Report of the 3rd National Ecosystem Modeling Workshop (NEMoW 3): Mingling Models for Marine Resource Management – Multiple Model Inference

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and B. Wells (editors)

U.S. Department of Commerce
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Executive Summary

The NOAA-National Marine Fisheries Service (NMFS) held a National Ecosystem Modeling Workshop (NEMoW) on March 18-20, 2014 in Seattle, Washington. This 3rd NEMoW was held as a national workshop analogous to National Stock Assessment Workshops, National Habitat Assessment Workshops, and National Economists Meetings for the purpose of engaging the NMFS ecosystem modeling (EM) community. Primary goals of these NEMoWs are to develop best practices and recommendations on how the NMFS EM community can best help the NMFS to meet its mandates and obligations. There were 43 participants, six invited speakers/observers, and six visiting observers.

The theme of NEMoW 3 was “Mingling Models for Marine Resource Management” and focused on approaches and best practices for multiple model inference (MMI) in the context of living marine resource (LMR) management. Specifically, the EM community gathered to discuss how MMI is used in other contexts; the social and management implications of using multiple models; and how the EM community can draw from these other fields and apply these approaches while considering the LMR management context. The stated objective of this workshop was to evaluate best practices for using multiple model inference in a living marine resource management context.

Ecosystem modeling for LMR management includes a range of quantitative representations of part or all of an ecosystem focused on a single LMR, aggregate groups of LMRs, or whole food webs with focal LMRs and the relevant biophysical context of the LMR or LMR group/food web. As such, an EM is a quantitative tool used for resource management that incorporates factors internal and external to a focal LMR or group of LMRs. The tools may be something as simple as a statistical analysis of regression model showing the correlations between a particular fish species and its habitat, or it may be as complex as an end-to-end model that incorporates oceanographic model output and interactions between fished species, fisheries, and protected resources. The important aspect of this definition is that an EM is focused on practical application for simply attempting to understand a system, for understanding trade-offs among ecosystem components, or to set specific management reference points.

NMFS has a wide range of major legislative mandates (Magnuson-Stevens Fishery Conservation and Management Act – MSA, Marine Mammal Protection Act – MMPA, Clean Water Act – CWA, Coastal Zone Management Act – CZMA, Endangered Species Act – ESA) that require a movement towards many levels of ecosystem-based management (EBM). NOAA’s mission, vision, and policy statements have promoted and continue to promote movement towards ecosystem-based management. Most of the NMFS mandates require the use of the best available science. NEMoWs have been designed to stimulate and advance the use of ecosystem models to ensure the best available science is developed and applied towards ecosystem approaches to management.

Since the first NEMoW, NMFS scientist have developed and begun to apply a variety of EM approaches in their regions. As more ecosystem models have been developed a need to

determine how to use multiple models to provide the best available science has arisen. Moreover, in the 2nd NEMoW, participants were given a broad overview of the use of multiple models in climate science. Participants learned how multiple models help to manage uncertainty in scientific advice provided by models. The NEMoW Steering Committee determined that the use of multiple modeling approaches warranted further exploration. With support from the Science Advisory board, the Steering Committee elected to hold a workshop focused on MMI.

Broadly defined, MMI is the application of multiple quantitative representations (models) of a system in an effort to improve the understanding of how the system works. The models used may vary only slightly with different initial parameters being used or with different structural configurations of parts of the model. Alternatively multiple models with very different structures and parameters can be used. The practice of using models enables the range of uncertainty in initial parameters and in model structure to be accounted for when considering results and conclusions drawn from the models. This practice has been used extensively in other fields such as weather prediction, climate science, and social sciences, and has helped to advance those fields and improve the utility of their models.

During NEMoW 3, participants discussed the types of MMI, the reasons for doing MMI, and the benefits of doing it. In addition, participants outlined the generally used methodologies for MMI and how those approaches may be used in ecosystem approaches to LMR context. These results are discussed in the body of this report. Key conclusions on best practices and recommendations are outlined below and are discussed more fully in the Results section of the report.

Key conclusions on best practices:

1) Clearly define the type of management advice the models provide as strategic or tactical.
2) Use a range of MMI analytical or quantitative approaches appropriate for the type of question, the types of uncertainty, and amount of data available. MMI approaches include:
    a. Single model ensembles (i.e., sensitivity analysis),
    b. Multiple model ensembles,
    c. Model selection and weighting schema (e.g., Bayesian, AIC),
    d. Biological Ensemble Modelling Approach ,
    e. Expert opinion approaches (Delphic methods, Fuzzy Logic Mental Models).
3) Evaluate model performance/forecasting skill to support model improvement, model selection, and development of model ensemble weighting schema.
4) Use social science considerations/metrics as part of the MMI evaluation process and in communicating the results from MMI processes.
5) Where MMI is being implemented implicitly, begin to explicitly demonstrate that MMI is being used.

Four recommendations emerge from these conclusions:

1) Adopt MMI best practices (described above).
2) Perform simulation studies to evaluate skill of models to be used for MMI.
3) Evaluate cases where MMI has been attempted by NMFS for LMR management.
4) Develop and maintain EM and MMI capacity and infrastructure.

Given several forthcoming initiatives and copious calls for EBM, NEMoW 3 was quite timely and most attendees thought NEMoWs should persist and smaller, inter-sessional NEMoW working groups should be developed to focus on specific issues common to many regions. The NMFS is in a favorable position to implement MMI when applying EM to key LMR issues. Doing so, will enable progress in EM and improve its utility for LMR management. While the development of expertise and technical capacity is still needed, there exists a reasonably established foundation for NMFS to build upon for future EM efforts.

Acknowledgements

The NEMoW 3 Steering Committee, on behalf of all NEMoW 3 participants, would like to thank the local host of the workshop, the Northwest Fisheries Science Center. We especially thank Phil Levin and Mindi Sheer for their efforts in setting up local arrangements, handling workshop logistics, and enabling a productive meeting.

We acknowledge the efforts of the invited speakers, and thank them for their participation. We had four participants outside of NOAA who presented and participated in the discussion. We appreciate the effort and participation of Nick Bond (Joint Institute for the Study of the Atmosphere and Ocean), Stefan Neuenfeldt (Technical University of Denmark), Katie Arkema (The Natural Capital Project), and Steven Gray (University of Massachusetts – Boston). From within NOAA, we had two participants: Alan Leonardi from the NOAA/Ocean and Atmospheric Research - Atlantic Oceanographic and Meteorological Laboratory and Jack Beven from NWS - National Centers for Environmental Prediction, National Hurricane Center. We are grateful for the work they put into presenting and participating, and appreciate their perspectives from other NOAA Line Offices.

We thank the NMFS Office of the Assistant Administrator and the NMFS Office of Science and Technology for partial funding support to help defray the costs of this workshop.

Finally, we thank the NMFS Science Board for their enthusiastic support.

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Introduction

For many years, scientists and administrators at NMFS have recognized the need for NMFS scientists who are involved with ecosystem modeling (EM) (in its various forms and array of contexts critical to the living marine resource (LMR) management mission) to routinely gather, share methodologies and discuss recent advancements in the field. Similar to National Stock Assessment Workshops (NSAWs), National Habitat Assessment Workshops (NHAWs) and National Economists Meetings, NEMoWs (National Ecosystem Modeling Workshops) were established.

The general objectives of NEMoWs are: 1) to address broad questions of national interest for applied LMR-oriented EM, 2) to provide a forum for ecosystem modelers within NMFS to network and share information on EM advancements and best practices, and 3) to provide a vehicle to advance EM for LMR within NMFS. The specific objective for this 3rd NEMoW (NEMoW 3) was to evaluate best practices for using multiple model inference (MMI) in a LMR management context.

In this spirit of advancing EM science for LMR management and with the stated objective of evaluating best practices for using multiple model inference in a living marine resource management context, NMFS scientists conferred for 3 days at NEMoW 3. This technical memorandum captures the essential points that emerged from this workshop.

NEMoW 3 was important for making continued progress in integrating ecosystem considerations into fisheries management as highlighted in the Magnuson-Stevens Fishery Conservation and Management Act. The methodologies will be important for marine mammal and endangered species population assessment as required in the Marine Mammal Protection Act, the Endangered Species Act, and more broadly for cumulative effects under the National Environmental Protection Act. In addition, these approaches will be important for incorporation into the science for habitat management conducted by the NMFS under multiple mandates. NOAA polices have EBM at the core of its mission, and these EM approaches are the analytical engine central to these ecosystem-based approaches.

Background

The topic of “mingling models for marine resource management” was chosen as a theme for NEMoW 3 for many reasons. The major legislative mandates for NMFS require a movement towards various levels of ecosystem-based management, and NOAA’s mission, vision, and policy statements continue to espouse an ecosystem approach. In addition, many of these mandates require the use of the best available science. Thus a need arises for EM to provide the best available science to inform NMFS in a variety of regulatory roles. As the NMFS EM effort matures among the regions, and more ecosystem models are developed NMFS scientists must determine how to use multiple models to provide the best available science. This does not necessarily mean best available model, and work in other disciplines indicates that using MMI usually provides better results than simply picking one model.

In a previous NEMoW focused on dealing with uncertainty in EM, participants briefly discussed the value of using multiple models for dealing with uncertainty in EM for LMR management. Several reports and publications since then have espoused this approach. Ensemble modeling is common in other disciplines, but less so in an EM context. To further explore this theme the NMFS organized and held a NEMoW with an emphasis on evaluating methods, protocols and rationales for using MMI in an LMR context. One of the best ways to deal with uncertainty in EM (especially structural uncertainty of complex models) and provide the best available science for decision-making is to use multiple models. NEMoW 3 examined the approaches for developing MMI and for communicating the results of MMI to stakeholders and managers in a way that can provide clear summary management advice while maintaining transparency of the scientific rationale used.

The workshop format for NEMoW 3 was designed such that NMFS Centers, offices, and labs could summarize their EM and MMI ongoing efforts. These presentations helped to provide invited speakers some context for MMI in NMFS. Center presentations were followed by a plenary discussion on the common themes and applications of MMI for EM across regions and management contexts.

After the context-setting plenary discussion of regional applications, plenary presentations on the mechanics and implications were held.

The first set of plenary presentations provided background information on MMI and information on MMI application in other scientific disciplines as well as MMI for LMR in regions outside of NMFS's jurisdiction. Two presentations followed by plenary discussion were held on the first day, and two presentations followed by breakout discussions and plenary discussion of breakout were held on the second day. This set of sessions was designed to consider the types and approaches of MMI that might be applied across NMFS regions.

The second set of plenary presentations was focused on social and management implications of using multi-models in an ecosystem-management context. This was followed by breakout discussion and plenary summary of the discussion. This session was designed to consider how the MMI approaches used in other disciplines and geographic regions may be suitable for MMI in a LMR context for NMFS regions.

The last day of the workshop was designed such that breakout groups (fortified with the information presented over the previous 2 days) could develop ideas for best practices in implementing MMI in a LMR context by NMFS and recommendations for moving forward with MMI. A brief plenary session was held to capture other themes in EM that should be explored in NEMoW working groups.

This approach fostered a range of interaction formats and allowed for the revisiting of any particular topic from multiple perspectives, building upon the strength of having the NMFS EM community gathered from the different regions. The primary workshop objective was to address each of the workshop's Terms of Reference (TORs) such that we could explore the options for implementing MMI and make reasonable recommendations of how the NMFS could proceed in implementing MMI in its EM endeavors.

Terms of Reference (TORs)

Theme: Mingling Models for Marine Resource Management – Multiple Model Inference

Objective: Evaluate best practices for using multiple model inference in a living marine resource management context.

1) Outline and review precursor steps - including determine the purpose for using multiple model inference in ecosystem assessment and outlining the capabilities and limitations of the models to be used for inference (e.g., is one model more capable of representing lower-trophic level groups?).
2) Outline and review the mechanics of multiple model inference (e.g., linking models, model ensembles).
3) Discuss management implications and review case studies. Specifically discuss the policy and sociological considerations when using different models that may have divergent results.
4) Report on current efforts underway or planned at NMFS centers/labs/offices.
5) Capture best practices for employing multi-model inference.
6) Capture general recommendations for moving forward with NMFS EM and future NEMoWs/NEMoW working groups (e.g., Atlantis Summit, Economic and Ecosystem Modeling).

Results

The participants discussed the types of MMI, the reasons for doing MMI, and the benefits of doing it. In addition, participants outlined the generally used methodologies for MMI and how they may be used in ecosystem approaches to LMR context. In addition, a set of best practices and recommendations were developed from this discussion. These workshop results are presented in this section. The remainder of the report provides abstracts and detailed summaries of presentations and discussions that led to these results.

MMI and the types of MMIs

Broadly defined, MMI is the application of multiple quantitative representations (models) of a system in an effort to improve the understanding of how a given system works. The models used may vary only slightly with different initial parameters being used or with different structural configurations of parts of the model. Alternatively models with very different structures and parameters can be used. The practice of using models enables the range of uncertainty in initial parameters and in model structure to be accounted for when considering results and conclusions drawn from the models. This practice has been used extensively in other fields such as weather prediction, climate science, and social sciences, and has helped to advance those fields and improve the utility of their models.

To consider MMI, first, a broad, general description of the types of modeling approaches used in all scientific fields should be considered. Table 1 gives a broad classification of models.

Table 1. Broad classes of models used in all scientific fields.

Type	Description
Statistical	Model projections or assessments are based on previous patterns observed in nature. What “normally occurs”
Dynamical (or Simulation)	Based on simulating first principles. Solves equations based on fundamental physical, chemical and biological laws and principles.
Hybrid (Statistical-Dynamical)	Linked Statistical and Dynamical. Statistical relationships may be used to force components of a dynamical model, or dynamical models may be used to estimate input parameters for a statistical model.

Secondly, to consider MMI, a broad understanding of the current types of multiple model methods is necessary. Table 2 gives a broad classification of multi-model methods.

Table 2. Methods for combining and comparing multiple models.

Type	Description
Qualitative Comparison	Models outputs are not averaged or combined quantitatively. Results are compared to explore the range of possible outcomes.
Consensus	Average output from other models with some weighting options
Ensemble	A collection of models run with slightly different initial conditions or methods of processing, presents range of possible outcomes Can be multi-model ensemble or single-model ensemble
Single-model ensemble	Model run many times at reduced resolution, with perturbed initial conditions, or altered structures of some component of the model. Also known as Sensitivity analysis.
Multi-model ensemble	Model suite that contains several models, less sophisticated models, and consensus models.

These broad classifications informed the discussion as to how MMI can be more formally applied to models for LMR management.

Reasons for and Benefits of MMI

For ecosystem models used in LMR management, considerable structural uncertainty exists. This uncertainty is in part attributable to uncertainty in our understanding of the underlying ecological processes and how to best quantify those processes. Additionally, uncertainty in the input parameter estimates results in uncertainty in the outputs of the model.

The structural uncertainty can be dealt with by either 1) choosing a model that is determined to be the "best" model through some model selection process or 2) use multiple models for analysis. Using the "best" model tactic can be problematic because the model may have been developed under one set of environmental conditions and as those conditions change, the "best" model may not adequately capture those conditions. Similarly, a certain model may be best in one aspect, such as reproducing the dynamic properties of a system but not the best in reproducing specific events. Often using the "best" model may lead to low-utility management advice.

The use of multiple models is becoming the most widely used tactic for applying models to solve problems. Multiple models and sensitivity analysis (i.e., single model ensembles) can be used to account for the structural uncertainty and parameter uncertainty of models and enable a consideration of a range of possible outcomes.

In addition to multiple modeling approaches, structural uncertainty can be addressed by exploring a range of management actions and their outcomes. This is commonly done using use closed-loop simulations (management strategy evaluations, or MSEs). The combination of multiple modeling approaches, single model ensembles, and MSEs will help account for a wide range of uncertainty. This combination should reduce the likelihood that a manager would be blindsided by an unexpected result of a management action. In other words, the conversation between scientist and managers is focused on the best action to take given the range of possible outcomes, rather than the best model to use.

Beyond these general reasons for and benefits of MMI, the invited presenters noted that, in their disciplines, MMI is used regularly and has resulted in considerable improvement in model projections and forecasts (e.g., reduction in the uncertainty in estimates of hurricane strength and trajectory, reduction in the uncertainty of climate projections, and reduction in the uncertainty of ocean circulation patterns). These model upgrades have improved the advice given to a wide range of stakeholders including emergency planners, the IPCC community of stakeholders, and oil spill response teams.

The presenters also noted that the rapid improvement in advice provided to management from MMI was in part attributable to models being used to assess how to improve data collection and the resultant improvements in data collection systems.

In summary using MMI has many benefits. They include:

- Evaluation: Use as a diagnostic tool to improve understanding and identify model/observation deficiencies
- Effectiveness: Improve accuracy and robustness over single model methods
- Efficiency: decompose complex problems into multiple sub-problems that are easier to understand and solve
- Error Reduction: combine diverse, independent models to reduce uncorrelated prognostic errors

However, when using MMI these requirements need to be met:

- Adequate Models: Models need to represent real-world
    - Do we understand processes? Are they adequately modeled?
- Adequate Data: Need data to validate and improve models
    - Do data exist to adequately validate/constrain models?
    - Can models help identify gaps in data and understanding?
- Adequate Diversity: Need adequate diversity of models
    - For multi-model approaches, are there enough models for an issue or an ecosystem to develop a robust ensemble?

Generally used MMI Methodologies

Within the broad classification of MMI approaches described above, specific methodologies have been developed or are being tested. Some of these methodologies and the disciplines in which they are commonly used are outlined based on the MMI classification in Table 2 and discussed below.

Qualitative Comparison

One approach to using multiple models is to run each model separately and present results for each to an expert or group of experts. The group of experts can select the output from "best model" to be used for final presentation to stakeholders. The group of experts can use their knowledge of the system to ascertain which model performs best given the current conditions being modeled. This forms the basis of advice to be passed on to stakeholders or policy-makers for making a decision on actions to be taken. This approach is analogous to a weather forecaster reviewing outputs from multiple models (and ensembles) to develop a forecast statement.

Rather than relying solely on the expert judgment of modelers, results from multiple models can be presented to a group of stakeholders. This approach has the advantage that it allows transparency in the science for decision-making. This can also be a disadvantage in that stakeholders may not have the level of subject or quantitative expertise that modelers have. Rather than making objective decisions from model advice, stakeholders may consider the best model to be the one that fits their preconceived notions (mental models).

Variations on these approaches include the following:
- Formal expert judgment approaches (e.g., Delphic Method)
- Presenting ranges of model output
- Presenting the central tendency model and extreme models

Qualitative comparisons have been employed by a few science centers (e.g., Alaska). Results from single species and multi-species models are often include in management plans to demonstrate the variability in biomass estimates when ecosystem interactions are considered.

Consensus Methods

Model output is averaged output from other models with some weighting options. This is not a model per se but rather combinations of other models. This can be a simple average or it can be more complicated, where past performance is used to correct biases or optimize combinations. Consensus models generally outperform their component individual models. The more independent the individual models are, the better the consensus does.

Consensus methods are commonly used by tropical cyclone modelers to reduce forecast error. In an effort to move towards ecological model ensembles, the International Council for Exploration of the Seas developed a workgroup to test these methods, and it is working towards establishing Biological Ensemble Modelling Approach (BEMA).

BEMA is a tool under development to study the impact of model structure and ensemble averaging on responses to climate change and fishing. This approach is designed to answer the following questions:
- How does variation between models of different complexity influence model results?
- What are the causes of variation between models (e.g., structure, methodology)?
- What is the effect of ensemble weighting and composition?
- Are general conclusions across models possible?

At this stage, BEMA has focused on presenting a range of outputs and identifying common trends among models. More detailed information on BEMA is given in the Abstract and Summaries of Plenary Speakers section of this report.

Ensemble Models

One way to create an ensemble is to change initial conditions, and rerun the same model - use a single model with a variety of configurations. This can be used to test determinism vs. non-determinism of the system. The level of non-determinism could then be used to develop improvements to the model and data streams.

Another approach for ensemble modeling is to use multiple diverse models that are trained on the same problem. It is best to have multiple forecasts, from separate model types, in most cases. Another best practice is to plot model mean and prediction variance around that mean, to demonstrate where they diverge.

To combine results from the alternative models with or without weightings requires skill assessment. Models that perform better can be weighted more heavily in an ensemble. In addition, some models can be discarded if rigorous statistical methods are applied by fitting them to data for a given system.

Ensemble modeling approaches in oceanography are based primarily on averaging methods. These methods include: simple means, means with individual bias corrections, means with collective bias corrections, regularization, and Bayesian Model Averaging (BMA).

BMA is a more formal procedure that has proven useful. BMA considers an ensemble of plausible models. Models vary in skill; calibration of this skill produces better forecasts. This approach works well in short-term weather prediction. About six or more models are needed for this approach.

Typically in ocean modeling, there is a learning period over which weights across models are optimized, then a forecast period uses those weights. Generally this will lead to better model performance. Ocean modelers use Whole Domain weighting, and 3D weighting, to allow weighting scheme to evolve to favor the strongest models.

Summary of MMI Approaches

A range of approaches from simple qualitative to complex ensembling are available and have been used in oceanography, climatology and meteorology for a few decades. The range of MMI approaches and the applicability of those approaches are summarized in Table3.

MMI for ecosystem modeling is in its early stages, and has thus far been limited to qualitative and consensus approaches. To move towards more complex ensemble methods will require higher frequency data streams and model skill assessment.

