## 2017 Coastal Master Plan

Strategy for Selecting Fish Modeling Approaches


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## Coastal Protection and Restoration Authority

This doc ument was prepared in support of the 2017 Coastal Master Plan being prepared by the Coastal Protection and Restoration Authority (CPRA). The CPRA wasestablished by the Louisia na Legislature in response to Huricanes Katrina and Rita through Act 8 of the First Extra ordinary Session of 2005. Act 8 of the First Extraordina ry Session of 2005 expanded the membership, dutiesand responsibilities of the 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. The Coastal Protection and Restoration Authority's mandate is to develop, implement and enforce a comprehensive coastal protection and restoration Master Plan.

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### 1.0 Introduction

Coastal restoration involves the alteration of environmental conditions that result in direct and indirect responses of individual fish and shellfish. These environmental effects from restoration include changes in hydrology, water quality, and physical habitat. Similar changes can also occuras a result of some coastal protection measures, such asthe creation of surge bamiers. The direct responses to these effects can be quantified as changesin the quality and quantity of habitat of specific life stages of species, or as responses in the growth, mortality, reproduction, and movement rates of individuals. Changes in these process ratesfor individuals can also cause indirect responses by changing the prey or predator of the species of interest without causing large direct responses to individuals of the species of interest. The combined direct and indirect responses may or may not be sufficient to affect local and regional population dyna mic of a species of interest. For this report, "fish" will be used to cover fish and shellfish.

The 2012 Coastal MasterPlan relied on quantifying changes in habitat for life stages of selected species. Habitat suitability has advantages but does not indicate how the response of individuals to habitat translates in changesin actual abundances and biomass. Thus, as with many large-scale ecosystem restoration programs, there is an interest by CPRA to develop fish models that go beyond habitat evaluation. Similar documents have been developed to support Everglades restoration (e.g., Ahmed et al., 2005), ecosystem-based fisheries management of the Chesapeake Bay program (CBFEAP, 2006), restoration of salmon in the Califomia Delta (Rose et al., 2011), and NOAA's integrated ecosystem assessment for the Gulf of Mexico ${ }^{1}$ (GOM) (Schimipa et al., 2012). The goal isfor the fish models eventually used in the 2017 Coastal MasterPlan to provide a quantitative analysis of how the effects on hydrology, water quality, and physical habitat on individuals (both direct and indirect effects) translate into local and regional population and food web responses.

This report is a scoping document on the strategy for selecting and applying fish models for the 2017 Coastal Master Plan. The development of the strategy is an important part of the process towards developing a systematic, transparent, and logic al scheme forincluding fish models in the 2017 Coastal Master Plan, but it must be recognized that adjustments may be needed as specific information is gathered and some factors, such asconstraints, are known in more detail.

### 2.0 HS and 2012 Coastal Master Plan

The 2012 Coastal MasterPlan included assessment of fish and shellfish habitat aspart of its evaluation of how projects would affect ec osystem services. The 2012 analyses used HSI for several species, including brown shrimp, white shrimp, eastem oyster, spotted seatrout, and largemouth bass. The HSl approach is based on relating key environmental variables to the quality of habitat for a life stage of a species, and has been widely used to assess river flow effects (e.g., those resulting from hydroelectric operations) on fish habitat.

HSI a nalyses involve specifying functions that assign values of zero to one over the range of each important environmental va riable (USFWS, 1980; Draugelis-Dale, 2008). These functions can be smooth or piece-wise linear. The basis of the shape of these functions are usually

[^0]determined by expert opinion and monitoring data. If there are multiple environmental variables, then the suitability values are a nithmetic ally orgeometric a lly averaged. This results in a single value of final suitability that is also between zero and one.

In the 2012 analysis, output from the other master plan models were provided for horizontal spatial grid cells at $500 \mathrm{~m} \times 500 \mathrm{~m}$ resolution, and the values of model outputs for selected years during the 50 -year projections was used asinput to the HSI functions. The annual suita bility value for each specieswas estimated for each $500 \mathrm{~m}^{2}$ grid cell, and the values for all the cells within a region were summed to obtain the total SI (Suitability Indices) value forthat region. These total SI values for a species could then be compared for different projects.

HSI has many advantages but also some key weaknesses (Roloff \& Kemohan, 1999; AhmadiNedushan et al., 2006; Elith \& Burgman, 2003; Gore \& Nestler, 2006). The main advantage to a habitat-based approach is that one avoids the challenges in modeling fish population and community dynamics, which is subject to debate about the model formulations, is dataintensive, and can be highly uncertain. Habitat is critic al to healthy and productive fish populations, and so determining how "restoration actions" will affect habitat relative to "no action" is an important step towards quantifying the ecologic al benefits and coststo fish of restoration actions. HSI models are also relatively easy to understand and explain.

The major disadvantage to habitat-based approaches is simply that they quantify habitat, which may or may not be directly corelated to fish abundance and provides little information on community level responses. The issue is that more habitat does not mean more fish, only that the restoration action created the capacity formore fish. Whether that new capacity is filled depends on what is limiting and controlling the fish population and community dynamics. For example, one can increase the habitat for juveniles, but if spawning is limited by other factors, then inc reased juvenile habitat will not affect the population abundance (i.e., the extra habitat will go unused).

### 3.0 Purpose and Organization of this Report

This report presents a strategy for selecting fish modelsto use for the 2017 Coastal Master Plan. Such a strategy document isneeded so that logic and reasoning for how the model/swere selected (and rejected) istransparent, easy to communic ate to others, and allowsfor easy midcourse changes in model selection if the questions or constraintschange.

Often the way ecological and fish model a nalyses are presented can create the appearance that the model was selected arbitrarily orin an ad hoc manner. Usually, only the structure and results of the final model are presented. The a nalysis is then viewed in isolation, without the benefit of knowing how and why the particularmodel, from the many possible models, was utilized. Models used by experienced modelers are never arbitrarily selected. There is a careful evaluation and thought processinvolved in selecting a model. However, thisthought process and decision making is rarely, if ever, documented. In this report, the characteristics of the models are explored so that their relevance to CPRA's puposes can be laid out. This report is the first step in a multistep process that results in CPRA determining a path forward for fish modeling in the 2017 Coastal Master Plan. This document will serve asa foundation for CPRA selecting their path forward, the justific ation forwhich will be described in a separate doc ument. This doc ument can be used to: (1) explain to others why certain models were eventually used, (2) ask others (e.g., state agency personnel, consultants) to use the strategy and see what models they would recommend, and (3) revisit the model recommendations if constraints or the
questions change. This doc ument is, therefore, not just a list of recommended models, but a tool that provides doc umentation on how and why models were selected.

# 4.0 Objectives, Questions, and Constraints of Fish Modeling for the 2017 Plan 

### 4.1 Objectives

The main objective of the fish modeling forthe 2017 Coastal MasterPlan is to provide a model/s that are well-suited to predict the potential responses of fish and shellfish species to simulated changes in the hydrology, water quality, and physical habitat due to restoration and protection actions. The hydrology, water quality, and physic al habitat effects of the restoration actions will be simulated by the other models. Thus, the fish models must also be capable of being linked to the other Integrated Compartment Modeling (ICM) approaches of the master plan so they can rec eive as inputs the changes in hydrology, water quality, and physical habitat. The fish models must also incomorate how environmental variables (i.e., those related to hydrology, water quality, and habitat) affect fish processes and abundance, and be able to provide a consistent set of outputs-across species and scenarios-on abundance or biomass over 20-50 years. Finally, the outputs of the fish models will be used as inputs to the Planning Tool, a decisionsupport tool for master plan efforts; the formatting requirements for this for the 2017 C oastal Master Plan have not yet been determined.

At the time of writing this report, not all of the details of the ICM (inputsto the fish model) were determined. In this report, the best availa ble information will be used on the likely form of the ICM, and the format of outputs from the ICMsthat will become inputs to the fish model/s. The use of fish model outputs as inputs to subsequent modeling is less demanding on specific formats, and thus will only be considered in general tems.

Second-orderconsiderations are that the model has been used previously in similarsituations, and is relatively straightforward to explain and present to the public. These are second-order considerationsbecause one must first select a model based on science (i.e., its appropriateness to address the questions being asked), a nd then if there are options within that subset of models, previous applications and ease of presentation would be considered. A model is not selected primarily because it has been used before or is easy to explain.

Another objective of the fish modeling forthe 2017 Coastal Master Plan is to have relatively few models that all generate common key outputs. It is not necessary that a single model be used for all questions and species. The other extreme approach to a single universal model would be to develop separate modelsfor each and every question, species, and location. Both extremes are problematic. A single universal model will likely require too many compromises to get a "model that fits all." Having dozens or more different models will create challenges in terms of comparing results a cross multiple models, communic ation of results, and effort. CPRA requested that, if possible, the same model be used for a species across basins (i.e., estuaries), although the modelscan differamong species.

### 4.2. Questions

The more specific and the fewerthe questions that are posed for the model to answer, the easier it becomes to develop a well-suited model. A focused question reduces the possible options for representing processes (e.g., which ones and in what detail) and also focuses in on
the temporal and spatial scalesthat are needed. Fewerquestions also help because then fewer compromises are required to obtain a single model that can address multiple questions that often involve emphasis on different processes and different spatial and temporal scales. A hypothetic al illustration would be the difference between these two questions: (1) what are the effects of wetland creation on shrimp, versus (2) how doesthe wetland-related habitat created by projects A, B, and C (i.e., acreages, land-water configuration, inundation frequency) in region X combine to affect a nnual shrimp summertime growth and abundance in September over the next 20 years. It is necessary to move from a multitude of possible models that could answer the first question, to a more limited number of modelsthat must have certain features (e.g., run 20 years, summertime growth, habitat effects on growth and mortality) for the second question.

There are three basic levels of aggregation of specific restoration projectsthat need to be considered to meet the needs of the 2017 C oastal MasterPlan, and CPRA has defined their specific questions to be answered by the fish models at each level of project aggregation:

1. How does each projectaffect the distribution and relative abundance (i.e., biomass or density) of species X versus Future Without Action (FWOA) over a 50 year period?
2. How do select sequences/combinations of projects within each coastal basin affect the distribution a nd relative abundance of species Xversus FWOA over a 20 year period?
3. How does a coastwide restoration/protection plan affect the distribution and relative abundance of species X versusFWOA overa 50 yearperiod?

CPRA hasdirected the focus of this document on fish modelsthat address levels 2 (coastal basin scale) and 3 (coastwide,) rather than level 1 (individual projects).

The spec ies of interest initially defined by CPRA are juvenile and adult life stages for oysters, brown shrimp, white shrimp, blue crab, and Gulf menhaden, as well as red drum, speckled trout, black drum, Atlantic croaker, sheepshead, striped mullet, bay anchovy, southem flounder, Gulf sturgeon, largemouth bass, sunfishes, and blue catfish. There are a variety of reasons for selecting species to focus on during a nalyses. The reasons behind selecting certain species include: commercial or rec reational importance; ecological importance; controversial relevance; expectations to exhibit large responses; and influenced by relatively expensive restoration actions. Whatever species are selected, it is important to then view these species in life history space of possible species so that it is confimed that the major life history types are represented. Analyses performed on a species-by-species basis can only covera subset of the possible species, and can therefore be criticized if a common life history type is not represented by any of the species modeled (e.g., there is no short-lived planktivore that extensively uses the marsh surface, but yet major responses are expected).

Continuing to try to foc us on the questions the models need to address, one can concentrate on the effects from a subset of the possible project types. The important subset is hydrologic restoration, marsh creation, oyster reefs, and sediment diversion. This is based on the results of the 2012 Coastal Master Plan analysesthat showed that the net changes in total HSl unitswere relatively large forthese project types and small forthe other project types (Table 1). Focusing on a small number of project typesfacilitates the model selection process by smplifying what features are needed in the models. If it is a prionity to assess the effects of bank stabilization on fish, then the models would need to include certain effectsasinputs (e.g., episodic turbidity) and be at a finer spatial scale than many of the other project typesin order to detect effects in the local area of the bank. Otherwise, a ny effects are lost in the averaging over larger spatial scales. By determining a priori that bank stabilization effects in the fish models are not needed, questions are more foc used and this leadsto easier selection of the models
and likely models that are more properly scaled-and therefore assumed to be more accuratefor the important project types like marsh c reation.

Table 1. The net change in total HSI unitsfor brown and white shrimp, oysters, and freshwater and saltwater fisheries per project type (with the number of projects included for each type) from 2012 C oastal Master Plan Modeling.

| Project Type (\# of projects) | Brown <br> Shrimp | Freshwater <br> Fisheries | Oyster | Saltwater <br> Fisheries | White <br> Shrimp |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Bank Sta bilization (5) | -50.4 | 1.6 | 0.3 | -3.1 | -17.1 |
| Ba mier Isla nd Rest. (4) | 70.9 | 0.0 | -88.5 | 0.0 | 0.4 |
| Hydrologic Restoration (15) | -1687.1 | 179.4 | -160.2 | -693.9 | -1339.9 |
| Marsh Creation (23) | 663.3 | -16.4 | -264.7 | 73.0 | -382.9 |
| Oyster Ba mierReef (3) | -97.0 | -229.0 | 11.8 | -0.1 | -203.9 |
| Ridge Restoration (16) | -20.7 | 5.9 | -22.5 | -39.2 | -25.5 |
| Sediment Diversion (11) | -7156.6 | 4608.8 | -3135.6 | -15489.9 | -8869.0 |
| Shoreline Protection (14) | -105.8 | -1.8 | -6.5 | -8.5 | -17.3 |

The term "effects" appears in the questions, and it must be made clearon what is meant by the effects of the projects. With HSI, effects are outputs of the ICM models that can be used to define the quality of the habitat for a life stage of a species. Examples include salinity and percent marsh cover. By going beyond HSI models, the definition of effects becomes more complicated. Outputs of the ICM models must still be used, but now the outputs must relate to the inputs of the fish model. The inputsto the fish model often result in complicated and subtle changes in growth, morta lity, reproduction, and movement rates of the fish that can make it difficult to interpret the effects of the project on a species. Whereas a change in salinity could be directly plugged into the HSI formula, salinity may not even appear as a variable or input in the selected fish model, and if it does, then it is necessary to carefully evaluate whether its use in the model is appropriate forwhat is required to answerthe questions. At some point, and it can be several steps, the change in salinity must affect growth, morta lity, reproduction, or movement. These are the basic rates represented in all of the possible fish models that could be selected.

Finally, there are certain outputs of the fish models that are required, which also helps focus the model selection. CPRA has indicated they are more focused on ensuring consistency in the predicted responses from the models across species than with mechanistic understanding of a particular response. Thus, it is critic al that any use of multiple models generate at least some outputs (e.g., abundance, biomass) that can be compared a cross species, basins, and scenarios. However, knowing that the abundance of speciesincreased in a scenario was due to faster growth or lower mortality is not as important. This also helpsin detemining how to represent the processes of growth, mortality, reproduction, and movement in the models. Less emphasis on mechanistic understanding allowsfor flexibility to use more empirically based relationships for growth, mortality, reproduction, and movement. Knowing that more flooding of the marsh due to an action (e.g., hydrological effect) simply results in fastergrowth is sufficient; it is not necessary to know whether it is due to inc reased total prey biomass ora shift of the prey composition to smaller-sized species that a re easierto capture. The caution is the relationships still need to be able to accurately respond to the range of changes expected in hydrology,
water quality, and habitat, and be related to key effects related to changes in hydrology, water quality, and habitat.

### 4.3 Constraints

Constraints here referto the practical considerations involved with implementing a model, such as monetary budgets, time schedule of when results are needed, and the availability of expertise and computer resources. There are constraints related to the fish modeling for the 2017 C oastal Master Plan that a rise from the schedule for plan development and from practical considerations. Fish model development may begin as soon asJ anuary 2014. Integration with the other master plan models and all model testing and validation needsto be completed by September 2015. Integration of the fish modelswith the other models is expected to begin in summer 2014. The production runs for the 2017 Coastal Master Plan modeling, including fish, are to end by spring 2016, with a 6 -month window for additional runs to be specified by CPRA as needed. All production runs, plus reporting, are proposed to be finished by December 2016.

Constraints from practical considerations fall into three categories of budget, expertise, and computing issues. Model development and a nalyses must not only be done in time for use in the master plan, but also within a defined budget and with the available expertise and staffing levels.

Computing considerationsinclude format and accessto source code, data transfer compatibility with the other models that will provide inputs to the fish models, and computing speed relative to simulations needed for predictions and assessment of uncertainty.

It is necessary that CPRA has ac cess to-and works with-the source code of any selected models. Many details in a model cannot be included aschangeable inputs (e.g., disc rete optionsfor different solution methods; choicesfor the relationship between salinity and fish growth). Even if offered as an input that can be changed, only a few options, of the many possible options, can be offered. This also appliesto outputting. Source code is the only way to have complete control over all aspects of the model, including the innerworkings and how outputs are reported. Only by having access to the source code can the model be modified to improve its a pplicability. Also, the code is really what the model calculates, whereas model documentation can leave out details or become outdated as the code is modified. When experienced modelers really want to know what the model computes, they go to the source code. This also affects a nother constraint in terms of the expertise needed; someone needs to know the programming language and invest some time in leaming the specific model code.

A second computing-related constraint is that any selected model must be able to be coupled to the other ICM models and receive their outputs as inputs. Two dimensions are considered with regard to how two models can be coupled: (1) imbedded or semiautonomous, and (2) two-way or one-way. Imbedded means that the receiving and donor models are solved together at the same time; the receiving model cannot be run separately of the donormodel. Semiautonomous means that the receiving model can be run without renunning the donor model by reusing the previously generated outputs of the donor model. Two-way means that the results of the receiving model can affect the calculations in the donor model at the next time step (e.g., land building affecting hydrodynamics) a nd so information must be passed in both directions. One-way assumesthere is no feedback from the receiving model to the donor model. Thus, the combination of semiautonomous and two-way is not viable (i.e., feedbacks oc cur but are solved separately). The way HSls were calculated in the 2012 C oastal Master Plan would be considered as semiautonomous because ICM models run first, and one-way because HSI results did not affect the ICM results. At a minimum, any selected fish models need to be capable of being used with the ICM models assemiautonomous and one-way.

There are some situations where two-way coupling could be important. For example, chlorophyll is simulated within the ICM model. If the responses of menhaden were simulated in a fish model, then the consumption of phytoplankton by menhaden may be important enough that menhaden consumption must be sent back to the ICM model at each time step in order to get a good solution to chlorophyll for the next time step to go back to the menhaden model. The other components of the ICM model all exchange information in a two-way coupling.

The third computing-related constraint is about computing speed. There are four components to the computing speed constraint: (1) time required persimulation, (2) number of simulations needed, (3) runs needed to formally assess uncertainty, and (4) available computing platforms and power. Components (1) and (2) detemine the minimum computing time needed, while (3) has some flexibility by using different methodsfor assessing uncertainty. Forexample, one can do a Monte Carlo uncertainty a nalysis that requires hundreds of simulations, or fewer, targeted runs as part of sensitivity a nalyses on key species or results. Component (2) is diffic ult to estimate because it also includes runsneeded formodel development, calibration, and validation, plus the set of final production runs. Component (4) would be provided by whoeverisgoing to do the modeling and production runs. At this point, it is emphasized that in the age of high-end computing, computing powershould be a second-order consideration when selecting a model. Of course, proposing a model that-given the availability of computing power-requires months of computing time is also not practical.

## 5. General Approach to Model Selection

### 5.1 Role of J udgment

One challenge is that fish modeling-and ecological modeling in general-is a scientific process that involves the judgment of the modeler. While this is true of all modeling, it is partic ularly apparent with fish and ecologic al modeling. To illustrate, considertwo other modeling disciplines: statistical and hydrodynamics.

Statistical modeling uses data to determine which model is best, based on goodness of fit (i.e., how well the model fits the data). Hilbom (1997) goes further and argues that ecological models should also be decided solely based on the fit to data. While there is some judgment involved with deciding the statistical model type and whethertransformations are needed, the decision as to which model to use is mostly driven by finding the simplest model that fits the data.

Hydrodynamicsmodeling usesa different approach for selecting and configuring a model. All hydrodynamics models solve the same basic set of fundamental physics equations (i.e., conservation of mass and continuity of momentum), but the judgment is how to set up the model grid (i.e., squares vs. triangles, resolution), the solution method, how to deal with subgrid scale processes (e.g., turbulence), and which datasets to use for boundary conditions.

Fish modeling does not have sufficient data to use the statistic al modeling approach of data determining the best model and does not have fundamental equations like hydrodynamics. Thus, decisions about model structure and what to include and exclude in fish models get pushed more towards the judgment of the modeler (i.e., "the art of modeling"). The strong role of the modeler's judgment in fish modeling does not weaken the power and utility of fish modeling, but does make model selection more difficult and a challenge to codify.

### 5.2 Selecting and Developing a Model

The topic of developing or selecting an ecologic al model has been widely disc ussed, usually at a very general level. It is worth summanizing some of these model selection pa pers here because their commonalities give credence that there is a good framework for CPRA to follow in selecting their models. Others have dealt with similar questions about model development and selection that supports the approach that it is suggested for CPRA use.

Wainwright and Mulligan (2004) state that models must have a clearly defined purpose, and that there is no universally accepted typology of models. They use a general classific ation scheme of:

- Conceptual type: empinical, conceptual, physic ally based or mixed
- Integration type: analytic al, numerical or mixed
- Mathematic al type: deteministic or stochastic or mixed
- Spatial type: lumped, semidistributed, distributed, GIS, 2-D, 3-D or mixed
- Temporal type: static, dynamic or mixed

They then define and disc uss stepsto model building: (1) define the problem, (2) space and time boundaries, (3) conceptua lizing the system, (4) model building, i.e., defining numerical algorithms and formalizing forchange (i.e., rates), (5) parameterization, verification, calibration, and validation, (6) sensitivity analysis, and (7) emors and uncertainty. They also provide some sage advice to modeling, which is paraphrased in Table 2.

Espinoza-Tenorio et al. (2012) propose a similar scheme for model building in the context of deciding which model suits ecosystem-based fisheries management. They classify models as: extensions of single-species a ssessment models; dyna mic multispec ies models; dyna mic system model, i.e., bottom-up (physical) and top-down (biological) forces interacting with 10-30 species; and whole ecosystem models. This is the same model classific ation sc heme as proposed by Plaganyi (2007). They specify five majorsteps (Figure 1) that starts with data compilation and then goes to step two, which is a clearstatement of the problem. This is followed by a review of existing approaches, including some issuesthat are considered to be constraints (e.g., cost). Their scheme also emphasizesthe iterative nature of modeling by showing loops back to the objective. Similarschemesfor building modelswere proposed by Fath et al. (2011) (Figure 2) and Jakeman et al. (2006) (Figure 3, with the steps described in Table $3)$.

