figure 35). The pattern can be made case-sensitive.

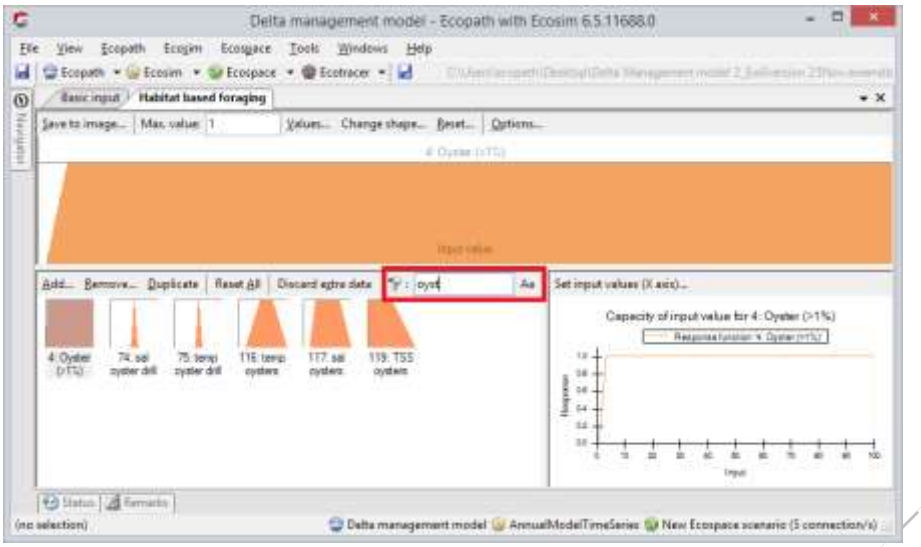

Figure 35: The same EwE habitat capacity user interface as in Figure 34, but now showing only environmental response functions with names containing 'oyst'. The name filter is highlighted by a red outline.

Note that the name pattern is not preserved when the user interface is closed. Also note that the name pattern does support neither the use of wildcards (e.g., ? or *), nor regular expressions.

Due to the high level of code re-use in the EwE software, all user interfaces that show forcing or mediation functions (Ecosim time forcing functions, Ecosim multi-stanza egg production forcing, Ecosim fishing effort and mortality, Ecosim time series, Ecosim mediation, and Ecosim price elasticity) also have gained the ability to filter their lists of functions by name.

3.2 Working with External Data Connections in Ecospace

Since 2012 Ecospace has had the ability to vary the content of specific input layers via external time series of maps, changing Ecospace input values over time and space with data derived from external GIS data sources (Steenbeek et al. 2013). Using this functionality for the Delta Management Ecosystem Model development has brought a series of shortcomings and impracticalities to light that have been addressed during this phase of the project.

3.3 Indexing of External Spatial-temporal Data

When applying external driver data to Ecospace maps, users need to be certain that this external data matches the spatial and temporal extent of an Ecospace scenario. Ecospace provides an indexing mechanism that performs a quick compatibility assessment of external data, which can be enabled or disabled via "Menu > Tools > Options > Spatial-temporal data > Allow background indexing of external data connections" (see Figure 36)

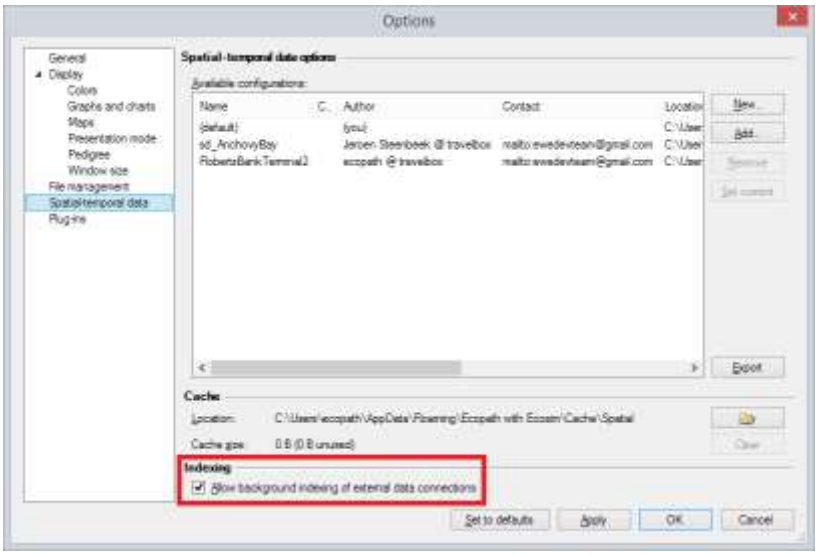

Figure 36: The EwE options interface where users can enable background spatial-temporal data indexing.