Table 3. Overview of MMI approaches with notes on the applicability of the approaches

Type of MMI approach	**Degree of relative Data Needs (Low, Moderate, High)**	**Most appropriate under conditions related to: Data level, model complexity, number of functional/structural forms, precision uncertainty, process uncertainty, etc.**	**Risk considerations, (Being wrong relative to magnitude of impact; Low, Moderate, High)**
Qualitative	Low	Data poor, high uncertainty	High risk of missing something
Delphic	Low	Low data	High
Ranges	Low-Moderate	Too many models, unclear processes, high process uncertainty	Moderate
Central tendency	Low-Moderate	Reasonably model precision, but uncertain processes	Moderate
Consensus		Precision and process uncertainty at least moderate data	Low-Moderate
Model averaging	Low-Moderate	Structure uncertainty, when no models are presenting extreme results	Moderate-High; averaging may hide qualitative differences and result in missing extreme events (e.g., extinction).
Data assimilation	Moderate - High	High data, reasonable process certainty, reasonable precision, range of model complexity	Low; incorporating new data within a model run enables course correction.
Ensemble		Multiple models, many levels of complexity, high process uncertainty	
Single model			
Single model-parameters	Moderate	Parameter uncertainty	Low- Moderate
Single model-structure	Moderate	Structural uncertainty	Moderate
Multiple models			
simple means	Low-Moderate	Structural uncertainty	Moderate
means with individual bias correction	Moderate	Structural uncertainty and precision, when data are available to determine model bias	Moderate
means with collective bias corrections	Moderate	Structural uncertainty and precision, when data are available to determine model bias	Moderate
regularization	Moderate-high	Structural uncertainty and precision, when data are available to determine model bias	Low-Moderate
Bayesian Model Averaging (BMA)	High	Structural uncertainty and precision, when data are available to determine model bias; requires a time series and a history of model runs to develop priors	Low-Moderate

Application of MMI to Ecosystem Approaches for LMR management

In some cases, simple approaches to MMI are already being used in a broad range of contexts. Most stock assessment and ecosystem model applications use sensitivity analysis (i.e., single model ensembles) implicitly. A more formal application and recognition of these approaches would help advance MMI within NMFS.

In applying MMI, several factors must be considered. The primary factor is the context in which the model is being used. Another major factor to consider is how common metrics form the outputs for a diversity of model types.

Generally ecosystem and habitat modeling approaches are simulation models. For ecosystem and habitat assessment, MSEs are commonly used and stakeholders are accustomed to seeing outputs from multiple management scenarios. Thus, this context is conducive to the use of qualitative comparisons where stakeholders are presented multiple model outputs for multiple scenarios. The BEMA methodology provides a good example of how to implement this approach.

Stock assessment and population assessment for protected resource models are generally statistical models that have some measure of model fit to past data. While model-fitting is not the same thing as skill assessment used for evaluating model performance in other disciplines, it is similar in that metrics of model fit (e.g., Bayesian Information Criterion, Akaike Information Criterion) are calculated. As such, model-fit metrics may be used to develop weighting schema and use model averaging to create model ensembles.

As most NMFS regions have a diversity of single-species, protected resources, habitat and ecosystem models, the potential to use these for ensemble exists. These models could be used in ensembles to develop biological reference points (BRPs) and for assessing the BRPs. This would require an evaluation of the BRPs across mandates and the development of common metrics or indicators.

The ability to use MMI evolved in the oceanography, climatology and meteorology disciplines and a similar track can be used to advance the application of MMI in LMR management. Applying advanced MMI techniques such as multiple model ensembles requires skill assessment. Skill assessment can be used to weight models for model ensemble and to make decisions on the best type of weighting methodologies to use.

This advancement was relatively easy for climate, weather and ocean models, because physical and ocean observations for evaluating models are collected frequently (daily to hourly). Ecological data is not collected as frequently (monthly to annually). For ecological models, other methods of skill assessment will have to be implemented so that appropriate weighting methodologies can be applied for multiple model ensembles.

For ecological models, skill can be evaluated using "operating models" of assumed hypothetical true systems to determine how sensitive the bias and precision of parameter estimates are to changes in structure of the estimation or simulation model. The actual structure of large ecological systems is unknown, so such analyses would have to be repeated across a large number of sensitivity analyses that use different hypotheses about that true structure in the operating model.

Conclusions

The overarching conclusion from the participants of NEMoW3 was that NMFS should proceed with MMI for LMR modeling and management with a few caveats. In data poor assessments, it may not be practical to develop multiple models with adequate variety in structure. However, in other instances, NMFS modelers are already doing MMI. Sensitivity analyses (i.e., single model ensembles) are commonly used across LMR modeling and management contexts.

MMI is used regularly in many other disciplines especially within NOAA (e.g., weather, climate and ocean modeling). Within those fields, MMI has brought about vast improvements in forecasting ability and system understanding. In those fields, modelers began to learn how to do MMI by just doing it and learning from their mistakes. The group consensus was that ecosystem modelers should just begin MMI where possible and work together to share results and techniques.

As we move forward with MMI for LMR management, modelers are advised to follow the best practices listed below. In addition, the recommendations listed below will allow the advancement of MMI and improvement in scientific advice for LMR.

Best Practices

1) Clearly define the management objectives and type of management advice targeted by the models (i.e., strategic or tactical).

   The need for clearly defined management objectives was reiterated from a previous NEMoW. With the added complexities of using multiple models, the need for early engagement with stakeholders is even more crucial. With additional input and discussion on social sciences during this workshop, a few suggestions emerged on how to work collaboratively and iteratively with stakeholders to develop models and understand their mental models. These approaches should help with stakeholder buy-in and help them understand the need for multiple models and the uncertainty involved with each modeling approach.

   A clear understanding of the type of advice needed (strategic vs. tactical) will inform how to implement MMI and communicate its results. For example, for tactical advice, formal statistical estimates of uncertainty based on weighted model ensembles may be needed. For strategic advice, summary tables from MSEs using multiple models and BEMA type approaches may be used.

2) Use an appropriate range of MMI analytical or quantitative approaches: single models with different assumptions, structures and initial conditions, and multiple models with considerable variability in structure and assumptions.

   In cases where only one model is available, single model ensembles (i.e., multiple runs with variations in the initial conditions or parts of the model structure) can be used. Ideally, multiple models with very different structure and assumptions would be used. The group noted a need to develop and include ecosystem models with factors other than trophic interactions at the core. For example, models with disease, coastal habitat, etc. will be necessary for better incorporating other stressors influencing LMRs.

3) Evaluate model performance/forecasting skill to enable weighting schema to be developed and used for formal model ensembles. Furthermore, skill testing will help to inform and improve data collection for improving models.

   Many of the participants expressed a desire to have ecosystem models used in a tactical sense to produce reference points. Developing weighting schema based on skill testing would enable strong inference based on model averaging.

   The group recognized that, within other disciplines, skill testing was relatively simple because models are run on a very regular basis (daily and more frequent) with data available on a similar basis. For LMRs, model runs are less frequent (usually annually) and new data are typically only available on a monthly to annual basis. As a result, skill evaluation using operating models as "truth" will be necessary.

4) Use social science considerations as part of the MMI evaluation process and in communicating the results from MMI processes.

   The group expressed a need to be able (and prepared) to communicate potential for complex response surfaces to managers. One approach for doing that is to present more aggregated (and likely more stable) outputs and then drill down into the more complex details.

   Many of the participants were concerned about the possibility that using multiple models would enable stakeholders to pick the model that best fit their desired outcomes. One suggestion was to use mental models (e.g., fuzzy logic cognitive maps) as a framework for communicating to managers and stakeholders, as a means for people to think about things in the same way and recognize others' perspectives.

Beyond social science considerations, the participants recognized a need to incorporate social science models within a range of models for MMI. As humans are drivers of ecosystems (i.e., the social-ecological system), understanding human responses to changes in ecosystem and how that, in turn, influences the ecosystem may be important.

5) Where MMI is being implemented implicitly, begin to explicitly demonstrate that MMI is being used.

   Many of the modelers indicated that they use MMI regularly. For example, stock assessment modelers often perform sensitivity runs (i.e., re-run the model with different initial conditions, alterations to the structure, with and without external ecosystem considerations). Sensitivity runs are analogous to single model ensembles. Some additional work may be necessary to formalize this approach as true MMI.

Recommendations

1) Adopt MMI best practices (described above).

The best practices describe previously were generally agreed upon by a representative group of ecosystem modelers within NMFS. This group and this report can be used to spread the best practices to other modelers and encourage the use of these practices.

2) Perform simulation studies to evaluate the skill of models to be used for MMI.

The group recognized that within other disciplines skill testing was relatively simple because models are run on a very regular basis (daily and more frequent) with data available on a similar time scale. For LMRs, model runs are less frequent (usually annual) and new data are available on a monthly to annual basis. This lower frequency of model runs and data availability necessitates other approaches for evaluating model skill.

Participants recommend a working group to develop methods for model skill evaluation. The methods would test a full range of ecological models (single-species fisheries/protected resources, habitat and ecosystem models) more formally, usually in part of mitigating some type of pressure or use. The general approach suggested was to develop a holistic operating model that simulated a generic ecosystem and other models would use simulated data from that model for development and skill assessment.

The operating model would be used to run a variety of pertinent scenarios (climate, overfishing, etc.) to generate new survey data. The test models would be used to produce predictions under the scenarios and compare test models' outputs to the operating model's simulated data. The working group would develop model performance metrics, the test models would then be compared using these performance metrics. This evaluation would provide a basis for a general weighting schema for commonly used ecosystem models. This schema could be adopted by the centers for future MMI applications.

3) Evaluate cases where MMI has been attempted by NMFS for LMR management.

The group agreed that we should develop NMFS-relevant case studies for testing ensemble models and MMI. This could be accomplished with a working group or through a subset of the NEMoW participants developing a white paper.

The group agreed that, before formal weighting schema are developed, case studies might be focused on strategic management (e.g., an MSE context). Given the broad array of LMRs and mandates in NMFS purview, it is important that case studies illustrate MMI application across mandates (e.g., fisheries, protected species, habitat, National Environmental Protection Act – NEPA).

Some case studies may use multiple models. Others may be focused on single model ensemble approaches - running different parameterizations and exploring different process structures or different initial conditions. In case studies, where the possibility of using multiple models exist, it is important to use models with as many different structures as possible to provide information on the utility of simple vs. complex models.

Within these case studies, risk assessment should be applied so that the outcomes are appropriate to the management question involved (is it a resource where susceptibility to rare stress/pressure events is significant to sustainability?, etc.). This may demonstrate that MMI approaches for combining and displaying model results may vary among contexts.

4) Develop and maintain EM and MMI capacity and infrastructure. Specific recommendations are outlined below.

- Assess and develop efficiencies with MMI.
  - Consider all 500+ fish stocks, 100+ marine mammal populations, 1000+ habitats, aquaculture species, the 20 LMEs, and the countless coastal areas that NMFS has to deal with.
  - Assess the possibility of combining current approaches (single-species models, multi-species models, EM) rather than building new models from scratch. (Cost-benefit analysis up front).
  - Three-front approach: 1) assessing data availability and tapping currently untapped resources; 2) computing resources; and 3) basic understanding that is constantly advancing in concert with model development.
- Develop training capacity for EM and MMI. Train and educate, internally and externally, when new practices, methods, standards or products are put into practice.
  - Generate smaller working groups across Centers to share expertise and

experience on MMI.
    - Build collaboration within the NMFS research community.
    - Find ways to blend stock assessment scientists and ecosystem scientists (working groups, research teams, etc.) so they have the opportunity to integrate the MMI approach with traditional fisheries approaches.
    - These training objectives could be achieved in NEMoW working groups.
  - Build computing infrastructure at the agency level.
    - Develop capacity for more efficient data reporting and transfer.
  - Develop standardized reporting of MMI predictions: averages and error, with the individual models available for transparency of alternative outcomes. IPCC and BEMA provide useful examples.

Beyond these recommendations specific to MMI for EM, the participants recommended that NEMoWs should continue to promote application and development of a wide range of ecological models to ensure the best available science is being used to meet NMFS mandates. For example, future NEMoWs could be held to develop more formal MSE capacity agency-wide, across multi-disciplinary teams. Specifically, use multiple, ecosystem and multi-species models to set up Harvest Control Rules (HCRs) for fishery stocks, marine mammal and protected resource populations. Simpler models/data streams would be used for short-term forecasts (e.g., allowable catch limits, population viability analysis) against those HCRs.

Abstracts and Summaries of Plenary Presentations

Summary of Introduction and Opening Remarks by Dr. Jason Link, NMFS Senior Scientist for Ecosystem-based Management

Jason Link began by welcoming all participants from NMFS Science Centers and other offices, other NOAA line offices, as well as invited guest observers and speakers.

Link reviewed the general objectives of the NMFS NEMoWs and provided some historical background on the origin of NEMoWs, why NEMoWs are still needed, and what we aimed to achieve at NEMoW 3.

In the opening remarks, he noted that NEMoW began as a bottom-up, grass-roots organization when a small group of modelers, who were beginning to develop models and apply them to LMR issues began to make contact with one another swapping ideas and information on best practices for implementing models into management. The group noted that it would be beneficial if they convene a forum where everyone involved at various stages of EM could convene. Bringing together these folks would enable more rapid development of models and advancement of new technology and approaches, as well as help set the stage to develop best practices for modeling and its application to LMR management.

In 2007, at the NMFS Santa Cruz Lab and with the support of NMFS and the Science Board, the 1st NEMoW was held. At that workshop, the participants developed an inventory of what models were being used and for what objectives. The participants also heard from external speakers (ecosystem modelers) who helped the group layout best practices for applied EM for LMR. At that time, only one out of seven centers had dedicated ecosystem groups; now, three to four centers have dedicated ecosystem groups.

In 2010, a 2nd NEMoW was held to address issues on bridging the credibility gap – handling uncertainty – in EM. In that workshop, centers provided updates on their modeling efforts and applications for LMR management. In addition external speakers helped the group develop a framework for considering all of the levels of uncertainty in EM (and resource modeling in general). In that workshop, the need for using multiple models to address uncertainty was raised. Hence, this 3rd workshop was convened to develop recommendations and best practices for using multiple model inference as a way forward.

After providing this context and background on the general purpose of NEMoW, Link set the stage for this workshop, he noted the following:

1) EM is moving from research toward more operations and application;
2) NMFS LMRs face a broad array of pressures beyond fishing and the need to address those stressors with models is expanding;
3) The levels of Ecosystem Management for which EM are applied is growing;

4) As EM comes to be used more operationally, modelers need to think about how the models can and should be applied in a variety of LMR processes

As EM has moved from research to applications and operations, it has also begun to be used not just in a strategic sense (i.e., Management Strategy Evaluation) but also in a tactical sense (e.g., developing ecosystem-savvy single species or ecosystem-based reference points). Modelers need to consider how we use these models, whether they are used for tactical vs strategic advice, and how to move EM from mostly research to giving operational advice.

The need for EM in LMEs and subregions of the LMEs is expanding as many LMRs face many pressures, not just fishing (Table 4). LMRs are facing not just many pressures but cumulative pressures with complex interactions. EM approaches are necessary to account for these pressures and interactions to provide useful LMR advice.

The relative importance of the pressures and resources in Table X vary from region to region and within subregions, so each Center's needs for modeling may vary according to the pressures. However, there are some topics of national interest that should be considered by all regions as they develop and apply EMs. Some topics of current interest nationally are:

- Climate change, Ocean Acidification, National Climate Science Strategy (NCSS)
- Habitat, Habitat Assessment Improvement Plan (HAIP)
- Forage
- Cumulative Impacts, Integrated Ecosystem Assessment (IEAs)
- Stock Assessment Improvement Plans (SAIP), Next generation stock assessments (NGSA)
- Protected Species Stock Assessment Improvement Plan (PS-SAIP)
- Risk Analysis, Multi Criteria Decision Analysis (MCDA)
- Data visualization

For LMRs, a need for three levels of Ecosystem Management exists. Those levels are

- Ecosystem Approaches to Fisheries (EAF) – Adding ecosystem factors into stock assessments for tactical management decisions
- Ecosystem-based Fisheries Management (EBFM) – strategic and tactical management to consider trade-offs within fisheries and other marine animals stocks
- Ecosystem-based Management (EBM) – strategic management to consider not just trade-offs within fisheries and other marine animals but within and among other sectors by using IEAs.

Modeling approaches to address all three levels should be considered in developing and applying EMs.

Within the different types of LMR management (e.g., fisheries, protected species, habitat) a variety of processes for incorporating scientific information and advice exist. Though there is some variability in the processes; the basic process is as follows:
1) Data – collect data to address the issue;

2) Modeling – synthesize the data in a way that is meaningful for addressing an issue;
3) Review – evaluate the possible approaches for addressing the issue;
4) Status determination – determine whether an issue should be addressed and how it should be addressed;
5) Performance review – evaluate whether the management objective achieved the desired outcome and why or why not?

To make models more operational for LMR management, modelers should consider the process in which their models are being used and how to make the model best fit the need.

A range of ecological models are needed and used in management – from single species to full system. Which type of model to use, in some way, is determined by the need. Because a variety of models are currently being used and developed in the centers, some infrastructure for developing MMI is already in place.

To wrap up his opening remarks, Link outlined the need for MMI and stated the charge for the workshop. MMI is needed because, ultimately, all models are wrong. By necessity, because of the complexity of ecological systems, some aspects of a system are simplified by ecological models. If just one model is used, the model can be mistakenly viewed as “truth” about the system and lead to myopia. This can have negative consequences; if the relative importance of simplified portions of a modeled system begins to change over time in the actual system. MMI is an approach to address uncertainty, and it is an approach that has been used successfully and commonly in other fields. MMI allows one to consider and even incorporate different views/assumptions of data and underlying structure/process/functional form. Multiple models allow a broader consensus upon reaching “the right answer” to an issue versus “the right model” to address the issue.

Table 4. Focal LMRs of NMFS based on national mandates and range of pressures they face.

	Pressures																				
	Overfishing	Bycatch	Climate Change			Ocean Acidification	Food Web Alteration	Invasive Species	Biodiversity Loss	Habitat Loss/Degradation	Disease	Eutrophication	Hypoxia	Toxic Deposition		Oil & Gas	Marine Litter	Dredging & Dumping	Food Security	Economic Security	Social Impacts
Focal LMR Area, Main Mandates, Main Focal Efforts			Thermal Habitat	Flow Regime	Sea Level									POPs	Metals						
Target Stocks																					
MSA, etc.																					
Stock Assessments																					
Protected Species																					
MMPA, ESA, etc.																					
SRGs, Section 7																					
Aquaculture																					
NAA, CZMA, etc.																					
Permitting, Siting Reviews																					
Habitat																					
CWA, CZMA, ESA, MSA, etc.																					
Permitting Reviews																					
Ecosystem and Aggregate Properties																					
NEPA, MSA, cross-mandates																					
cumulative impacts, IEAs																					

Extended Abstracts on EM and MMI efforts at NMFS Centers

Ecosystem modeling efforts at the NOAA/NMFS Alaska Fisheries Science Center

submitted as a background document to the:
3rd NMFS National Ecosystem Modeling Workshop (NEMoW 3)
18-20 March 2014, Seattle, WA

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Food web modeling

Scientists with the (AFSC) Resource Ecology and Ecosystem Modeling (REEM) program previously developed mass-balance food web models of large marine ecosystems (LME) in Alaska, including the eastern Bering Sea, Gulf of Alaska, and Aleutian Islands. These food web models are updated frequently and are used regularly in fishery management advice in annual Stock Assessment and Fishery Evaluation (SAFE) reports. Recently, this suite of models was expanded with the completion of a model of the Chukchi Sea. Using the same food web modeling framework, the researchers focused on a set of network metrics to draw comparisons with nearby subarctic ecosystems—the eastern Bering Sea and Gulf of Alaska, and a more distant Arctic ecosystem, the Barents Sea.

The Chukchi Sea is a seasonally ice-covered, peripheral sea of the western Arctic Ocean. It lies north of the Bering Strait off the northwestern coast of Alaska. Comparison of the network metrics highlights distinctions that lead to the eastern Chukchi Sea having the lowest total production/biomass (P/B) ratio of the systems examined; the P/B of the nearby eastern Bering Sea was about double that of the eastern Chukchi Sea. In practical terms, this characteristic implies that the eastern Chukchi Sea is fundamentally different from the adjacent eastern Bering Sea – they have roughly comparable total biomass density but the total production of the Chukchi Sea is 45% that of the eastern Bering Sea. Thus, the standing biomass in the Chukchi Sea is not expected to be highly resilient to commercial fishing or other high-mortality events such as that which might be expected following a large-scale oil spill. Further research into the production of species/functional groups and their response to extraction or disturbance could be useful for evaluating the impact of future fisheries on the food web and predicting response to potential environmental disturbances related to energy extraction.

Multispecies Statistical Modeling

Recently, model runs have been completed for the Bering Sea using a 10km2 Regional

Ocean Modeling System (ROMS) model coupled to a Nutrient-Phytoplankton-Zooplankton (NPZ) model to produce detailed hindcasts for the period 1970-2012 and forecasts using IPCC scenarios through 2040. These results drive a climate-driven Multispecies Statistical Model (MSM) for use in a management strategy evaluation of three groundfish species from the Bering Sea (walleye pollock, Pacific cod, arrowtooth flounder). First, ROMS model results modulate bioenergetics, food supply, growth, recruitment, and species overlap (i.e. functional responses and predation mortality) as fit in the MSM using hindcast-extracted time series. Then the MSM model is applied to downscaled IPCC climate projections via a ROMS and NPZ model projection of temperature, circulation, and zooplankton abundance. Results of model simulations have helped REEM scientists understand and predict how future climate driven changes to the system may impact predation and fishery harvest limits.