The question of model selection hasled the Food and Agric ulture Organization (FAO) to offer a general document on best practices for selecting models for ec osystem-based fisheries management (FAO, 2007). FAO also uses the scheme proposed by Plaganyi (2007) to classify models (Figure 4). FAO recommends multiple models and emphasizesthe adage that good modeling should "avoid excessive detail." They list the majorsteps for the development of models forecosystem-based fisheries management. The major step of model scoping involves: (1) define the question to be addressed; (2) list the important potential features and use conceptual models and the following stepsto drill down to necessary components for inclusion in the final model; (3) define scales of each process and component (e.g., spatial, temporal, taxonomic, process resolution, and forcings); and (4) fisheries model resolution. The second and third majorstep after model scoping are model validation and performance evaluation and technical challenges. The FAO guidelines also urge caution in using preexisting packages. FAO states: "The definition of the relevant subsystem and from there the model specification should be achieved following a clear, logical and consistent process." Various statements about best modeling practices from the FAO report are listed in Table 4.

Table 2. Phrasesworth repeating about model selection and strategy from Wainwright and Mulligan (2004).

1. Remember that all models are partial and will never represent the entire system. Models are neverfinished. They always evolve as one's understanding of the system improves (often with thanks to the previous model). In this way all models are wrong (Steman, 2002)! Nevertheless, it is important to draw some clear lines in model development which represent "finished" models which can be tested thoroughly and intensively used.
2. Models are usually built for a specific purpose so be careful of yourself or others using them for purposes other than those originally intended. This issue is particularly relevant where models are given a potentially wide user base through distribution via the Intemet.
3. Do not fall in love with your model (it will not love you back).
4. Do not distort reality or the measurement of reality to fit with the model, however convincing your conceptualization of reality a ppears to be.
5. Reject properly disc redited models, but leam from their mistakes in the development of new ones.
6. Do not extrapolate beyond the region of validity of your model assumptions, however powerful it makes you feel.
7. Keep ever present the distinction between models and reality. The sensitivity of a model to climate change is not the sensitivity of reality to climate change.
8. Be flexible and willing to modify your model asthe need arises. Note that this is "modify" not "expand upon."
9. Keep the objectives ever present by continually asking "What is it that I am trying to do?"
10. Asin all aspects of science, keep the model honest and realistic despite any short-term financial or statusgain that may seem to accrue from doing the opposite.


Figure 1. Figure taken from Espinoza-Tenorio et al. (2012) to show modeling process in their review of models for ec osystem-based fisheries management.


Figure 2. Flow diagram describing model building strategy taken from Fath et al. (2011).


Figure 3. Schematic describing model building strategy taken from J a keman et al. (2006).

Table 3. Explanation for the steps of building models taken from Jakeman et al. (2006) in Figure 3 of this report.

| Steps | Description |
| :---: | :---: |
| Define model purpose | It is a truism that the reasons formodeling should have a large influence on the selection of a model fa mily or families |
| Specify modeling context | This sec ond step identifies: <br> - the specific questionsand issues that the model isto address; <br> - the interest groups, including the clients or end-users of the model; <br> - the outputs required; <br> - the forcing variables (drivers); <br> - the accuracy expected or hoped for, <br> - temporal and spatial scope, scale and resolution; <br> - the timeframe to complete the model; <br> - the effort and resourc es available for modeling and operating the model; <br> - flexibility; for example, can the model be quickly reconfigured to explore a new scenario proposed by a management group. |
| Conceptualize system, specify data and other priorknowledge | It might employ aids to thinking such as an influence diagram, linguistic model, block diagram or bond graph. The conceptualization step is important even if a model is not designed from scratch because time and money-aswell as the clients' beliefs-restrict one to using a "c anned" model. Conceptualization exposes the weaknesses of the canned approach and perhaps ways to mitigate them. This third step defines the data, prior knowledge and assumptions about processes, the degree of aggregation and the spatio-temporal resolution (intervals and accuracy) of the outputs also have to be chosen. |

Select model features: nature, family, form of uncertainty specific ation

Detemine how model structure and parametervalues are to be found

Any modeling approach requires selection of model features, which must conform with the system and data specification a mived at above. Major features such as the types of variables covered and the nature of their treatment (e.g.
white/black/grey box, lumped/distributed, linear/nonlinear, stochastic/deterministic) place the model in a partic ular family or families. Model structure specifies the links between system components and processes.

In finding the structure, prior science-based theoretic al knowledge might be enough to suggest the form of the relations between the variables in the model. Shortage of records from a system may prevent empinical modeling from scratch and force reliance on scientific knowledge of the underlying processes. Choice of structure is made easier by such knowledge, and it is reassuring to feel that the model incomorates what is known scientific ally about the parts of the system. However, empirical studies frequently find that a much simplerstructure is adequate for a specified pupose.
(Table $\mathbf{3}$ continued)

| Steps | Description |
| :---: | :---: |
| Choose estimation/performance criteria and algorithm | Well-exec uted general-purpose parameter estimation (identification) packages and more specialized packages for hydrological and other uses have now been available for many years. They may not be able to handle complex, integrated models with specia lized structures. |
| Identify model structure and parametervalues | This combines the previous two steps and uses an iterative process of finding a suitable model structure and parameter values. |
| Verification including diagnostic testing | Once identified, the model must be "conditionally" verified and tested to ensure it is sufficiently robust, i.e., insensitive to possible, but practically insignificant, changes in the data and to possible deviations of the data and system from the idea lizing a ssumptions made (e.g., of Gaussian distribution of measurement emors, or of linearity of a relation within the model). It is also necessary to verify that the interactionsand outcomes of the model are feasible and defensible, given the objectives and the prior knowledge. Of course, this eighth step should involve aswide a range of quantitative and qualita tive criteria as circumstances allow. |
| Quantific ation of uncertainty | Uncertainty must be considered in developing any model, but is particularly important-a nd usually difficult to deal with-in large, integrated models |
| Model evaluation or testing | Finally, the model must be evaluated in the light of its objectives. For simpler, disciplinary models, a traditional scientific attitude can be taken towards "validation" (nonfalsific ation or provisional confimation, strictly). That is, confimation is considered to be demonstrated by evaluating model performance against data not used to construct the model. However, this style or level of confirmation is rarely possible (or perhaps even appropriate) for large, integrated models, especially when they have to extrapolate beyond the situation forwhich they were calibrated. If so, the criteria have to be fitness for purpose and transparency of the process by which the model is produced, rather than consistency with all available knowledge. |



Figure 4. Model classific ation scheme taken from Plaganyi (2007).

Table 4. Statements collected from the 2007 FAO Report on best modeling practices.

| Ecological-related attributes | Best Practice <br> Model <br> aggregation | When developing conceptual models, err towa rds a finely <br> resolved ta xonomic resolution. Once model development <br> progresses to strategic ortactical model uses, it is important to <br> aggregate based on shared characteristic sof the species and <br> resolution <br> to omit the least important if the food web is becoming large |
| :--- | :--- | :--- |
| and unwieldy. |  |  |

(Table 4 continued)

| Ecologic al-re | ted attributes | Best Practice |
| :---: | :---: | :---: |
| Model components | Movement | Commentary: Incomorating movement into a model can fall into one of two categories. Immigration into the model domain can be dealt with failly simply and straightforwardly, such as by using an empinic al formulation based on data from surrounding areas. In some instances, movement of species or other ecosystem components into a model domain can also be represented by using simple forcing functions. On the other hand, representing movement explicitly within a model is a challenging topic with several altemative methods for consideration, such as whether to assume movement is density dependent or habitat dependent. This includes testing sensitivity to a range of movement hypotheses, and where possible, parameterizing movement matrices by fitting to data. If decision rules are used to drive movement, attention should be focused on whether the resultant changes in distribution are sensible. As with other complicated model features, best practice involves including only as much detail asnecessary. |
| Modeling predatorprey interaction | Predator-prey bidirectional feedback | Predator-prey interactions should be represented in models as bidirectional unless sufficiently strong motivation can be provided that it is a dequate to include a one-way interaction only. Bidirectional interactions are desirable at the strategic level, but may not be relevant at the tactical level if the associated interaction strengths are low. |
| Modeling predatorprey interaction | Predator-prey functional relationships | Acknowledge the paramount importance of the appropriate form for functional responses (the prey-predatorinteraction terms) and feeding selectivities and suita bilities, and test sensitivity and robustness to altemative forms. |
| Extemal forcing | Environmental forcing | Carefully considerwhether environmental forcing is required to capture system dynamics. Care must be exercised in selecting the basisto generate future forcing for use in predictions and closed loop simulations. |
| Extemal forcing | Otherprocess error (i.e., random variation) | Other process error-a rising from natural variation in model parameters-needs to be included in projections, whether they be strategic ortactic al, when that variation contributes substantially to uncertainty in model outcomes. |
| Extemal forcing | Other anthropogeni c forcing | Other anthropogenic pressures on marine ecosystems include all the major nonfisheries anthropogenic influences such as pollution, large scale changes in freshwaterflow or water properties, and habitat degradation. Anthropogenic forcing on shallow coastal and estuarine systems should be considered in conceptual models and if found to lead to appreciable pressures on the system, then thisforcing should be included empincally (e.g., simply asa forcing tem) in any strategic models and management strategy evaluations for the system. |

(Table 4 continued)

| Ecological-re | ted attributes | Best Practice |
| :---: | :---: | :---: |
| Model structure | Potential for altemative stable states | Include consideration of models, especially strategic models forec asting the consequences of environmental change, which contain the capacity (e.g., flexibility in choice of functional relations) that allow for pla usible phase shifts, either directly (in accordance with past observations) orasan emergent property of the functions of the model. Even if such a functional form is used, it must be recognized that, until a threshold is crossed by the system, it may not be possible to parameterize the threshold point. Given such uncertainty, possible thresholds may need to be evaluated on either a theoretical or an empinical basis. |
| Model structure | Nontrophic interactions | If conceptual system understanding indic ates that a nontrophic interaction is a critical determinant of the dynamic of interest (e.g., biomass or abundance of a target group), or if management could be based around this interaction, then its inclusion is highly desirable. |
| Dealing with uncertainty | Ability to fit to data | Fitting to data is best practice, and this requires careful specification of likelihoods. |
| Dealing with uncertainty | Parameter uncertainty | Best practice requires explicit evaluation of the effects of uncertainties in model parameters for management advice. Bayesian methods and bootstrapping are considered best practice for quantifying parameter uncertainties in extended single-species models and Minimum Realistic Models (MRMs). Best practice for quantifying parameter uncertainties in more complex ecosystem models is curently not clear. At a minimum, improving current practic es requires: (1) that there is an explicit accounting of the number of parameters that are being estimated and the numberfixed, (2) qualitative estimates of the uncertainty in every parameter, and (3) sensitivity analyses. Best practices formass-balance/static models are to develop and fully document a formal data "pedigree" (or quality ranking), and if possible, inc lude emor ranges for estimates, with input from data providersasto potential biases. Further, sensitivity analyses may be conducted using available routines. Fordynamic models, best practice is to fit to asmuch data as possible using appropriate likelihood structures, while being clearabout both potential biases a rising from fixing parameters, as well asfully reporting emor ranges resulting from freeing parameters. In the case of fixing parameters, additional sensitivity a nalyses (e.g., resampling, Monte Carlo routines) should be used to assess model sensitivity to the assumptions. An important component of best practice is using results of sensitivity a nalyses to guide future data collections and the continuation of key time series. |
| Dealing with uncertainty | Model structure unc ertainty | Consideration of model structure uncertainty involves first identifying altemative qualitative hypotheses for all of the processes considered likely to have an important impact on the model outputs, formulating these hypotheses mathematically (or as the values of parameters of a general relationship), and then assigning weightsto each hypothesis. |

(Table 4 continued)

| Ecological-related atributes | Best Practice |  |
| :--- | :--- | :--- |
| Dealing with | Ease of | Object-oriented design in the programming of ecosystem |
| uncertainty | modularization |  |
| models. |  |  |

The general approach described by FAO isfollowed in this document. FAO says that the first steps are to compile an inventory of the ecosystem components and identify the research activities, then manage activities, agencies, and stakeholders. Issues and questionswould then be determined, and a conceptual model constructed based on the ecosystem structure and the issues identified. Then, one consults the library of ecosystem models, identifies several appropriate analogues and from them, developsa model or modelsthat are relevant to the management issues.

The U.S. Amy Corps of Engineers (USACE) has also put forth a guide for using ecological modeling for ecosystem restoration (Swannack et al., 2012). They categorize models as: analytic al (e.g., Lotka-Volterra), conceptual, index (e.g., HSI), simulation (e.g., CASM), statistic al, and spatial (e.g., Geographical Information Systems [GIS]). As part of model selection, they describe two issues: ensuring the model selection aligns with the problemsto be addressed, and whetherto develop a new model orto use an existing model. Once a specific problem has been identified and both the planning and modeling objectives have been clearly defined, the basic approach is asfollows: (1) develop a conceptual model identifying the specific causeeffect relationships a mong important components of the system of interest, (2) quantify these relationships based on a nalysis of the best information possible, which can include scientific data or expert opinion, (3) evaluate the information yielded by the model in terms of its ability to provide information that describesoremulates system behavior, (4) a pply the model to address questions regarding the effects of partic ular project altematives, and (5) perform periodic posta udits of model applic ations to manage confidence in the model. They further state that "model development iterates through a series of intermediate developmental phases (each a more mature form of its predecessor and sometimes halting further development because information needs are found to have been met)."

When developing conceptual models astemplates (Step 1) for quantitative models, USACE guidance states that sixgeneral steps should be followed: (1) precisely define objectives and criteria for evaluation, (2) bound the system of interest, (3) represent the conceptual model, (4) describe the expected pattems of model behavior, (5) identify data quality and quantity, and (6) identify context for model use.

The USACE guidance expands on quantitative model development (Step 2) by suggesting five steps: (1) linking to the conceptual model, (2) selecting the general quantitative structure, time
unit, and spatial scale for the model, (3) identifying functional forms of model equations, (4) estimating the parameters of the model equations, and (5) executing the baseline model.

Model evaluation (Step 3) in the USACE scheme is to detemine if the model is acceptable for its intended use, and isdependent on calibration, verific ation, and validation. Step 4 is a pplic ation and involves three sequential activities: (1) define project altematives, (2) apply the model to altematives and a future-without-project altemative and to any altemative scenarios, and (3) a nalyze and interpret results.

Recently, Schmolke et al. (2010) discussed ecological models supporting environmental decision making. They summarized from the literature the elements of good modeling practice (Table 5). This shows again that there is general agreement of the stepsinvolved in good model development, selection, and application. They go on to discuss why good modeling practice is generally not used, even if the resulting models are excellent. These reasons are: lack of involvement of decision makers and stakeholders in model development; lack of incentives for modelers to invest the effort; and lack of coherent teminology. They propose an approach for documenting model development, testing and analysis, and application to aid in communication they call the TRACE (Transparent and Comprehensive Ecologic al Model) documentation (Figure 5 and 6). They say that TRACE documentation (with the associated bookkeeping in modeling notebooks) will ensure that models are not perceived as black boxes, can be easily reviewed, can be easily evaluated for theirrelevance to answer the questions, and can be assessed by decision makers and other stakeholders. TRACE is for effective documentation, but does not say how to implement best modeling practices.

Borrett et al. (2008) went further and developed software (Prometheus) that indic ates how to build process models. The software is designed to support model building from conceptual development to evaluation, use, and publication. The software has six features: (1) provides an interactive way for a user to add and edit generic processesto a domain library, (2) allows for manual construction of models from a domain library in an interactive and graphic environment, (3) allowsfor easy comparison a mong altemative models through side-by-side solution and presentation of results, (4) can automatic ally search through candidate models derived from a library and retum a reduced set of the models that best match the observed data, (5) processes can be deleted or parametervalueschanged interactively, and (6) generates graphical representations of the model structure. These are features that would likely be undertaken asthe model is specified, but they would usually be done manually. This software is probably not a good idea forthe master plan modeling, but the list of features is useful.

Table 5. Table taken from Schmolke et al. (2010) identifying elements of good modeling practices.

| Element | Description |
| :--- | :--- |
| Inclusion of stakeholders | Ongoing communic ation between stakeholders and <br> modelers during model building, a critic al factor for the <br> success or failure of modeling projects. <br> Definition of objectives at the outset of a modeling <br> project, that includes the a ssessment of the actual <br> management issue, key variables and processes, data <br> availability, kind of outputs required, and how they will <br> inform decisions. |
| Formulation of objectives | Formalization of the assumptions a bout the system and <br> preliminary understanding of its intemal organization and <br> operation. <br> Identification of the most appropriate modeling approach <br> in the context of the goal of the modeling project. |
| Conceptual modelDetemination of the optimal complexity level forthe <br> problem at hand. <br> Application of multiple modelsto the same problem, <br> which can decrease the uncertainty about the <br> appropriate model approach and main a ssumptions. |  |
| Choice of model approach of model complexity |  |
| Detemination of model parameters from empinical data |  |
| orby means of calibration of the model outputson the |  |
| basis of data. |  |



Figure 5. The TRACE doc umentation procedure taken from Schmolke et al. (2010).

## 1 MODEL DEVELOPMENT

1.1 Problem formulation: Context in which the model will be used, and the type of audience addressed; specification of the question(s) that should be answered with the model; statement of the domain of applicability of the model, including the extent of acceptable extrapolations; assessment of the availability of knowledge and data; specification of necessary model outputs.
1.2 Design and formulation: Description of the conceptual model; description and justification of the modeling approach used and of the complexity; entities and processes represented in the model; most important, the applied assumptions about the system.
1.3 Model description: Detailed description of the actual model, and how it has been implemented (programs, software platforms, scripts).
1.4 Parameterization: List of all parameter values used in the model, the data sources, and how the parameter values were obtained or calculated; uncertainties associated with each parameter.
1.5 Calibration: Documentation of the data sets used for calibration; which parameters were calibrated; what optimization method was used.

## 2 MODEL TESTING AND ANALYSIS

2.1 Verification: Assessment of whether the model is working according to its specifications; documentation of what tests have been conducted.
2.2 Sensitivity analysis: Exploration of the model behavior for varying parameters; documentation of which parameter combinations have been tested; justification of used parameter ranges and combinations.
2.3 Validation: Comparison of model or submodel outputs with empirical data that were not used for parameterization or calibration; documentation of data sources; what parts (submodels) have been validated; what validation methods were applied.

## 3 MODEL APPLICATION

3.1 Results: Outputs that are used to inform decisions; description of simulation experiments (scenarios) conducted; statistics applied to analyze model outputs.
3.2 Uncertainty analysis: Uncertainties in model outputs used for recommendations; description of variance, noise, and bias in empirical data; determination of stochasticity in the model; description of model uncertainty which can be assessed through application of different models or submodels; best- and worst-case scenarios.
3.3 Recommendation: Description of how initial question(s) could be answered; summary of conclusions drawn from model; clarification of extrapolations used (in time and space).

Figure 6. The TRACE doc umentation procedure described in Schmolke et al. 2010.

### 5.3 The Approach

Whatever the specific scheme, there are always five components that must be undertaken: (1) define the question, (2) organize and assess the data, (3) develop conceptual models, (4) develop a library of existing models, and (5) specify model and evaluate. These steps are sometimes presented assingle stepsin some schemesand are broken down in multiple, sequential stepsin other schemes. Regardless of the details of the scheme, these steps are present in almost all proposed strategies and must be done with any plan CPRA uses.

The step of defining the question is relatively complete. Relevant data sources are summarized in Section 7 and include one of the major sources of model inputs (i.e., the ICM model outputs) and the major monitoring sources (LDWF) and (SEAMAP). Also provided is an outline of how to obtain additional sourc es of data, such asprocess studies, a nd options for presenting the information in the form of life cycles, space-time plots, and life tables. Development of a conceptual model will require a team of experts, although key concepts of configuring a conceptual model are discussed in Section 6 and AppendixA. Finally, Section 8 summarizes the initial library of existing models.

This leavesthe final of the five major stepsin all schemes: model specification and evaluation. Specification involves creating equations that simulate the growth, mortality, reproduction, and movement of the species of interest that matchesthe conceptual model. Model evaluation includes the subsequent steps of calibration, verific ation, validation, and use in scenario a nalyses. At thistime an approach is offered formodel specific ation and evaluation and some examples of the types of models predicted to emerge. But to use best modeling practices requires that some of the earlier steps must be performed before determining the model specific ation, astheir results affect model selection. A critical step not yet completed for the 2017 C oastal Master Plan is the fina lization a conceptual model to use as a benchmark against the existing models. The basis for a conceptual model already exists (e.g., those developed under the CLEAR (Coastal Louisiana Ecosystem Assessment and Restoration) program, numeric al models for the Mississippi River Gulf Outlet Restoration study) and fina lizing a conceptual model can be done relatively easily.

Once candidate models are identified, then the technic al constraintswould be applied. It is very important that the constraints are imposed after the five steps are complete. In this manner, one can keep track of how the constraints influenced model selection. If the constraints change in the future, it is easy and tractable to go back and see if other models deemed appropriate but impractical before are now practical.

The fundamental challenge is how to select a model, which will involve some modific ations in orderto be used. AppendixA includes 13 guiding principles or concepts that should be used to develop a common view of what is needed and to evaluate the existing models for overlap and completeness.

### 6.0 Concepts for Selecting an Appropriate Conceptual and Numerical Model

A set of concepts have been identified that should be considered asone selects or develops a fish model. These concepts are: (1) life cyclesand strategies, (2) va riability, uncertainty, and stoc ha sticity, (3) genera lity-precision-rea lism, (4) nonequilibrium theory, sta bility, and rec ruitment,(5) scaling, (6) explicit versus implic it representation,(7) population definition, (8)
density dependence, (9) verification, calibration, and validation, (10) sensitivity and uncertainty analysis, (11) multiple modeling strategies, (12) food web dynamics, and (13) hidden assumptions and domain of applic ability. Each of these concepts is described in more detail in AppendixA.

Basically, applic ation of these concepts, combined with a detailed conceptual model of how fish are influenced by restoration or other system changes and the specific questionsand data availability, lead to the specification of an appropriate numerical model. The concepts act as a type of checklist as one selects and developsa model. Available models can then be evaluated to determine how well they capture the concepts, questions, and data, and also identify what can be simplified and what needs to be modified oradded.