When this option is enabled, Ecospace will perform a shallow check whether all external data map needed for the Ecospace scenario run time can be physically found, and whether the spatial coverage of this map partially or entirely overlaps with the Ecospace map (Figure 37).

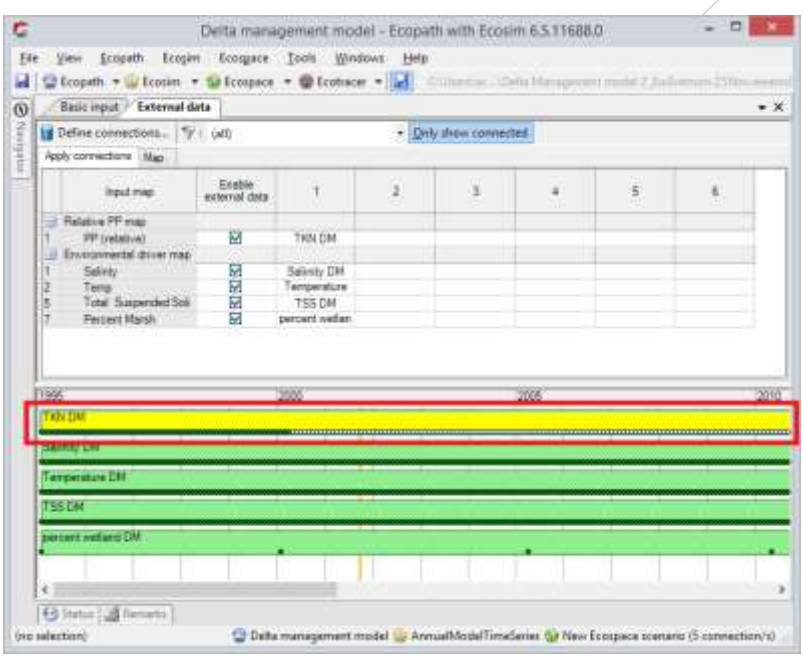

Figure 37: Ecospace spatial data indexing in progress. Here, "TKN DM" data is partially assessed until mid-2000. All other data connections are free of problems.

The color coding used throughout this interface is simple: (i) green indicates that no problems have been found between the entire data set, individual data points and the Ecospace scenario; (ii) yellow indicates that potential problems have been located such as partial spatial

overlap between one or more external maps and the Ecospace scenario; (iii) red indicates that definite errors were encountered, which occurs when defined external spatial maps cannot be physically located; and lastly (iv) the color grey is used to indicate that an indexed assessment has not yet been performed.

4.0 Bug Fixes

In addition, a series of bugs have been fixed to make sure the current EwE user interface behaves as expected. For a complete list of bug fixes and changes to the EwE software please refer to the online EwE change log, accessible via http://sources.ecopath.org/trac/Ecopath (full link https://docs.google.com/document/d/1CXOgNcS1NIpR9FaFyqGKQPBSsggZK-RnWjuTXj9P7ew).

Appendix C. Model Code

1.0 Ecopath with Ecosim Software

The Ecopath with Ecosim (EwE) desktop software was used and extended for the development of the 2017 Coastal Master Plan Community model. The EwEConsole application is a command line application built from the EwE Core components that allows EwE to be run from a command line file to facilitate linking of EwE into the ICM model.

This document describes how to deploy and use the EwE source code for running the EwE model simulations for the activity.

Note that familiarity with basic operation of the EwE6 software is assumed, such as how to load and run Ecosim and Ecospace scenarios, and how to explore scenario results. The manual (Christensen et al. 2008), also part of the software under 'help', provides the information as well.