For this approach, recruitment estimates were first derived from a multi-species stock assessment models (MSM) fit to historical survey and fishery data. The model was run in multi-species mode, where each species is linked through a predation sub-model, as well as in single-species mode, where no predation interactions occur. This produced a time-series of spawning stock biomass and recruitment from the multi-species and single-species models. ROMS model estimates for mean water column temperature and spring and fall zooplankton biomass were then used as covariates on a Ricker stock recruitment curve, such that:

$$log(\hat{R}_{p,y}) = \log(\alpha_{R,p} \cdot SSB_{p,y-1}) - \beta_{R,p} \cdot SSB_{p,y-1} + \beta_{Z,p}^{spr} \cdot Z_y^{spr} - \beta_{Z,p}^{fall} \cdot \left(\delta_{p,1,y}^{fut} \middle/ Z_y^{fall} \right) + \varepsilon$$

Where $\hat{R}_{p,y}$ is estimated recruitment in year y for species p, $SSB_{p,y-1}$ is the spawning stock biomass from the multi-species model, Z_y^{spr} and Z_y^{fall} are the total spring and fall zooplankton biomasses predicted from the ROMS/NPZ model for the Bering Sea, $\delta_{p,1,y}^{fut}$ is the ration of the youngest age class for each species, and $\alpha_{R,p}$, $\beta_{R,p}$, $\beta_{Z,p}^{spr}$, $\beta_{Z,p}^{fall}$ are parameters of the recruitment function fit through maximum likelihood to recruitment from the multi-species model ($R_{p,y}$) such that $\varepsilon \sim N(0, \sigma^2)$. Model estimates were compared via AIC and top models for each species were selected for use in projections of the multi-species model under future climate scenarios from ROMS/NPZ projections based on down-scaled IPCC climate model scenarios (Fig. 1).

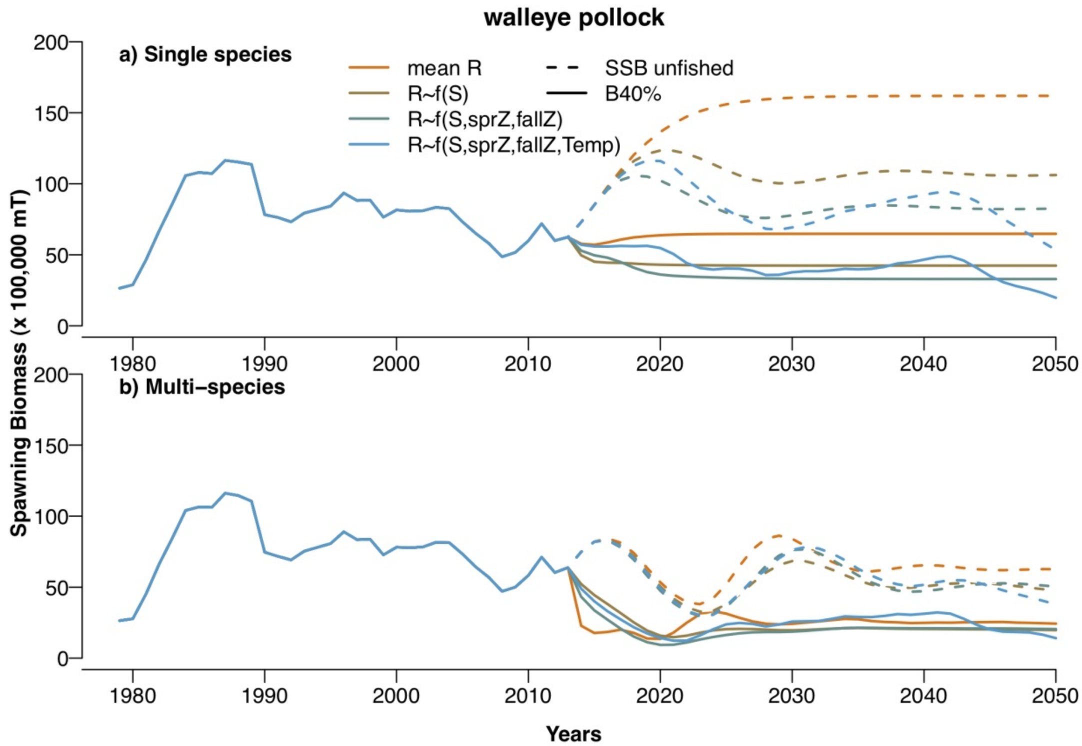

Figure 1. Projected spawning stock biomass for walleye pollock predicted from single (a) and multi-species (b) modes of MSM under various recruitment relationships and no harvest ("SSB unfished"; dashed line) or harvest that yields 40% of SSB on average during the last five years (2045-2050) of the projection (B40%; solid line).

End to End modeling

The Forage and Euphausiid Abundance in Space and Time (FEAST) model is a length based, spatially explicit bioenergetics model, that comprises the fish portion of the vertically integrated model of the North Pacific Research Board's Bering Sea Integrated Ecosystem Program (BSIERP). The vertical model itself contains 5 modules: climate, oceanography (ROMS), lower trophic levels (NPZ), fish, and fisheries (FAMINE). FEAST models 14 fish species linked to 5 zooplankton groups (Fig. 2) and 20 fisheries specified by sector, gear and target species. Species include walleye pollock, Pacific cod, arrowtooth flounder, salmon, capelin, herring, eulachon, sandlance, myctophids, squids, shrimp, crab, epifauna, and amphipods; these have a two-way interaction with six groups from the Nutrient - Phytoplankton - Zooplankton (NPZ) module: small copepods, oceanic/shelf copepods, oceanic/shelf euphausiids, and benthos. Temperature and advection estimates from the physical oceanography portion (ROMS) are used in the fish bioenergetics and movement components. The model has a spatial resolution of approximately 10 Km and will be run both with past climate (1970-2010 hindcast) and three different climate projections stemming from three different climate models. In addition, FEAST is the "real world" model to be used in a Management Strategy Evaluation for walleye pollock and Pacific cod, two of the main commercial groundfish in the Bering Sea.

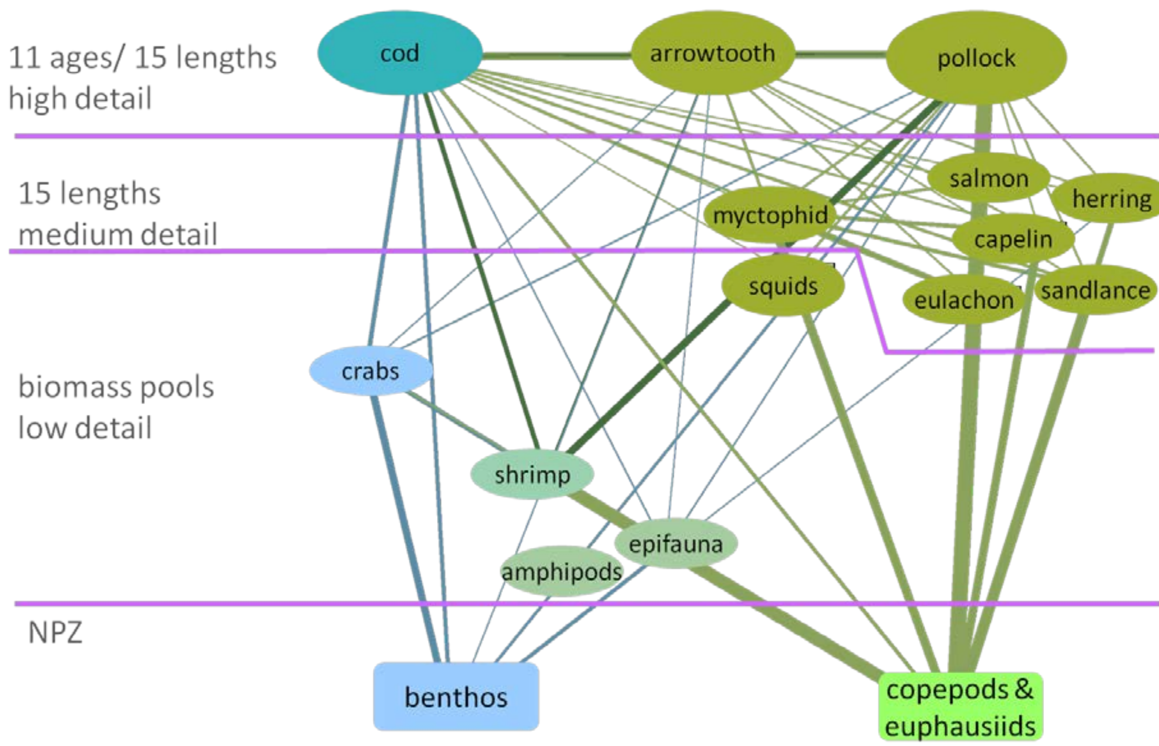

Figure 2. Food-web underlying FEAST, showing level of detail for the groups modeled. Lines depict trophic flows, line thickness is proportional to magnitude of flow and color represents pelagic (green) or benthic (blue) routes.

Individual-based modeling

Groundfish recruitment in the Gulf of Alaska is thought to be controlled by physical processes (i.e. climate and transport) and biological processes (i.e. growth and predation) experienced between offshore spawning sites and the end of the young of year (YOY) stage. As part of the North Pacific Research Board's Gulf of Alaska Integrated Ecosystem Research Program (GOAIERP), AFSC modelers are using a Regional Ocean Modeling System (ROMS), a Nutrient-Phytoplankton-Zooplankton (GOANPZ) model, and Individual-Based Models (IBMs) to examine recruitment mechanisms and derive indices related to recruitment for five ground fish species;

arrowtooth flounder, walleye pollock, Pacific cod, Pacific Ocean perch, and sablefish. The work will also incorporate the indices into the existing Ecosim model of the Gulf of Alaska to explore the consequences of recruitment variability on the GOA ecosystem and fisheries. Indices produced, and conclusions about the effects of physical and biological processes on the GOA ecosystem under different physical regimes will aid in the management of these important fish stocks.

Ecosystem modeling efforts at the NOAA/NMFS Northeast Fisheries Science Center

submitted as a background document to the:
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prepared by:
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Prototype Multispecies Bio-economic Analysis for Georges Bank

Development of multispecies and ecosystem models has an extensive history at the Northeast Fisheries Science Center (NEFSC). Here, we focus on one element of current NEFSC modeling efforts designed to support Ecosystem-Based Fishery Management (EBFM). Other initiatives not explicitly covered here span the spectrum from development of extended single-species models to application of end-to-end ecosystem models to evaluate requirements for the broader dimensions of marine ecosystem-based management.

Both the New England and Mid-Atlantic Fishery Management Councils have recently signaled their intent to explore and implement options for EBFM. The Ecosystem Assessment Program (EcoAP) of NEFSC has worked closely with the Scientific and Statistical Committees of both councils to develop options for EBFM tailored to the emerging management preferences of each council. In collaboration with the Population Dynamics, Oceanography, and Social Sciences Branches at NEFSC, EcoAP has been exploring options for development of a flexible analytical framework for EBFM in the Northeast. Principal elements of the approach include (1) establishment of a transparent connection between single species and ecosystem-based advice using multispecies assessment models as a natural bridge, (2) development of multiple operating models to test assessment models and candidate management procedures, (3) application of assessment models spanning a spectrum of complexity to evaluate the issue of model uncertainty (4) application of formal strategies of multimodel inference in applying results from the multispecies assessment models (5) use of these results to assess uncertainty and risk, and (6) evaluation of tradeoffs in a bioeconomic context. The models under development are designed to accommodate spatial structure and to incorporate consideration of climate variability and change.

As a proof of concept, we are currently developing a prototype multispecies analysis for a 10 species complex for Georges Bank (Figure 1). With colleagues at Renssalaer Polytechnic Institute and Woods Hole Oceanographic Institution we are developing and applying protocols to handle data and create model output that is traceable, repeatable, described, verified, validated, efficient, transparent, and available to user communities. The approach is based on fundamental principles in informatics. Data streams feeding into this process encompass fishery-dependent (both ecological and social-economic) sources, fishery-independent surveys, food habits data to identify and quantify biotic interactions among species, and oceanographic and climate data to track external forcing mechanisms. To further enhance communication with stakeholders we are developing options for data and model visualization to aid in the interpretation of multispecies model outputs.

The core analytical elements of the process involve development and testing of a set of indicators, multispecies assessment models, social-economic modules linked to the assessment models, and forecast models developed outside the assessment model framework to complement predictions made using these assessments. The interplay between the operating models and the other analytical elements of the approach is envisioned as an iterative process (Figure 1). The analysis culminates in a risk analysis accounting for key uncertainties and in the context of multiple candidate management procedures. The process is designed to provide management advice in the form of annual catch limits to match existing requirements under current management approaches on Georges Bank. The results will be provided as an interactive web-based product (Figure 1).

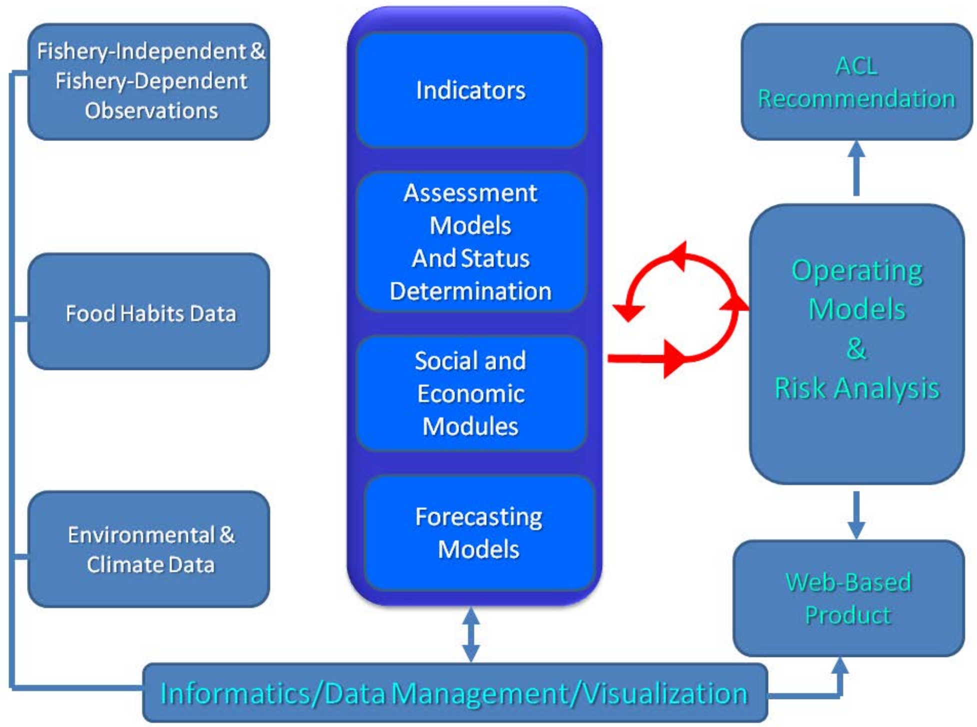

Figure 1. Key structural elements of the NEFSC prototype multispecies analysis of Georges Bank.

Our overall approach entails the use of four different assessment models encompassing simple multispecies production models applied both to individual species and to defined functional groups, multispecies delay-difference models that implicitly accommodate simple demographic structure (again for individual species and functional groups), and a complex multispecies statistical catch-at-age model applied to individual species (Figure 2). Single species analogues of these models are familiar to resource managers in the region and we have deliberately attempted to frame our approach in a way that trades on this familiarity. Multiple estimation techniques including maximum likelihood, state-space, genetic algorithm and Bayesian methods will be applied to the production models in both aggregated and disaggregated forms to assess aspects of estimation uncertainty.

A key issue in assessment and management of the Georges Bank system is the centrality of the mixed-species nature of the fishery. We define our functional groups as species that are caught together and share basic ecological characteristics (similarity in life history attributes, body size, etc.). Our interest in testing the performance of assessment models based on functional groups defined in this way centers both on their importance as key structural elements of the system and recognition that we cannot fully control the fishing mortality rates on the individual species comprising these mixed-species assemblages. These species, inter alia, share similar histories of exploitation and environmental forcing. Tests will be made to assess the performance of the functional group models against models in which the full species identity of all components is retained to see if they offer any advantage in assessing mixed-species fisheries.

Economic modules link to the assessment models to produce revenue streams and measures of profitability. They are being developed for direct use in tradeoff analysis. For the economic module we are also employing an empirical multispecies portfolio model approach to assess risk. We are developing forecast models using new methods in nonlinear time series analysis to complement the assessment models. We are using two operating models to serve as a virtual test beds to examine the performance of the assessment models and to evaluate the efficacy of alternative management procedures. These models, Hydra and EcoSim, are currently in different stages of development. Hydra is a length-structured model developed at NEFSC. It is designed to be spatially structured and to allow for multiple fleet sectors although these features have not yet been implemented. The model is designed to accommodate climate/environment forcing on biological and ecological processes. The operating model will be used to test the performance characteristics of several simpler assessment models that can be used to provide reference points for management action. The initial focus will be on ecosystem-based fishery management to meet the needs of the New England and Mid-Atlantic Fishery Management Councils. Our application of EcoSim as an operating model will build on developments by Kerim Aydin at AFSC. Kerim's work substantially increases the flexibility and transparency of the EcoSim framework.

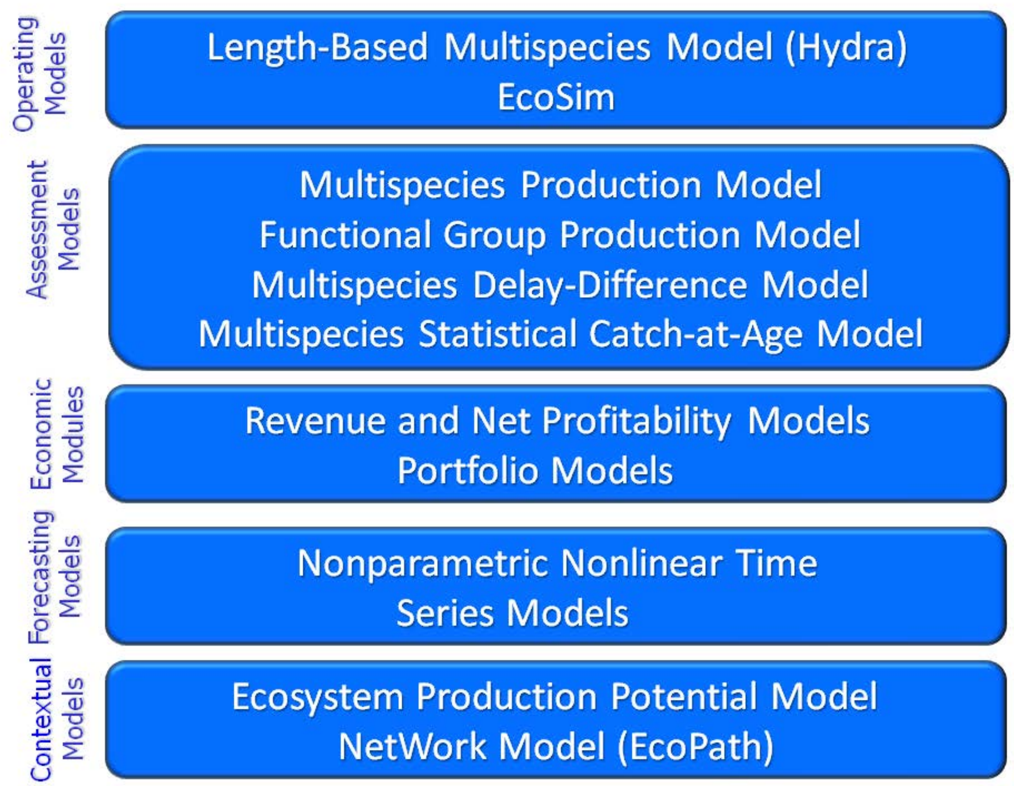

Figure 2. Modeling elements to be employed in the prototype multispecies bio-economic model for Georges Bank.

Ecosystem modeling efforts at the NOAA/NMFS Southwest Fisheries Science Center

submitted as a background document to the:
3rd NMFS National Ecosystem Modeling Workshop (NEMoW 3)
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Chinook salmon habitat, life-cycle, and DEB modeling

Pacific salmon use a wide range of habitats throughout their life cycle, including river, estuarine, and marine ecosystems. This poses a significant challenge to our understanding of their population dynamics, because habitat conditions in one ecosystem and life-stage can have consequences that manifest in the following ecosystem and life stage. However, most salmon models do not capture the habitat variability in each ecosystem or incorporate the critical linkages between ecosystems. The Salmon Ecosystem Simulation And Management Evaluation (SESAME) project aims to address these issues for Chinook salmon from California's Central Valley. SESAME uses a series of coupled physical-biological simulations to produce key spatiotemporally explicit habitat variables in each system: river, estuary, and coastal ocean. We use these habitat variables (temperature, flow, and food) to drive a Dynamic Energy Budget (DEB) model for Chinook salmon to explore how salmon grow from eggs to mature adults while moving across this complex landscape.