The credibility of the models with other scientists, decision makers, and the public depends on how well and transparently these concepts are dealt with during development of the conceptual and numeric al models. All of the fish modeling approaches generate what appear to be abundances and biomasses of species overtime and into the future. Care must be taken to ensure that the expectations of these models by others are realistic in terms of the uncertainties and interpretations of model predictions. Model results are better interpreted in a comparative mode and forlarge responses and trends, rather than used for specific predictions of biomasses in certain loc ations and in specific years.

### 7.0 Data: Available Inputs to Fish Models

### 7.1 Types of Data

Model inputs can be categorized as parametervalues, environmental driving variables, and initial and boundary conditions. Model outputs are state variablesovertime (a nd potentially overspace), and intemediate output variables such as averaged process rates (e.g., growth rates), and information about flows among state variables (e.g., budgets, diets). Sources of data for specifying inputs and checking outputs can be the outputs of other models, field monitoring data, and field process studies and lab results.

### 7.2 ICM Model Outputs

Fish models included in the 2017 Coastal Master Plan will use as inputs the outputs of the ICM framework. This data source is critic al bec ause it includes some of the effects of the proposed restoration and protection actions: water quality, hydrology, and physic al habitat. Use of output from other models as inputs to the fish models createsissues about unc ertainty; the outputs are often treated as deteministic values (no variance,) a nd often the variance is unknown. It is also important to note that ICM outputs do not include predictions of changes in certa in potentially important biota, such as fish predators. Thus, inclusion of indirect responses of the fish must be investigated as part of the fish modeling.

The ICM framework has at least three componentsthat would provide inputs to the fish models: ecohydrology, wetla nd momhology, and vegetation subroutines (Figure 7). A bamierisand change subroutine within the ICM may also provide inputs to the fish models. The ICM will be run to simulate the master plan effects versus future without action. The finest temporal and spatial resolution of the available outputs from the ICM (Table 6) is important, as the outputs can easily be averaged to obtain values over longer temporal and coarser spatial scales if that is more appropriate for the fish models. Spatial resolution and scaling is partic ularly important when linking fish models with physical and water quality models (Rose et al., 2010) or to structural
habitat (Peterson, 2003) because movement iscomplexand differentially determined for speciesthat differentially respond to physical-chemic al conditions and habitat types. In orderto provide an idea of ICM outputs available to the fish modeling, the 2012 a nalyses is described, with some updating to what the 2017 a nalyses potentially will be. There is also an opportunity for a djustments to the 2017 ICM a nalysesto generate output on certain time and space scalesfor the fish modeling, or possibly generating additional outputsto use as inputs to the fish modeling that were not generated in the 2012 analysis.

Temperature, Salinity, Depth, Water quality variables, ChI, Detritus


Figure 7. Subroutines of the ICM that may provide inputsto the fish model/sfor the 2017 Coastal Master Plan. The variables exc hanged a mong the ecohydrology model, wetland mophology model, and vegetation model from the 2012 Coastal Master Plan are also listed.

The ecohydrology modeling domains (Figure 8) in the 2012 a nalysis were divided among three regions of the Louisiana coast: Pontchartrain-Barataria Basin (PB), Atchafalaya Basin-Terrebonne (AA), and Chenier Plain (CP) (Meselhe et al., 2013). Note that these model domainsinclude both the basins that are the subject of the model and surrounding areaswhich are included in the domain to ensure appropriate boundary conditions are generated. The two-dimensional mass-balance, link-node ecohydrology model simulated several hydrologic and chemical state variables using the Euler method with a 43 -sec ond (CP and AA) and 60-second (PB) time steps over 50 years (2010-2060, LA CPRA 2012). The smallest unit of time for modeling fish vital rates would be a daily ( 24 -hour for a full day, 12 -hour for daylight hours) time step. Daily averaged outputs from the 144060 -sec ond time steps or the 200343 -sec ond time steps of the ecohydrology models would serve as the averaged 24 -hour inputs to drive the vital rates of the fish models. The outputs a vailable from the ecohydrology model in the 2012 a nalysis are listed in Table 6. All variables from the ecohydrology model changed with respect to time but were uniform in space within the compartment (Meselhe et al., 2013).

In the 2012 analysis, the number and spatial resolution of the compartments within each ecohydrology model domain varied. The 2012 PB ecohydrology model had 89 compartments (Figure 9), the AA model had 169 compartments (Figure 10), and the CP model had 157 compartments (Figure 11). For 2017, the compartments are expected to be smallerand generally of the order of $5 \mathrm{~km}^{2}$ within wetland dominated parts of the estuary.

The boundary conditions to the ecohydrology modelswere riverine flows, distributary and diversion flows, atmospheric inputs, a nd runoff discharges. Forthe 2012 plan, mean elevation and percent of land of the ecohydrology spatial boxeswas calculated every five years by the wetland mophology model. Whether a cell wasland orwaterat $30 \mathrm{~m} \times 30 \mathrm{~m}$ spatial resolution and the elevation of that cell was detemined. The elevation wasaveraged, and the land and water cells were summed forthe proportion of land, foreach encompassing spatial box of the ecohydrology models. This information was provided at the start of the model runs and updated within the ecohydrology model at year 25 of a 50 -year run.

The fixed grid wetland mophology model (Couvillion et al., 2013) ran on an annual time step over 50 years (2010-2060, LA CPRA 2012) and predicted changes in wetland morphology resulting from changing environmental conditions (e.g., eustatic sea-level nise [ESLR], land subsidence, freshwater and mineral sediment supply reductions). The model determined the coastal wetland surface elevation (m NAVD 88), coastwide land and water area ( $\mathrm{km}^{2}$ ) and landscape configuration (percent land, percent water, and percent edge). Outputsgenerated from the wetland morphology model in the 2012 analysis are listed in Table 6. All variablesfrom the wetland momhology model changed with respect to time but were uniform in the grid cells. The spatial resolution was $30 \mathrm{~m} \times 30 \mathrm{~m}$ and each cell was either land or water with a single elevation at each year. Land configuration (percent land and percent edge) wasestimated at the $500 \mathrm{~m}^{2}$ resolution (Figure 12) for the other master plan models (Figure 7). Outputs for percent land and water, percent edge, and elevation could be used as inputs to the fish modelsfor the 2017 C oastal Master Plan.

The wetland mophology model used salinity, water level (stage) and sediment accumulation outputs generated from the ecohydrology model, and plant community distribution generated from the vegetation model, as its inputs (Figure 7). These inputs were rasterized to provide inputs for each $30 \mathrm{~m}^{2}$ cell of the wetla nd morphology model (Couvillion et al., 2013). Daily water stage from the ecohydrology model boxes were used to define the maximum water levels and the total a mount of time each $30 \mathrm{~m}^{2}$ cell was inundated for the year (Couvillion, pers. comm.), and sediment loads were used to compute the elevations of the cells (Couvillion et al., 2013). Forthe 2012 a nalysis, plant community composition for each of the $500 \mathrm{~m}^{2}$ cells in the vegetation model at year 25 was rasterized to update the component $30 \mathrm{~m}^{2}$ cells of the wetland morphology model to upland, forest, swa mp, fresh, brackish, intermediate, or saline marsh vegetation (Couvillion, pers. comm.).

The fixed grid wetland vegetation model (Visser et al., 2013) projected the annual vegetation composition (1 Submerged Aquatic Vegetation [SAV], 19 Emergent Aquatic Vegetation [EAV] types) at $500 \mathrm{~m}^{2}$ resolution (Table 6). Annual SAV cover within a $500 \mathrm{~m}^{2}$ cell was related to the area of water in the cell, water depth, salinity, and watertemperature. The 19 EAV types had species-specific tolerances defined for water level variation and average salinity so that their respective a nnual cover within each $500 \mathrm{~m}^{2}$ cell was determined by the annual water level variation and average annual salinity for the cell. These inputs (e.g., stage, salinity, a nd temperature) came from the ecohydrology model, including daily stage to detemine annual water level variation and the total amount of time cellswere wet and dry for the year (Couvillion, pers. comm.). The a vailable outputs for the vegetation model from the 2012 analysis are listed in Table 6. Annual SAV and EAV cover, and wetland vegetation types within the 500 $\mathrm{m}^{2}$ cells from the vegetation model (Figure 13) could provide inputsfor structural habitat in the fish and shellfish model/s.

Table 6. The 2012 Coastal Master Plan compartment models and their generated outputs. The possible temporal and spatial resolution of outputs available for each model output is listed. 2012 HSl models are listed that used the averaged sea sonal and/or annual inputs from the other master plan models (e.g., monthly salinity at $0.25 \mathrm{~km}^{2}$ resolution) where OYS = Ea stem oysters; SHR (BSH and WSH) = independent brown and white shrimp models; SST = spotted seatrout; BAS = largemouth bass HSI models.

| 2012 Master Plan Model | Available Outputs ${ }^{2}$ (units) | Finest <br> Possible <br> Temporal Resolution ${ }^{3}$ | Spatial Resolution in 2012 Models ${ }^{4}$ | 2012 <br> Smulation Period | 2012 HSI Inputs: temporal and (spatial) resolution |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Ecohydrology model | Stage (m) | Daily | 0.04-5800 | 2010-2060 |  |
|  | Depth (m) | Daily | km ${ }^{2}$ |  |  |
|  | TSS (mg/L) | Daily |  |  |  |
|  | Accretion( $\mathrm{g} / \mathrm{m}^{2}$ ) | Annual |  |  |  |
|  | Salinity (ppt) | Daily |  |  | OYS: monthly ( $0.25 \mathrm{~km}^{2}$ ) |
|  |  |  |  |  | SHR: monthly ( $0.25 \mathrm{~km}^{2}$ ) |
|  |  |  |  |  | SST: monthly ( $0.25 \mathrm{~km}^{2}$ ) |
|  |  |  |  |  | BAS: monthly (0.25 km²) |
|  | Tidal Range(m) | Daily |  |  |  |
|  | Total $\mathrm{N}(\mathrm{mg} / \mathrm{L})$ | Daily |  |  |  |
|  | Temp ( ${ }^{\circ} \mathrm{C}$ ) | Daily |  |  | SHR: monthly ( $0.25 \mathrm{~km}^{2}$ ) |
|  |  |  |  |  | SST: monthly ( $0.25 \mathrm{~km}^{2}$ ) BAS: monthly ( $0.25 \mathrm{~km}^{2}$ ) |
|  | $\mathrm{NO}_{3}+\mathrm{NO}_{2}(\mathrm{mg} / \mathrm{L})$ | Daily |  |  |  |
|  | $\mathrm{NH}_{4}(\mathrm{mg} / \mathrm{L})$ | Daily |  |  |  |
|  | DON (mg/L) | Daily |  |  |  |
|  | Total P (mg/L) | Daily |  |  |  |
|  | Soluble P (mg/L) | Daily |  |  |  |
|  | Chl-a ( $\mu \mathrm{g} / \mathrm{L}$ ) | Daily |  |  |  |
|  | Detritus (mg/L) | Daily |  |  |  |
|  | $\mathrm{K}\left(\mathrm{m}^{-1}\right)$ | Daily |  |  | BAS: monthly (0.25 km²) |
|  | WaterAge (days) | Monthly |  |  |  |
|  | NRM ( $\mathrm{g} / \mathrm{m}^{2}$ ) | Annual |  |  |  |

[^1](Table 6 c ontinued)

| 2012 Master Plan Model | Available Outputs (units) | Finest <br> Possible Temporal Resolution | Spatial Resolution in 2012 Models | 2012 <br> Simulation Period | 2012 HSI Inputs: temporal and (spatial) resolution |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Wetland morphology model | Total land and waterarea ( $\mathrm{km}^{2}$ ) | Annual | $30 \mathrm{~m} \times 30 \mathrm{~m}$ land or watercells | 2010-2060 |  |
|  | \% Land, \%Water | Annual | $500 \times 500 \mathrm{~m}$ |  | OYS: 5 yrs ( $0.25 \mathrm{~km}^{2}$ ) <br> BSH: 5 yrs ( $0.25 \mathrm{~km}^{2}$ ) <br> BAS: 5 yrs ( $0.25 \mathrm{~km}^{2}$ ) <br> SST: 5 yrs ( $0.25 \mathrm{~km}^{2}$ ) <br> WSH: 5 yrs ( $0.25 \mathrm{~km}^{2}$ ) |
|  | \% Patch edge | Annual | $500 \times 500 \mathrm{~m}$ |  |  |
|  | Accretion Rate (cm/yr) | Annual | $30 \mathrm{~m} \times 30 \mathrm{~m}$ |  |  |
|  | Elevation (m) | Annual | $30 \mathrm{~m} \times 30 \mathrm{~m}$ |  |  |
|  | Soil OC storage ( $\mathrm{tC} / 0.25 \mathrm{~m}^{2}$ in upper 1 m ) | Annual | $500 \times 500 \mathrm{~m}$ |  |  |
|  | Soil OC sequestration potential (tC/ha/yr) | Annual | Hectares |  |  |
| Vegetation model | Vegetation composition - 19 EAV and 1 SAV | Annual | $500 \times 500 \mathrm{~m}$ | 2010-2060 | SHR, SST: \% marsh vegetation ( $0.25 \mathrm{~km}^{2}$ ) BAS: \% EAV; \%SAV ( $0.25 \mathrm{~km}^{2}$ ) |



Figure 8. Louisiana coastal modeling domains covering Pontchartrain and Barataria (red), Atchafalaya-Terrebonne (blue) and Chenier Plain (yellow).


Figure 9. The Pontchartrain and Barataria Basin ecohydrology model domain from 2012 analysis.


Figure 10. The Atchafalaya Basin ecohydrology model domain from 2012 analysis.


Figure 11. The Chenier Plain ecohydrology model domain from 2012 a nalysis.


Figure 12. Example of outputs for percent la nd ( $500 \mathrm{~m}^{2}$ resolution) ac ross Pontc hartrain and Barataria Basins using EverVIEW; left (upper) panel showsland percentage without restoration action and with Mid-Barataria Sediment Diversion (lower); right panel shows the difference in percent land between upper and lower panels (taken from Couvillion et al., 2013)


Figure 13. Distribution of the thin mat vegetation type after a 50 -year simulation forthe entire Louisiana coastline. Each pixel in the image represents a $0.25 \mathrm{~km}^{2}\left(500 \mathrm{~m}^{2}\right)$. Each pixel iscolored according to fraction of the area covered by the thin mat vegetation type. Areaswith no cover by thin mat are colored grey (figure taken from Visser et al., 2013)

### 7.3 Field Data

There are two major long-term fish monitoring programs: LDWF and SEAMAP. Both programs span multiple decades and many sampling stations. Basic fish sampling variables are measured, such asCatch Per Unit Effort (CPUE), sample biomass, length subsampled within samples, as well as aging and fecundity in some cases. The bDWF monitoring and special project programsare briefly summa rized in Table 7, and an example showing DWF fisheries-independent sampling stations for a single coastal study area (CSA, total of 7 CSAs across Louisiana) is shown in Figure 14. The NOAA NMFS, SEAMAP started in 1981 for the Gulf. SEAMAP stations are located at depth stratums on the shelf (Gulf States Fisheries Management Council [GSFMC], 2011), a nd stations are randomly selected for sampling in proportion to the shrimp management zones (Figures 15 and 16). SEAMAP conducts winter, spring, a nd fall surveys for selected fish species (WI: grouper and tilefish; SP: Bluefin tuna; FA: fall spawning fishes such as mackerel, snapper, drum). Plankton samples are collected for enumerating and identifying fish eggs and larvae, invertebrates, and zooplankton. Additionally, 42 -foot semiballoon trawl samples are conducted during the summer and fall to enumerate the catch and sizes of groundfish, shrimp, and other invertebrates. Water chemistry variables and chlorophyll-a concentrations are collected at the sampling stations during the sea sonal trips using CTD casts in order to estimate primary production along the shelf.

Both LDWF and SEAMAP datasets have been used previously to form long-tem abundance indices for a nalyses of inshore and offshore fishery populations (Thomas, 1999; Switzer et al,. 2009; de Mutsert \& Cowan, 2012; Sable \&Villamubia, 2011a, b) and for stock assessments (West et al., 2011). Both datasets have recently undergone even more extensive evaluation, updating, and error checking as part of a nalyses for the Deepwater Horizon oil spill so clean datasets should be available. Abundance indicescustomized forthe fish modeling can be developed. These indices are referred to asthey relate to abundances without unknown scalars. The LDWF and SEAMAP data were collected for other puposesthan as a basis forvalidation of fish and food web models. The use of these data for model evaluation should be done with caution and with the collaboration of those who are intimately familiarwith the data collection methodsto ensure the data are properly interpreted. Any derived indic es are useful fortrendsbut require major assumptions on gear efficiency (Rozas \& Minello, 1997) and extensive extrapolation to estimate population-level abundances or biomass (Minello et al., 2008).

Table 7. Brief summary of the marine and inland fishery independent monitoring (FIM) programs conducted by DWF, with mention of some other long-term special projects and sampling studies (LDWF 2000, 2002) that could provide data forfish models.

| Program | Description of IDWF Project |  |
| :---: | :---: | :---: |
| Marine FIM | Ground fish tra wl survey for shrimp, crabs, groundfish since 1966 | - 16 ft otter trawls monthly a nd then bimonthly from March-October in deeperinshore waters |
|  |  | - 6 ft balloon trawlsweekly from March-August in shallower inshore waters used primarily to set brown and white shrimp sea sons based on juvenile numbers, length distributions |
|  | Finfish surveysforjuvenile and adult finfish, also shrimp and crabssince 1982 | - 50 ft purse seines monthly (bimonthly in Sept-Dec) in shallow soft/vegetated and hard-bottom habitats for juveniles |
|  |  | - Experimental gill nets and trammel nets monthly(bimonthly April-Sept) sample largerjuvenile and adult finfish |
|  | Oyster monitoring since 1980 | - Meter squa res a nnually (June-J uly) on public seed oyster grounds for numbers, sizes, dead seed, and sack oysters |
|  |  | - 24 inch dredge samples once in Mar, April then twice in May-J une and Aug-Oct for spat count, numbers and sizes of oysters, numbers dead, fouling organisms |
|  |  | - Nestier trays set to experimentally mea sure monthly growth and mortality in the field |
| Inland FIM | Inland surveys since about 1985 | - Electrofishing in spring and fall for estimate numbers, lengths of game fish, and theirforage base |
|  |  | - Gillnets deployed quarterly for sampling larger fish |
|  |  | - Baited hoop netsquarterly |
|  |  | - Rotenoning once per summer for numbers, sizes of fish |
| Fishery Sampling | Commercial fishery surveys | - Commercial fishery trip tic ket program since 1999 |
|  |  | - Trip interceptor program since 1994 |
|  |  | - Dealersurveys since 1990 |
|  | Recreational fishery surveys | - Marine Recreational Fishery Statistics Survey (MRFSS) in coordination with NOAA and GSMFC since 1998 |
|  |  | - C harter boat pilot survey since 1997 |
| Age and Growth Lab | Age, growth, and fecundity data since 1994 | - Age, growth, and fecundity sampling of major ma rine finfish taken from LDWF FIM and fishery dependent samples, SEAMAP for age-structured stock assessments |
| LOOP | Data collected from 1978 to | - Monthly water quality, C hl concentrations, |
| Environmental Monitoring | 1995 from offshore LOOP facility through Terrebonne and Barataria Basins | zooplankton, benthos, nekton samples |

### 7.4 Process Studies and Lab Results

There are several process studies from one- to two-year field projects a nd from laboratory experiments. These include diet a nalyses, habitat usage, growth and reproduction, tagging, stable isotopes, and otherfocused studies on specific hypotheses. Some are summarized in life history reports (e.g., Sta nley \& Sellers, 1986; Lassuy, 1983; Muncy, 1984; Pattillo et al., 1997), but the existing life history summaries are generally more than 10 years old. As a whole, these process studies are piece meal rather than comprehensive but provide valuable information, often to permit estimation of model process parameters related to growth, mortality, reproduction, and movement. Some of the studies are local to Louisiana and the Gulf, while other studies exa mined other systems but still provide useful information on rates. How to efficiently include all of these studies is a challenge. A short list has been compiled of studies and their information in Table 8 as an example of the available process studies and their potential information contributions for fish modeling.


Figure 14. LDWF fisheries-independent marine sampling station locations in Coastal Study Area 1 (LDWF Final Report, 2010).


Figure 15. NMFS gulf shrimp la nding statistic al zones used for the summer and fall SEAMAP groundfish/shrimp trawl surveys (SEDAR27-RD-05).


Figure 16. All SEAMAP stations for Gulf of Mexic o (SEDAR27-RD-05).