This document contains the following sections:

- Contents of the technical deliverables package;
- Computer requirements for running the EwE model;
- How to build the EwE software from the source code;
- How to build the EwE Console application from the source code;
- How to prepare the EwE models on a local machine for running the EwE simulations;
- How to run the EwE simulations for the activity.
- How to run the EwE Console.

1.1 Contents

The technical deliverables package ("Activity 2 EwE Code") contains the following items:

- A file named "EwE6-sources.zip", which contains the source code of the Ecopath with Ecosim desktop software;
- A file named "EwE6-models.zip", which contains the EwE model databases used for the 2017 Coastal Master Plan community model;
- A file named "EwE6-drivers.zip", which contains the spatial-temporal data used to drive the model;
- A file named "EwE6-program.zip", which contains the EwE6 program built from the source code in EwE6-sources.zip;
- A file named "EwEConsole-Sources.zip", which contains the source code of the EwE Console application;
- A file named "EwEConsole-Model-SpinupData.zip", which contains the EwE model in an .xml format, a sample command file used to configure a run and the Spatial Temporal configuration file;
- A file named "EwEConsole-Program_v.6.5.11928.zip" which contains a compile version of the EwE Console application.

1.2 Computer Requirements for Running EwE Model

The EwE desktop software can be executed only under the Microsoft Windows operating system with the following software installed:

- Windows XP Service Pack 3 or newer (Vista, Windows 7, Windows 8.x);
- .NET Framework 4. This can be installed from http://www.microsoft.com/es-es/download/details.aspx?id=17851. Note that you will need the full .NET Framework 4 installation, .NET Framework 4 Client Profile is NOT sufficient for running the EwE software;
- Microsoft Office 2007 or newer, or Microsoft Access 2007 database drivers. These database drivers can be downloaded for free from http://www.microsoft.com/download/en/details.aspx?id=4438;
- For building the EwE software from sources a version of Microsoft Visual Studio 2010 or newer version is needed. Visual Basic Express editions are not supported in this deliverables package.
- A file decompression tool such as WinZip, 7-zip, WinRAR, or Windows Explorer with file compression enabled.

Please make sure your computer system meets these requirements before attempting to run and execute the EwE desktop software.

1.3 Building EwE6 from Source Code

The source code is provided as a ZIP file, which contains a snapshot of the EwE 6.5 source code at the end of the simulations of the 2017 Coastal Master Plan community model. Perform the following steps:

- Extract the entire content of the file "EwE6-sources.zip" to a location on your hard disk, for instance to "…\My Documents\EwE6". Please remember this folder location;
- Using Windows Explorer, navigate to the extracted EwE source code, and open subfolder "Sources" (for example, "…\My Documents\EwE6\Sources");
- Double-click the file "EwE6.sln".

The sources will now be loaded in your installed copy of Visual Studio.

- In Visual Studio, select "Menu > Build > Build Solution" to compile the source code into a version of EwE6.

The "Build Solution" command will compile the EwE source code into the desktop version of the Ecopath with Ecosim modeling approach. Visual Studio is configured to place this program, "EwE6.exe", in a folder "\Program" in the EwE sources folder (for example, "…\My Documents\EwE6\Program").

To launch the Ecopath with Ecosim desktop software, perform the following:

- Double-click the file "EwE6.exe" from the folder "\Program" in the EwE sources folder (for example, "…\My Documents\EwE6\Program\EwE6.exe"). It might be handy to create a desktop shortcut to this file for quick access…

1.4 Building EwE Console Application from Source Code

The source code is provided as a ZIP file, which contains the code necessary to build the EwE Console application using the current EwE6 source code loaded above. Perform the following steps:

- Extract the entire content of the file "EwEConsole-Sources.zip" to a location on your hard disk, for instance to "…\My Documents\EwEConsole". Please remember this folder location;
- Using Windows Explorer, navigate to the extracted EwEConsole source code;
- Double-click the file "EcospaceConsole.sln".

The sources will now be loaded in your installed copy of Visual Studio but will be missing a reference to the EwE Core source code.

- In Visual Studio, remove the reference to any missing projects by right clicking on the project in the "Solution Explorer" and select "Remove" from the menu;
- In Visual Studio, add the reference to the missing code by right clicking on the "Solution EcospaceConsole" in the "Solution Explorer" and selecting "Add > Existing Project" then navigate to the location of the EwE6 code you unzipped earlier "…\My Documents\EwE6\Sources" and locate the "EwECore\EwECore.vbproj";
- Repeat the process for any missing references;
- In Visual Studio, select "Menu > Build > Build Solution" to compile the source code into a version of EwE Console application.