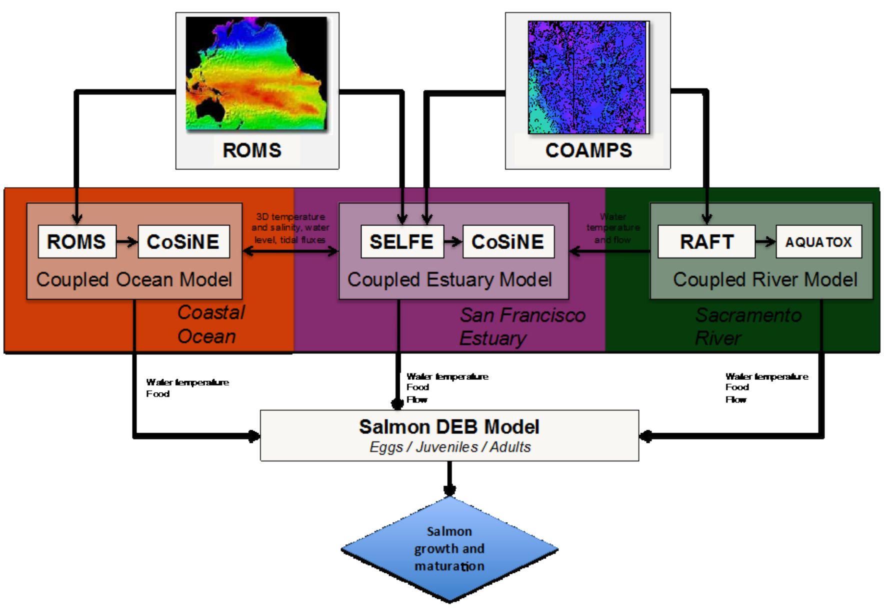
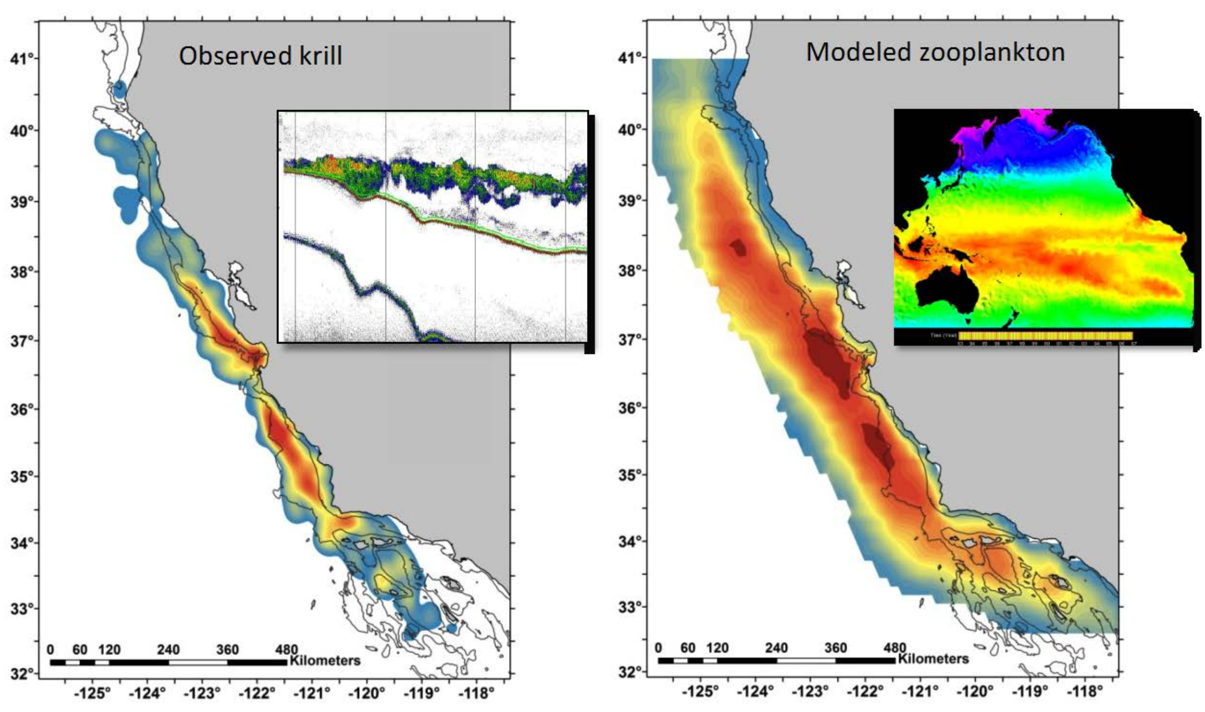


Figure above demonstrates the basic model structure for the SEAME project.

ROMS-CoSINE krill estimations

Below summary from: Santora, J.A, W.J. Sydeman, M. Messie, F. Chai, Y. Chao, S.A. Thompson, B.K. Wells, and F. Chavez. 2013. Triple check: Observations verify structural realism of an ocean ecosystem model. Geophysical Research Letters.40:1-6

Improvements in fisheries and ecosystem management could be made if the prediction of key zooplankton, such as krill, were possible using ocean ecosystem models. To examine structural realism, hence the validity of a coupled physical-biogeochemical model, we compared measured spatiotemporal dynamics of krill and seabird abundance off California to hindcasted mesozooplankton derived from an independently designed model. Observed krill and modeled mesozooplankton (Z2) displayed latitudinal coherence but distinct longitudinal offsets, possibly related to unrealistic bathymetry in the model. Temporally, Z2, *Thysanoessa spinifera* (a neritic krill species) and seabird density and reproductive performance were well correlated, indicating that quantitative prediction regarding marine predators in upwelling ecosystems is within reach. Despite its basin-scale framework, the ROMS-CoSiNE model captures zooplankton and top predator dynamics regionally in the central California region, suggesting its utility for management of marine ecosystems and highlighting rapid advances that can be made through collaboration between empirical scientists and ecosystem modelers.



Shown above is the observed (acoustics) and estimated krill distribution from CoSINE along the CCS. There is significance coherence between these data.

Habitat modeling for green sturgeon using ROMS-CoSINE products

Below summary from: Huff, D.D., S.T. Lindley, B.K. Wells, and F. Chai. 2012. Green sturgeon distribution in the Pacific Ocean estimated from modeled oceanographic features and migration behavior. Public Library of Science. 7:e45852

The green sturgeon (*Acipenser medirostris*), which is found in the eastern Pacific Ocean from Baja California to the Bering Sea, tends to be highly migratory, moving long distances among estuaries, spawning rivers, and distant coastal regions. Factors that determine the oceanic distribution of green sturgeon are unclear, but broad-scale physical conditions interacting with migration behavior may play an important role. We estimated the distribution of green sturgeon by modeling species-environment relationships using oceanographic and migration behavior covariates with maximum entropy modeling (MaxEnt) of species geographic distributions. The primary concentration of green sturgeon was estimated from approximately 41–51.5° N latitude in the coastal waters of Washington, Oregon, and Vancouver Island and in the vicinity of San Francisco and Monterey Bays from 36–37° N latitude. Unsuitably cold water temperatures in the far north and energetic efficiencies associated with prevailing water currents may provide the best explanation for the range-wide marine distribution of green sturgeon. Independent trawl records, fisheries observer records, and tagging studies corroborated our findings. However, our model also delineated patchily distributed habitat south of Monterey Bay, though there are few records of green sturgeon from this region. Green sturgeon are likely influenced by countervailing pressures governing their dispersal. They are behaviorally directed to revisit natal freshwater spawning rivers and persistent overwintering grounds in coastal marine habitats, yet they are likely physiologically bounded by abiotic and biotic environmental features. Impacts of human activities on green sturgeon or their habitat in coastal waters, such as bottom-disturbing trawl fisheries, may be minimized through marine spatial planning that makes use of high-quality species distribution information.

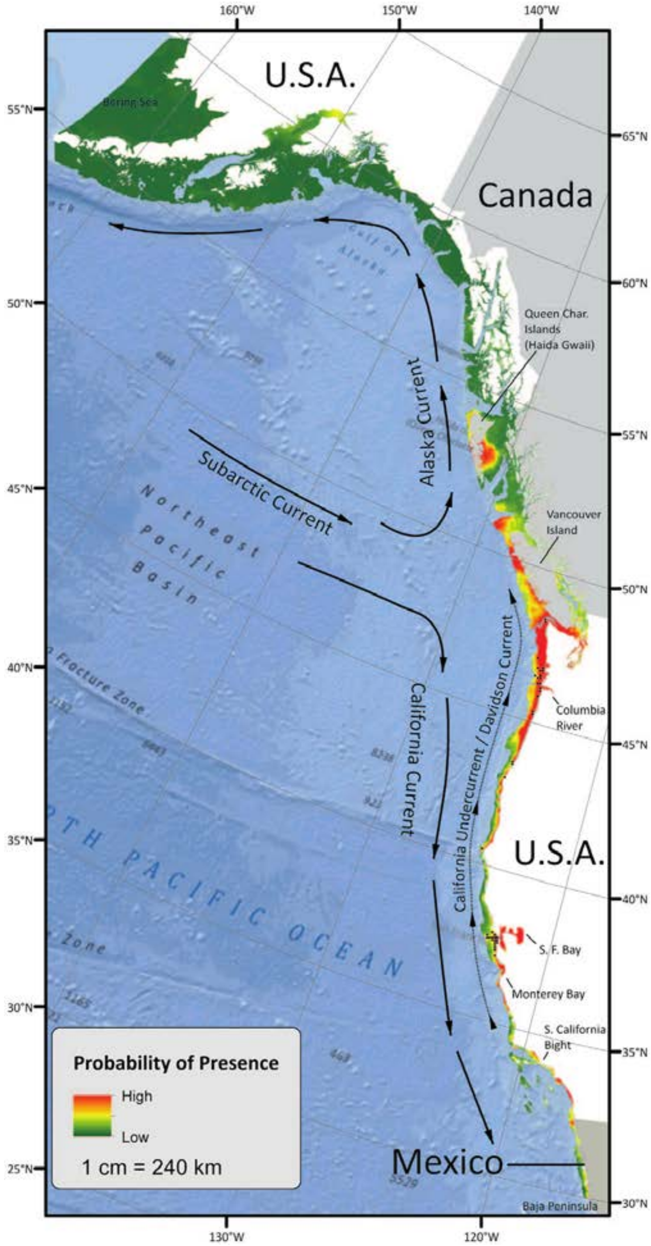


Figure above demonstrates model output for the sturgeon habitat models.

Krill fishery and ecosystem modeling

Below summary from: Watters, G.M., S.L. Hill, J.T. Hill, J.T. Hinke, J. Matthews, and K. Reid. 2013. Decision-making for ecosystem-based management: evaluating options for a krill fishery with an ecosystem dynamics model. Ecological Applications 23:710-725.

Decision-makers charged with implementing ecosystem-based management (EBM) rely on scientists to predict the consequences of decisions relating to multiple, potentially conflicting, objectives. Such predictions are inherently uncertain, and this can be a barrier to decision-making. The Convention on the Conservation of Antarctic Marine Living Resources requires managers of Southern Ocean fisheries to sustain the productivity of target stocks, the health and resilience of the ecosystem, and the performance of the fisheries themselves. The managers of the Antarctic krill fishery in the Scotia Sea and southern Drake Passage have requested advice on candidate management measures consisting of a regional catch limit and options for subdividing this among smaller areas. We developed a spatially resolved model that simulates krill–predator–fishery interactions and reproduces a plausible representation of past dynamics. We worked with experts and stakeholders to identify (1) key uncertainties affecting our ability to predict ecosystem state; (2) illustrative reference points that represent the management objectives; and (3) a clear and simple way of conveying our results to decision-makers. We developed four scenarios that bracket the key uncertainties and evaluated candidate management measures in each of these scenarios using multiple stochastic simulations. The model emphasizes uncertainty and simulates multiple ecosystem components relating to diverse objectives. We summarize the potentially complex results as estimates of the risk that each illustrative objective will not be achieved (i.e., of the state being outside the range specified by the reference point). This approach allows direct comparisons between objectives. It also demonstrates that a candid appraisal of uncertainty, in the form of risk estimates, can be an aid, rather than a barrier, to understanding and using ecosystem model predictions. Management measures that reduce coastal fishing, relative to oceanic fishing, apparently reduce risks to both the fishery and the ecosystem. However, alternative reference points could alter the perceived risks, so further stakeholder involvement is needed to identify risk metrics that appropriately represent their objectives.

Plankton ecosystem dynamics in response to wind forcing, using ROMS-NEMURO

E. Bjorkstedt's group is using a 2-D, cross-shelf slice model to simulate circulation and plankton ecosystem dynamics in response to wind forcing. The model is implemented in ROMS-NEMURO. Effects of low-frequency variability in sea level on thermocline depth are imposed by nudging alongshore-current structure. An individual-based model for rockfish early life history stages is used to simulate the growth of larvae released into the plankton at different times during the winter parturition season. NEMURO zooplankton fields (meso- and micro-) are used to construct the prey field for optimally foraging larvae. Potential survival, conditional on the date-of-birth, is calculated from average size-dependent mortality for each 'mini-cohort' over the course of the first 50 days.

An index of recruitment is calculated by integrating the product of the probability of survival (conditional on date of birth) and the distribution of birth dates. This recruitment index is a per capita measure of recruitment success analogous to recruitment deviations from stock assessments. We assume that the distribution of birth dates is constant from year to year, and find the distribution that yields the best correlation between the resulting recruitment index and recruitment deviations from stock assessments. Recruitment index performs reasonably well, successfully capturing 1999 year class missed by the MWT survey. Extensions of this work to examine the effects of variable predator fields (possibly indexed by PZoo in NEMURO) holds promise for improving fits, and explaining discrepancies between model predictions and RecDev associated with ENSO events.

Ecosystem modeling efforts at the NOAA/NMFS Pacific Islands Fisheries Science Center

submitted as a background document to the:
3rd NMFS National Ecosystem Modeling Workshop (NEMoW 3)
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prepared by:
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The Pacific Islands Fisheries Science Center is comparing two independent ecosystem models' projections of climate and fishing impacts in the central North Pacific (CNP). Similarities and differences in the models' treatment of the same climate and fishing scenarios lend insight into both projected impacts and areas of uncertainty.

We compare both a size-based and a species-based ecosystem model. Both ecosystem models are driven with output from NOAA GFDL's prototype Earth System Model 2.1 (ESM 2.1) and a range of fishing mortality levels. ESM2.1 is a coupled climate model (Delworth et al. 2006, Gnanadesikan et al. 2006) and biogeochemical model (Dunne et al. 2005), forced by the IPCC SRES A2 (Nakićenović et al. 2000). ESM2.1 outputs phytoplankton densities for three functional groups across two size classes. As a result of increased stratification and reduced nutrient input to the euphotic zone, ESM2.1 projects CNP phytoplankton biomass to decline by 9 – 19% over the 21st century.

The two ecosystem models in our comparison are structurally and computationally quite different. The size-based food web (SBFW) model uses size-based predation to drive continuous growth and mortality across all consumer sizes ranging from zooplankton to large fish (Blanchard et al. 2012). Conversely, the species-based model (Ecopath with Ecosim, EwE) uses detailed species-based diets and trophic relationships (Howell et al. 2012). Comparing these models' output provides insights that may not be evident when using each model individually, as is often the case. In particular, differences in their handling of identical climate and fishing scenarios can reveal previously overlooked uncertainties in both the impacts of climate change and fishing mortality, as well as in the ecosystem models themselves. Additionally, areas of model agreement lend confidence to projections of future ecosystem impacts.

We examined biomass and catch of small and large exploitable fish. Based on data from the Hawaii-based longline fishery, we determined the threshold for entry to the fishery to be 1 kg (Polovina and Woodworth-Jefcoats 2013). Small (1 – 15 kg) and large (> 15 kg) size groupings were based on the size at which fish are fully exploited by the fishery (15 kg). Small fish were subject to one quarter the level of fishing mortality as large fish.

The magnitudes of catch and biomass projected by both models agreed well. Additionally, both models projected a decline in large fish catch and biomass when fishing and climate change were combined. This decline in large fish biomass led to a marked increase in small fish abundance and to a decline in the proportion of large fish included in the total catch. Both models also projected the greatest catch of large fish at a moderate level of fishing mortality (F = 0.4), suggesting a possible maximum yield for the CNP.

Despite broad model agreement, there were some interesting areas where the models differed. Perhaps the greatest difference between the two models was the degree to which variability at the base of the food web propagated to the top trophic levels. Variability in the SBFW modeled catch and biomass was 2 – 27 greater than that modeled by the EwE model, with the greatest differences seen for large fish. Additionally, the interannual variability in the EwE model seemed to track small phytoplankton more closely while the SBFW model tracked large phytoplankton. This disparity can be at least partially explained by differences in the models' structure, though it does raise the question of which aspects of projected climate change will have the greatest ecosystem impacts: changes in phytoplankton abundances as suggested by the EwE model, or changes in phytoplankton size structure, as suggested by the SBFW model. Additional model output disparities included the degree to which increased fishing mortality leads to both increased catch and associated prey release, and whether climate change and fishing will have synergistic or tempering effects.

Now that our initial comparison is complete, we are moving forward with both model verification and development. The upper trophic levels of the EwE model are fairly well resolved in terms of feeding relationships. Yet, as trophic level decreases so too does the trophic resolution. We will use diet and stable isotope data from the CNP to improve mid-trophic-level structure in the EwE model. We will also be using size and abundance data for CNP zooplankton and mid-trophic-level fish to verify the structure of the SBFW model.

In addition to verifying and improving both models' structure, we will also be using them to evaluate a suite of CNP climate projections. A number of models included in Climate Model Intercomparison Project 5 (CMIP5; Taylor et al. 2012) contain biological data at one or two trophic levels. Using these data for a larger ecosystem model comparison will provide greater insight into potential climate and fishing impacts in the central North Pacific.

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Ecosystem modeling efforts at the NOAA/NMFS Southeast Fisheries Science Center

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Ecosystem-based management (EBM) has become a central paradigm in the Gulf of Mexico (GOM). In particular, a comprehensive Integrated Ecosystem Assessment (IEA) program has been initiated in the GOM by the Southeast Fisheries Science Center (SEFSC) to organize science in order to inform decisions in EBM at multiple scales and across ocean use sectors (Levin et al., 2009, 2013). In March 2013, the Gulf of Mexico Fisheries Management Council's Standing and

Ecosystem Scientific & Statistical Committees passed two motions expressing their desire to incorporate IEA products into single-species stock assessments and living marine resource (LMR) management decisions on a regular basis (http://www.noaa.gov/iea/transfer-knowledge/gulf-of-mexico-council-support.html).

Simulation models are essential tools for guiding EBM. Simulation models used at the SEFSC for informing EBM include a diversity of single-species and ecosystem models. However, multi-model approaches at the SEFSC are in their very infancy. In the following, we provide an overview of the different simulation models being used to inform EBM in the GOM. Then, we describe how these models are contributing, or may eventually contribute to multi–model approaches in the GOM. Finally, we briefly summarize a number of studies being conducted at or funded by the SEFSC that are informing or are going to inform simulation models and multi-model approaches in the GOM.

Simulation models used at the SEFSC

Most of the simulation models used at the SEFSC are ecosystem models employed within the GOM IEA program. These ecosystem models include Ecopath with Ecosim (EwE) and OSMOSE models for the West Florida Shelf (WFS), an EwE model for the U.S. coast of the GOM (referred to as 'GOM Shark EwE'), and an Atlantis model for the whole GOM (referred to as 'Atlantis-GOM'). The WFS is one of the main subregions of the GOM, under high and increasing fishing and environmental pressures (Coleman et al., 2004; Okey et al., 2004; Karnauskas et al., 2013). The OSMOSE model that was designed for the WFS, which we refer to as 'OSMOSE-WFS', is the first OSMOSE model being developed in the U.S. OSMOSE is an individual-based, multi-species modeling approach, which is increasingly being applied worldwide to inform EBM (Shin and Cury, 2001, 2004). In particular, OSMOSE has been used within a multi-model approach to explore the impacts of exploitation scenarios in different marine ecosystems (Smith et al., 2011; Travers et al., 2010).

The other simulation models used at the SEFSC for informing EBM consist of: (1) an EwE model for Galveston Bay, Texas; (2) an ecosystem simulation model for South West Florida; (3) a Stock Synthesis (SS) model for the gag grouper (Mycteroperca microlepis) population of the GOM incorporating red tides; (4) a compartment based systems model for brown shrimp (Farfantepenaeus aztecus) in GOM estuaries representing the influence of abiotic parameters on shrimp production; (5) a population model for white shrimp (Litopenaeus setiferus) in the northern Gulf of Mexico considering the impacts of the abiotic environment on shrimp vital rates; and (6) population models for a few fishery species in Galveston Bay taking into account the effects of watershed-based activities on the harvest of these species, complemented by a loop analysis.

Ecosystem simulation models developed for the WFS

Ecosystem simulation models developed for the WFS and used within the GOM IEA program include two EwE models ('WFS Reef fish EwE' and 'WFS Red tide EwE') and the OSMOSE-WFS model. WFS Reef fish EwE was constructed by David Chagaris and Behzad Mahmoudi from the Fish and Wildlife and Research Institute (FWRI). WFS Reef fish Ecopath provides a snapshot of the WFS ecosystem over the period 2005-2009 (Chagaris, 2013; Chagaris and Mahmoudi, 2013). Alisha Gray and Cameron Ainsworth from the University of South Florida (USF) designed WFS Red tide EwE, which is similar to WFS Reef fish EwE and aims to investigate the impacts of red tide outbreaks for gag grouper (Gray et al., 2013). OSMOSE-WFS was developed by Arnaud Grüss from the SEFSC and Rosenstiel School of Marine and Atmospheric Studies (RSMAS), University of Miami (UM) and colleagues (Grüss et al., 2013a, 2013b, in. prep.). OSMOSE-WFS is currently a steady-state model describing trophic interactions in the WFS over the period 2005-2009. OSMOSE-WFS builds on WFS Reef fish Ecopath in that the two models share a number of characteristics (e.g., the spatial domain considered, reference biomasses). However, OSMOSE-WFS and WFS Reef fish Ecopath differ greatly in both their structure and assumptions. In particular, diets reconstructed from empirical data are input into Ecopath, while diet compositions emerge from simulations in OSMOSE. The use of the OSMOSE-WFS, WFS Reef Fish Ecopath/EwE and WFS Red tide EwE models is interesting to have different perspectives on the same questions, while being able to identify from where discrepancies between the different models may originate.