Table 8. An example list of some available process studies and their potential information contributions for fish modeling.

| Citations for Process Studies | Potential Information for Fish Models |
| :---: | :---: |
| Adamack et al. (2012); Rozas and Minello (2011) | Salinity effects on prey and brown shrimp consumption, growth |
| Baltz et al. (1993); Baltz et al. (1998); Baltz and J ones (2003) | Microhabitat use (marsh edge, depth, salinity, turbidity, DO, prey density) by estua rine fish and shellfish |
| Baker and Minello (2010) | Growth and mortality of juvenile white shrimp |
| Boswell et al. (2011); de Mutsert (2010); MacRae (2006) | Relative species composition and biomass estimatesfor estua rine habitats |
| C allihan (2011) | Movement, spawning, ha bitat use by spotted seatrout |
| Eby et al. (2005) | DO effects on prey distribution and juvenile croakergrowth |
| Facendola and Scharf (2012) | Diets, bioenergetics of red drum |
| Fry (2011); Fry and Chumchall (2011); Wissel and Fry (2005) | Stable isotopes for species interactions, ha bitat use and residency times of estua rine fishes |
| Kanouse et al. (2006) | Nekton use and distribution in SAV |
| Kneib (1984, 1994); Kneib and Wagner (1994) | Nekton use of marsh habitat |
| La Peyre et al. (2003) | Parasite effects on oyster survival |
| Lopez et al. (2010) | Reproduction and prey distribution of killifish |
| Miller et al. (2000) | Temperature, salinity effects on juvenile fish growth |
| Millerand Brylawski (2003) | Bioenergetic rates from laboratory for blue crab |
| Minello (1999); Minello et a.l (1991, 2003); Minello and Zmmerman (1992); Minello and Webb (1997); Reed et al. (2007); Rozas and Reed (1993); Rozas and Minello (1998, 1999, 2001,2010); Zmmeman and Minello (1984) | Nekton density and fine-scale habitat use of marsh habitats |

Nye (2008); Nye et al. (2011)
Peterson et al. $(2000,2004)$
Piazza and La Peyre (2007)
Rakocinski et al. (2006)
Rooker et al. (1998)
Scharf (2000)
Simons et al. (2013)
Soniat and Ray (1985); Soniat and Brody
(1988); Soniat et al. (1998)

Stunz et al. (2002)
Bioenergetic rates from laboratory and diets of Atlantic croaker
Laboratory growth rates of juvenile mullet, spot
Nekton density and biomass with marsh flooding
Abiotic effects on juvenile spot growth
Habitat use pattems by scieanids
Growth and mortality of juvenile red drum Gulf trophic interaction database to describe species distributions and food web interactions/diets
Environmental and prey effects on oyster survival
Growth of juvenile red drum

### 7.5 Key Information from the Literature

There are a suite of diagrams and tablesthat greatly aid in the development of fish models. These are not from a single process study or monitoring program, but ratherare a synthesis of the available information. The sources include life history summary documents, the information and background sections of stock assessment reports, review papers, and simple population modeling a nalyses undertaken for environmental impact assessments. Stock a ssessments typic ally summarize a variety of the information except for young-of-the-year life stages, which are often lumped as spawner-rec ruit relationships. An example of a review document on fish life history and distributions in the Gulf is Pattillo et al., (1997). Useful diagrams include: (1) life cycle diagrams; space-time plots by life stage and season, (2) habitat-time plots by life stage and season, and (2) food web diagrams-maybe by seasons-showing energy flows. These diagrams are discussed in more detail in AppendixA. Tabularinformation includes basic life history data and life tables. Basc life history data are length-weight relationships, weight-at-age, stage durations and mortality rates, maturity schedule by length or age, and fecundity by weight or age. These are quantitatively presented in a life table (Table 9). Life tablesexist for most all of the species of interest from power plant 316b impact assessments, ea rier a nalyses of liquefied natural gasimpacts, and the ongoing assessment of the effects of the Deepwater Horizon oil spill.

Summarizing the results of the monitoring programs, process studies, and life history data is an ongoing effort that requires an agreed upon bookkeeping method. At the beginning, the following should be defined and used consistently throughout the data synthesis and modeling: (1) teminology and definitions of life stages, (2) how spatial regions and locations are referred to, and (3) the birthday for aging fish. People and studieswill referto tems like "larvae" and "juveniles" and mean different things. The bithday is important bec a use otherwise it is not clear if a 2 -year-old fish is 24 monthsold or 36 months old. A standard nomenclature from the beginning of the effort will greatly help properinterpretation of studies and modeling results.

Another useful summarization is information about how the va rious outputs of the IC Ms relate to growth, mortality, reproduction, and movement of the fish species of interest and other species included in food web modeling. An example would be a lab experiment that relatesjuvenile fish growth to salinity. If the information says the salinity affects prey availa bility (Rozas \& Minello, 2011), then it is necessary to determine a way to go from prey to growth (e.g., bioenergetics [Adamack et al., 2012]). Another example would be how to represent changesin edge habitat on shrimp growth and mortality. Basically, one can start with the ICM outputs used as inputsto the 2012 HSI analysis; these were considered important before and thus it seems rea sonable that they should be related to growth, mortality, reproduction, or movement in the fish models. There may be additional relationships needed, but the 2012 HSI inputs are a very start.

Table 9. Example life table for Atlantic croaker.

| Life Stage | Start Numbers | Duration <br> (d) | Mortality (1/d) | Bycatch F Mort | Stage Survival | Female (\%) | Mature (\%) | Weight (g) | Fecundity |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Eggs/Larvae | 1.0E+7 | 22 | 0.5 | 0.0 | 0.000125 | 50 | 0 |  |  |
| Early J uvenile | $1.25 \mathrm{E}+3$ | 120 | 0.023 | 0.002 | 0.306 | 50 | 0 |  |  |
| Late J uvenile | $3.83 \mathrm{E}+2$ | 223 | 0.023 | 0.002 | 0.078 | 50 | 0 |  |  |
| Age-1 | 42.4 | 365 | . 000822 | 0.0 | 0.292 | 50 | 0 | 99.93 |  |
| Age-2 | 12.8 | 365 | . 000822 | 0.0 | 0.549 | 50 | 50 | 304.5 | 465403 |
| Age-3 | 6.8 | 365 | . 000822 | 0.0 | 0.549 | 50 | 100 | 562.6 | 884453 |
| Age-4 | 3.7 | 365 | . 000822 | 0.0 | 0.549 | 50 | 100 | 853.2 | 1356391 |
| Age-5 | 2.1 | 365 | . 000822 | 0.0 | 0.549 | 50 | 100 | 1100.1 | 1757343 |
| Age-6 | 1.1 | 365 | . 000822 | 0.0 | 0.549 | 50 | 100 | 1477.8 | 2370726 |
| Age-7 | 0.9 | 365 | . 000822 | 0.0 | 0.549 | 50 | 100 | 1477.8 | 2370727 |
| Age-8 | 0.6 | 365 | . 000822 | 0.0 | 0.549 | 50 | 100 | 1477.8 | 2370728 |
| Age-9 | 0.2 | 365 | . 000822 | 0.0 | 0.549 | 50 | 100 | 1477.8 | 2370729 |
| Age-10 | 0.1 | 365 | . 000822 | 0.0 | 0.549 | 50 | 100 | 1477.8 | 2370730 |
| Age-11 | 0.06 | 365 | . 000822 | 0.0 | 0.549 | 50 | 100 | 1477.8 | 2370731 |
| Age-12 | 0.03 | 365 | . 000822 | 0.0 | 0.549 | 50 | 100 | 1477.8 | 2370732 |
| Age-13 | 0.02 | 365 | . 000822 | 0.0 | 0.549 | 50 | 100 | 1477.8 | 2370733 |
| Age-14 | 0.01 | 365 | . 000822 | 0.0 | 0.549 | 50 | 100 | 1477.8 | 2370734 |

### 8.0 Summary of Available Candidate Models (Model Library)

There a variety of ways to categorize the existing models. None of the schemes are simple and exact (Brooks \& Tobias, 1996). Some models are quite complicated and cannot be fully described by a discrete series of categories, while other models contain some a spectsin one category and other a spects in a nother category. Some type of categorization is needed in orderto be able to describe models relative to each other, and to avoid just refeming to them by their nondescriptive name (e.g., CASM). One can start with a simple categorization of formula-based, population dynamics, multispecies, community, and ecosystem. Then a fivecategory scheme can be used to summanize modelsgathered from the literature and personal experience. This is the initial list of models. Based on the scientist's judgment, the initial list was na rrowed down to nine modelswith good potential, and these modelswere summarized in some detail to allow evaluation of them relative to the "ideal" conceptual model. The initial list of models is shown in Appendix B, and the more detailed summaries of the na rowed-down list of models are in AppendixC.

A major distinction is whetherthe models are formula-based or rate-based. The HSI approach used in the 2012 Coastal MasterPlan is formula. There are no rates involved; the outputs of the ICM models are entered into HSI equations, a nd the results of the equations for habitat suitability by speciesare summed. Going to ratesis a fundamental change in the approach and the mathematics. The models in the initial list use equations to represent the rates of change of the abundances or biomasses of the species. Thus, the model is formulated on how other species and environmental conditions affect the rates of change of the species. Mathematic principles were used to solve the equations of rates to obtain the abundances or biomasses overtime.

There are formula approaches available other than HSI. These include modeling the condition index of individual fish and using life tables to convert the added or lost individuals into production added orforegone. The point is that HSI models are part of a broaderclass of approaches that are simply direct calculations.

Once one moves from rates and population dynamics, it is necessary to select certain mathematicsto represent and solve the equations. There are three basic mathematical approaches used: (1) differential equations, (2) difference equations, and (3) matrix algebra, which can also be expressed as differential ordifference equations. There are other approaches, such as partial differential equations and integral projection, but these approaches are for relatively simple models that emphasize general mathematic results rather than sitespecific management analyses.

We used our experience and literature searching to develop a list of about 30 possible modeling approaches and examples. We list these in Appendix B. Some of the models are general software packages (e.g., Ec opath with Ecosim [EwE]); we summarized specific implementations in the following order of prionity: (1) Louisiana version, (2) GOM version, (3) version that simulated a key habitat (e.g., wetlands), and (4) recent implementations.

We used an imperfect, but useful five category taxonomy:

| Cumency | Biological <br> Organization | Spatial | Temporal | Reproduction |
| :--- | :--- | :--- | :--- | :--- |
| State variable | Single-species | Point | Seasonal | Forced recruitment |
| Age structured | Multispecies | Spatially explicit | One year | Full life cycle |
| Stage structured | Community |  | M ultiple years |  |
| Individual-based | Food web <br> Ecosystem |  |  |  |

The categoriesfor biological organization can be viewed as follows. Multispecies includes a few species ( $<5$ ) and their interactions (predation and competition), but the sum of species biomasses does not give one total fish biomass. Community level involves sufficient number of species so that their summed biomassistotal biomass, at least at the trophic level of the community (e.g., forage fish). The food web level of organization then includes explicit representation of the prey and predators of the species of interest, and can be simple (like multispecies) or complicated (like community). Once the environmental variables are added as being simulated, it is nec essary to move to the ecosystem level. The reproduction category also needs some explanation. Models can start with a specified number of starting young (i.e., forced recruitment), or the young can be produced dynamic ally based on the model simulated adults (i.e., full life cycle). Multiyear runscan be eitherforced recruitment or full life cycle.

From the long list of models (Appendix B), it was determined that it was necessary to na rrow the possibilities to nine fish-oriented modelsthat seem to match the very preliminary conceptual model of the problem. The reasonsfor eliminating the other models are noted in the Appendix B. The nine selected for further evaluation were summarized in much more detail in AppendixC. The more detailed summariesinclude headings of: level of complexity and realism, spatial representation, temporal aspects, fish processes, parameters and inputs, outputs, mathematics, computing details, and technical information. At this time, some aspects specific to the model's relevance to the 2017 Coastal Master Plan questionswere noted. These include possible spatial configurations and their use for 50 -year simulations at the scales of the basin and coastwide. These detailed models will be used as the basis for illustrating several options for selecting a pathway forward by CPRA. More models can be added to the list and detailed summaries in the appendices.

We also identified four modeling approaches specific for oyster responses. While oysters are included in some of the fish-oriented approaches, we also identified specific modeling approaches that focus on oysters bec ause of their biology (sessile shellfish), ecologic al and economic importance, and are often at the center of controversy. These are listed in Appendix $B$ (but not Appendix C) and are summarized below after the more general fish-oriented approaches.

### 9.0 Potential Modeling Approaches for the 2017 Coastal Master Plan


#### Abstract

This section highlights 11 possible modeling approachesforconsideration. These approaches are described below, with examples that are forillustrative purposes only and not as suggestions that the exact example model should be used. Some of the approaches may be determined to not be useful or not feasible. Some of the approaches can be used to ensure continuity from the 2012 to 2017 a nalyses, and others can be used as the basisfor more informed interpretation of a nalyses actually included in the 2017 Coastal Master Plan. CPRA may want to know the sensitivity of the results that are actually used in the 2017 Coastal Master Plan. For example, CPRA might want to know whether representing food websaffects the results obtained from a simpler single species a na lysis.


## Approach A: Repeat the 2012 Analysis

This approach would use the same HSI functions and preparation of the ICM outputs as used in the 2012 Coastal Master Plan as part of the 2017 assessment. Ba sically, repeat the 2012 a nalysis but with the new outputs from the ICM. Ideally, the old 2012 restoration actions would also be repeated-if these change from 2012 to 2017-in order to provide a bridge from the 2012 to 2017 plans. This a nalysis could be for intemal purposes only a nd would enable CPRA to say how much the change from the 2012 to 2017 ICM resultswould have affected the HSI results.

## Approach B: Revise and Improve the HSI Functions

HSI a nalysis is often criticized and yet remains a solid, fall-back approach for assessing the responses of large-scale restoration programs. Those involved should leam from the ecosystem restoration programs that are at a laterstage of development than Louisiana's master plan. For example, fish population dynamics modelswere developed for the Everglades restoration program (DeAngelis et al., 2000; Duke-Sylvester \& Gross, 2002). However, most recent restoration planning efforts have relied on HSI a nalyses using outputs from hydrodyna mic models because of the large role hydrology has on fish population dynamics, the need to produce results quickly and efficiently, and the ease of understanding by nonexpert stakeholders (D. DeAngelis, pers. comm.). In the Chesapeake Bay, Secor (2009) started the executive summary of the workshop proceedingsabout modeling forthe Chesapeake Bay restoration with:

Modeling efforts within the Chesapeake Bay have failed to effectively link water quality and habitat degradation or restoration to changes in living resource populations. Habitat suitability models represent a principal meansto develop such associations but have not seen extensive development or application within the Chesapeake Bay ecosystem.

While HSI analysis is often criticized, it remains a practical and tractable way to assess fish responses to restoration actions. However, there are several areas for potential improvement to the HSl-based analysis that were used forthe 2012 C oastal Master Plan. There is a theory underlying HSI and how the relationships are detemined and applied relates to nic he theory. Secor (2009) defined four ways HSI relates to habitat:

- Potential habitat Ha bitats that fulfill threshold conditions for survival, often estimated through ecophysiologic al tolerances;
- Prefered habitat Productive or behaviorally advantageous ha bitats, such as those supporting feeding, reproduction, or predation refuges, often estimated by habitats a ssocia ted with high densities or through behavioral studies;
- Realized habitat The subset of potential habitat actually occupied, depending on population status may be larger or smaller than prefered habitat domain, estimated through statistical treatments of distribution maps;
- Essential habitat Habitatsthat support key life history functions such as growth, reproduction, and early survival. This classification has been adopted in U.S. fisheries mana gement, but the term "essential" has resulted in some a mbiguity in its application. A curent definition entails ranking habitats by their relative contribution to population sustainability.

How the relationships in the HSI are estimated determines which habitat is being measured. Guisan and Zmmermann (2000) differentiate between theoretically or laboratory derived relationships for the HSI and empinically estimated relationships. They say the theoretic ally derived HSI estimates the fundamental nic he, while the empinic ally derived estimates the realized niche. They caution that the empinic ally derived relationship has benefits in terms of it being data-driven (defensible) but can be difficult to use forpredicting responses to new conditions. The HSI analysis in the 2012 C oastal Master Plan is considered near the simple end of possibilities and relatesto the theoretical niche because relationshipswere derived based on qualitative information and opinion. Four a reas forimprovement are: (1) estimation (or at least confimation) of relationships used in the 2012 Coastal MasterPlan (a nd a ny subsequent versions) based on empiric al field data, (2) use of fish density as the response variable, (3) use of statistical methods to estimate the relationships, including variance and validation, and (4) more refined use of the ICM model outputs in terms of how to average the ICM outputs spatially and especially tempora lly to a llow dynamic inputs. The HSI a nalyses should continue to be life stagespecific as much as possible. They should also consider how the wamertemperatures found in the Gulf relates to the suita bility relationships borrowed from other systems and from laboratory studies and possible interaction effects, such as nonlinear responsesto some temperature and salinity combinations. A previous evaluation of the HSI approach for Louisiana coastal restoration started on the track of comparing the relationships to other HSI analyses (DraugelisDale, 2008).

Much has been done with HSI-like analyses (e.g., DeAngelis et al.,1998; Guisan \& Zmmermann, 2000; Cumutt et al., 2000; Rubec et al,. 2001; C lark et al., 2004; Guisan \& Thuiller, 2005; Mazzotti et al., 2008; Baselga \& Araujo, 2010; Bond et al., 2010; Feyrer et al., 2011; J ohnson et al., 2013; Knudby et al., 2010; Zom et al., 2012), partially as a result of the interest in predicting climate change effects on habitat. These studiesdemonstrate newer methods and expansions beyond the 2012 C oastal Master Plan HSI models that could be considered for the 2017 C oastal Master Plan.

## Approach C: Community-like Analysis

This approach would use models like CASM (orTroSim) or Ecopath with Ecosim (EwE) to represent a multispeciesto food web level of biological organization at a series of stations within the estuary (point models). The emphasiswould be on how food web interactionscould affect the responses of species of interest. A recent version of CASM was used that was specifically
developed forcoastal Louisiana asan example of how modelssuch as CASM, TroSim, and EwE could be used in the 2017 Coastal MasterPlan. The example application of CASM was supported through the USACE and developed to simulate the species biomass responses in Barataria Basin to the proposed operational altematives for the proposed Medium Diversion at Myrtle Grove. CASM wasset up to receive the generated temperature, salinity, and depth outputs from the RMA hydrodynamic model in order to evaluate the potential effects on species biomass and distribution due to simulated FWOA and future with project (FWP) conditions (Figure 17). CASM food web model for Barataria Basin is depicted in Figure 18, with the trophic pathways to and from brown shrimp highlighted for better demonstration of the linkages.

First, a single estuary-wide CASM food web model was run using all daily environmental inputs averaged from field data stations across the entire system, and the predicted seasonal biomasses for species were calibrated to estuary-wide species estimates calculated from the field data. Second, the estuary-wide calibrated CASM food web model wasthen run for the 18 stations (polygons) that had varying daily environmental inputs, either estimated from the nearby field stations or else generated from the RMA hydrodynamic model. Species biomasses were simulated for one yearat each of the 18 CASM stations. The daily biomasses only are shown of brown shrimp at all 18 stations, and then the daily biomasses of multiple species at one station (Figure 19). Simulated temperature, salinity, and depth outputs generated by the RMA model for each operational scenario can then be used asthe inputs at each of the 18 CASM stations. One would then compute the difference in average annual biomasses of each of the species, and spatial plots of average species biomass at the 18 stationscan demonstrate the change in biomass distribution within the basin (Figure 20).


Figure 17. The 18 CASM stations (polygons) overlaid on the RMA hydrodynamic model grid for Barataria Basin.


Figure 18. Part of the food web diagram of CASM designed for Barataria Basin to better demonstrate the trophic linkages to and from brown shrimp juveniles.


Figure 19. (Top) Daily brown shrimp juvenile biomass at each of 18 CASM stations. (Bottom) Daily biomasses of several species generated from CASM food web at Station 5 in Barataria Basin.


Figure 20. Example spatial plot of change in juvenile brown shrimp biomass (in $\mathrm{gC} / \mathrm{m}^{2}$ ) at 18 CASM stations in mid-April.

The food web and design of the stations for evaluating FWOA and FWP effects within and across basins could be similar for the 2017 Coastal Master Plan modeling. Food web models such as CASM, TroSim, and EwE do not consider fish movement a mong the spatial compartments, so it would be best recommended to set up the models for larger or similargeographic regions within the basins and for a large enough spatial resolution where fish movement can be assumed to be unimportant. Careful attention is needed in order to realistic ally represent the sea sonspecific effects of some of the restoration and protective actions.

CASM curently incomorates and models species (i.e., a food web) and relationships for effects perhaps more relevant to restoration and projection than the other food web models, and represents water chemistry and lower trophic level (LTL) dyna mics much like nutrient-phytoplankton-zooplankton (NPZ) models. CASM simulates producer (e.g., phytoplankton, benthic algae) by using daily inputs for surface light intensity, nutrient concentrations nitrogen, phosphorous, and silica ( $\mathrm{N}, \mathrm{P}, \mathrm{S}$ ), and temperature to control photosynthesis of the producers. CASM also uses partic ulate organic carbon (POC) and total inorganic sediments (TSS) concentrations as inputs to determine light attenuation within the model, and POC inputs are used in the state variable equations for detemining POC and dissolved organic carbon (DOC) concentrationswithin the model. The otherinputs used by CASM to control (e.g., temperature) or modify species processes within the model are depth, salinity, current velocity, and wind speed (the introduction of dissolved oxygen [DO] from water surface). The ecohydrology model also simulates ambient light conditions and primary production (e.g., phytoplankton
concentrations) based on surface light, temperature and nutrients, and the turbidity/extinction coefficient due to suspended solids and particulates in the water column. Thus, CASM could use the end chlorophyll concentrations generated by the ecohydrology model as direct inputs of daily producerbiomass ratherthan simulating them. Therefore, CASM might use daily temperature, salinity, stage, ambient light/turbidity, chlorophyll concentration, detritus, POC, and DOC generated from the ecohydrology model (Table 6) as inputs for prey concentrations and environmental conditionsthat drive the species processes. The current CASM could also use the annual depths generated by the wetland morphology model. Some further expansion and adjustments to the current CASM used for the Louisiana Coastal Association (LCA) Myrtle Grove application could incoporate and then describe species responses based on differences in structural ha bitat (e.g., vegetation types, marsh edge, SAV, nonvegetated bottom) that could be annually outputted from grid cells of the wetland momhology and vegetation models of the master plan (Table 6). The generated outputs from the grid cells of the other master plan models, which result from the FWOA and various FWP simulations, would be averaged in each basin for the inputs to the encompassing CASM stations; the changes in biomass or distribution of key specieswithin the basin food webs could then be evaluated.

CASM was also used in a similar point model applic ation for the Mississippi River Gulf Outlet (MRGO) restoration program (Bartell et al., 2010). CASM stationswere situated at 23 nodes of the UNO hydrodynamic model for Pontchartrain Basin (Figure 21), and the food web wassimilar to the food web in Barataria Basin (Figure 22). The model was used to evaluate different restoration altematives on species biomass distribution within the basin (Figure 23).


Figure 21. The 23 CASM stations set up at nodes of the UNO hydrodynamic model for the MRGO restoration study (Bartell et al. 2010).


Figure 22. Partial food web diagram of CASM MRGO taken from Bartell et al. 2010.


Figure 23. Example results comparing sheepshead biomass distribution for Future Without Project and Future With Project scenario from the CASM MRGO (Bartell et al. 2010).

TroSim (Fulford et al., 2010) is a modified version of the CASM-COASTES (Bartell, 2003) that was developed to evaluate oyster restoration in Chesapeake Bay. The TroSim food web is comprised of fewer species groups and centered around oysters (reefs). The TroSim food web is comprised of several phytoplankton and zooplankton size and/or functional groups: larval fish, oysters, and ctenophores; ctenophores, oysters, pelagic fish (anchovy and menhaden), and reef and nonreef associated fish groups. There are curent efforts underway to parameterize and validate the TroSim model forthe legacy oyster reefs off of Bay St. Louis in the Mississippi Sound (Milroy et al, in progress).