1.5 Preparing EwE Models on a Local Machine

The EwE6 software is now ready to be used for running the simulations for the 2017 Coastal Master Plan Community model.

First, the contents of the EwE model and Spatial-temporal driver data will need to be extracted to your computer:

- Extract the entire content of the file "EwE6-models.zip" to a location on your hard disk (for instance to "…\My Documents\EwE6\Models"). Please remember this folder location;
- Extract the entire content of the file "EwE6-drivers.zip" to a location on your hard disk (for instance to "…\My Documents\EwE6\Drivers"). Please also remember this folder location;

Second, the EwE6 models will need to know where to find spatial temporal driver data. For this, EwE6 will need to be pointed at the spatial-temporal data that you extracted to your system. In EwE6, perform the following steps:

- Launch EwE6.exe as described above;
- In EwE6, launch the options interface (Menu > Tools > Options);
- In the options interface, open the "Spatial-temporal data" tab;
- In the "Spatial-temporal data" tab, beside "Available configurations", press the button "Choose…" on the right side. This will open a standard Windows interface for selecting a file that provides a set of spatial-temporal data;
- In this file selection interface, select the file "SpatialConfig_CMP2017_22Nov_Ecopath.xml" in the folder where you extracted the data from the zip file "EwEConsole-Model-SpinupData.zip" (for instance, "…\My Documents\EwE6\Drivers\SpatialConfig_CMP2017_22Nov_Ecopath.xml") and press "OK".

The spatial-temporal data configuration that you selected should now show as one of the available configurations.

- Select this new configuration, and press the button "Set current";

EwE6 is now set to find spatial-temporal data in the configuration file for the 2017 Coastal Master Plan community model. Close the options interface.

Now, the EwE models for the activity can be loaded and executed:

- To run the simulations load the file "CMP2017_22Nov_Ecopath.eiixml" from the same directory that you unzip the files in "EwEConsole-Model-SpinupData.zip".

The EwE6 software will now load the desired simulations for the activity. If this does not work, please make sure that your database drivers are up to date; see the "Computer requirements" section above.

- In EwE6, with the desired EwE model for the activity loaded, please load the only available Ecosim and Ecospace scenarios;
- Run the Ecospace model.

1.6 Running EwE Console Application on a Local Machine

The zip file "EwEConsole-Program_v.6.5.11928.zip" contains a compile version of the EwE Console application that can be configured to run on a local computer.

- Unzip the contents of "EwEConsole-Program_v.6.5.11928.zip" into a local directory (for instance to "…\My Documents\EwE6\EwEConsole\Program"). This directory will contain the support files and executable for the EwE Console application
- Unzip the contents of "EwEConsole-Model-SpinupData.zip" into a local directory (for instance to "…\My Documents\EwE6\EwEConsole\Data"). This directory will contain the model file and spin-up period data need to run the model.
- Unzip the contents of "EwEConsole-Documentation.zip" into a local directory (for instance to "…\My Documents\EwE6\EwEConsole\Data"). This directory will contain documentation files for configuring the EwE Console application command file and Spatial Configuration file.

To run the EwE Console application:

- Configure a EwE Console application command file to point to the EwE model file and spatial configuration file on your local machine. An example command file "SampleCommandFile.txt" is can be found in the directory you unzip the contents of "EwEConsole-Program_v.6.5.11928.zip";
- Documentation for configuration of the command file and spatial configuration file can be found in the directory you unzipped the contents of "EwEConsole-Documentation.zip"
- Once you have configured the command file and spatial configuration files you can run the EwE Console application by passing the command file to the command line of "EcospaceConsole.exe". This executable file can be found in the directory you unzipped the contents of the zip file "EwEConsole-Program_v.6.5.11928.zip".

2.0 OECL Model Code

The Fortran source code used to convert the daily salinity, temperature and total suspended solids data into the Ecospace OECL oyster driver layer is supplied in the "EwEConsole-Sources.zip in the sub diretory "OECL Executable".