In 2013, OSMOSE-WFS, WFS Reef Fish EwE and WFS red tide EwE were used to inform SEDAR (SouthEast Data, Assessment, and Review), a management council process designed to improve the reliability of single-species stock assessments in the GOM (http://www.sefsc.noaa.gov/sedar/). In particular, estimates of instantaneous natural mortality rates for gag grouper were produced with the three ecosystem models. Biomass, catch and productivity (i.e., production over biomass) parameters of the WFS Reef fish Ecopath model were rescaled to obtain an Ecopath model for the early 1950s, from which Chagaris and Mahmoudi (2013) evaluated the natural mortality rates of three life stages (stanzas) of gag grouper (younger juveniles, older juveniles and adults) from 1950 to 2009, under alternate assumptions about compensatory survival and predation. The authors found interannual variability of gag grouper natural mortality to decrease with age and compensatory improvements in survival during periods of low abundance. Gray et al. (2013) showed with WFS Red tide EwE that mortality due to red tides was by far greater than predation mortality for adult gag grouper over the period 2005-2009.

Grüss et al. (submitted) evaluated the natural mortality rates of younger juvenile, older juvenile and adult gag grouper over the period 2005-2009 using OSMOSE-WFS. OSMOSE-WFS and WFS Reef fish Ecopath agree on the magnitude of the instantaneous natural mortality of the different life stages of gag grouper over the period 2005-2009, but not always on the main causes of this mortality (i.e., predation or other causes). Predation mortality rates of younger and older juvenile gag groupers are higher in OSMOSE-WFS than in WFS Reef fish Ecopath, and OSMOSE-WFS identified predators of juvenile and adult gag groupers that were missed in WFS Reef Fish Ecopath. One major finding in Grüss et al. (submitted.) is that the bulk of the natural mortality of adult gag grouper over the period 2005-2009 did not come from predation. The natural mortality rates of adult gag grouper due to causes other than predation evaluated with

OSMOSE-WFS and WFS Reef Fish Ecopath/EwE for the period 2005-2009 were consistent with the red tide mortality on adult gag grouper estimated by WFS Red tide EwE for this time period.

Simulation models developed for the whole GOM

Skyler Sagarese from the SEFSC and RSMAS, UM is developing the GOM Shark EwE model within the GOM IEA program. GOM Shark EwE is being constructed primarily to assess the ecosystem impacts of alternative fishing policies on large coastal sharks in the coastal areas of the GOM. Different exploitation scenarios (direct versus indirect fishing mortality (menhaden bycatch)) were explored with the model. Preliminary results with GOM Shark EwE suggest that alterations to fishing patterns for the commercial shark and menhaden fisheries would lead to substantial changes in relative biomass for both higher trophic level predators and lower trophic level organisms, and significantly impact the trophic structure of the coastal areas of the GOM.

Cameron Ainsworth from USF and his students in collaboration with the SEFSC and RSMAS, UM, are designing the Atlantis-GOM model. The development of Atlantis-GOM is funded by Florida Sea Grant and the C-IMAGE (Center for Integrated Modeling and Analysis of the Gulf ecosystem) consortium. Atlantis-GOM is a highly sophisticated model whose spatial units (polygons) cover both the continental shelf and deep waters of the GOM. The construction and parameterization of Atlantis-GOM has required a number of preliminary studies, in particular to reconstruct fisheries catches in the GOM during the past 25 years, produce spatial distribution maps for the model and generate diet matrices for the numerous functional groups represented in the model. Atlantis-GOM is currently being calibrated and should be operational within a few months for use within the GOM IEA program.

Skyler Sagarese and colleagues from the SEFSC incorporated red tides in the SS model designed for the gag grouper population of the GOM for SEDAR in 2013 (SEDAR 33), within the GOM IEA program. Using the base SS model (13 age classes: 0, 1… 12+ year old individuals) and an abbreviated version of this model (3 age classes: 0, 1-4 and 4+ years old individuals), natural mortality (M) of each plus group was linked to a red tide index. Five scenarios based on candidate red tide indices and methods for inclusion in the SS model were devised and compared. Regression analysis provided strong evidence for a relationship between deviations in M and evaluated environmental indices for both base models. Environmental consideration of red tide generally improved model fit in comparison to base models with no red tide, with significant relationships identified between each environmental index and M deviations when using the model method in the SS model. Hereafter, the SS model designed for the gag grouper population of the GOM incorporating red tides is referred to as the ‘Red tide SS model’.

Simulation models developed for other regions of the GOM

The Galveston Lab is devising anEwE model for Galveston Bay. The model focuses on penaeid shrimps and represents an alternative approach to examining ecosystem impacts on shrimp production. One immediate impetus for constructing the Galveston Bay EwE model was the ongoing project entitled “Developing linked watershed-marine ecosystem service models to evaluate coastal management strategies”. This project aims to examine how changes in land cover affect runoff and water quality and, ultimately, the production of penaeid shrimps and other fishery resources in Galveston Bay. The Galveston Lab would need someone with EwE expertise to help complete the Galveston Bay EwE model.

Kelly Kearney from NOAA/AOML Miami and RSMAS, UM and colleagues from AOML Miami and the SEFSC are developing an ecosystem model for South West Florida within the NOAA COCA (Coastal and Ocean Climate Applications) project to predict ecosystem effects of dual climate change and water management change scenarios. This model builds on an existing mechanistic trophic model for Florida Bay. It will be used to: (1) examine trophic interactions for two socio-economically important species of the South West Florida ecosystem, spotted seatrout (*Cynoscion nebulosus*) and gray snapper (*Lutjanus griseus*); and (2) determine how interacting water management/climate changes might affect these two species, their prey, or other species. Spotted seatrout and gray snapper are indicator species used to determine the success of the Comprehensive Everglades Restoration Project (CERP), designed to improve the quantity, quality, timing, and distribution of water flow to the Everglades and South West Florida estuaries. Therefore, outcomes of the South West Florida ecosystem model will be useful to produce decision support tools depicting the impacts of climate change and water management change scenarios on the vulnerability and health of South West Florida ecosystem.

The Galveston Lab is currently building a compartment based systems model for brown shrimp in GOM estuaries, in which shrimp production is influenced (through growth and mortality) by temperature, salinity and access to emergent marsh vegetation (hereafter referred to as the ‘GOM brown shrimp model’). The objective of these modeling efforts is to introduce environmental variability into the SS model used for brown shrimp stock assessments.

The Galveston Lab in collaboration with Texas A&M University has developed a stage-based population model for white shrimp in the northern GOM considering the impacts of salinity and access to protective vegetated marsh habitat on the vital rates (growth, mortality, fecundity) of juveniles of the species (hereafter referred to as the ‘GOM white shrimp model’) (Baker et al., in press). The model indicates that modest changes in juvenile growth and mortality due to abiotic factors have a greater impact on shrimp stock size than the full range in fishing mortality over the past few decades. These results suggest that variability in juvenile survival may be a strong driver of adult stock size and that the environmental factors that regulate juvenile growth and mortality need to be properly understood for the effective management of coastal nurseries and white shrimp stocks.

The Galveston Lab is also developing population models for a few fishery species in Galveston Bay forced by a marine water quality model, which is itself forced by a watershed model, based on the modeling approach of Toft et al. (2013). These linked watershed-marine models allow evaluating how the productivity of fishery species is affected by water quality (temperature, salinity, nitrates), which is itself affected by freshwater discharge and nitrogen loading. Because linked watershed-marine models are only designed to examine effects on a few fishery species (including oysters and blue crab, *Callinectes sapidus*), a loop analysis was conducted to describe interactions and linkages in Galveston Bay food web and provide a tool to assess hypotheses about food web responses (Carey et al., 2013).

Multi-model approaches in the GOM

We distinguish between three types of multi-model approaches: (1) using a reference set of operating models (OMs); (2) inter-model comparisons; and (3) ensemble modeling.

A reference set of OMs is built from a single simulation model. Each OM is a version of the simulation model representing a plausible 'state of nature' (Plagányi et al., 2007). Using a reference set of OMs is useful to address parameter uncertainty (i.e., uncertainty surrounding model parameters stemming from, e.g., observation errors), process uncertainty (i.e., uncertainty surrounding the way processes are considered in the simulation model) or future uncertainty (i.e., uncertainty on future exploitation and environmental patterns). In the GOM, reference sets of OMs were used for the Red tide SS model to determine the best candidate red tide indices and methods for inclusion of the indices in the SS model (to address parameter and process uncertainties). Reference sets of OMs may also be used for: (1) the South West Florida ecosystem model to seek scientific conclusions robust to uncertainty of food web processes in the face of water management and climate changes (to address future uncertainty); and (2) the GOM brown shrimp model to identify the best candidate environmental indices and methods for inclusion of the indices in a SS model (to address parameter and process uncertainties).

Inter-model comparisons involve models with different structure and assumptions. However, inter-model comparisons require models being compared to share a number of characteristics (e.g., the spatial domain considered, species and processes represented) depending on the questions that need to be addressed. Inter-model comparisons are interesting to have different perspectives on the same questions, while being able to identify from where discrepancies between the different models being used may originate. In parallel to model uncertainty (i.e., uncertainty related to the structure and assumptions of models being used), inter-model comparisons can also address parameter uncertainty if references sets of OMs are constructed from some of the models being used. Inter-model comparisons in the GOM have been conducted only in the WFS through the collective evaluation of the natural mortality rates of gag grouper by OSMOSE-WFS, WFS Reef fish Ecopath/EwE and WFS Red tide EwE.

Other inter-model comparisons may be implemented in the GOM with: (1) OSMOSE-WFS, WFS Reef fish Ecopath/EwE, WFS Red tide EwE and Atlantis-GOM to evaluate the instantaneous natural mortality rates of socio-economically important species of the GOM, including red snapper (*Lutjanus campechanus*) and red grouper (*Epinephelus morio*), and to run Management Strategy Evaluations (MSEs) in the WFS; (2) GOM Shark EwE, WFS Reef fish EwE and WFS Red tide EwE to assess the ecosystem impacts of alternative fishing policies on large coastal sharks in the GOM; (3) Galveston Bay EwE, linked watershed-marine models and loop analysis in

Galveston Bay to investigate how the productivity of fishery species like blue crab is affected by freshwater discharge and nitrogen loading; (4) the Galveston Bay EwE, GOM brown shrimp and GOM white shrimp models to evaluate how the mortality and production of penaeid shrimps are impacted by their environment (biotic or abiotic) in Galveston Bay; and (5) the Red tide SS and WFS Red tide EwE models to collectively assess the mortality rates of different life stages of gag grouper due to red tide outbreaks in the 2000s.

Ensemble modeling is a framework exposing an ensemble of simulation models with different structure and assumptions to identical exploitation and environmental scenarios, using multiple realizations of each exploitation scenario and each environmental scenario (Gardmark et al., 2013). Ensemble modeling addresses model, process and future uncertainties, and can also address parameter uncertainty if references sets of OMs are constructed from some of the models being used. Ensemble modeling are useful to disentangle model and process uncertainties from future uncertainty by comparing results among models within a single climate-exploitation realization, and within models among climate-exploitation realizations, respectively (Gardmark et al., 2013). Simulation models in the ensemble must be subjected to the same environmental forcing and fishing levels (Gardmark et al., 2013). Furthermore, to enable comparisons across models, simulated responses in biomasses or catches must be presented as the change in simulated biomasses or catches from the simulated biomasses or catches at the beginning of simulations within each model, relative to the biomasses or catches at the beginning of simulations estimated by a reference stock assessment model (see Fig. 2 in Gardmark et al., 2013).

Here, we provide an example of ensemble modeling for the WFS, exposing WFS Reef fish Ecopath and OSMOSE-WFS to identical exploitation and environmental scenarios to evaluate potential future biomasses, catches and food web processes in the WFS (Fig. 1). The ensemble modeling planned for the WFS will incorporate other simulation models, including WFS Red tide EwE and Atlantis-GOM, but, for simplicity, we consider here a simplified ensemble modeling with only one EwE model and one OSMOSE model. This simplified ensemble modeling will be developed in two steps consisting in: (1) producing a mass-balanced WFS Reef fish Ecopath model providing a snapshot of the WFS ecosystem in 2009, and a calibrated steady-state OSMOSE-WFS model describing the trophic structure of the WFS in 2009; and (2) running forward projections from the WFS Reef fish Ecopath model using the Ecosim module, and from the steady-state OSMOSE-WFS model by exposing the model to exploitation and environmental scenarios after the spin-up phase. In other words, the second step for an ensemble modeling in the WFS will consist in running forward projections with both WFS Reef fish EwE and a dynamic version of the OSMOSE-WFS model.

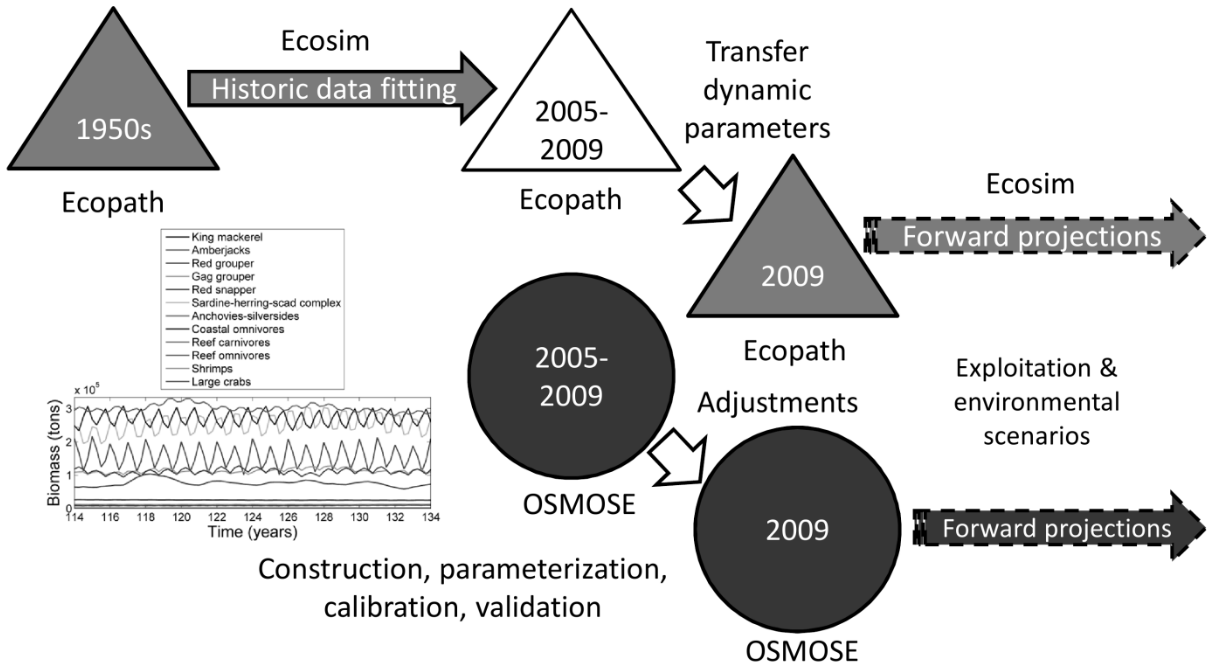

Fig. 1. Schematic representation of the development of an ensemble modeling for the West Florida Shelf (WFS) exposing the WFS Reef fish Ecopath and OSMOSE-WFS models to identical exploitation and environmental scenarios. The ensemble modeling will be developed in two steps, consisting in: (1) producing a mass-balanced WFS Reef fish Ecopath model and a calibrated steady-state OSMOSE-WFS model, both describing the trophic structure of the WFS in 2009; and (2) running forward projections with WFS Reef fish Ecopath using the Ecosim module, and with a dynamic version of the OSMOSE-WFS model.

The first step for an ensemble modeling in the WFS is partly completed. Biomass, catch and productivity parameters of the WFS Reef fish Ecopath model were rescaled to obtain an Ecopath model for the early 1950s, from which Chagaris (2013) evaluated changes in biomasses, mortalities and trophic interactions in the WFS over the period 1950-2009 as well as vulnerability exchange rates using the Ecosim module. Vulnerability exchange rate estimates need to be transferred to the Ecopath module, while biomasses, catches and fishing mortality rates in Ecopath need to be adjusted to match biomasses, catches and fishing mortality rates estimated by reference stock assessments for 2009. The resulting Ecopath model, which provides a snapshot of the WFS ecosystem in 2009 will need to be mass-balanced. The steady-state OSMOSE-WFS model was calibrated so that the biomasses of all the high trophic level (HTL) groups of fish and invertebrate species represented in the model match biomass levels observed over the period 2005-2009. This steady-state model needs to be recalibrated using both biomass and fisheries catch data to ensure that both biomasses and catches predicted by the steady-state OSMOSE-WFS model match the biomass and catch levels estimated by reference stock assessments for 2009. Before recalibrating the steady-state OSMOSE-WFS model, fishing mortality rates in the model will be set to the fishing mortality rates estimated by reference stock assessments for 2009.

The second step for an ensemble approach in the WFS will consist in running forward projections with WFS Reef fish EwE and a dynamic version of OSMOSE-WFS under alternate exploitation and environmental scenarios. Before running forward projections, Fmsy's, i.e., the fishing mortality rates at which fisheries catches reach a maximum, will be estimated for both WFS Reef fish EwE and OSMOSE-WFS. Exploitation scenarios will be defined based on the Fmsy's estimated and potential Harvest Control Rules (HCRs). Environmental scenarios will be explored to evaluate the impacts of climate change on biomasses, catches and food web processes in the WFS. When forward projections are run and exploitation and environmental scenarios explored, WFS Reef fish EwE and OSMOSE-WFS will be subjected to the same environmental forcing. Thus, the biomasses of plankton groups considered in both WFS Reef fish EwE and OSMOSE-WFS may be subjected to identical changes (reflecting changes in environmental conditions) in both models.

Studies informing simulation models and multi-model approaches in the GOM

The development of simulation models and multi-model approaches in the GOM would not be possible without a number of studies being conducted at or funded by the SEFSC. These studies include – but are not limited to: (1) applications of a biophysical modeling approach, the Connectivity Modeling System (CMS), to red snapper, gag grouper and red grouper populations of the GOM; (2) the development of a large database gathering information about diets and trophic interactions in the GOM, the 'Gulf of Mexico Species Interaction (GoMexSI)' database; (3) the construction of candidate red tide indices for input for stock assessment models; and (4) research surveys organized by the SEFSC.

Mandy Karnauskas from the SEFSC in collaboration with RSMAS, UM has applied the CMS to red snapper and gag grouper, and is going to apply this modeling approach to red grouper. The CMS uses outputs from hydrodynamic models and tracks the three-dimensional movements of advected particles through time, given a specified set of release points and particle behaviors (Paris et al., 2013). To estimate expected annual recruitment strength due to oceanographic factors alone, particles representing eggs are released from known spawning locations on a yearly basis, and are tracked through time with a realtime oceanographic hindcast which gives a best estimate of the specific oceanographic conditions at each point in time (HYCOM, http://www.hycom.org). The percentage of particles that successfully reach settlement habitat, given the parameterized biological limitations (e.g., pelagic larval duration), then represents the expected recruitment anomaly for that year. This technique has been used to provide estimates of recruitment over the most recent decade to the red snapper and gag grouper stock assessments conducted within the SEDAR process (Karnauskas et al., 2013a, 2013c). This technique is also going to be employed to deliver estimates of recruitment for red grouper over the recent period to SEDAR, and to produce spatial distribution maps for young-of-the-year red and gag groupers for the OSMOSE-WFS model.

James Simons from the Center for Coastal Studies at Texas A&M University and colleagues are supporting the GOM IEA program by compiling the GoMexSI database (Simons et al., 2013; http://gomexsi.tamucc.edu/). The development of the GoMexSI database is primarily intended to inform the diet compositions entered in GOM EwE and Galveston Bay EwE, and to provide information to OSMOSE-WFS and Atlantis-GOM for the estimation of a few input parameters (minimum and maximum predator over prey size ratios and accessibility coefficients in OSMOSE-WFS, and gape sizes in Atlantis-GOM).

John Walter from the SEFSC and colleagues developed indices of red tide severity from a generalized additive model (GAM) that predicts the probability of a red tide bloom using a suite of satellite derived remote sensing products and the FWRI Harmful Algal Bloom database. These indices are intended to be incorporated as environmental covariates into stock assessment models, and particularly into the SS model developed for gag grouper for SEDAR 33. Walter et al. (2013) created several indices constituting different spatial and temporal partitions based on hypothesis regarding the spatial and temporal overlap of gag grouper populations with red tide blooms.

Research surveys organized by the SEFSC are useful, among other things to produce spatial distribution maps for the ecosystem models developed within the GOM IEA program (Drexler and Ainsworth, 2013; Grüss et al., 2014). These research survey include the SEAMAP (Southeast Area Monitoring and Assessment Program) groundfish/trawl (GSMFC, 2011), the NMFS BLL (National Marine Fisheries Service bottom longline) (Ingram et al., 2005) and the SEAMAP reef fish video surveys (Campbell et al., 2013; Gledhill et al., 2005) and the acoustic surveys conducted at the Mississippi labs.

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Ecosystem modeling efforts at the NOAA/NMFS Northwest Fisheries Science Center

submitted as a background document to the:
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Northwest Fisheries Science Center: Multi-model inference, linking models, and model ensembles

Since the last National Ecosystem Modeling Workshop, several innovative steps have been taken by scientists at Northwest Fisheries Science Center and collaborators to link models, to consider model ensembles, and to draw inference from multiple models. Some of these efforts are described below, with examples primarily drawn from the California Current Integrated Ecosystem Assessment (IEA, http://www.noaa.gov/iea/CCIEA-Report/index.html). While some avenues are extremely promising, wide gaps are evident, and there is a need for a concerted West Coast effort to fill these gaps. For instance, if oceanographic projections under climate change were available, these could tie directly into ecosystem, population, and individual-based models already in use.