Ec osim is a nother candidate model to use for the community like a nalysis. There are some major differences between CASM and Ecosim. These include that Ecosim is usually run multiple years with self-regenerating populations, that allows for limited separation of juveniles and adults of the same species, and the output is best viewed asannual values. Ecosim has difficulty dealing with speciesthat immigrate and emigrate to the model spatial domain. A third member of the EwE fa mily of models is Ecospace, for which there is a Gulf version (Walters et al., 2010), for which movement among spatial cells within the domain can be explicitly represented. While Ecosim is undergoing recoding and the source code is available, Ecospace does not appearto be a part of that software upgrade. Furthemore, it is much less used and tested than Ecosim and thus the use of Ecospace here is not recommended.

There are several Ecosim models for the Gulf. These include Gulf estuarine versions(de Mutsert et al., 2012; Althuser, 2003) and versions more offshore (Walters et al., 2008) and on the West Florida Shelf (C. Ainsworth \& D. C haganis, pers. comm.; Okey \& Mahmoudil; 2002). A recent version of the EwE model was developed for Breton Sound and used to evaluate potential nekton community responses to freshwater diversions (de Mutsert et al., 2012). The Ecopath food web model (Figure 24) was developed using species biomass data collected from LDWF to determine the fish and shellfish speciesto include and their initial biomasses. SpeciesCPUE and salinity from the DWF data were also used to describe the salinity tolerances of the species, and response functions were incorporated into EwE to modify the feeding rate of the speciesbased on simulated salinity in the model. Ecosim wasthen used to evaluate the potential changesto species biomasses under scenarios of low, medium, and high monthly salinities over 20 years (Figure 25).


Figure 24. The Breton Sound Ecopath model (from deMutsert et al., 2012) with the sizes of the dots representing the relative size of the biomass pools and the $y$-axis indic ating the modelgenerated trophic levels of the pools based on diets.


Figure 25. Relative species biomass composition from the Ecopath based model (Before - After) and then at the end of the three 20-year salinity scenarios (from de Mutsert et al., 2012).

The EwE food web and design would be similarto de Mutsert et al. (2012), with the potential model expansions and steps for using EwE to evaluate the 2017 C oastal Master Plan effects similarto what was described above for CASM. Like CASM (and TroSim), EwE is a point model so it would be best recommended to set up the modelsfor large or similargeographic regions within the basins at a spatial resolution where fish movement can be assumed to be unimportant. The Breton Sound EwE incorporated salinity only as an input variable (de Mutsert et al., 2012), though continued work with EwE for Barataria Basin is to incoporate temperature and habitat (open watervs. vegetation) as input variablesto modify the speciesfeeding rates. The EwE simulates producer groups (i.e., phytoplankton, benthic algae, SAV), as well as detnitus, strictly as prey groupsusing the same state variable formulations to describe population growth as the rest of the specieswithin the food web. That is, producergrowth is not dependent upon nutrients, light, or temperature as it is in water quality models, NPZ models, or CASM. However, the EwE might use the averaged chlorophyll and detritus concentrations averaged for regions of the ecohydrology model (Table 6) to initial lize the prey biomass pools. The EwE might also use the monthly temperature and salinity averaged for regions from the ecohydrology model (Table 6 ) as inputs to modify the species feeding rates. Incorporation of seasonal (e.g., month- or week-specific) effects of some of the restoration and protective actionsin the 2017 MasterPlan (e.g., diversions) is doable but will be challenging because one would need to adapt the time stepping used to solve what is essentially an annual output model like EwE. The EwE under development (Cowan \& Lewis, in progress) might also be able to use the annual percent land or percent edge variable generated by the wetland mophology model (Table 6) as inputsto modify the species feeding rates.

## Approach D: Estuarywide Spatial Analysis

This a pproach would use models like the spatially dynamic multistock production model (SDMPM, Ault et al., 1999), the spatially explicit individual-based model (SEIBM, Fulford et al., 2011; ALFISH, Gaff et al., 2000), or the small fish submodel parts of Atlantis (Fulton et al., 2004; Ainsworth et al, in progress) to represent single species, a few species, or else life history types with an emphasis on movement within the estuary in response to plan effects. A grid on a scale like the $500 \mathrm{~m} \times 500 \mathrm{~m}$ used for the 2012 wetla nd morphology and vegetation models (twodimensional, not vertic al) with a domain of the estuary would be used. The finer-scale habitats and spatial configuration from the wetland morphology model might even be best to map to and then describe the fish movement (and interactions) models. The direct mapping of a fish model grid to the other ICM models to evaluate structural and dynamic habitat differences on estuary-wide fish movement and distribution/production is a good and defensible means for coupling the models forthe masterplan. The reason to focus on basin- (estuary) wide spatial a nalysis of selected fish species (or life history types) is because this a pproach would allow for movement of fish within the estuary in response to plan effects. Such movement could be very important in detemining the overall responses of the fish.

Illustrated here is an estuary-wide spatial analysis using a pink shrimp-spotted seatrout agestructured production model for Bisc ayne Bay, FL (Ault et al., 1999). Ault's spatially dynamic multispecies production model (SDMPM) tracked daily cohorts of pink shrimp and spotted seatrout at age a in space from spawning, through settlement and recruitment asthey grew. The SDMPM was coupled to a two-dimensional hydrodyna mic model of Biscayne Bay (Wang et al., 1988) that included 6,364 tria ngular elements and 3,407 nodes, with grid spacingsbetween nodes in the order of 500 m . The SDMPM used the hydrodynamic model outputsfor water temperature and salinity to modify bioenergetic growth-via consumption and respiration-and current velocity to modify behavioral movement, settlement probability, a nd physic al transport. Coral, seagrass, hardbottom, and barebottom habitats specified in the hydrodynamic model (Figure 26) were used to modify movement and fishing mortality within the SEMPM. The spatial simulationswere run forsingle yearsto evaluate timing of spawning for spotted seatrout and the relative size of the seatrout cohorts.


Figure 26. Simulated habitat qua lity in tems of growth rate potential for spotted seatrout and fish density on days 1, 150, 300 and 360 (from Ault et al., 1999).

Fulford et al. (2011) used an individual-based approach to model juvenile spot movement and distribution based on habitat differences and habitat choice in the lower Pascagoula River, Mississippi, by expanding on the habitat mosaic concept described in Peterson (2003).
Temperature, salinity, and habitat data collected in the study a rea were georeferenced and converted to a GIS shape file using kiging and resampled to a cell size of $100 \mathrm{~m}^{2}$. Time series of temperature and salinity data representing three periodswere simulated, and structural habitat was defined at 2.8 m spatial resolution and classified as high marsh, low marsh, forest, water, and man-made structures. Model habitat scores were assigned to structural and environmental data separately and then the two combined fora single habitat quality score foreach cell based on a response surface fordaily growth of the juvenile spot. The simulated dynamic and structural habitat quality scores related to the spot growth then detemined the movement pattems, distribution, and condition of the juvenile spot for the different periods of simulation.

Gaff et al. (2000) grouped fish speciesinto small and large groups as defined by differencesin their movement, habitat access, a nd vulnerability to wading bird predation in the Florida Everglades. Their model, ALFISH, simulated size-structured groups of large and small fish, where the larger ones could prey on the small fish group. The marsh landscape was modeled as 500 $\mathrm{m}^{2}$ spatial cells on a grid across southem Florida, and a hydrology model predicted water levels in the spatial cells on 5-day time steps. Fish populations spread a cross the marsh during flooded conditionsand then retreated into water cellswhen water levels receded. ALFISH was used to provide information on the effects of the Everglades restoration plans on fish biomass and prey availability to wading birds.

Atlantis is a nother candidate model to use for the estuary-wide spatial a nalysis. ATLANTIS (Fulton et al., 2004) is a coupled physic al-biogeochemical ecosystem model that isspatially resolved
(including vertic al layers) and includes the full trophic spectrum (including the human dimension with fishing). Typic al a pplic ations include physic al transport a mong spatial cells, simulation of the nutrients and lowertrophic level groups, and representation of fish and othervertebrates using an age-structured formulation.

Ongoing ATLANTIS modeling efforts the Gulf model include a version for the entire Gulf (Ainsworth et al., in progress) and a version forthe MS-LA-TX shelf to evaluate the effects of hypoxia (Mason et al, in progress). The parameterization forATLANTIS (i.e., diets, biomasses, physic al-biological coupling of processes) is intensive and it often takes many years to get a working model of the system. Also, the code isquite complic ated and often requires an expert in Atlantis to set up a site-specific version. Methods to determine the species biomasses (Drexler \& Ainsworth, 2012) and species diets as inputs to ATLANTIS (Ainsworth et al., 2010) are available, and the Gulf food web has been constructed and simulations performed (Ainsworth et al, in prep; Figure 27).


Figure 27. ATLANTIS model forthe Gulf of Mexico (from C. Ainsworth, in prep.).

A version of ATLANTIS for the 2017 Coastal Master Plan would use a small subset of the equations and modules that are needed to simulate the age-structured fish population dynamics; this would be done fora few species only. ATLANTIS can also handle the many species needed for a point model in the community level analysis (Approach C). The focus here is on its use for Approach D that requires multiple linked spatial cells. ATLANTIS is still in development forthe GOM, and would take a major multiyear effort to develop a version for an estuarine food web of Louisiana. Therefore, it is not recommended that ATLANTIS be utilized for the 2017 Coastal Master Plan modeling. However, the spatially explicit age-structured modeling approach for fish populations in ATLANTIS is a potential approach formodeling fish and theirfood web interactions within the estuary. The ATLANTIS goveming equation for modeling fish biomass (as nutrient pools) is similar to that of CASM and Ec osim in that biomass growth is detemined from consumption of
prey and morta lity from predation. If a spatially explicit approach is taken, then one could use the idea and bookkeeping approach of the equations of ATLANTIS and recode a version that only simulates a single species or a very limited food web for the master plan.

Thistype of estuary-wide spatial analysiscould be done for a single species that is sensitive to both structural habitat (e.g., marsh, nonvegetated hard bottom, soft bottom, edge) and dynamic environmental conditions such as salinity, temperature, and turbidity. Single species for consideration might include brown shrimp or spotted seatrout. Altematively, a model of brown and/or white shrimp modeled separately, and spotted seatrout could be constructed in a similar way to Ault et al. (1999) to explicitly include the predator-prey interactions of two suspected sensitive and important estuarine species. A version of the modeling could also use groups of fish life history types, rather than specific species. A lot of the estuarine species exhibit similar life history strategies (Figure 8) and share common movement pattems and trophic positions within the food web. For example, a large predatory fish group (e.g., spotted seatrout, red drum, black drum), a benthic invertebrate group (e.g., Penaeid shrimps, crabs), a small marsh resident fish group (killifish, minnows, gobies), and a planktivorous forage fish group (e.g., bay anchovy, gulf menhaden, striped mullet, silversides) might sufficiently represent the life history types for an estuary-wide spatial analysis.

## Approach E: Detailed Movement Analysis

This a pproach would use individual-based or particle-tracking models within hydrodyna mics models to simulate the short-tem (i.e., weeks) displacement and spatial distributions of key life stages of a very few speciesin response to large-scale diversions. The reason to focus on detailed movement is because large-scale diversions are a major part of the restoration plan, and possible spatial shifts in distribution have been controversial.

Illustrated here is a detailed movement analysis with a movement model of individual fish simulated within a Finite-Volume Coastal Ocean Model (FVCOM) model of Breton Sound estuary. The model consisted of two coupled submodels: hydrodynamics (FVCOM) and fish movement (particle tracking with behavior). Both submodels used the same spatial grid (Figure 28). The submodelswere coupled by the hydrodynamics being run first and generating water velocities, water depths, and salinity valuesevery 30 minutesforeach spatial cell. The valuesfor the surface layer were then used asinputs to the fish movement submodel to track the behavioral movement of individuals.


Figure 28. FVCOM and fish PTM model grid.
Model simulationswere camied out over a period of 91 days, from April 1 until J uly 1, 2010. Three diversion scenarios were simulated (Figure 29): baseline diversion (BD), pulse diversion (PD), and oil spill mitigation diversion (OSMD). Shown here are the simulations with an intermediate salinity species. For each of the three diversion scenarios, the percentiles of individuals ( $10,30,50,70$, and 90 ) are shown, based on the salinity experienced by individuals (Figure 30 ) and the distances of individuals from the diversion structure (Figure 31). These percentiles were computed by outputting information on individuals on each 30 minute time step. For each time step, the distances from the diversion and the salinities experienced by all individuals were outputted. These values were then used to form an empinc al cumulative distribution function, one for distance from diversion and a nother one for salinity. The 10th, 30th, 50th (median), 70th, and 90th values of distance and salinity from each of the cumulative distribution functions (i.e., every 30 minutes) were recorded and these were plotted overtime. The plots of the percentiles show how the probability distribution of values progressed through time.

This type of a nalysiscould be done for a few of the sensitive species to assess how the diversions could affect their location and any salinity stress.


Figure 29. Three diversion scenarios simulated in the coupled FVCOM-fish partic le tracking model for Breton Sound where (a) is baseline, (b) is pulsed, and (c) is oil spill mitigation discharge (Rose et al., in review).


Figure 30. Percentiles of individual fish that experience the salinity based on the simulated (a) BD scenario, (b) PD scenario, and (c) OSMD scenario.


Figure 31. Percentiles of individual fish at distances from diversion based on the simulated (a) BD scenario, (b) PD scenario, and (c) OSMD scenario.

## Approach F: Detailed Habitat Analysis

Some aspects of the effects of the restoration actions necessary are simulated in the ICM models at coarser spatial scales than organisms react. An example is the ICM output of a mount of marsh-water edge in each $500 \mathrm{~m} \times 500 \mathrm{~m}$ cell and the finer-scale $30 \mathrm{~m} \times 30 \mathrm{~m}$ spatial arangement of marsh and water. Fora few species, such as brown shrimp, there is extensive data (e.g., Zmmerman \& Minello, 1984; Baltz et al., 1998; Minello, 1999; Rozas \& Minello, 2002; Rozas \& Minello, 2010) on their use of edge and marsh surface that is only accessible during inundation that varies on hours to days. One could envision developing a fine-scale (e.g., meters, hours) model of different types of marsh a rangements a nd elevation pattems and simulating growth, mortality, and movement within this small (e.g., $1 \mathrm{~km} \times 1 \mathrm{~km}$ ) habitat map.

The results would be scaled to the estuary by adding up the results of a series of different habitat maps by the approximate area each occupied in the estuary. This is viewed as stratified design, where the strata are defined based on habitat type and magnitude of effects. This can be quite tricky.

This a pproach is illustrated using an a nalysis of climate change (i.e., future conditions) on brown trout. The model simulated trout abundance in stream reachesthat were 600 m long, and divided into pool, run, and riffle cells. Mean lengthsused are 2 m for pools, 1.6 m for runs, and 0.4 m for riffles. The model simulated daily dynamics of brook and rainbow trout for 100 years. The model was run for a set of about eight stream types (each 600 m long) for baseline and a climate change scenario. The final trout abundance, averaged overthe final 50 years, was recorded. Using GIS, these final abundances were extrapolated to all areas on the map that were of that stream habitat type. A difference map wasthen computed to show the responses of trout to climate change relative to baseline (Figure 32).

One could imagine preparing a similarapproach using a more relevant model, such as the brown shrimp model developed by Roth et al. (2008). This model has been applied to a series of marshes in different degrees of degradation (Figures 33 and 34 ), and also is presently being applied to constructed marshes. The scale of the model is 1 m cells and hourly water levels. This type of approach would allow the response of a key life stage of a few speciesto be simulated on a fine habitat scale, and then extrapolated to the basin. This approach would only be done for a very few species.


Figure 32. Relative change in abundance of brook and rainbow trout due to the three simulated climate change sc enarios (from Clark et al., 2001).


Figure 33. Degrees of marsh fragmentation from GISimages of Galveston Bay and Caminada Bay used in the brown shrimp IBM (from Roth et al., 2008).


Figure 34. Simulated brown shrimp results for the four marsh fragmentation stages (Roth et al., 2008).

## Approach G: Simple Fisheries Analysis

Another class of models to use would be those used in basic fisheries population dynamic s and stock assessment. These models would be either spawner-rec ruit type models or life table (ageor stage-structured) approaches. The spatial resolution would be a single boxfor the estuary and the outputting time step would be annual. Metrics analogous to Yield per Rec ruit, Spawning Potential Ratio, recruit per adult, age-1 equivalents, and finite population growth rate ( $\lambda$ ) could be generated for baseline (FWOA) and with the projects. The critical aspect would be to know how to change the recruitment or certain elements of the life ta ble as functions of ICM model outputs. What is attractive about this approach is that it rests on the long history of fisheries modeling and it is relatively simple. However, the link to ICM outputswill be challenging. One could envision using the literature to derive a relationship between spring-averaged salinity and larval stage growth rate. Then using the ICM output to calculate how larval growth rate would change from the baseline and making that adjustment to the larval stage duration in the life table. The metrics derived from the life table would then be compared between FWOA and FWP.

Ba mthouse et al. (1990) illustrates a version of this using information for striped bass in Chesapeake Bay and menhaden in the Gulf. They linked the spawner-recruit relationship with an age-based life table (Leslie model) and simulated population dynamicsfor 100 years. They then derived concentration-response relationships between contaminant concentration and Young of Year(YOY) survival and age-specific fecundity. They ran the model without and with the contaminant and computed the reduction in recruitment averaged over the last 50 years (Figure 35 ).


Figure 35. The percent reduction in average annual Gulf menhaden recruitment (from Bamthouse et al., 1990).

## Approach H (Oyster-spec ific): Oyster Lanval Transport Model Alone or Coupled to a Population Model

This a pproach would be used to evaluate the effects of fluctuating environmental conditions in estuaries on oysterlarvae distribution and settlement pattems. There are also several extensions to the transport model, including representing the growth and mortality of the larvae and using the output of the larval transport model asinput to population models of the post-settlement stages.

Oyster larval transport modeling is based on particle-tracking modeling, often with the addition of larval vertic al behavior. In some versions, larval growth and survival have also been added as biologic al components to the individual particles. The particle-tracking model with biological attributes is then coupled to ocean circulation models such as the Finite Volume Coastal Ocean Model (FV-COM) and the Regional Ocean Modeling System (ROMS). As usually implemented, this modeling approach might not be well-suited for the masterplan because the physical transport (i.e., velocities) needed to move the particles must come from relatively fine spatial resolution hydrodynamics models, which the ICM models are not. However, oyster larval transport models could be useful to CPRA if used in specific loc ations where hydrodynamic models have already been developed, calibrated, and tested.

An example of an estuary-wide oyster larval transport model is described in North et al. (2008) for Chesapeake Bay. North et al. (2008) created the larval transport model by linking the Regional Ocean Modeling System (ROMS) model hydrodynamic model and a particle-tracking model that included larval behavior and settlement submodels. The ROMS for Chesapeake Bay (Li et al., 2005) had a horizontal grid spacing of about 1 km and had 20 vertic al layers. The hydrodynamics model had been used previously to predict tidal elevation, tidal and subtidal currents, and temperature and salinity distributions in Chesapeake Bay. The particle-tracking model was used to calculate the movement of particles that mimicked oyster larvae (North et al., 2006), where movement of particleswas based on advection, subgrid sc ale turbulence, and larval swimming behavior. The model tracked the trajectories of oyster larvae in three dimensions and predicted settlement locations on specific oyster reefs. The settlement submodel determined if a pediveliger-stage particle encountered suitable habitat. Suitable habitat was based on the cultch GIS-layer polygonsfrom the Maryland Bay Bottom Survey conducted in the late-1970s and 1980. The North et al. (2008) model did not consider biological processes like larval growth and survival because they specific ally evaluated the influence of physic al conditions and larval movement and settlement on dispersal distance, encounter with suita ble ha bitat, and subpopulation connectivity. However, growth and survival of larvae has been related to salinity, temperature, turbidity, and predation mortality and could be added to the biology represented in the particles (e.g., Metaxas \& Sa unders, 2009; Dekshenieks et al., 1996). North et al. (2008) performed simulations with different larval swimming behaviors a nd with a ROMS simulation of 1995 to 1999. For each year, the authors calc ulated the dispersal distances of the settled larvae, percent transport success as the number of partic les that encountered an oyster barper number of particles released, and correlated these predictions with the simulated environmental conditions.

Another example of a model of oyster larvae transport and settlement is the model for the oyster reef complex of the Lynnhaven River System in lowerChesa peake Bay (Lipcius et al., in draft; Lipciuset al., 2008). A three-dimensional hydrodynamic model was used to define the locations of the optimum oyster reefs based on simulated salinity, temperature, a nd water elevation
conditions under restocking and stock enhancement management actions. Simulated larvae were then released from 45 potential reef sites and the destinations of the larvae were tracked. While the details of the model are not yet available from Lipcius et al. (in draft), Lipcius et al. (2008) summa rized early results from the oyster la rval transport modeling as an example of a complex metapopulation and used model resultsto quantitatively describe how restocking and restoration were affected by the connectivity among the reefs. For example, a network connectivity a nalysis of the larval transport model results demonstrated that some reefs were sources of larvae while other reefs were sinks.

Validating the predictions (e.g., dispersal paths, distances, settlement distribution) of larval transport models is not a trivial problem because of the difficulties with measuring larval dispersal in the field. Metaxis and Sa unders (2009) state that it this difficulty that led to the development of predictive biophysical models as a tool in the first place. Despite the diffic ulty in validating model predictions of larval transport and distribution, the models are inc reasingly being used to predict larval transport, assess population connectivity, and evaluate the role of different biological and physical factors on larval dispersal of marine benthic invertebrates. A biophysic al transport model was recently developed to evaluate larval distribution and oyster reef restoration strategiesfor Mobile Bay, Alabama (Kim et al., 2013).

In addition to adding growth and survival effects to the la rval transport model, a nother extension isto couple the transport model with a population model for the settled stages. The population models are often size-based. Dekshenieks et al. (2000) is an example of the coupled models approach. A three-dimensional circulation model, a nd associated la rval transport model, was solved at 15 minute intervals, while the post-settlement model was solved with a one hour time step. Both were solved for the same spatial grid. Five-year simulationswere performed and the coupled modelsgenerated spatial mapsof total oysters, adult oysters, eggs spawned, and recruits for each of the horizontal spatial cells, averaged over the time steps in the fifth year. Additional simulationswere performed to assess the responses to high- and low freshwater inflows, high- and low temperatures, decreased food, and decreased seston.

Weber et al. (2013) offer an altemative formulation of a post-settlement population dynamics model that receives spat settlement inputsfor detemining rec ruitment on reef sites based on the larval transport model from North et al. (2008). An oyster habitat layer was constructed for Chesapeake Bay and 8,480 polygonswere identified and included asindividual oyster bars in the oyster demographic model. The larval transport model was simulated for a wet, dry, and average year to predict the number of oyster larvae that settled among the oyster bars forthe different water yeartypes. The oyster demographic model then was run for 10 years, with oyster growth rates modeled in yearly increments using the von Bertalanffy growth function and sizebased annual mortality estimates that have been measured by salinity zones in the estuary. The demographic model is used to project oyster abundance within Chesapeake Bay for oyster restoration altematives that include different levels of harvest, shell planting and spat planting for combined sequences of wet, dry, and average climate years.

## Approach I (Oyster-specific): Growth of Individual Oysters

This a pproach would use a bioenergetics or a dynamic energy budget (DEB) model to simulate how changing environmental and food conditionswould affect the growth of individual oysters. Some aspects of the effects of the restoration actions that would be inputs to a growth model are simulated in the ICM models at spatial resolutions of $500 \mathrm{~m} \times 500 \mathrm{~m}$ to $1 \mathrm{~km}^{2}$ and could be
scaled and linked to a series of point models representing the post-settlement oyster populations at reef sites within the estuaries. ICM outputs such as salinity, temperature, chlorophyll concentration, turbidity, water depth, and sedimentation have been shown to affect individual oyster processes such as filtration, reproduction, spawning, and mortality rates in the laboratory a nd field (Powell et al., 1992; Klinck et al., 1992; Hoffman et al., 1992; Soniat et al., 1998; Schulte et al., 2008; Soniat et al., 2012). A growth model would be able to combine simultaneous changes in these variablesto produce how growth of oysters on a reef would be affected. This approach could be particularly useful to CPRA in evaluating how the effects of restoration actionswould affect the spatial distribution of oystergrowth in key reefs.

We illustrate the oyster growth approach using an analysis of salinity change via freshwaterflow on individual oysters at two reef sites in Apalachicola Bay, Florida (Wang et al., 2008). An oyster model that simulated key growth processes (e.g., ingestion, assimilation, respiration, reproduction) wascoupled with the three-dimensional hydrodynamic model of Apalachic ola Bay to examine the effects of changes in freshwater flow and salinity on oyster growth rates. The oyster growth model was a modified version of the model developed for oysters in Galveston Bay (Powell et al., 1992; Hoffman et al,. 1992; Klinck et al., 1992). Oysters were simulated at two sites: a less-freshwaterinfluenced oyster reef and a more-freshwater-influenced oyster reef. The model simulations for oyster growth at the two sites were validated with field mea surements of oyster growth from the loc ations. Simulations for low- and high flow conditions by the hydrodynamic model were run with the oyster model and compared with the baseline reference simulation. The simulations indicated that oystergrowth a ppeared to be more variable at the more-freshwater-influenced oyster reef site due to changes in freshwaterinflows influencing salinities as well as other environmental factors such as food availability. There exist some long-tem field sampling data-including densities, growth and surviva-for several reef sitesin coastal Louisia na (LaPeyre et al., 2013 a ,b; Soniat et al., 2012), that could potentially be used asthe reference reefs forthe initial development and validation of an oyster growth model.

The model of Grangere et al. (2009) illustrates a different version of this growth approach by coupling a DEB model for Pacific oysters (Pouvreau et al., 2006) with a biogeochemical model that simulates phytoplankton concentration for the Baie desVeysestuary in France. The DEB model simulated oyster growth and reproduction in relation to phytoplankton prey concentration (Figure 36). The biogeochemical model simulated phytoplankton concentration (as chlorophyll) regulated by environmental conditions (i.e., temperature, light, nutrients). Simulations of the coupled modelswere compared with available data to validate the simulation of phytoplankton dynamics and oyster growth dynamics. Once validated, the coupled model wasused to explore the physiological response (growth) of oysters to year-toyearvariation in environmental conditions (including niver inputs and temperature) for the estuary. This approach is an example that could use the outputs from ICM models-if phytoplankton concentrations are an output-as inputs and generate predicted changes in oyster growth.


Figure 36. Conceptual diagram of the coupling of the biogeochemical submodel and the oyster dynamic energy budget model for Baie des Veys estuary (Grangere et al., 2009).

## Approach J (Oyster-specific): Food Web Approach Centered on Oysters

This approach would use the community like models described in Approach C (CASM, TroSim, or EwE), but to represent the food web specific to oyster reefs at different locations within the estuary (i.e., series of point models). The emphasis would be on how food web interactions could affect the responses of oysters on the reef (i.e., the model would be oyster-centric). TroSim (Fulford et al., 2010) wasdisc ussed briefly in Approach C. TroSim is a modified version of the CASM-COASTES (Bartell, 2003) model that was developed to evaluate oyster restoration in Chesapeake Bay, and current work is being performed to parameterize and validate the TroSim model for oyster reefs in the Mississippi Sound (Milroy et al, in progress). The existing TroSim food web is centered on oysters (reefs), and represents several phytoplankton and zooplankton size or functional groups, ctenophores, pelagic fish, and reef and nonreef associated fish groups.

A food web model of the oyster reefs could be used in the 2017 C oastal Master Plan. A version of CASM orTroSim centered on oysters would be set up to receive the generated outputs from the ICM models to drive the producer and consumer population growth rates within the oysterrelated food web. This would allow simulation of oyster responses to the effects of the master plan. Asdisc ussed in Approach C, CASM currently incorporates and models specieswithin a food web and relationships for effects perhaps more relevant to restoration actionsthan the other food web models. CASM represents waterchemistry and lowertrophic level (LTL) dynamics much like nutrient-phytoplankton-zooplankton (NPZ) models. A CASM (or TroSim) model of oysters, and its associated food web, would simulate producer (e.g., phytoplankton,
benthic algae) biomass by using daily inputs for surface light intensity, nutrient concentrations, and temperature to control photosynthesis of the producers. Many of the inputs of an oyster version of CASM could come from the outputs of ICM models(Table 6), including temperature, nutrients, water depth, salinity, and curent velocity. A series of point models of the oyster food web could be developed and applied to assess master plan effects on oyster biomass dynamics.

The current versions of CASM and TroSim simulate one yearonly using a daily time step, do not account for oyster spawning or recruitment, a nd only consider salinity and temperature effects on speciesconsumption and growth. However, the growth equationswithin the models are bioenergetics-based such that they can be modified to more resemble the more complete oyster growth models of Wang et al. (2008) and Grangere et al. (2009) described in Approach I and to include spawning and recruitment of oysters.

## Approach K (Oyster-spec ific ): Oyster-parasite Model

This a pproach would use host-parasite models to evaluate the transmission and spread of oyster diseases based on the annual environmental conditionswithin the estuary. These models would be like that used to evaluate MSX disease in oysters forChesapeake Bay (Hofmann et al., 2001). The Hofmann et al. (2001) model was a physiologically based model structured around the transmission, proliferation, and death rates of the pa rasite and the oyster. Temperature, salinity, and oyster food supply (chlorophyll concentration) were extemal forcing variables that determined ingestion, respiration, and mortality rates of the oyster. Temperature determined parasite concentration in the water column and sporulation, as well as parasite growth in the oysters. Salinity also detemined paraste concentration and then growth within the oysters. The model was run with a time step of 1 hour over 10 years using environmental data from Chesapeake Bay, and simulationswere performed to test how changing environmental conditionswould affect the prevalence and intensities of the MSX disease in oysters.

In the Gulf, Perkinsus marinusis responsible for high mortality rates of oysters in the region, and the transmission of the parasites and death rates of the oysters are also driven by temperature, salinity, and food supply (Soniat, 1996; La Peyre et al., 2009; Soniat et al., 2012). A number of experimental studies on the physiological responses of oysters to Perkinsusdisease are available (Chu et al., 1993; Paynter, 1996; Soniat et al., 1998; La Peyre et al., 2003). With some effort, a host-parasite model for oysters in coastal Louisiana could be developed, tested, and applied to evaluate the effects of the master plan on oyster disease and spread.

### 10.0 Suggestions for Steps to Support Model Selection and Model Application


#### Abstract

The proposed Path Forward for Fish and Shellfish Modeling forthe 2017 Coastal Master Plan is presented in a separate document, and it builds on the information presented here. Several steps need to be completed in order for the model selection to be fina lized. For example, some key data need to be analyzed and conceptual models reviewed and modified if necessary. Most of these steps can be initiated now and performed in parallel with the fina lization of the fish modeling. These steps and their products will be necessary, regardless of the specific set of approaches and modelsfinally used. These steps are:


(1) Select one or more of the existing model selection schemes or modify an existing scheme to be specific to the master plan modeling. There is general agreement in the science community on the stepsformodel development and application (Tables 3-5 and Figures 1-4).
(2) Develop a set of c onceptual models. This is an important step in all of the model selection schemes. Many examples of conceptual models and suggestions on how they should be constructed are available (e.g., Ogden et al., 2005; Thom et al., 2003; Fisc henich, 2008; DiGennaro et al., 2012). Conceptual models in various forms already exist, as do several numerical models, which can be used as a basis for this.
(3) Establish a mechanism for close interaction between ICM modeling and fish modeling to ensure the best information is used as inputs to the fish modeling. While the coupling is one way and the fish modeling is the most downstream, there may be options for outputting from ICM models as input to the fish models that is different from how ICM output will be reported in the masterplan.
(4) Determine the coupling protocols for the entire ICM, including fish models. This will act as a tec hnical constraint on the selection of the fish modelsand also is needed to determine how uncertainty will be propagated through the entire set of coupled models. CPRA may want to look at formal couplers used by othergroups with integrated models, such as CCA, OPENMI, and USEPA's FRAMES. This would also be an opportunity to avoid potential confounding that can a rise from different versions of ICM being used in different basins. Standardization within models ac ross space, and planning for the best outputs to use among models, greatly helps the quality and interpretability of the a nalyses.
(5) Decision on how to document the fish model specific ation and evaluation step/ $\mathbf{s}$. One option is the TRACE approach (Figure 5 and 6), although there are other options. A formalized a pproach should be taken.
(6) Initiate data preparation and develop a plan on how to improve the existing HSI functions. The fish modeling will also make use of the same monitoring data.
(7) Clarify the technical constraints and inc orporate the constraints in the final selection of models and approaches. These include the schedule for completion of fish modeling and ICM models, computing capabilities, and staffing availability and expertise.
(8) Evaluate whether any of the oyster-spec ific approaches, none of which generate coastwide predictions, should be used for spec ific locations and restoration actions.
(9) Develop an initial plan for calibration, verification, and validation, that will then be finalized when the final suite of approaches and models are specified. The details of the approaches selected would not greatly affect the calibration, verification, and validation strategy, and data can be organized and a nalyzed immediately. Code-independent optimization programs (e.g., PEST) were used with CASM; some of the general models have their own built-in optimization routines (e.g., Ec osim), and fisheries stock assessment relies heavily on robust pa rameter estimation methods (Foumier et al., 2013). The Watershed Systems Group of the USACE in Portland, Oregon, have improved upon PEST and also have developed Bayesian and other optimization programsto use with any model codes. Model calibration and validation would also benefit by periodic reviews by local experts who would provide immediate feedback on the realism and plausibility of model results.

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## APPENDIX A: Concepts used to select or develop conceptual and numerical models

## Concept 1: Life Cycles and Strategies

A life cycle diagram follows individuals as they progress through the life stages from birth to death (Caswell, 2001). Developing a life cycle diagram foreach species of interest isvery helpful when developing a model. A typical fish life cycle is eggs, yolk-sac larvae, larvae, young-of-the-yearjuveniles, juveniles, and adults. Fish species often show complicated and diverse life cycles (Balon, 1979). Individuals in different stagescan show major changes in their physiology, behavior, diets, and habitats utilized, including some stages oc curing within estuaries and other stages in inshore and offshore waters (Beck et al., 2001). An example of a life cycle diagram forPena eid shrimp is illustrated in Figure 37. Thus, restoration actionsin an area may only affect one or a few of the life stages, and affected individuals then spend other stages being exposed and influenced by conditions unrelated to the restoration action.


Figure 37. Life cycle diagram for Peneaid shrimp.

A life history strategy is detemined by the combination of vital rates with the life cycle. Species, whose individualsgo through the cycle rapidly as determined by theirvital rates, can be grouped in one strategy ( $r$-selected), while other specieswhose individualsgo through the life cycle slowly can be considered a different strategy (K-selected). This is useful for model development because it provides a way to share parametervalues a mong species, for grouping speciesinto functional groups, and because population responsesto
perturbations-including restoration actions-are expected to be similaramong species that have similarstrategies. Winemiller and Rose (1992) expanded the classical rK scheme (Pianka, 1970) into a three-end member scheme specific ally for fish species (Figure 38). Fish species fall somewhere on the surface defined by age or size of maturity, fecundity, and juvenile survivorship. This model wasthen expanded by McCann and Shuter (1997) to include the salmonids and bioenergetic sof reproduction and growth, and used by Vila-G ispert et al. (2002) to cluster European fish species.


Figure 38. Life history strategies for fish species based on age of maturity, juvenile survivorship, and fecundity defined by Winemiller and Rose (1992).

Life tablesprovide a meansfor quantitatively summanizing the life history cycle and strategy of a species. Life tablesshow the typical duration and mortality rates by stage and age. Forstages defined by size, life tables also show the entering weight and lengths, and for adults, they show the fraction mature and eggsperindividual by stage or age. An example of a life table for Atlantic croakeris shown in Table 9.

Another diagram related to life cyclesand strategies that is helpful for model development is space-time plots of abundance or biomass distributions. Two particulartypes are abundance by location, season, and life stage (space-time plots) and by habitat, season, and stage (habitat-time plots). Able (2005) categorized coastal fish species based on their degree of estuarine dependency and connectivity between estuaries and marine environments. He defined sixcategories: (1) breed and live in estuaries, (2) breed in estuaries and marine environment, (3) breed in manine environment but juveniles use estuaries, (4) breed in manine environments and juveniles use both marine and estuaries, (5) breed in marine environments and juveniles more abundant in marine environments; juveniles use estua ries as stragglers, and (6) diadromous. Pihl et al. (2002) presented groupings of species based on the habitat they utilize within estuaries. Nine habitats were defined (e.g., tidal freshwater, salt marsh, subtidal soft substratum), their availability in different estuaries quantified, and then fish species were cross-
referenced to these nine habitatsbased upon whetherthe species used the habitat for spawning, nursery, feeding, or migration. A general format for a space-time thought to be useful for model selection for the master plan is shown in Figure 39. These should be modified and adapted as actual model development proceeds.

| Winter |  | Eggs | Larvae | Juveniles | Subadults | Adults |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Estuary | Top |  |  |  |  |  |
|  | Middle |  |  |  |  |  |
|  | Lower |  |  |  |  |  |
| Shelf | Inshore |  |  |  |  |  |
|  | Offshore |  | Eggs | Larvae | Juveniles | Subadults |
| Adults |  |  |  |  |  |  |
| Spring |  |  |  |  |  |  |
| Estuary | Top |  |  |  |  |  |
|  | Middle |  |  |  |  |  |
|  | Lower |  |  |  |  |  |
| Shelf | Inshore |  |  |  |  |  |
|  | Offshore | Eggs |  |  |  |  |
| Summer |  |  |  |  |  |  |
| Estuary | Top |  |  |  |  |  |
|  | Middle |  |  |  |  |  |
|  | Lower |  |  |  |  |  |
| Shelf | Inshore |  |  |  |  |  |
|  | Offshore |  |  |  |  |  |
| Fall |  | Eggs |  |  |  |  |
| Estuary | Top |  |  |  |  |  |
|  | Middle |  |  |  |  |  |
|  | Lower |  |  |  |  |  |
| Shelf | Inshore |  |  |  |  |  |
|  | Offshore |  |  |  |  |  |

Figure 39. Example of a stage-specific space-time plots by season where the cell colors indicate relative abundance of a life stage. White cells mean life stage is not present, light grey cells mean life stage is moderately abundant, and dark grey mean life stage is abundant. The habitat-time plot would have a similarformat except the second column of locationswould be replaced by habitat types (e.g., marsh, edge, channels, open water, inshore, offshore). A map of the estuary would accompany these plots showing the location areasand habitat types plotted in geographic space.

## Concept 2: Variability, Uncertainty, and Stochasticity

Fish exhibit elevated spatial and temporal variation in population abundance and vital rates (Rose, 2000). Part of thisvariation is due to difficulties in measurement and part is due to true variation among individualsand areas. Even with multiple sampling locations and relatively frequent sampling (e.g., weekly), many estuarine-dependent fish species are notorious for exhibiting wide fluctuations in abundance year-to-yearthat do not appearto simply be related to a single environmental factor. The complex life cycles that involve stagesusing different environments, with the general high sensitivity of fish's vital rates to environmental variation,
often result in fish population abundances showing great variation overtime and in their spatial distributions.
It is important to distinguish the sources of varia bility because they affect the interpretation of data used for calibration and validation and the design of sensitivity and uncertainty a nalyses. A convenient classific ation used for modeling for fisheries management (Ha rwood \& Stokes, 2003) is: (1) process stochasticity, or natural variation, (2) observation emor, (3) model struc ture errors, and (4) implementation errors.

It is preferable to make a subtle but important additional distinction. Process stoc hasticity is not considered to be uncertainty, and the combined effects of stochasticity and uncertainty are called variability. One can tell the difference between the two sources of variability by determining if more measurements would reduce the variability. If more measurements help, then one is dealing with uncertainty, whereas when more measurements do not reduce the variability, one is dealing with stochasticity. For example, more sampling stations result in more confidence in a spatial map of temperature, but there are true spatial differences in temperature that will remain, regardless of where and how many samples are taken; that is, measurements do not converge to a single value. Appreciating how variability results from uncertainty and stoc hasticity sources is important for a ssessing the fish responses to restoration actions. Also, a sensitivity or uncertainty analysis requires specification of how much to vary parameters and what the assumed variability means.

Observation error is also important. Predicted and observed abundances are compared aspart of model validation, and thus the variability a round each becomesimportant to properly interpret how the well the model fits the data.

Unc ertainty and stochasticity also relate to the type of model that is developed. Deterministic models assume all parametervalues, environmental variables, and other inputs are fixed values. These can vary in time and space (e.g., temperature,) but there is nothing random about their values. Stochastic simulations use pseudorandom numbersto add variation to model inputs or processes, such that if the same simulation is repeated with a different sequence of pseudorandom numbers, one does not achieve the identical results. How the degree of randomness is added, and to what inputs a nd processes, is very important to interpretation. It is widely recognized that a deterministic model fails to capture the true variability observed in nature. However, it is quite tricky to make a stochastic model that correctly generates rea listic variability. If only a few of the possible inputs or processes are varied, then the variability in model outputs is underestimated relative to the real world and cannot be intempreted as expected, given the range of possible outcomes. Often, stoc hastic model outputsare compared between runs asif the variance in predictionswasthe total variance, and thus differences are infered between runsthat are mostly due to how the stochasticity was represented, s rather than being relevant to real differences expected in nature. For example, if one only variestemperature in a model, then the results can only be interpreted as how robust the model is to temperature variation, not the variability expected to exist in nature.

## Concept 3: Generality-Prec ision-Realism (Levins)

Levins (1966) proposed that the development of a model involved the trade-offs between generality, realism (accuracy), and precision. He stated that you cannot have all three. While his idea is still being debated (Orzack, 2005; Evans et al., 2013), the concept of trade-offs a mong these three features is useful when developing a model. To have a very general model
necessarily means that it cannot be very rea listic or precise (quantitative predictions) for a specific location. If one wantsa highly precise model, one must sacrifice realism (i.e., the model should be kept focused) and generality, meaning it cannot be easily ported to other places.

The idea of trade-offs appliesto fish modeling for the master planin determining whether separate modeling approaches should be used for different speciesin different basins. For example, use of a single modeling approach for everything is emphasizing generality at the expense of site-specific realism and precision. Using different models for every species and basin would be emphasizing realism and precision overgenerality. The key is that decisions about which and how many different modeling approaches to use involvestrade-offs.

## Concept 4: Nonequilibrium Theory, Stability, and Recruitment

There are very few fish speciesin the Gulf that can be considered to be in a true equilibrium condition. Equilibrium is one form of stability in which abundance is constant yearto year. Most all fish populationsare not in deteministic equilibrium, but rather show a dynamic equilibrium in which abundancesvary yearto yearbut within a bounded range. Some fish populations in the Gulf have also shown long-tem trends.

Much of the interannual variability in abundance is related to variation in recruitment. Rec ruitment is defined asthe number of individuals surviving to some size or age after which annual mortality becomesless variable. For example, survival to about 70 mm has been used for brown shrimp, as this is when they leave the marshes and move offshore. Surviving for one year is a common definition of recruitment for many fish species. Trying to understand and predict annual recruitment has been the "Ac hilles heel" of fisheries management for decades. This is because the highly variable nature of survival of young-of-year stages makes mea surement difficult and because it is the portion of the life-cycle where density-dependent mortality is assumed to occur.

How one deals with nonequilibrium dynamics, rec ruitment, and density-dependent survival is critical to successful modeling of fish responses to restoration actions. It is not necessary to solve the rec ruitment problem ordeal with all forms of density-dependence, but one does need to be a ware of these concepts and how the models selected treat them in order for the modeling to be credible and to ensure the modeling results are properly interpreted.

## Concept 5: Scaling

Consideration of scale is fundamental to model development. Three dimensionsto scale asit pertainsto model development are temporal, spatial, and biological. Temporal scale refersto the time step used in the solution method, the time step/sat which model predictions can be outputted (e.g., daily, sea sonally, annually), and the length of model simulations (e.g., one year or multiple years). Spatial scaling refers to the resolution of spatial cells in the model (e.g., 500 m $\times 500 \mathrm{~m}$ ) and the domain covered by the model (e.g., lower portion of the estuary). These are also called "grain" and "extent."

Biological scaling is more complicated and involves four major components: (1) curency, (2) organizational level, (3) processes, and (4) prediction level. The currency is what is followed in the model calculations asstate variables and their units. For example, one can simulate total
biomass of forage fish, abundances in age-classes of a single species, biomass by size classes, or follow individuals.

Organizational level is very important and refers to how the state variablesfit together in the model. Organizational levels can be single-species, multispecies, community, food web, and ecosystem. Multispecies is when some, but not all, species are followed in the model, and thus the sum of biomasses over fish species in the model does not equal total fish biomass. Community involves following most or all species and thustheir summed biomass can be considered total fish biomass. Food web then adds explicit representations of the prey and predators of the species of interest. Ecosystem iswhen explicit representation of environmental conditionsisadded to a food web model. The organizational level of a model is often shown as a life cycle (single-species) or a food web diagram with a rrowsindicating flows of biomass or energy.