J-SCOPE (University of Washington JISAO, PMEL, NWFSC)

A seasonal ocean prediction system (J-SCOPE, http://www.nanoos.org/products/j-scope/home.php/) has been developed for the coastal waters of the Pacific Northwest. The goal has been to provide seasonal (six to nine month) predictions of ocean. The J-SCOPE model system is based on climate forcing as specified by the Coupled Forecast System (CFS) global climate model. The CFS is a coarse-scale, coupled atmosphere-ocean-land model that assimilates both in-situ and satellite-based ocean and atmospheric data. J-SCOPE uses CFS to force a high-resolution (grid spacing ~1.5 km) version of the Regional Ocean Modeling System (ROMS) that includes a state-of-the-art biogeochemical module and nutrient, phytoplankton, zooplankton, detritus (NPZD) module, with an additional detrital pool and oxygen submodel. The ROMS predicts specific oceanic properties crucial to the nearshore and coastal marine ecosystem such as temperature, currents, upwelling, pH, oxygen concentration, and plankton distributions. J-SCOPE has been used to reforecast 2009 and 2013 sardine distributions, and these forecasts will be expanded for other pelagic species and for Dungeness crab, as well as to provide forecasted ecosystem indicators for the Integrated Ecosystem Assessment.

Salmon population projections under climate change

Crozier et al. (2013 IEA, forthcoming) employed a salmon life cycle model to evaluate the impact of climate change on three populations of threatened Snake River spring/summer Chinook salmon (*Oncorhynchus tshawytscha*). The authors used downscaled temperature and stream flow projections for the 2040s from 10 global circulation models (GCMs) and 2 emissions scenarios to characterize freshwater climate changes. They conducted a sensitivity analysis of ocean conditions by systematically varying periods of relatively favorable and unfavorable climate regimes from the historical record. Scenarios for ocean conditions consisted of alternative percentages of years when ocean conditions during early ocean entry by salmon were considered favorable (negative mean annual Pacific Decadal Oscillation [PDO] values) and unfavorable (positive PDO values) for survival. Among other results, the authors found that management actions leading to higher survival through the hydrosystem (dams) successfully mitigated for the increased extinction risk due to climate conditions in all three populations. Abundance still declined from baseline under the worst ocean scenarios in two populations. Whether this recent improved survival can be sustained is not clear. But these results suggest a significant opportunity for recovery in these threatened populations.

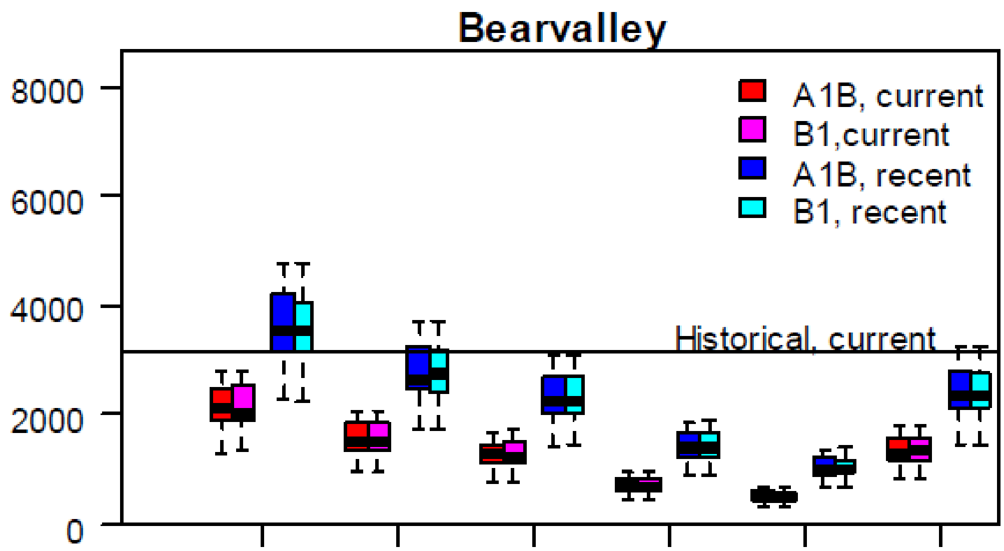

Figure 1, from Crozier et al. (forthcoming 2013 IEA). Median spawner abundance of Bear Valley Creek (Salmon River) Chinook salmon, as a function of freshwater climate scenarios (A1B or B1), hydrosystem survival ("Current", or improved survival rates labelled "recent"), and ocean conditions. Ocean conditions are characterized in terms of the percent of years with consistently positive PDO, and are compared with the actual historical time series ("Historic"). The baseline scenario used the historical freshwater and ocean conditions and the "current" hydrosystem management, and is shown by the horizontal line. The boxes show the range across all global climate models (GCMs) for a given scenario (line shows the median GCM, the boxes show the interquartile range, and the whiskers show the full range of all GCMs).

Forage fish

Forage fish play a key role in the California Current food web. Internationally, these species sustain over one quarter of global fish production. Key questions for forage fish in the California Current are: 1) What is the likely response to climate change, 2) What are the ecological implications of recent declines in abundance of sardines 3) What is the support for , and implications of , recent hypotheses related to fluctuations in sardine and anchovy stock 4) How can harvest control rules for forage fish be modified to account for both the ecological role and population dynamics of these species . One of the strengths of NOAA ecosystem modelling on the West Coast (SWFSC and NWFSC) is that we have applied two models to questions related to the role of forage fish in the food web (Atlantis and Ecosim, see Kaplan et al. at http://www.noaa.gov/iea/CCIEA-Report/management-testing/index.html), and models such as ECOTRAN (forthcoming 2013 IEA), and NEMURO-SAN (SWFSC) could be brought to bear on these questions of climate effects. These different ecosystem modeling approaches could support SWFSC empirical modeling and stock assessments for sardine. Multiple model inference using different model structures and assumptions is crucial in handling and quantifying uncertainty around complex ecosystem models and these ecological processes.

Coupled Economic-Ecological models

Direct coupling of ecosystem models to economic methods allows the translation of fisheries catches into jobs and broader economic revenue, rather than simply dockside revenue. In the context of the IEA, population and ecosystem modelers have projected salmon and groundfish harvests under different management scenarios for dams and catch share systems. Using input-output models such as IMPLAN, economists at SWFSC and NWFSC are able to translate this into economic impacts and employment at the coastwide, state, and community (port) levels (see analyses by Gray et al and Thomson at http://www.noaa.gov/iea/CCIEA-Report/management-testing/index.html). These models are intended to capture the economic response over short time scales. Notably, new mandatory economic data collection for West Coast catch share fisheries is leading to rapid improvements in the economic models, and could facilitate more dynamic models of fishing and human behaviour.

Multiple Model Ecosystem modeling efforts at the NOAA/NMFS Chesapeake Bay Office (NCBO)

submitted as a background document to the:
3rd NMFS National Ecosystem Modeling Workshop (NEMoW 3)
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prepared by:
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Background Information on NCBO Ecosystem Models

The NOAA Chesapeake Bay Office (NCBO) Modeling and Analysis Team develops and implements modeling tools and statistical analyses to support ecosystem-based management of the Chesapeake Bay's living resources and NOAA trust resources in the bay. These tools and models are designed to synthesize information about many features of an ecosystem and provide:

- Increased understanding of interactions among the components of the Bay's ecosystems,
- Improved synthesis based on standardized ecosystem data,
- Improved ability to evaluate and adapt ecological monitoring efforts in the region, and
- The ability to simulate the outcomes of a range of possible management actions to clarify tradeoffs among the interests of stakeholders.

NCBO modeling efforts are geared toward supporting ecosystem-based fisheries management (EBFM) in the Chesapeake Bay. The primary models for EBFM are the Chesapeake Bay Fisheries Ecosystem Model (CBFEM) and Chesapeake Atlantis Model (CAM). Both modeling approaches share a common trophic structure, which allows some insight into questions concerning model complexity.

The Chesapeake Bay Fisheries Ecosystem Model (EwE/Ecospace)

The CBFEM is a trophic model of the Chesapeake Bay developed using Ecopath with Ecosim (EwE) software. The Ecopath module of the CBFEM uses estimates of the biomass of 58 trophic groups representing the fisheries species of the Bay and their predators and prey to create a mass-balanced snapshot of the organisms and trophic linkages in the Bay as they existed in 1950. The biomass pools represent either a single species or a group of species that constitutes an ecological guild. Some biomass pools were divided into ontogenetic age categories (e.g., young-of-the-year and adult). The model is used to simulate management strategies using the Ecosim module. Variability in the simulation module is driven by a time series of primary productivity and by several time series of fishing effort on the major trophic groups. The model has been fit to a time series (1950-2009) of relative abundance indices for the major trophic groups.

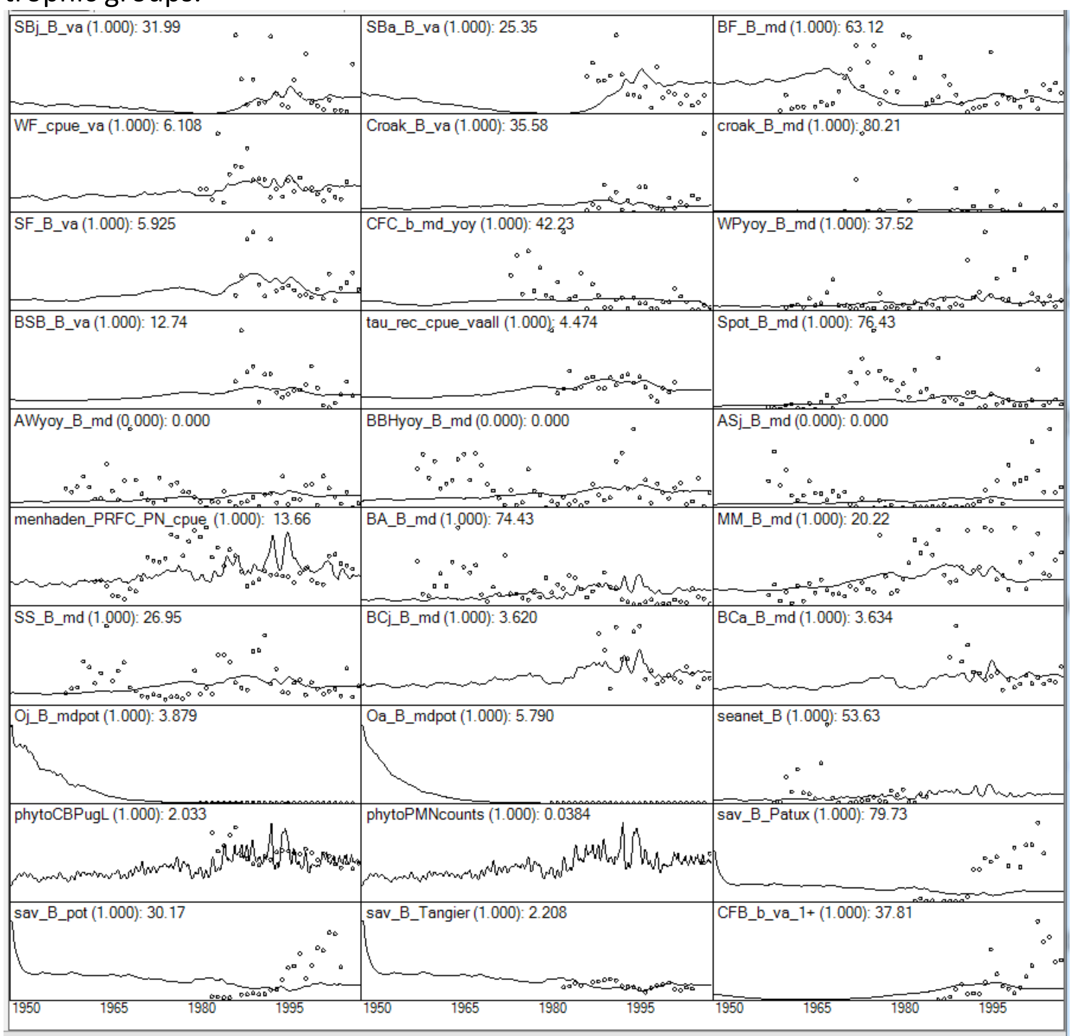


Figure 1. CBFEM Ecosim output compared to observed fish biomass indices, 1950-2009.

Currently, the team is developing a spatial version of the CBFEM using the Ecospace module of EwE. The spatial model will incorporate spatial forcing functions of key environmental parameters (salinity, temperature, and dissolved oxygen) to improve the representation of seasonal changes in trophic group distributions.

The Chesapeake Atlantis Model

CAM, based in the Atlantis software developed by the Australian Commonwealth Scientific and Industrial Research Organization (CSIRO), has been developed to a stage such that it simulates the biogeochemical cycles and the fisheries food web of the Chesapeake. This model is an approach for conducting formal management strategy evaluation—a simulation that accounts for tradeoffs in performance across a range of management objectives. It provides the decisionmaker with information on which to base a rational decision, given the decisionmaker's objectives, preferences, and attitude concerning risk; it does not prescribe an optimal strategy or decision.

CAM differs from many recent Atlantis models due to the extreme nature of the Chesapeake system and its management challenges. Chesapeake Bay is the largest estuary in the US. The watershed for the Bay is very large (>165,760 square km/ 64,000 sq. mi.), encompassing portions of 6 states and the entire District of Columbia, and numerous metropolitan areas (largest include: Norfolk, Richmond, and Charlottesville, VA; Washington DC; Harrisburg, PA; Baltimore, MD; and Cooperstown, NY). The system bridges multiple jurisdictions, so the system is subject to a complex mix of regulations as well. There is a growing population of more than 17 million people, as well as a relatively large agricultural sector, all of which contribute to exceptionally high nutrient loads to the system. Residence time for nutrients and particulate matter is relatively high (90-180 d), due to high levels of freshwater flow from river inputs and consequent lower-layer counterflow. The Chesapeake is extremely shallow, with a mean depth of only 6.5 m; consequently, benthic dynamics are critical. Turbidity is high enough to limit plant growth, even in relatively shallow areas of the Bay. Deeper areas of the system are subject to seasonal hypoxic and anoxic events. There is a relatively strong freshwater influence, with multiple large river inputs in the system, as well as numerous small tributaries (> 100,000 streams, creeks and rivers). Chesapeake Bay is just north of a major biogeographic break, consequently there is seasonal variation in animal populations with southern populations present during summer and more northerly populations predominating in fall-spring. Most Bay populations migrate out of the system at some point during the year, consequently, their populations are subject to mortality outside the system, and the parameterization and simulation of such groups can be problematic. The Chesapeake has some of the most extreme ranges of water temperature for any coastal system; winter extremes can be as low as 1ºC. Because of the lack of deep water refuge from such temperature extremes, the relatively few species that remain throughout the year become mostly inactive or enter torpor during this portion of the year. Marsh, submerged aquatic vegetation (SAV), and oysters all provide habitat important to the functionality of the Chesapeake system. However, over the last three decades, marsh and SAV have been declining steadily due to high nutrient loads, development, shoreline hardening and coastal inundation associated with climate change. Once abundant oysters were responsible for large reef tracks that dominated Bay habitat and affected circulation patterns, but oysters are now nearly extirpated from the system (Wilberg et al.

(2011) estimates the current population is less than 1% of the original population in Maryland). Humans have a long history of exploitation in the Chesapeake, and the current system is highly modified compared to that of the early 1800's due to heavy oyster harvests by dredging. Harvest rates from both the commercial and recreational sectors remain high for a variety of species including fish, shellfish and birds.

It has been a challenge to balance the complexity of the model necessary to capture the most critical dynamics of the system with the simplification necessary to allow reasonable run times. The current model incorporates the 7 largest tributaries (brackish portions only), and incorporates 97 spatial polygons that vary in depth, salinity, and bottom type (mainstem only) characteristics. The resulting model resembles a rough cartoon of the Bay (Figure 2). The model has 5 depth layers (including 1 sediment layer).

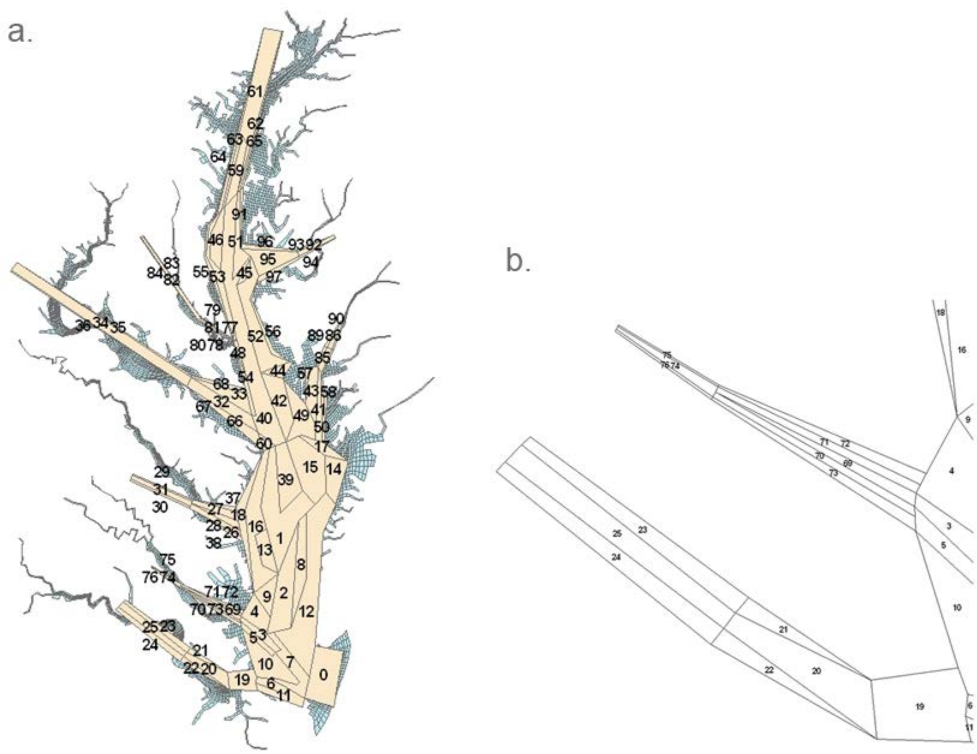


Figure 2. CAM polygons; (a) 97 spatial 'boxes' (b) detail of two southernmost tributaries.

CAM includes 55 biological groups, including 26 invertebrate and 29 vertebrate groups. Three of these groups also function as biogenic habitat (submerged aquatic vegetation, oyster), and provide refuge for animals to decrease their predation mortality. Like other Atlantis models, CAM also simulates 4 bacterial groups (attached and free-living water column bacteria, and aerobic and anaerobic benthic bacteria in the sediments) for bacterial cycling of available nutrients and 3 detrital groups (refractory, labile, and carrion).

Physical forcing in the current model is driven by the Navy Coastal Ocean Model (NCOM) Relocatable Model. NCOM has a horizontal resolution of 1/30 degrees, roughly 3 km in the CAM domain (http://ecowatch.ncddc.noaa.gov/amseas/) . The Hybrid Coordinate Ocean Model (HYCOM) provides boundary conditions, and atmospheric forcing is from Coupled Ocean-Atmosphere Mesoscale Prediction System (COAMPS). Tidal forcing is included. NCOM is, in essence, a summary of Regional Ocean Modeling System (ROMS) model output. Current work is underway to drive CAM with a full ROMS model.

Focal Project for Multiple Model Inference

Objective

Recently, the EPA-National Center for Environmental Economics (NCEE) enlisted the support of the NCBO Modeling and Analysis Team to aid with estimating the impacts of Chesapeake Bay Total Maximum Daily Load (TMDL) Regulations on Chesapeake Bay Fisheries. This is part of larger project by the NCEE to do a cost-benefit analysis of the TMDL.

The purpose of this analysis is to assess the impacts of eutrophication on the major fisheries of the Chesapeake Bay and estimate the potential economic benefits to the fisheries associated with reduced nutrient loading prescribed in the Total Maximum Daily Load (TMDL) regulations for the Bay.

Chesapeake Bay

The Chesapeake Bay is the largest estuary in the continental United States, located midway along the Atlantic coast of the United States. The surface area of the tidal portion of the Chesapeake Bay system is approximately 10,000 km2, while the area including tributaries is estimated to be 18,580 km2. More than 20 major tributaries drain into the Bay from a watershed that stretches across six states: New York, Pennsylvania, Maryland, Delaware, Virginia, West Virginia, and the District of Columbia. The largest of these tributaries, the Susquehanna River, provides more than half of the freshwater flow to the Bay. The waters of the Chesapeake Bay and tidal portions of its tributaries are governed by Maryland and Virginia.

The Bay is a partially mixed estuary, with an average tidal range of approximately 1 m at its mouth to less than 30 cm at its head (cited in 1989). Salinity within the Bay ranges from less than 0.5 ppt at its northern extreme to 32 ppt near its mouth. The Bay can be divided into three major salinity regions: oligohaline (0-5 ppt), mesohaline (6-18 ppt), and polyhaline (> 18 ppt). Water temperatures in the Bay vary greatly throughout the year, reaching 28-30ºC in late summer and 1-4ºC in late winter (Murdy et al., 1997).

The estuarine circulation pattern of a flow of deeper, more saline water into the Bay from the Atlantic Ocean—which serves to transport larval fishes and crabs from the ocean to their nursery habitats—alternates with a flow of shallower, fresh water originating from surface runoff and precipitation out of the Bay—which serves to transport juvenile fishes from tributaries to the coastal waters of the Atlantic. This transport mechanism is very important to the population dynamics of many Bay species.

The mixture of freshwater from the tributaries and seawater from the coastal ocean creates and maintains a variety of brackish habitats within the Bay. Tidally influenced habitat types in the Bay include: pelagic waters, nearshore littoral areas, and the benthic zone. Littoral habitats, such as marshes on intertidal lowlands, aquatic grass beds in the shallow flooded flatlands, and oyster reefs, are highly productive, serving as nursery areas to many fish and shellfish species, facilitating rapid growth under relatively protected conditions. The diversity of habitats within the Chesapeake Bay system enables it to support nearly 3,000 species of plants and animals within its waters and tidal margins.