Processes a re considered to be the guts of the model. Processes are the vital rates that determine how individuals progress through their life cycles. Modeling of fish involves four basic processes: (1) growth, (2) mortality, (3) reproduction, and (4) movement. Mortality and reproduction affect the numbers of individuals a live at a ny given time directly; growth affects body size and thus affects biomass (number xweight) and can indirectly affect mortality and reproduction because these are often related to body size. Morta lity rates generally decrease with size in many organisms, and maturity and fec undity generally inc rease with size. Movement affectswhere individuals are located, and the environmental (e.g., temperature) and biological conditions(e.g., prey, competitors, predators) they experience. These then can affect growth, mortality, and reproduction. While the movement of eggsand larvae are dominated by physics (i.e., transport), juveniles and adults can exert signific ant control via behavior over how they move. However, the physics are also important for the older life stages because behavioral movement often usesthe physics and related outputs (e.g., salinity) ascuesfor movement.

The final of the four aspects of biologic al scaling is the prediction level. Prediction level refers to the output of the model and how model results should be interpreted. Ideally, models for the master plan will attempt to operate at the population level for species of interest, which can be in single-species, multispecies, food web, orecosystem models. This way, the a nnual predictions of abundance and biomass of a speciesfora basin can be compared over 50 years between a simulation with no restoration projects (FWOA) and a simulation that includes the effects of restoration projects. One can then present how much abundance and biomass would change (e.g., numbers of adult individuals, kg ) over the next 50 years as a result of the restoration projects. However, while the approach of simply modeling every square meter of basin seems intuitive, this may not be practical nor generate the best predictions. Otherstrategies that use point predictionsin space and scale-up to broader regions may be more effective.

Prediction level also refers to how model results should be compared ac ross different simulations. The most straightforward comparison between altemative simulations would be the change in population-level (basin-wide orsub-basin), abundance, and biomass. To generate credible predictions of basin-wide abundances and biomass requiresthe model results can be scaled to the basin and a high level of rigorin calibration and validation. Often a baseline simulation is established (FWOA in this case) and then it is compared to abundances and biomasses between the simulation with the project to those without the project. It is easier to achieve the rigorto allow expressing results aspercent changesfrom baseline than as changes in abundances and biomass. To get to the level of changesin abundance and biomass requires
that the baseline generates realistic abundances and biomass for the sub-basin or basin. It is also important to emphasize that the fish modelsare not forecasting tools. None of the models will generate abundances and biomasses expected in the future forspecific years and locations. Model predictions for 10 years into the simulations are not what is expected to be measured in the year2023 at that location. This is not achievable and in fact, is not how model predictions for fisheries stock assessment to set quotas are intepreted. The major issue for the master plan is how well predictions can be viewed as abundance and biomass at the population level forsub-basins and basins.

## Concept 6: Explic it versus Implic it Representation

The linkages between the effects of the restoration actionson environmental conditions-via changes in hydrology, waterquality, and habitat-and the fish responses can be explicitly or implicitly represented. A model does not necessarily have to have a variable labeled "salinity" in order to include a salinity effect on growth rate and similarly, simply because a model has a salinity knob does not mean it can just be changed to simulate the effects of the restoration action on growth. Sometimes a function can be easily added to the model, or a built-in option used, and the exact relationship between growth rate and salinity isthereby added to a model. A salinity time series is specified and the model that never mentioned salinity now simulates the effects of salinity on growth rate exactly as desired. On the other hand, an existing model can already receive salinity as an environmental input and have a salinity effect on growth rate, and it could be not what is desired or supported by the data and be extremely diffic ult or even impossible to correct. What are important are not the labels of an existing model, but rather the actual equations. While documentation is helpful, often the only true way to see exactly how a model represents a processis by looking at the computer code itself.

Environmental variablescan also result in interactive effects on vital rates, where the response is larger than would be expected by the effectsif they had occured separately. Such effects can be represented mathematically (e.g., cross-product tem in a regression), but it isvery rare they are built into existing models. For example, temperature and salinity have been shown in the lab to interact on their effects on growth; the effect of wa mertemperatures depends on the salinity value. Interaction effectscan create nonlinearities in model responses and so are important to include if they exist.

Implicit versus explicit representation also a ppliesto spatial and temporal considerations. Implicit representation is referred to in oceanographic modeling assubgrid scale phenomenon. One does not have to simulate the spatial and temporal scales of every process in order to include their effects in simulations. For example, prey encounters oc cur on millimeters and second scales, but one does not have to build a model that includes predator-prey encounters using millimeter-sized spatial cells and a one second time step. Similarly, temperature is not truly uniform within a $500 \mathrm{~m} \times 500 \mathrm{~m}$ spatial cell, but it is not necessary to model cells within the 500 m cell (explicit) to represent the variability in temperature. We can do it implicitly by generating randomness around the single temperature value used each time for the 500 m cell. However, there are limitations to the implicit approach to representing variability in that it becomesvery difficult to have memory from one time to the next. Implicit representations are better at adding varia bility that is not state dependent (i.e., independent from time step to time step).

## Concept 7: Population Definition

It may seem odd that defining the populationsin a model is subject to judgment. Many of the fish species in a fish model show complex life cycles. Individuals migrate a mong different habitats, including from the marsh to offshore (e.g., brown shrimp). They also show movements and mixing across the Gulf and varying degrees of site fidelity. Thus, models of sub-basins and basins will involve individuals that exit and enter the model domain and mix with other individuals from other basins, some of which are not included in the modeling at all. For the majonity of species of interest, one will not have closed populationswithin the model domains. Yet, multiyearsimulations that include reproduction from modeled individuals often a ssume closed populations (i.e., the area modeled isisolated and individualscomplete their life cycle there). It is necessary to deal with open populations, but one must be careful with regard to how the model predictions are interpreted, i.e., define predictions over multiple years in terms of saying they are long-tem population responses.

## Concept 8: Density-dependence

Density-dependence is the most controversial of all the concepts. Density-dependence refers to how vital rates-growth, mortality, reproduction, and movement-change in response to the number of individuals present. Compensatory density-dependence is when high numbers of individuals cause slowed growth, higher per capita mortality, reduced reproduction, or movement to less optimal habitat (i.e., where mortality is higher, or growth or reproduction is lower). Compensatory density-dependence is a negative feedback and acts to stabilize the population (i.e., leads to equilibrium). Depensatory density-dependence is when mortality inc reases or reproduction decreases at low numbers of individuals, and is a positive feedback and a destabilizing factor at low abundances. The foc us must be on compensatory densitydependence, which is also the basisfor sustainable harvesting (e.g., the inc rease due to fishing is offset by compensatory changes in vital rates). The difficulty is that while it is known that compensatory density-dependence exists and operates, it has been diffic ult to quantify it with high precision. A common way to quantify density-dependence is through a spawner-recruit relationship in which recruitment levels off (Beverton-Holt) or even beginsto dec rease (Ricker) at high spawning biomasses. Density-dependence is a nother concept that requires attention to understand how it is dealt with (including if it is ignored) as the fish models are developed. It is possible to overestimate responses to restoration actions (both positive and negative) if they occur at high abundances when density-dependence would dampen the responses.

## Concept 9: Verification, Calibration, and Validation

Verific ation, calibration, and validation are three very important steps in establishing model c redibility. Swannacket al. (2012) offer definitions:

Calibration: The process of adjusting model parameters within physic ally defensible, and ecologic ally reasonable, ranges, until the resulting predictions give the best possible fit to the observed data. In some disciplines, calibration is also refered to as "parameter estimation."
Verification: Examination of the algorithms and numerical tec hnique in the model to ascertain that they truly represent the conceptual model, and that there are no inherent numerical problems with obtaining a solution. In some disciplines, verific ation is also referred to as "code testing."

Validation: The process of confiming a model's applicability, usually conducted by applying a calibrated model to a set of data separate from that used in the calibration processto demonstrate the accuracy of predicted results. In some disciplines, validation is also referred to as "evaluation, skill/fitnesstesting, or postauditing."

Verific ation is often not documented and is underappreciated. Software testing is required to ensure consistency between the conceptual model and the implementation.

Calibration is needed because parametervalues are taken from multiple sources that involve other species, systems, time periods, or laboratory conditions. Thus, when all the values are simply plugged in, it is quite reasonable that some additional a djustment will be needed to have all the parametervalues fit together and for realistic model behavior to result. Ca libration can vary from ad hoc adjustment by the modeler until desired qualitative behavior (e.g., equilibrium) occurs to formal optimization being used to detemine the parametervalues that minimize the differences between predicted values and observed data (e.g., nonlinearleast-squares).

Validation is a more elusive goal than calibration; yet, it is what many people immediately look at to determine if they "believe" the model results. Even what is meant by "validation" has been debated for dec ades (Rykiel, 1996). Many people have listed types of validation; here, the list proposed by Wainwright and Mulligan (2004) is utilized: (1) face validation, i.e., the evaluation of whether model logic and outputs appear reasonable, (2) Turing tests, where "experts" are asked to distinguish between real-world and model output (by a nalogy with the test for artificial intelligence, (3) visualization tec hniques, often associated with a statement that declares how well the modeled results match the observed data, (4) comparison with other models; note the high likelihood of developing an argument based on circular logic here, (5) intemal validity, e.g., using the same dataset repeatedly in a stochastic model to evaluate whetherthe distribution of outcomes is always reasonable, (6) event validity, i.e., whether the occurrence and pattem of a specific event are reproduced by the model, (7) historical data validation using split-sample techniquesto provide a subset of data to build a model and a second subset against which to test the model results, (8) extreme-condition tests, i.e., whether the model behaves"rea sonably" under extreme combinations of inputs, (9) traces, e.g., whetherthe changes of a variable through time in the model are realistic, (10) sensitivity a nalyses to evaluate whether changes in parametervalues produce "reasonable" changes in model output, (11) multistage validation (comesponding to the stages $\mathrm{a}, \mathrm{b}$, and c noted above), (12) predictive validation, which is a comparison of model output with actual behavior of the system in question, and (13) statistic al validation, indicating whether the range of model behavior and its error structure match that of the observed system.

While calibration and validation sound simple, they are actually very complic ated and often controversial in practice, especially with modeling used forinforming management decisions. It will be impossible to do a simple validation of the fish models for the masterplan. The data simply do not exist. Thus, one must be very careful and mindful how the model behavior is examined in order to judge whether the model is sufficiently realistic and robust to address the questions. Using less straightforward approaches rather than predicted versus observed comparisonsis likely, and focus should be on whether the model generates roughly similar aggregate outputs (e.g., total biomass) and spatial and temporal pattems in abundance that one can glean from the literature and monitoring data. These will be qualitative to semiquantitative comparisons, rather than the reporting of a goodness-of-fit statistic between
predicted and observed values. Thus, the process for calibration, and especially validation, will need to be clearly described and documented.

## Concept 10: Sensitivity and Uncertainty Analysis

Sensitivity a nalysis and uncertainty analysis are used to establish the robustness of model results and to identify those parameters that greatly influence model behavior. Sensitivity a nalysis uses small changes in parameter values, usually a pplied equally a cross all parameters (e.g., $\pm 10 \%$ ). Unc ertainty a nalysis uses realistic variation in parametervalues, which can differ among the various parameters. It gets very confusing because Monte Carlo methodscan be used for sensitivity a nalysis, unc ertainty a nalysis, a nd for representing va riability (stochasticity and uncertainty) in stochastic models. The key is how much inputs are varied and whetherthey are varied only at the beginning of a simulation (sensitivity and uncertainty analyses) or throughout a simulation (stochastic model).

Developing models forthe master plan also involvesusing outputs of other models asinputs. The variability of these inputs then depends on how they were simulated in the other models. Even more complicated is that in some cases, the inputsto the fish models go through several steps of output from one model being input to a nother model before getting to be inputs to the fish models. Some of these modelsmay be stochastic modelsthemselves. Thus, the propagation of variability, stoc hasticity, and uncertainty through coupled models is of particular concem here.

## Concept 11: Multiple Modeling Strategies

Given the complicated nature of the questions, multiple species of interest, and multiple basins, it is very likely that more than one modeling approach will be developed for the masterplan. It is also possible that more than one modeling approach will be used for the same question or species. The use of multiple models for the same purpose is a powerful way to deal with uncertainty about which is the best model. For example, one could envision a situation in which both CASM and EcoSim are used, and their predictionscompared. There are several waysto do multiple orensemble modeling. Climate change requires each modeling group to use a few common inputs, but then letsthem develop theirown models and many other inputs and parametervalues. Then the predictions are brought together and presented as multiple lineson a graph. The other extreme is to require the different models to use the same values of inputs and parameters wheneverthey overlap between the models. Comparison of outputs across models then allows examination of structural uncertainty a mong the models. There is a continuum of possible data sharing between these two extremes. If a multiple model strategy is used forthe masterplan, a cleardescription of how common data are shared and how outputs are compared is necessary.

Part of multiple models is the idea of using different modeling approaches for different aspects of the questions. It is possible to use different models for different species and different models for different aspects of the questions. For example, one could envision a model of a food web that simulates the bioma sses of species of interest overtime using one spatial box to represent the estuary. Such a model would not deal with spatial distributions, but rather compare biomasses between FWOA and a simulation with all projects in the estuary included. Then a separate model would be used to address a specific aspect of the question about how diversions-one of the restoration actions-affect spatial distributions. A model that only
simulates the spatial distribution of a key life stage of one of the species of interest, given a spatial map of environmental conditions, would be developed and used. This would very likely result in better predictions(e.g., higher accuracy and more confidence) of biomasses changes and spatial distribution changes for the species of interest, than trying to answer both aspects of the question in a single spatially explicit food web model that runsfor 50 years.

## Concept 12: Food Web Dynamics

Food web dynamicsinvolve how one species affects a nother. The majorinteractions are competition for resources and predator-prey relationships. While it's relatively easy to develop a conceptual model of a food web, translating the a rows showing flows, either of shared resourcesamong speciesforcompetition or between prey and predator, is a major challenge. Food web modeling hasbeen done fordecadesand most all of the models reviewed forthe master plan still use the same basic formulations(e.g., type 2 functional responses). New approaches have been proposed (e.g., stoichiometry; size-based; see Belgrano et al., 2005), but these still seem to be more in the theoretical a nalyses than resource management decision making. One of many examples isthe recent paper by Abrams (2010) who illustrates how including flexible foraging into simple food web modelscan affect the results, and states "one could argue that this makesfood webs hopelessly complex. It clearly addsto the list of processes that an ecologist must consider in predicting the population/community consequences of environmental perturbations." He goes on to say more optimistic ally that, at least for flexible foraging, the options are finite. The debate over prey-dependent (used in most of the models reviewed) versus ratio-dependent (DeAngelis, 2012) is another example of major theory arguments that have resulted in relatively slow advancement and adoption in applied food web modeling. Thus, any food web orcommunity level modeling for the master plan will need to be done with caution and knowing that the existing models have shown moderate success and show little progress from earlier models, despite basic arguments about the theory of the interactions. However, the 2017 Coastal Master Plan is not the time to try new approaches that have not been tested yet.

## Concept 13: Hidden Assumptions and Domain of Applic ability

There can be many hidden assumptions in the modelspotentially used in the 2017 Coastal Master Plan. These assumptions include aspects about the range of input values over which certain relationships are valid, disconnects between written documentation and what the code actually does, labeling of inputs with general names but then using them in very specific ways or in a way that depends on other inputs or the specific form of a equation, and the actual solution methodsused.

To illustrate, consider a model that hasan input labeled "salinity." However, the equation that uses salinity was estimated on a range of values and used a linear relationship over the na row range. The new use of the model wantsto use a value outside of that range and thus the model will continue to use the linear relationship even though it is not valid. A published paper on the model may have one description orlack details, and the only way to know what is really being computed is to look at the source code. For example, the variable "salinity" in the paperwas used in an equation, but the model now usesa different equation. Even the label "salinity" to an input can create problems when the model is used by others to address new questions. Only a very few of the possible effects of salinity will be in the model and often salinity is used in a
model as an "effective salinity." The value of salinity has a different meaning within the model than what was measured in the field because it combined with othervariables and only applies to the specific relationships. Finally, the solution method needsto be considered because the order of solving things can affect results, and the numerical aspects of the solution need to be confirmed because new faster rates may be simulated under master plan conditionsratherthan in earlierversions of the model.

Another example of hidden assumptions is that the Ecosim model uses a different way to represent feeding between predators and prey than most of the other food web-capable models. Ecosim uses a foraging arena approach that can generate very different densitydependent relationships than the classical Holling type relationships (Ahrenset al., 2012). Yet there is no easy option to check the sensitivity of Ec osim results to the foraging a rena representation versus other representations. If one uses Ecosim, then one inherits the assumption of foraging arena theory.

## APPENDIX B: List of Existing Rate-based Models Reviewed During Process of Narrowing Down Approac hes to be Considered for the 2017 Coastal Master Plan

The reference specific to each model is listed and each is categorized for the five schemes. The reason the model is eliminated from being furtherevaluated forthe 2017 Coastal Master Plan is also listed. A blank "Reproduction" category meansthat the model simulated one yearand how reproduction was represented was not applicable. Although most models are eliminated for potential approaches in the master plan, all listed models here have components and information that are useful and potentially could be incomorated within the suggested approaches.

| Model | Location | Habitat | Cumency | Biological Organization | Spatial | Temporal | Reproduction | Reason Eliminated for Master Plan |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Fisheriesmodel Bamthouse et al., 1990 | None - for Gulf menhaden and Chesapeake Bay striped bass |  | Age-structured | Single species | Point | Multiple years | Full life cycle | Not eliminated and used to illustrate an approach. |
| Lotka-V olterra Whipple et al., 2000 | None - assessing modeling approachesfor fishing and predator interactions |  | State va riable | Multispecies | Point | Multiple years | Implicitly represented | Lotka-Volterra-type models are highly aggregated and thus do not allow for sufficient realism and do not allow forthe representation of the many effects to hydrology a nd water quality expected under the master plan. |
| LDWF blue crab stock assessment West et al., 2011 | LA | Coastwide | State va riable | Single species | Point | Multiple years | New recruitsand fully recruited life stages | This is a simple fishery model based on abundance by age with tems for annual recruitment, morta lity, and catch. Adapting for the effects of the master plan would be difficult as the YOY life stages are treated in aggregate asannual incoming recruits. |


| Model | Location | Habitat | Cumency | Biological Organization | Spatial | Temporal | Reproduction | Reason <br> Eliminated for Master Plan |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| LDWF striped mullet assessment West et al., in progress | LA | Coastwide | Age-structured stock assessment | Single species | Point | Multiple years | Full life cycle | A statistical catch-at-age model; does not pemit easy simulation underfuture hydrological and water quality conditions. |
| LDWF spotted seatrout assessment West et al., in review | LA | Coastwide | Age-structured stock assessment | Single species | Point | Multiple years | Full life cycle | A statistic al catch-at-a ge model; does not pemit easy simulation underfuture hydrological and water quality conditions. |
| Brown shrimp bioenergetics growth model Adamack et al., 2001 | TX/LA | TX/LA salinity gradients | State variable | Single species | Point | Single year | Juvenile stage | A growth model of an individual; does not address responses of orga nisms related to mortality and reproduction. However, individual growth models were considered as an approach specific to oysters. |
| Multispecies fisheries model Kinzey \& Punt, 2009 | Aleutian Shelf | Aleutian Shelf | Age-structured | Multispecies | Point | 1964-2003 | Full life cycle | While a simple food web model is useful, the formulation of this model is specific to fisheries data and tailored to pollock, mackerel, and cod. |
| Spatially-explicit age-structured a ssessment model Porch, 2004 | GOM | East and West of MS River | Age-structured | Single species | Spatially explicit | Multiple years | Full life cycle | This is a typical agestructured stock a ssessment model that lumps all YOY stages into a spawnerrecruit relationship that would be difficult to modify to smulate masterplan effects. |


| Model | Location | Habitat | Cumency | Biological Organization | Spatial | Temporal | Reproduction | Reason Eliminated for Master Plan |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Ecopath with Ecosim (EwE) Walters et al., 2008 | GOM | Entire Gulf | Age-structured forseveral populations <br> State variables for others | Ecosystem | Point | 1950-2004 | Forced recruitment | EwE was not eliminated and wasused to illustrate an approach; Gulf and Louisiana versions exist. |
| EwE <br> Ma et al., 2010; Christensen et al., 2009 | Chesapeake Bay | Estuary | Age-structured for several populations. State variable for others | Ecosystem | Point | 1953-2002 | Forced recruitment | EwE was not eliminated and wasused to illustrate an a pproach; Gulf and Louisia na versions exist. |
| EwE de Mutsert et al., 2012 | Breton Sound | Estuary | Age-structured forseveral populations. State variable for others | Ecosystem | Point | Multiple years | Forced recruitment | EwE was not eliminated and wasused to illustrate an a pproach; Gulf and Louisia na versions exist. |
| EwE <br> Chagaris et al., 2013 | West Florida Shelf | Shelf including estuaries and ports | Age-structured for several reef fish populations. State variable for others | Ecosystem | Point Spatially explicit <br> w/Ecospace in development | 1950-2009 | Forced rec ruitment | EwE was not eliminated and was used to illustrate an approach; Gulf and Louisiana versions exist. |
| EwE <br> Lewis \& Cowan, in progress | Barataria Basin | Estuary | Age-structured forseveral populations. State variable for others | Ecosystem | PointSpatia lly explicit <br> w/Ecospace in development | Multiple years | Forced recruitment | EwE was not eliminated and wasused to illustrate an approach; Gulf and Louisia na versions exist. |
| EwE <br> Frisk et al., 2011 | Delaware Bay | Estuary | Age-structured for several populations. State variable forothers | Ecosystem | Point | 1966-1997 | Forced recruitment | EwE was not eliminated and wasused to illustrate an a pproach; Gulf and Louisia na versions exist. |
| CASM Bartell et al., 2010 | Pontchartrain Basin | Estuary | State variables | Ecosystem | Point | 1989-2007 | Forced recruitment | CASM was not eliminated and was used to illustrate an approach; Louisiana versions exist. |