Chesapeake Bay Fisheries

Finfish species inhabiting the Chesapeake Bay have a wide variety of life history strategies. For example, the American eel (*Anguilla rostrata*) is a catadromous species, spending most of its life in tributaries of the Chesapeake Bay, returning to the Atlantic Ocean to spawn. Some marine fishes, like the weakfish (*Cynoscion regalis*) enter the Bay to feed and spawn seasonally and then return to the coastal ocean. Anadromous species, like the American shad (*Alosa sapidissima*) and striped bass (*Morone saxatilis*) spend most of their adult lives migrating in the Atlantic Ocean, but return to Bay tributaries to spawn. Other species, like the white perch (*Morone americana*) spend their entire lives within the Chesapeake Bay system, undergoing 'semi-anadromous' seasonal migrations within the Bay.

The diversity of habitats within the Chesapeake Bay, combined with wide ranges of temperatures throughout the year, result in very dynamic seasonal changes in fish assemblages. During late summer and early autumn, fish diversity reaches its maximum due to a movement of tropical species into the lower portion of the Bay. When the cooler temperatures of autumn arrive, most marine fish within the Bay begin to migrate either south to Cape Hatteras, North Carolina, or offshore to the edge of the continental shelf. During winter, the abundance and diversity of fish in the Bay is relatively low. However, by early spring, abundance and diversity rebound significantly as anadromous species enter the Bay, followed soon after by the warm-temperate and subtropical summer residents.

Due to the complexity of the Chesapeake Bay ecosystem, it is necessary to develop EM tools to simulate interactions between these many different species, to quantitatively estimate how they interact within the larger food web and how human impacts are likely to affect this complex system.

Since the early 1800s, the Chesapeake Bay has supported a variety of large-scale commercial and recreational fisheries of both finfish and shellfish. The predominant invertebrate fisheries in the Chesapeake Bay have included the eastern oyster (*Crassostrea virginica*), blue crab (*Callinectes sapidus*), soft clam (*Mya arenaria*), and hard clam (*Mercenaria mercenaria*). The large-scale finfish fisheries have included striped bass, American shad, river herring (*Alosa aestivalis*), white perch, bluefish (*Pomatomus saltatrix*), Atlantic menhaden (*Brevoortia *tyrannus*), summer flounder (*Paralichyths dentatus*), weakfish, Atlantic croaker (*Micropogonias undulates*), and spot (*Leiostomus xanthurus*). Several species, like white perch and Atlantic croaker, have sustained significant harvest levels, although trends in the commercial and recreational landings have varied over the last several decades. Striped bass landings may be the most dramatic in terms of variability from the 1960s to present. Many species, such as the eastern oyster, American shad, and striped bass, have suffered overexploitation in the Chesapeake Bay. Overfishing and the collapse of several Bay and coastal fish stocks during the 1900s prompted the creation of fisheries management agencies both along the Atlantic Coast and within the Chesapeake Bay.

In coastal areas, the Atlantic States Marine Fisheries Commission (ASMFC) serves as a deliberative body, coordinating the conservation and management of fisheries in near-shore state waters along the eastern seaboard from Maine to Florida (to 4.8 km or 3 miles off the coast). The Mid-Atlantic Fishery Management Council (MAFMC) is responsible for managing fisheries in federal waters, which occur predominantly off the mid-Atlantic coast (from 4.8 to 322 km or 3 to 200 miles offshore). Within the Bay, tidal fisheries are managed on a jurisdiction-specific basis, by the Virginia Marine Resources Commission (VMRC), the Maryland Department of Natural Resources (MD DNR), and the Potomac River Fisheries Commission (PRFC). The three jurisdictions have agreed upon management strategies, as outlined in Chesapeake Bay fisheries management plans, for commercially and recreationally targeted species within the tidal portion of the Chesapeake Bay.

Chesapeake Bay Water Quality

The 1972 Clean Water Act (Section 303(c)) requires states and the District of Columbia, to establish water quality standards (WQS) that identify each waterbody's designated uses and the criteria needed to support those uses. "The CWA establishes a rebuttable presumption that all waters can attain beneficial aquatic life uses, i.e., fishable and recreational (i.e., swimmable) uses."

Though an extensive restoration effort has been underway in the Chesapeake for over 25 years, inadequate progress on attaining water quality standards has been made. As a result, the U.S. Environmental Protection Agency (EPA) established the Chesapeake Bay Total Maximum Daily Load (TMDL) —the largest ever developed by EPA. This TMDL identifies the pollution reductions (for nitrogen, phosphorous, and sediment) necessary across the entire Chesapeake Watershed to meet applicable water quality standards in the Bay and its tidal rivers and embayments. These pollution limits are further divided by jurisdiction and major river basin based on a suite of watershed-water quality modeling tools, monitoring data, and collaboration with state and regional partners.

The TMDL is intended to make sure that all pollution control measures needed to fully restore the Bay, tidal rivers, and embayments are implemented by 2025. The TMDL is focused on meeting criteria that ensure the tidal waters are capable of supporting the designated uses of the bay (esp., key finfish and shellfish habitats).

In addition to the assessment of eutrophication effects, this modeling approach will allow us to assess the effectiveness of TMDL on fisheries production. This work will establish a framework for translating changes in nutrient loadings to changes in ecological production and changes in an important class of ecosystem services, the support of commercial and recreational fisheries production, provided by the Chesapeake.

Ecosystem Modeling Approach

The purpose of this analysis is to assess the impacts of eutrophication on the major fisheries of the Chesapeake Bay and estimate the potential economic benefits to the fisheries associated with reduced nutrient loading prescribed in the Total Maximum Daily Load (TMDL) regulations for the Bay.

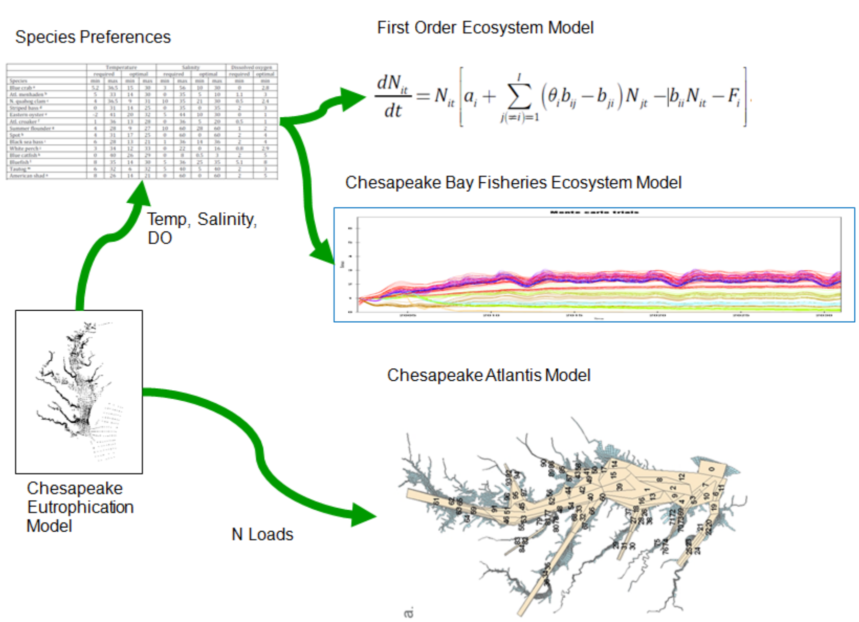
The initial approach for this analysis was centered on linking multiple Models. We used nutrient load output for the EPA's Estuarine Eutrophication model (http://www.chesapeakebay.net/about/programs/modeling/) to drive ecological rates (e.g, production) in the CBFEM. The linking of these models was run in a few different scenarios in a factorial design. The first level of scenarios was focused on nutrient loads (with and without TMDL regulations implemented), and the second level was focused on how changes in nutrients influence secondary production (Nixon's agricultural model and a production shunt model). The biomass change in key fish species between the nutrient load scenarios was the output used for economic models to estimate benefits associated with TMDL loads. Two economic models were used – a multi-stage inverse demand system to estimate benefits to consumers in commercial fish markets and a random utility site-choice model to estimate benefits to recreational fishers.

Because adequate quantitative information about the influence of water quality parameters on fish population dynamics was not available for parameterizing available ecological models and because the model scenarios on how changes in nutrients influence secondary production were too general, the results from the initial approach were too divergent to be informative. As a result, we have outlined a new approach. The new approach involves using 3 different ecosystem models (the CBFEM, CAM, and a first-order ecosystem model of key fisheries species). In addition, the new approach uses output from the EPA's Estuarine Eutrophication model more thoroughly.

To estimate the water quality influences, we have developed habitat volume models based on water quality (salinity, temperature, and dissolved oxygen) parameter estimates from the Eutrophication model and species tolerances for these parameters from literature review. Estimates from the habitat volume will be used to force two different fisheries ecosystem models, a simple fisheries ecosystem model based first order species interactions and the CBFEM, an ecotrophic fisheries model. Two fisheries ecosystem models were used to account for the structural uncertainty of the models. In these ecosystem models, time-varying water quality conditions will be used to drive changes in the habitat volumes of the fished species. Specifically, habitat volume changes will drive changes in the population production rates and changes in the overlap of habitat volumes of predator-prey pairs drove changes in the interaction rates. In addition, the CBFEM will include habitat volume forcing functions for non-fisheries species (e.g., zooplankton, benthic invertebrates) in the ecosystem. To assess the impacts of TMDL regulation on the fisheries, these models will be run using habitat volumes calculated from the Eutrophication model based on watershed scenarios with and without the TMDL Watershed Implementation Plans and assuming constant fishing rates. The biomass change in key fish species between the nutrient load scenarios will be the output used for economic models.

CAM is better-suited to incorporate water quality changes directly. For this model, nutrient loadings (i.e., concentration rates, including Ammonia, Nitrate-Nitrite, and total suspended solids) from the EPA's Chesapeake Watershed model are aggregated into CAM's spatial boxes. Along with initial concentrations for each nutrient, these loadings drive the biogeochemical cycles simulated in CAM, and in turn, drive the growth rates and interactions of the trophic groups in the model. The biomass change in key fish species between the nutrient load scenarios is the output used for economic models.

Using 3 different ecosystem models (with wide variety in the level of complexity) for this analysis will enable some level of accounting for uncertainty in model structure uncertainty. Ultimately, we want to be able to combine the outputs from these models (biomass change in key fish species between the nutrient load scenarios) to adequately propagate the uncertainty in the output for use in the economic modeling approaches and provide reasonable estimates of the benefits of the TMDL regulations to Chesapeake fisheries. A schematic of this multi-model approach is presented below.



Summary of Center MMI in EM Efforts

AFSC

Kerim Aydin reported for the AFSC and focused on a couple of projects underway or planned at this center.
The AFSC has developed an operational ensemble of models, including an EwE model, a multispecies statistical model, the FEAST (Forage Euphausiids Abundance in Space and Time) model and an IBM (GOAIBMS).
Primary Issues addressed at the AFSC include: (1) climate change; (2) oil and gas exploration (in the Arctic); (3) the conservation of endangered species (Stellar Sea Lions); and (4) groundfish interactions (optimal yield, multispecies management, MSEs).
Climate change is a major issue in Alaska. Specific attention is given to the potential impacts of climate change on sea temperatures and seasonal sea ice, which influences the abundance of ice algae. Ice algae are of critical importance to early reproduction in copepods; copepods have higher ingestion rates when feeding on ice algae than when feeding on ambient water column phytoplankton. Moreover, cold years favor increases in abundance of large zooplankton at the expense of decreases in the abundance of small zooplankton.

The Bering Sea Project (BEST/BSIERP) is an end-to-end framework which links: (1) climate scenarios to physical oceanography (ROMS; 10km grid with 10 depth layers); (2) physical oceanography to lower trophic levels (nutrients, phytoplankton and zooplankton); (3) lower trophic levels to upper trophic levels (FEAST); and (4) upper trophic levels to economics and spatial fisheries. The Bering Sea Project has required a good amount of field work. Some of the primary objectives of the Bering Sea Project are to: (1) evaluate recruitment and how recruitment is correlated with climate; (2) understand interactions between plankton and fish under climate change; (3) understand interaction between mean summer SST and pollock survival; (4) look at the past and the future using IPCC climate forecasts; and (5) compare multiple models and figure out how to conduct MMI.

Work conducted for the Bering Sea Project allows the evaluation of “potential” recruitment using three different approaches. The first approach consists in: (i) correlating single species recruitment from stock assessment to measured ocean conditions (SST, bottom temperature, wind, surveyed predators); and then (ii) running forecasts using correlates and error “measured” from IPCC climate models. The second approach consists in: (i) running a ROMS-NPZ high resolution 3D model using measured ocean conditions; then (ii) evaluating correlations with recruitment from multispecies assessment; and then (iii) running forecasts using correlates and errors from the ROMS-NPZ model driven by IPCC climate models. Finally, the third approach consists in: (i) running a ROMS-NPZ high resolution 3D model using measured ocean conditions; then (ii) running a FEAST mechanistic fish model with feedback to plankton; and then (iii) running a FEAST model driven by IPCC climate models.
Currently, comparison of reference points based on management strategies uses only the best model from a stock assessment but it would be interesting to use MMI in the near future.

A spatial economics toolbox for fisheries called “FishSET”was created to better inform policy decisions by predicting how a variety of factors might influence fishers’ behavior.

NWFSC

Isaac Kaplan reported projects related to MMI, model linkages and ensemble modeling that are underway or planned at the NWFSC. These projects include:

1) J-SCOPE – a seasonal forecast system model, which uses a 6-9 month forecast to drive a ROMS-NPZ model. The outputs from this model can be found on the NANOOS website. The model is not yet running on a scale of decades but rather a few months. Currently, J-SCOPE forecasts are input in a GAM used to predict sardine presence (over a 6-8 month time frame). This forecasting platform may be potentially useful for several other LMR issues.
2) Salmon population projections – freshwater and marine climate projections to get parr-to-smolt survival in the 2040s. There is currently no information on climate projections for nearshore marine areas. For these areas, recent history is used to derive a scenario based on the Pacific decal oscillation (PDO).
3) Forage fish in the California Current ecosystem – 4 models have been developed and it would be good to use a combination of these models. Atlantis and EwE were used to investigate the impacts of depleting forage fish for the California Current. Convergences and divergences in models’ output were analyzed. Two other ecosystem models are also going to be utilized to assess how depletion of forage fish impacts the California Current food web in a context of climate change: (i) the Northern California Current ECOTRAN model; and (ii) the highly sophisticated NEMURO-SAN model.
4) Coupled economic-ecological models – IOPAC (Input-output model for Pacific Coast Fisheries modeling framework to look at the direct and indirect impacts of fisheries management decisions on economy and employment. IOPAC was linked with Atlantis to examine the impacts of fishery management decisions to the greater economics of the region. Atlantis needed to be re-coded to include fleet dynamics and predict spatial fishing effort, catch, bycatch and profits under different management schemes.

SWFSC

Brian Wells reported that the center is largely in a capacity building mode and focuses on linking models. The major efforts include:

1) Salmon Life Cycle – coupled bio-physical models across the chinook salmon landscape – Three different coupled models were designed: (1) a ROMS-CoSiNE model for the coastal ocean; (2) a SELFE – CoSiNE model for the San Francisco estuary; and (3) a RAFT-Aquato model for the Sacramento River. These thee coupled models were coupled to a salmon DEB model (considering all life stages, i.e., eggs and larvae, juveniles and adults) so as to predict salmon growth and maturation. The hard part of the work was linking estuarine and ocean systems due to disparate spatial resolutions. The authors are

validating the models by comparing ROMS to observed data. The group is moving towards data assimilation of biological data.

2) Habitat – ROMS-NEMURO outputs put into GAMs to evaluate good/bad recruitment for a few species. The purpose of this approach is to determine how ocean environment changes habitat suitability.
3) Rockfish/Antarctic krill – high resolution prey-predator model, essentially used to simulate the growth of rockfish larvae released into the plankton at different times during the winter parturition season.

PIFSC

Jeff Polovina reported that the PIFSC primarily use EwE and a Size-based Food Web Model focusing on the central pacific pelagic ecosystem in the context of climate change. Both models are driven by the GFDL climate models. Phytoplankton time series were input in both EwE and the Size-based Food Web Model. EwE and the Size-based Food Web Model were primarily used to track changes for tuna, shark and large fish (e.g., mahi mahi) populations, under different exploitation and climate scenarios. EwE and the Size-based Food Web Model agreed on the impacts of fishing and climate change on the percent of large fish caught. By contrast, climate change impacts on the age structure of fish species are different between the two models. The Size-based Food Web Model shows changes in age structure over time related to climate, while EwE shows no change in age structure.

Other efforts at the center include:

1) Extending EwE and the Size-based Food Web Model using output from multiple climate models;
2) Comparing the output of a single-species Pacific swordfish stock assessment model to that of a SEAPODYM swordfish model;
3) Building an Atlantis model for Guam;
4) Modifying the French Frigate Shoals islands EwE model to evaluate the impacts of future climate on seals;
5) Using models to determine the influence of environmental variables on the carrying capacity of Pacific reef sharks;
6) Using models to evaluate the influence of environmental variables on the nesting of Japan and Florida Loggerheads (lagged by ~25 years).

NEFSC

Michael Fogarty reported EM efforts that are underway or planned at the NEFSC, focusing on the Georges Bank prototype Multispecies Assessment. The Georges Bank prototype Multispecies Assessment is a collaborative effort between various groups within the NEFSC, which attempts to provide a natural bridge between single-species assessment and ecosystem considerations for managers. A Multispecies approach may alleviate the number of efforts required for multiple single-species assessments.

The different steps of the Georges Bank prototype Multispecies Assessment consist of: (1) developing and maintaining data streams (observations, food habits data, environmental and climate data); (2) using data to feed assessment models; (3) using social and economic modules; (4) running forecasts models; (5) producing indicators and summarizing results through visualization tools; and (6) using operating models and risk analysis to be able to provide recommendations and web-based products.

Within the project, EwE, Atlantis and a length-based multi-species model (Hydra) are used as operating models. Stock assessment models include: (i) a multispecies production model; (ii) a functional group production model; (iii) a multispecies delay-difference model; and (iv) a multispecies statistical catch-at-age model. Economic modules consist of revenue and net profitability models and portfolio models. Finally, forecasting models use nonparametric nonlinear time series analysis.
The project looks to take novel approaches using food web diet as either direct model inputs or more as auxiliary data (i.e., Bayesian priors).
Hydra is a multispecies, size-structured model. It takes into account the impact of environment on growth, maturity and fecundity and considers multiple recruitment functions. Maximum likelihood is used to tune the model. Spatial and multi-fleet aspects must be developed for the model.

The multispecies production assessment model (i) uses flexible functional relationships for within species interaction dynamics (predation: type I, II, and III functional response; competition); (ii) incorporates environmental covariates; (iii) has a spatial structure (allows for movement between regions); (iv) uses multiple estimation methods (maximum likelihood, genetic algorithms, Bayesian methods).
The objectives for the Georges Bank prototype Multispecies Assessment for the coming year are to: (1) have operating models ready for full simulation testing of assessment models and management procedures; (2) have assessment models fully operational with a spatial structure included; (3) have linked models to economic modules; (4) have identified key indicators to complement models and to offer alternative approaches; (5) apply MMI (using a weighting scheme or not); and (6) have developed a novel data visualization tool with academic partners.

NCBO

Howard Townsend reported that the team has multiple efforts addressing several issues in the region. The primary MMI effort is a Total maximum daily load: Cost-benefits study. As nutrient loads are decreased through water quality regulations, it is important to understand how the removal of nitrogen may have some positive impacts (e.g. water quality) and some negative (potential loss of primary productivity). This is moving into the realm of ecosystem management.
The components of this project are:

1) EPA's Chesapeake Eutrophication Model (CEM) is the basis for ecosystem models used to assess habitat volume changes associated with regulation-based changes in nutrient loads.

2) Habitat volume models based on CEM and species preferences for salinity, temperature and dissolved oxygen.
3) Application of habitat volume models to multiple single species models.
4) Application of habitat volume (and habitat overlap) to production and consumption equations in the Chesapeake Bay Fisheries Ecosystem Model (CBFEM) – based on EwE – with built in forcing functions.
5) EPA's Chesapeake Watershed Model (CSM).
6) Application of nutrient loads from CSM to Chesapeake Atlantis Model (CAM)
7) Outputs from single species models, CBFEM, and CAM will be fed into economic models estimating the commercial and recreational values of Chesapeake fisheries.

SEFSC

Arnaud Grüss reported that EBFM is now a central paradigm in the Gulf of Mexico and an IEA has recently been initiated. In March 2013, the Gulf of Mexico Fisheries Management Council's Standing and Ecosystem Scientific & Statistical Committees passed two motions expressing their desire to incorporate IEA products into single-species stock assessments and LMR management decisions on a regular basis.
Simulation models used by SEFSC include 2 EwE ('WFS Reef fish EwE' and 'WFS Red tide EwE') and 1 OSMOSE model for the West Florida Shelf ('OSMOSE-WFS'). OSMOSE-WFS is the first OSMOSE model developed in the US. MMI using OSMOSE-WFS, WFS Reef fish EwE, WFS Red tide EwE and other ecosystem models is underway.
Another EwE model was designed to measure the impacts of large coastal sharks. Other ecosystem models have been developed for the Gulf of Mexico, including an Atlantis model for the whole Gulf of Mexico, a Galveston Bay EwE model, a South West Florida ecosystem model, a Red Tide SS model for gag grouper, population models coupled to a watershed model for Galveston Bay, and other models.