| Model | Location | Habitat | Cumency | Biological Organization | Spatial | Temporal | Reproduction | Reason Eliminated for Master Plan |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| CASM <br> Watkins \& Sable, in progress | Barataria Basin | Estuary | State variables | Ecosystem | Point | One year |  | CASM was not eliminated and was used to illustrate an approach; Louisiana versions exist. |
| TroSim Fulford et al., 2010 | Chesapeake Basy | Estuary | State variables | Food web | Point | One year |  | TroSim was not eliminated and was used to illustrate an approach; related to CASM and was highlighted as an approach specific to oysters. |
| TroSim Milroy et al, in progress | MS Sound | Legacy reefs offshore Bay St. Louis | State variables | Food web | Point | One year |  | TroSim was not eliminated and was used to illustrate an approach; related to CASM and was highlighted as an approach specific to oysters. |
| Atla ntis Ainsworth et al., in progress | GOM | Entire GOM | Age-structured | Ecosystem | Spatially explicit w/crude orno movement | Under development |  | While there is a Gulf version being developed, Atlantis is complicated and would be technically diffic ult to set up for the master plan and for a Louisiana version. |
| Atlantis Mason et al., in progress | GOM | MS-LA-TX shelf including estuaries | Age-structured | Ecosystem | Spatially explicit w/crude orno movement | Under development |  | While there is a shelf version for Louisiana, Atlantis is complicated and would be tec hnic ally diffic ult to set-up for the master plan and other locations within estuaries of Louisia na. |
| Atlantis Ainsworth \& Coleman, in progress | GOM DWHOS | Desoto Canyon | Age-structured | Ecosystem | Spatially explicit w/crude orno movement | Under development |  | While there is a Gulf version being developed, Atlantis is complicated and would be tec hnic ally diffic ult to set-up forthe master plan and Louisiana. |


| Model | Location | Habitat | Cumency | Biological Organization | Spatial | Temporal | Reproduction | Reason Eliminated for Master Plan |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Trout IBM Clark et al., 1999, 2001 | Appalachian Mountains | Pools, runs, riffles of streams | Individual | Multispecies | Spatially explicit | Multiple years | Full life cycle | Not eliminated and used to illustrate an approach. <br> However, while some of the spatial aspects of the model are relevant, the fine spatial resolution (meters) of the model and its custom code specific to brook and rainbow trout in <br> Appalachian streams make use of this specific model impractical. |
| Shrimp IBM Roth et al. 2008 | Louisiana/Texas | Marsh, marsh edge, open water | Individual juvenile brown shrimp | Single species | Spatially explicit | One year |  | Not eliminated and used to illustrate an approach. However, the fine spatial resolution (meters) of the model limits the geographic scale of model predictions |
| Atlantic croaker IBM Creekmore, 2011 | Northem Gulf shelf | Shelf water habitat grid for DO, Chl, elevation | Individual <br> Atlantic croaker | Single species | Spatially explicit | Multiple years | Full life cycle | The model is specific to croaker on the shelf and how hypoxia affectsgrowth, mortality, and reproduction. Estua ries are treated very simply a nd so incorporation of master plan effects would be difficult. |
| Spatially explicit <br> IBM (SEIBM) <br> Fulford et al., 2011 | Lower Pascagoula River, MS | High and low marsh, forest, water | Individual juvenile spot | Single species | Spatially explicit | Seasonal |  | Not eliminated and used to illustrate an approach. |
| Tidal marsh community IBM Sable \& Rose, in draft | Northem Gulf/ Louisia na | Interior marsh, marsh edge, marsh ponds, open water | Individualsfor six tidal marsh species | Food web | Spatially explicit | One year |  | The fine spatial resolution and limited domain and single year simulations limit how the predictionscan be extrapolated. |


| Model | Location | Habitat | Cumency | Biologic al Organization | Spatial | Temporal | Reproduction | Reason Eliminated for Master Plan |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| PTM-IBM Rose et al., in review | Gulf | Caemarvon Diversion | Individual fish larvae | Single species | Spatially explicit | Seasonal |  | Not eliminated and used to illustrate an approach. |
| Spatial dynamic multistock production model (SDMPM) Ault et al., 1999 | Biscayne Bay, Florida | Shallow lagoon coral, seagrass, hardbottom, soft bottom habitats | Age-structured | Multispecies | Spatially explicit | One year | Full life cycle | Not eliminated and used to illustrate an approach. |
| Spatially explicit matrix models Hunter \& Caswell, 2005 | None - demo for adding spatial component to matrix models |  | Age- and stagestructured | Single species | Spatially explicit | Multiple years | Full life cycle | Theoretic al description for how to make matrix models smulate multiple spatial regions, and unclearhow to adapt to the master plan effects. |
| ALFISH <br> Gaff et al., 2000 | Florida Everglades | Marsh, water | Age-structured | Multispecies | Spatially explicit | Multiple years | Full life cycle | Model formulation was specific to small and large fish groups in the Everglades |
| OSMOSE for Integrated Ecological Assessment Grus et al., 2013 | Gulf | Entire Gulf | Individual | Multispecies | Spatially explicit | Multiple years | Full life cycle for some; forced rec ruitment for others | While OSMOSE, which is sizebased, may have some utility asan altemative to EwE and CASM, it is being set-up forthe entire Gulf (not Louisiana) and is still in the early stages of development. |
| Oyster-Specific Models |  |  |  |  |  |  |  |  |
| Shell-neutral oyster stock assessment model Soniat et al., 2012 | Breton Sound | Station data for the public seed oyster grounds | Size-structured | Single species | Point | $\begin{aligned} & \text { Single year } \\ & \text { runs using data } \\ & \text { for } 1999 \text { to } \\ & 2011 \end{aligned}$ |  | Focus of the model is on short-term (1-2 year) projections of harvest and would be difficult to adapt to longer term predictions and master plan effects. |


| Model | Location | Habitat | Cumency | Biological Organization | Spatial | Temporal | Reproduction | Reason <br> Eliminated for Master Plan |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Oyster demographic model Weberet al., 2013 | Chesapeake Bay | 8480 oyster bars in estuary | Size-structured | Single species | Spatiallyexplicit | 10-year runs | Spat rec ruitment on bars detemmined by female spawners, shell plants, and larval transport | Not eliminated and mentioned as an altemative for a postsettlement oyster population model. |
| Oyster reef model J ordanCooley et al., 2011 | Chesapeake Bay | Oyster reefs | State variables forvolume of live oysters, dead oysters, sedimentation | Single species | Point | Multiple years | None | Theoretic al model that would be difficult to a pply and make site-specific for loc ations in Louisiana. |
| Oyster larval transport model <br> Lipcius et al., in draft | Lynnhaven River System in lower Chesapeake Bay | Tidal niver complex | Individual oyster larvae particles | Single species | Spatiallyexplicit | Seasonal |  | Not eliminated and used to illustrate an approach. |
| Oyster larval transport model North et al., 2008 | Chesapeake Bay | Estuary | Individual oyster lavae particles | Single species | Spatiallyexplicit | Seasonal |  | Not eliminated and used to illustrate an approach. |
| Oyster larval transport model Kim et al., 2013 | Mobile Bay | Estuary | Individual oyster larvae particles | Single species | Spatiallyexplicit | 10-day simulations for larval period |  | Not eliminated and used to illustrate an approach. |
| Oyster larval growth model Dekshenieks et al., 1996 | Chesapeake Bay | J a mes River | Size-structured larval growth | Single species | Spatiallyexplicit | Seasonal |  | Mentioned in an approach for extending larval transport modelsto include larval growth a nd survival. |
| Coupled larval transport and reef population model <br> Dekshenieks et al., 2000 | Galveston Bay | Estuary | Size-structured larval transport model with sizestructured reef population models | Single species | Spatiallyexplicit | Multiple years | Full life cycle | Not eliminated and used to illustrate an approach. |


| Model | Location | Habitat | Cumency | Biological Organization | Spatial | Temporal | Reproduction | Reason <br> Eliminated for Master Plan |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Oyster population growth model Wang et al., 2008 | Apalachicola Bay | Two reef sites in estuary | Size-structured reef population model | Single species | Point | Single year simulations |  | Not eliminated and used to illustrate an approach. |
| Dyna mic Energy Budget model Gangere et al., 2009 | Baie des Veys Estuary, France | Estuary | State variable | Single species | Point | Single year simulations |  | Not eliminated and used to illustrate an approach. |
| Oyster disease model Hofmann et al., 2001 | Chesapeake Bay | Estuary | State variable | Host-parasite | Point | Multiple years |  | Not eliminated and used to illustrate an approach. |

## APPENDIX C: Summary of Details for Selected Rate-based Modeling Approaches for Fish and Shellfish in the 2017 Coastal Master Plan

The table content and format is similar to that used by Plaganyi (2007) to compare modeling approaches used in ecosystem-based fish management. The citation listed under the approach is common with Appendix B, and is used as the primary reference for the infomation in the table. Other references are noted within the rowswhen used to provide information outside of the example reference. Additional references and capabilities were important to note in some cases so that it was not seen as a limitation orimpossibility with the approach.

| Model | Matrix projection models <br> (MPM) Bamthouse etal., 1990 | Breton Sound Ecopath with Ec osim (EwE) deMutsert etal., 2012 | Barataria Basin <br> CASM <br>  <br> Sable, in progress | Chesapeake Bay TroSim Fulford et al., 2010 | Breton Sound Fish PIM Rose et al., in review | SEIBM Fulford et al., 2011 | SDMPM <br> Aultetal.,1999 | Spatially-explicit IBMs Clark etal., 2001 | NGOM Atantis Ainsworth etal., in progress |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Level of complexity and realism |  |  |  |  |  |  |  |  |  |
| a) No. of modeled species or groups | Single species, a few multispecies matrix models exist (Rose \& Sable, 2009) | 39 including phytoplankton, zooplankton, SAV, benthos; 60 groups in WFS model incl. multiple plankton groups, seabirds, sharks (Chagaris et al., in progress) | 30 including phytoplankton, zooplankton, periphyton, zoobenthos; SAV and EAV groups incorporated (Ba rtell et al., 2010) | 23 including phytoplankton, zooplankton, larval fish and oysters, oysters | Single species | Single species | Two-species predator-prey model | Usually single species; few multispecies and community IBMs exist (Sable \& Rose, in draft) | 90 functional including primary producers, mammals, turtles and birds |
| b) Size or age structure represented | Focus | Age-structured with stanza breaks to separate juveniles and adults commonly represented; added agestructure for reef fish populations (Chagaris et al, in progress) | No | No | No | Individual sizes of juveniles | Age cohorts of prey and predator populations | Yes-emergent from modeling individuals for full life cycle | Yes |


| Model | MPM | EwE | CASM | TroSim | Fish PTM | SEIBM | SDMPM | IBMs | Atantis |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| c) Species interactions | Some examples of multispecies and community models exist (Rose \& Sable, 2009) | Focus | Focus | Focus | Single species | Single species | Seatrout predator-pink shrimp prey | Few multispecies competition and predator-prey (Rose et al., 1999) and food web models (Sable \& Rose, in draft) | Focus |
| d) <br> Environmental inputs to existing model | Daily, monthly, a nnual salinity, temperature, depth, turbidity, marsh, edge, open water | Monthly, annual salinity; Monthly temperature, marsh habitat in progress (Lewis \& Cowan, in progress) | Daily surface light, a ir and water temperature, nutrients, depth, velocity, suspended sediments, POC, sa linity | Daily surface imadiance, water temperature, nutrients, suspended sediments, POC | 30-minute inputsfor depth, velocity, salinity | Temperature and salinity; structural habitat for high marsh, low marsh, forest, water, man-made structures | Coral reef, seagrass, hard bottom, bare bottom habitats, salinity, temperature, velocity | Daily velocity, depth, temperature; also daily marsh, edge, and water habitat (Roth et al., 2008) and DO, salinity (Sable \& Rose, in draft) | Daily, monthly surface irradiance, water temperature, nutrients, depth, velocity, DO |
| Spatial Representation |  |  |  |  |  |  |  |  |  |
| a) Ha bitat | Limited to a few spatial boxes (Hunter \& Caswell, 2005) | Spatial division limited by assumptions of Foraging Arena Theory; structural habitat possible Ecospace addition for exploring $\sim 10 \mathrm{~km}^{2}$ and larger resolution for MPAs, fishing pressure, reefs in progress (Chagaris, et al.) | Flexible spatial division to represent differences in habitat quality; structural habitat as vegetation types incorporated (Bartell et al., 2010) but needs further work | Spatial boxesto represent differences in habitat quality among oyster reefs | PTM on spatial grid of FVCOM or other hydrodyna mic model for spatial resolution of 20-500 m in estuary | Flexible finescale spatial division to represent differencesin struc tural habitat <br> HEXSIM uses hexagons at the spatial resolution defined by GIS input data | SDMPM on grid of 2-D hydrodynamic model of Biscayne Bay with grid spacing between nodes on order of 500 m | Flexible spatial division to represent finescale differences in habitat quality | Flexible spatial division to represent differencesin physical habitat quality; differences in substrate or geographic features (Fulton et al., 2004, 2011) |


| Model | MPM | EwE | CASM | TroSim | Fish PTM | SEIBM | SDMPM | IBMs | Atantis |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| b) <br> Movement | Simulate course movement among 2-3 spatial boxes (Hunter \& Caswell, 2005) | None with EwE Course movement with forced migration a mong spatial cells in Ec ospace needs further work (Chagaris et al., in progress) | None | None | PTM is passive transport from hydrodyna mics with fish behavior added | Yes | Yes | Yes | Forced migrations into and out of model domain; advection of OM, nutrients, plankton |
| Calibration and parameter uncertainty | No formal fitting to time series data; sensitivity a nalysis of simple matrix models common (Caswell, 2001) | ECORANGER used to mass balance models based on uncertainty, also to fit to annual time series of abundance and catch data (Chagaris et al., in progress) | Fitting to monthly biomass data for systematic calibration and parameter sensitivity using PEST(Sable et al., in draft) | Fitting to monthly biomass data for calibration | Diffic ult to calibrate PTMs/IBMs; multiva riate a nalysis of individuals difficult; distribution of species could be validated in future field studies | Fish abundance and condition data collected for habitat strata for model <br> development and validation, and sensitivity of movement parameters evaluated <br> Predicted length distributions by habitat type could be validated with field studies <br> Distribution of species by habitat could be validated in future field studies | Predicted growth of seatrout calibrated with sizes at age from field studies; densities by habitat type validated with field study for pink shrimp; sea sonal abundance of pink shrimp compared with field study | Model calibration and uncertainties diffic ult to deal with in highly parameterized IBMs; distributions and predicted average growth of speciescan be validated with finescale distributions from field studies, sizes at age from lab and field (Roth et al., 2008; Sable \& Rose, in draft) | No optimization program for fitting to data; parameter derivation and sensitivity a nalysis performed for model construction |


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| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Model transparency and ease of use | Relatively easy to construct and explain | Free online software makesit very easy to use; code not transparent or readily available | Input files and code customized per project and not easily transparent, readily available | Input files a nd code customized per project and not easily transparent, readily available | Customized code not easily transparent or readily available | SEIBM framework described in study relatively transparent and HEXSIM is free online software | Input files and code was customized for project and not easily transparent orreadily available | Input files and code customized per projectand not easily transparent or readily available | Input files and code customized perproject and not easily transparent; code is large and difficult, not readily available |
| Model adequacy to assess short-, medium-, and long-tem effects | Good for assessing medium (differences among years) and long-term effects | Good for assessing medium (differences among years) a nd long-tem effects | Good for a ssessing annual and within year effects; multiyearsimulations need work | Good for a ssessing a nnual and within year effects | Good for a ssessing annual and within year effects | Good forshorttem effects (within year) | Good for a ssessing a nnual and within year effects | Most used for assessing a nnual and within year effects; few examples of multiyear IBMs exist including Clark et al., 2001; Rose et al., 1999; Creekmore, 2011 | Good for assessing medium-term (differences a mong years) and long-tem effects |
| Model Description and Technical Information |  |  |  |  |  |  |  |  |  |
| Model units | Numbers | Biomass (g/m²) | Biomass ( $\mathrm{gC} / \mathrm{m}^{2}$ ) | Biomass ( $\mathrm{gC} / \mathrm{m}^{3}$ ) | Numbers Densities | Numbers, individual sizes, individual energy densities, biomass | Numbers, densities, sizes | Numbers, densities, individual sizes, biomass | Numbers, biomass, size-at-age of fish; $\mathrm{gN} / \mathrm{m}^{3}$ for lower trophic levels |
| Time step of model outputs | Annual | Annual | Daily | Daily | 30 minutes to daily | Daily | Daily | Daily | Daily to a nnual |
| Capable of simulating multiple years | Yes | Yes | Can be run for multiple years but needssome work | Can be run for multiple years but needssome work | Single year | Single year | Could be run for multiple years | Yes | Yes |
| Fish processes represented In model | Growth Survival Reproduction Movement | Growth Survival | Growth Survival | Growth Survival | Movement | Growth Survival Movement | Growth Survival Reproduction Movement | Growth Survival Reproduction Movement | Growth Survival Reproduction Movement |


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| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Densitydependent processes in model | Functional responses for growth, survival, reproduction movement can depend on age, stage, ortotal abundance (Sable \& Rose 2008, 2010) | Foraging arena theory assumes feeding response dependson vulnerable prey biomass | Type II feeding response for consumers dependson prey and predator biomasses | Type II feeding response for consumers depends on prey biomasses | No | No | Type II feeding response for seatrout based on shrimp density | Type II feeding responses based on prey availability; movement of speciesto higher prey and/orlower predatorareas | Flexible Type I-III feeding responses based on prey availa bility; movement of species to higher prey areas; Beverton Holt spawner-recruit functions for reproduction |
| Stochastic processesin model | Growth, survival parameterscan be stochastic (C a swell, 2001; Sable \& Rose, 2008, 2010) | No | No | No | No | Stoc hastic variation on movement | No | Stochastic variation on survival, growth rates of individuals | No |
| Model assumptions | Age orstagespecific differences in survival orgrowth, data available, and important to population dynamics | No movement of fish <br> Trophic interactions important | No movement of fish <br> Trophic interactions important | Point model represents reef <br> Trophic interactions important | Diversion operation displacesor disperses species; species have and move according to optimum salinities | Structural habitat score (quality) based on distance from open water cells <br> Species move according to available habitat and grow according to cumulative temperature and salinity exposure | Spawning time affects larval transport and settlement <br> Space-time history affects species growth and survival of age cohorts | Individual variation in vital rates, movement, or exposure important to population dynamics | Fish move to areas of higherprey <br> Forced migration in and out of domain <br> Trophic interactions important |


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| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Technical Information | RAMAS software available for download Excel has tool boxforsimple matrix model analysis Customized models coded in Fortran Runson PC | Software free and runs on PC <br> Coded in VB and C originally, new in Fortran <br> Code available upon request perproject | Coded in Fortran <br> Code and exe.file available upon request perproject <br> Runs on PC | Coded in <br> Fortran and adapted from CASM <br> Code and exe. file available upon request perproject <br> Runs on PC | Coded in Fortran <br> Use of particle tracking algorithms from hydrodynamic model | HEXSIM software free and runs on PC | Coded in Fortran | Customized modelscoded in Fortran | Coded in $\mathrm{C}++$ <br> Code available upon request perproject but laborand time intensive for setup |
| Possible model setup and spatial design for evaluation of the 2017 <br> Coastal Master Plan effects | Basin-wide model | Basin-wide point model or else forlarge subregions of basin (upper, mid, lower estuary) | Multiple CASM stations positioned within basin to represent geographical areas with environmental conditions <br> Spatial resolution of CASM stations should be coarse enough to meet a ssumption that fish movement is not important | TroSim point models set up for existing or planned oyster reef/s within basin | Set up for rec eiving basin of diversions and would be set to compartments of ec ohydrology model | Could be set to finest available model grain for ICM models $500 \mathrm{~m}^{2}$ resolution for the 2012 Coastal MasterPlan models | Could be set to finest available model grain for ICM models $500 \mathrm{~m}^{2}$ <br> resolution for the 2012 Coastal Master Plan models | Could be set to finest available model grain for ICM models <br> Example IBMs often on much finer spatial resolution than master plan models | Basin-wide orelse multiple Atlantis polygons positioned within basin to represent major geographicalareas with environmental conditions |
| a. Projectspecific at 50 years | Not suggested unless la rgescale, basinwide effects | Not suggested unlesslargescale, basinwide effects | Not suggested unless large-scale, basinwide effects | Evaluate local oyster reef project effects, or large-scale, basin-wide effects of project | Evaluate species displacement and cumulative exposure to salinity based on diversion operation | Not suggested unless la rgescale, basinwide effects | Not suggested unless la rgescale, basinwide effects | Good for evaluating fine scale differences in structural and dynamic habitat, if fine-resolution habitat data exist | Not suggested unless large-scale, basinwide effects |

Model
MPM
EwE
CASM
TroSim
Fish PTM
SEIBM
CPRA Modeling Needs


Good for
evaluating short-
tem dispersal and movement cumulative sa linity exposure within basin due to large diversion pulses

Not good for overtime orfor projects that do not directly affect flow, velocity, or salinity

SDMPM
IBMs
Atantis

Maybe good for basin-wide projections in relative biomass change and shifts in seasonal and/or spatial distribution within basin over
time

## Atlantis

incorporates other model outputsas inputsand thuscan evaluate cumulative project effects based on
the results generated by other

| Model | MPM | EwE | CASM | TroSim | Fish PIM | SEIBM | SDMPM | IBMs | Atlantis |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| c. Coast-wide cumulative effectsat 50 years | Model would need to represent a coastwide population (e.g., West et al., 2011) <br> Coastwide cumulative effectswould need to be collapsed into single va riables for age- or stagespecific response functions for a coast-wide population | If EwEs developed for each basin, then cumulative coastwide effectswould assume additive effects from basin-wide models <br> Assume no movement or exchange between basin modelsfor species | If CASMs developed for each basin, then cumulative coast-wide effectswould assume additive effects from basin-wide models <br> Assume no movement or exchange between basin models for species | If TroSims developed for oyster reefs within basin, then cumulative effects would assume additive effects from basin-wide reef models | Not good | Not good | Not good | Not good | Good if Atlantis models developed foreach basin and used shelf polygons from AL-LA-TX model for connection among basins (Mason et al, in progress) |


[^0]:    ${ }^{1}$ KAR is a member of the M odeling Subc ommittee

[^1]:    ${ }^{2}$ Not all outputs were necessarily produced for all groups or altematives.
    ${ }^{3}$ Some outputs can be generated at finer temporal resolution than what was used in the 2012 Coastal Master Plan
    ${ }^{4}$ Signific ant improvements to the resolution for some of the models are expected for the 2017 C oastal Master Plan.