Three types of MMI are being or are going to be used at the SEFSC:

- Reference set of OMs –A reference set of OMs is built from a single simulation model. Each OM is a version of the simulation model representing a plausible "state of nature". Using a reference set of OMs is useful to address parameter uncertainty, process uncertainty or future uncertainty.
- Inter-model comparisons – They involve models with different structure and assumptions. However, inter-model comparisons require models being compared to share a number of characteristics depending on the questions that need to be addressed. Inter-model comparisons offer different perspectives on the same questions, while being able to identify from where discrepancies between the different models being used may originate. They address model uncertainty.
- Ensemble modeling – Framework exposing an ensemble of simulation models with different structure and assumptions to identical exploitation and environmental scenarios, using multiple realizations of each exploitation scenario and each environmental scenario. Ensemble modeling addresses model, process and future

uncertainties. Ensemble modeling are useful to disentangle model and process uncertainties from future uncertainty by comparing results among models within a single climate-exploitation realization, and within models among climate-exploitation realizations, respectively

Abstracts of Invited Speakers Presentations

Ecosystem Modeling – Lessons from Seasonal Weather Prediction

Nicholas A. Bond University of Washington/JISAO

This paper has two objectives: (1) to review current practices in seasonal weather prediction and (2) to summarize some recent examples of the use of climate models for marine ecosystem projections. An individual model simulation has uncertainty from two sources: initial condition sensitivity, and with model formulation (including but not just parameterizations), sometimes termed "structural uncertainty". The chaotic nature of non-linear systems means there are fundamental limits on the horizons over which phase changes are predictable. The second source of error, the structural uncertainty, tends to dominate the uncertainties associated with initial conditions for longer-term forecasts. Multi-model ensembles are being used to reduce the errors and uncertainties from individual models. Techniques have been developed that allow dynamic evolution of model combinations for shorter-term predictions, but it is uncertain whether they add meaningful value to longer-term projections. In particular, the relative performance of models based on comparisons between hindcast simulations and observations varies substantially with region, parameter, and specific period of simulation. The ambiguity in the evaluation of competing models, and that past performance does not guarantee future skill, may mean there is no clear "best" method for handling model error. Both dynamical and statistical downscaling have their place in modeling marine ecosystems; the latter generally offers the opportunity to more completely assess the potential ranges of outcomes.

Uses, Strengths, and Weaknesses of Numerical Models in Tropical Cyclone Forecasting

Jack Beven, NOAA/NWS/NCEP/NHC

The National Hurricane Center (NHC) uses a variety of numerical weather prediction models to forecast the location, intensity, and size of tropical cyclones. The models range in complexity from simple statistical based on past cyclone behavior to complex dynamical based on integration of the equations of atmospheric dynamics. The NHC routinely uses a multi-model ensemble in its operations, although single-model ensembles are playing an increasing role. The increasing skill of the guidance models has led to significant decreases in NHC track forecast errors over the last 25 years. The NHC keeps statistics on its track, intensity and size forecasts, and these are used in such products and the cone of uncertainty and the wind speed probabilities.

Ocean Ensemble Modeling: Applications for Ecosystem Modeling & Prediction

Alan Leonardi, NOAA/OAR/AOML

Across disciplines, models help scientists to understand systems and communicate processes and relationships in those systems. Models are not perfect and are subject to error and bias. Thus they require data for validation and fine tuning. Models are useful for clarifying gaps in understanding, identifying areas where additional information (e.g. observations) are needed, and identifying areas where additional model improvements are needed. The goal for developing good, useful models is to produce models with low bias and low variance. As model complexity increases variance increases. Conversely as complexity decreases bias increases. Modelers must optimize model complexity to achieve the best performance. To ensure model utility, ocean modeler use ensemble approaches and use models to assess the impact of observations on model forecasts. Ocean modelers use 1) single model ensembles – a single, deterministic model is run with a variety of configurations and combined to address a single problem, 2) multiple model ensembles – multiple diverse models are trained on the same problem and outputs combined to form consensus viewpoint – to account for the bias and error in models. They use 1) Observing System Evaluations (OSEs) - the systematic withholding of observations from assimilating systems to quantify the degradation of the system's performance when those observations are neglected – and2) Observing System Simulation Experiments (OSSEs) – modeling experiments used to evaluate the impact of new/proposed observing systems on operational forecasts – to improve observation and data collection systems for models.

In the Gulf of Mexico Oil of 2010, the use of multiple models for predicting the spread of oil helped with the oil spill response. However, some stakeholders focused on the results of one model with extreme estimate in the spread of oil and caused some undue alarm.

Biological Ensemble Modelling in the Baltic Sea

Stefan Neuenfeldt, Denmark Technical University - Aqua

With reference to:
Anna Gårdmark, Martin Lindegren, Stefan Neuenfeldt, Thorsten Blenckner, Outi Heikinheimo, Bärbel Müller-Karulis, Susa Niiranen, Maciej T. Tomczak, Eero Aro, Anders Wikström, and Christian Möllmann 2013. Biological ensemble modeling to evaluate potential futures of living marine resources. Ecological Applications 23:742–754. http://dx.doi.org/10.1890/12-0267.1

Informed natural resource management requires approaches to understand and handle sources of uncertainty in future responses of complex systems to human activities. In Gårdmark et al. 2012 We simulated the long-term response of Eastern Baltic cod (Gadus morhua callarias) to future fishing and climate change in seven ecological models forming a gradient in food-web complexity, from single-species to food-web models. We modified the models to include climate forcing, and created identical fishing and climate scenarios that we simulated in all models to study the potential dynamics of Eastern Baltic cod during 2009-2100.

The seven models, ranging from single-species to food-web models, differed in their simulated responses of cod to fishing and future climate change. By decomposing the model ensemble into sub-sets according to key ecological assumptions we showed that species interactions feedbacks greatly influence the simulated responses to fishing and climate change.

Sources of uncertainty (or differences) in simulated species responses can be sought in two steps. First, the model ensemble can be used to contrast the variation in responses stemming from statistical uncertainty in climate scenarios to that from differences in ecological model assumptions (i.e., model structure uncertainty). For example, the large range of simulated cod SSB for the low fishing and no climate change was caused only by differing assumptions among ecological models, as the results are based on a single climate realisation. In contrast, a comparison across climate realisations of the same scenario showed that this variation alone results in 19-97% CV of simulated SSB. Secondly, sources of structural model uncertainty should be sought. That is, model assumptions with key influence on the simulated responses are identified by contrasting different categories of models within the ensemble against each other. This showed the key influence of model uncertainty in relation to predator-prey interactions. By using the ensemble approach accounting for both types of uncertainty, we showed that models without stabilising feedbacks between cod and their prey both show more fluctuating responses to fishing, within a given climate scenario, and are more sensitive to the statistical uncertainty of climate projections.

Ecological model assumptions can be identified as having key influence on the variation in simulated futures based on two aspects, (1) those creating large disparities in responses among models within a given climate realisation, and (2) those affecting the extent to which the ecological models magnify or dampen the underlying variation in simulated future climates. For both aspects, an ensemble of models that cover a range of complexity in terms of species interactions is necessary, and for the latter, the ensemble needs to be analysed across climate realisations. In our example, the assumption of no effects of prey availability on cod and the assumption of environmental forcing acting through an explicit stock-recruitment relationship rather than implicit recruitment and population level forcing, appears to be key.

While the ensemble modelling needs to be further refined for the case of cod (for example, by enlarging the model ensemble to include models that have either an explicit stock-recruitment function or lack prey feed-backs on cod, and not only the combination), it illustrates how the ensemble approach can be used to identify key processes. These can then be used to guide further model development, as well as experimental tests of key mechanisms. For example, our results raise the question of the degree to which cod is limited by fish prey and zooplankton availability. To indeed enable identification of key processes, ensembles need to be composed of models of different sets of ecological processes, rather than alternative numerical implementations of essentially identically described processes as is commonly done in climate studies.

By compiling the model simulations in an option table we evaluated the impact of fishing under future climate change, and showed that in all models intense fishing prevented recovery and climate change further decreased the cod population.

The outcome, and eventually the conclusions, of ensemble modelling of species responses to future climate and human use obviously depend on ensemble members. Our results showed the great influence of the composition of the ensemble for the mean, range, and temporal pattern of simulated responses of cod to climate change and fishing. Correspondingly, methods used to create weighted ensemble averages have large effects on, for example, simulated mean responses. While an ensemble mean can be used to highlight general directions of responses, it can easily be misunderstood as a possible trajectory of the simulated species' response. Because the mean response shows much smaller inter-annual variation than the individual model simulations, the species' dynamics may look misleadingly stable when judged from the ensemble mean. Yet, ensemble means, and in particular means weighted by, for example, past performance of the models, are often used and proposed. However, averaging the simulated responses may also hide qualitative differences, like extinctions in our case, and should therefore be avoided. Instead, it is the range of simulated responses that forms important information for e.g., management, and the impact of varying ensemble membership should be assessed.

But if we cannot provide average responses to exploitation and climate change, what part of the simulated range should decisions on management actions be based on? The solution is to look for management actions that are robust to the uncertainty in model structure. Robust management has been proposed as a solution to handle uncertainty (in general) in marine fisheries, and is often applied in management strategy evaluations. Although the concept can be applied within a single model, the ensemble approach is particularly suitable for seeking management solutions that are robust to uncertainties relating to food-web processes. Option tables provide an example of how robust conclusions on management impacts can be sought; a compilation of comparisons within models of simulated responses in relation to specified reference (or target) levels enables a check for robustness across all models. Note that robustness is thus based on individual responses of all models, and not on the mean response of the ensemble. Moreover, because comparisons are made within models, results from both qualitative and quantitative models can be included. In our case, the general conclusions are quite simple, intense fishing prevents rebuilding of the fish population and risks extinction, whereas less fishing, at the lower target fishing mortality, does not. The strength lies in that these conclusions are indeed general, as they are valid independent of whether we are using a simple single-species biomass model or a full food-web model, and for all climate variability tested. Thus, successful management of exploitation no longer becomes a question of which model to rely on, but which management actions that should be taken based on common knowledge from all available models.

Iterate and collaborate: mingling ecosystem service models to inform decisions

Katie Arkema, The Natural Capital Project

In the traditional narrative, people put pressure on the environment. But if we instead focus on all of the rich and diverse ways that ecosystems sustain and fulfill human life, we can close this loop to better understand how the environment benefits people and direct investments, resource management & decision-making to promote sustainability of natural environments and foster human wellbeing at the same time. There have been lots of recent calls for sustaining environmental capital and incorporating benefits from nature into policy, but how do we move beyond words to action? Design our research questions based on what questions we hear from the stakeholders, policy and decision-makers and local partners. This presentation provides an example of the iterative and collaborative approach applied in Belize. This approach ensures that scientists understand policymakers' needs and policymakers understand the tools and models being used.

With reference to:
"Identification and valuation of Adaptation Options in Coastal-Marine Ecosystems: Test case from Placencia, Belize." Rosenthal, A., Arkema, K., Verutes, G., Bood, N., Cantor, D., Fish, M., Griffin, R., and Panuncio, M., (2013). Identification and Valuation of Adaptation Options in Coastal-Marine Ecosystems: Test case from Placencia, Belize. The Natural Capital Project, Stanford University, World Wildlife Fund.

Climate change is expected to have numerous consequences for human health and welfare over the long term. Over the medium term, we can mitigate some of the most costly impacts by adapting to the environmental changes that will occur as a result of increasing annual temperatures, changing weather patterns, and novel ecosystem and agricultural conditions. These changes are particularly uncertain and concerning for coastal regions, where sea levels are predicted to rise, ocean water will become warmer and more acidic, and the composition of sea life used for food and recreation by people could disappear. Even though climate change will affect human societies by disrupting not only man-made infrastructure, but also the ecosystem services upon which humans rely for their wellbeing and sustenance, adaptation analyses often face constraints when aiming to capture the potential impacts to ecosystem services as a result of climate change and the economic implications of such changes when considering adaptation options. This study aims to address this gap by using ongoing work to characterize ecosystem services of coastal-marine ecosystems in Belize, to be able to inform the selection of adaptation options and the cost-benefit analyses of such options. Such an approach will allow decision-makers in Belize and beyond to consider a broader suite of costs and benefits than would have otherwise been available.

Our approach improves upon traditional CBA by including the valuation of ecosystem services, addressing variation in the distribution of costs and benefits across an area, and helping to identify who and what bear the risk of climate change effects or the benefits of corresponding adaptation measures. Our approach also draws upon extensive stakeholder engagement and collaboration with policy makers to ensure the relevance and feasibility of adaptation scenarios. This collaborative process proved useful in the coastal zone planning process with CZMAI and the Belize Climate and Development Knowledge Network (CDKN) initiative led by WWF.

A natural capital approach to climate adaptation begins with an assessment of current provision of ecosystem services. Next, scenarios are developed that account for climate change impacts, human activities and development, and alternative adaptation options. Finally, ecosystem service models (InVEST) are used to assess the ecosystem service impacts and possible costs and benefits of alternative adaptation scenarios, which are then compared in a CBA framework (Figure 1). Ideally, these steps are iterated to refine options and outputs, and to improve final decisions governing adaptation measures.

Mixed Models/Mixed Messages: Could mental modeling help?

Steven Gray, University of Massachusetts - Boston

The ecosystem-based fisheries management (EBFM) framework has been a popular paradigm for understanding-- and making decisions about—living marine resources (LMR) for almost two decades. The rationale for moving away from single species assessments toward more comprehensive multi-species and environmentally-based models is clear since these modeling frameworks provide scientists and managers a chance to more accurately understand LMR dynamics and explicitly consider complex trade-offs between management decisions, environmental change, and competing uses of marine systems. As a result, the last decade has seen an increase in ecosystem-based and ensemble modeling approaches used to understand the complex dynamics of fisheries resources. Although these new modeling approaches are considered more representative of complex socio-ecological dynamics, one area of EBFM and ensemble modeling that is currently understudied is how to communicate complex, and possibly divergent, model results to various fisheries stakeholders who may hold inconsistent interests and beliefs (so called mental models) about fishery dynamics. In this talk, I try to address some of these issues from a social science perspective by first reviewing what can be learned from communicating complex and mixed model results to decision-makers from the field of climate change communication. Next, using two recent case studies, I demonstrate how different fishery stakeholders make different inferences/decisions based on the same model result, because of differences in their beliefs about social or ecosystem dynamics. Finally, I demonstrate the use of a fuzzy-logic cognitive mapping software tool, called Mental Modeler (www.mentalmodeler.org) that can be used by ecosystem modelers and natural resource managers: (1) to provide insight into understanding the different beliefs and decision-making of stakeholder groups and (2) to collaboratively model complex fishery systems with stakeholders so that assumptions about social-ecological dynamics can be explicitly discussed prior to empirical or simulation model building.

Although academic and observational studies related to communicating the results of ensemble modeling in fisheries is in its nascency, the fields of climate science and risk communication have been engaged with this topic for some time and can provide some insight for fisheries scientists. For example, a recent report from the US Climate Change Science Program (2009) entitled Best Practice Approaches for Characterizing, Communicating and Incorporating Scientific Uncertainty in Climate Decision-making, led by M. Granger Morgan from Carnegie Mellon University, outlines guidelines for climate scientists seeking to communicate mixed-model results to decision-makers and addresses, among other areas, the cognitive challenges in estimating uncertainty and the best way to communicate uncertain model results. Specifically, two findings from the report seem to hold particular promise in a fisheries ensemble modeling context, namely that (1) the presence of high levels of uncertainty or divergent mixed model results may provide stakeholders with an agenda an opportunity to “spin the facts” and (2) recipients of information will process any message they receive through previous knowledge and of the issue at hand. The report also suggests using a ‘mental model’ approach which allows scientists a way to communicate the results of ensemble models by first understanding the belief systems of their audiences.

To demonstrate how using a mental model approach might be used in a fisheries context, two case studies will be presented using data collected from stakeholders involved in the summer flounder fishery in the mid-Atlantic US and from recreational fishery stakeholders in Germany. In both case study examples, differences and similarities in the structural and functional characteristics of stakeholder mental models were measured using Fuzzy-Logic Cognitive Maps (FCM). Specifically, we compared stakeholder groups’ aggregated beliefs, using graph theory indices, to quantify differences across groups. In both examples, reliable trends across stakeholder groups were found which matched differences in the simulated decisions based on these beliefs. Finally, I review the architecture and use of an FCM-based software called Mental Modeler which is an analytic tool used to collect and analyze the structure and function of beliefs systems of scientists, natural resource managers and other natural resource stakeholders in a participatory planning context.

Summary of Invited Speakers Presentations

Bond

Nick Bond presented on Lessons EM can learn from seasonal weather prediction.

Current practices in seasonal weather prediction are to use multiple tools - statistical forecast tools and dynamical forecast tools. The primary dynamical forecast tool is the National Multi-Model Ensemble (NMME). Some others tools available from international sources. They consolidate the tools to make forecast maps with likelihoods of forecasts of temperature, precipitation and other meteorological parameters.

For these modeling approaches, sample verification of forecasts is made by different models within an ensemble. Some years are easier to forecast than others. Some parameters are easier to forecast than others. Some regions of the world are easier to forecast than others. Generally, the ensemble prediction is either the best or one of the best in terms of anomaly correlation scores.

Ensemble modeling approaches in this field are based primarily on averaging methods. These methods include: simple means, means with individual bias corrections, means with collective bias corrections, regularization and Bayesian Model Averaging (BMA).

BMA is a more formal procedure that has proven useful. BMA considers an ensemble of plausible models. Models vary in skill; calibration of this skill produces better forecasts. This approach works well in short-term weather prediction. About 6 or more models are needed for this approach.

Other points raised were that with long-range forecasts, model variation is greater within models than between models, because they often have similar pedigrees, rely on similar foundations, and not totally independent. Generally, how reliable models are is based on past performance. As a result, there is considerable turnover in top-rated models based on hindcasts at global and regional scales. There is almost no chance that one model will be the best in consecutive blocks of time.

In summary, Bond noted the following:

- No single best method for averaging climate model output exists, though protocols for averaging should include evaluation of past performances of different models;
- Multimodel ensembles represent a key tool for climate forecasts AND increasingly for short-term forecasts;
- On long time horizons, model structure uncertainty dominates sensitivity to initial conditions, so using multiple models with different structures is necessary;
- Output from global climate models (perhaps with statistical downscaling) can complement output from vertically integrated numerical, dynamical models.

Bond also noted that measuring skill in models is harder to do with EMs than climate/weather models, because climate models get more data in higher frequency; so climate/weather modelers have more data and time steps to work with than ecosystem modelers. EMs' "skill" is fitting to raw data that has confounding issue with sampling error Ecosystem modelers should consider "sampling" forecast skill, and using proxy forecast samples for latent variables

Beven

Jack Beven presented on the uses, strengths and weaknesses of numerical models and model ensembles in tropical cyclone (TC) forecasting

He gave a short description of the type of forecasts that the National Hurricane Center (NHC) produces with models. Forecast parameters made every 6 hr with a focus on the Position and intensity, radii of 34 kt, 50 kt, and 64 kt winds for up to 5 days in advance, location of 12-ft seas up to 5 days in advance. He noted that models are NOT used as black boxes; humans always have the final say in the forecast, not the models. Specifically, what NHC forecasts is the motion of the storm (the track forecast) and intensity.

The track forecast is a "relatively" simple problem because storms are steered by larger weather systems; like a cork in a stream. Important features are relatively large and easy to measure, and dynamical models forecast track quite well. However, TC intensity is more difficult to evaluate as the forecast relies on multiple processes and scales. It depends on the track, wind, temperature, moisture over core and near environment. It also depends on internal processes—eyewall replacement cycles, etc.—that are poorly understood.

In addition to considering the multiple models available, a forecaster also bases his forecast on the previous forecast to provide constraint on the current forecast. Drastic forecast changes in direction (windshield-wipering) and intensity damage credibility of the forecast. Changes in forecast are slower than those predicted by models (that's the human constraint).

To provide some ideas on how NMFS might move towards more formal use of MMI, Beven presented a history of TC forecast models. The computer that supported original models was invented in the 1950s. Early models were statistical. Statistical-dynamical models developed in the 1960s for track, in 1990s for intensity. Increased computing power starting in the 1990s improved track forecasting skill. Additional incremental improvements were made in the 2000s. Error intervals have narrowed over decades.

In addition to the history, Beven provided an overview of the current model and ensemble approaches in use. Those are summarized in Table X. This table may be useful for thinking about LMR model analogs.

Type	Description	Examples	Utility and other notes
Statistical	Based on previous storm behavior What "normally occurs"	Main Statistical Model: CLIPER (climatology persistence)	-Based on the past, no current knowledge, no dynamical data -Track, intensity, size and location of storms for a time of the year that are moving in a particular direction -Can be used to evaluate more complex models (a skill baseline) but should NEVER be used as a serious forecast by itself
Simplified dynamical (trajectory)	Follow cork in stream analogy, where cork (hurricane) has no impact on stream		-Smoothed, simplified; useful when environmental flows are simple (e.g., deep tropics) - Need to know which one (deep, medium or shallow) is appropriate - Less effective overall than dynamical models
Dynamical	Based on first principles Solve fundamental physical laws	Most sophisticated Solve fundamental physical equations for a wide range of processes 3D Global and regional types Several different versions from around the world; more in development	Different models perform well/badly on different days but over a year their skills end up more or less averaging out and complementing one another
Dynamic-regional	-Specific for forecasting hurricanes -Higher resolution, more limited coverage close to storm area		-Better representation of storm means better at interactions with environment -Better for intensity forecast than global model -Still a lot of work to do on intensity predictions
Dynamic-global	-Developed for general weather prediction -Horizontal resolution = 7 to 25 miles (most of the time, too large to depict core of hurricane) -Handle large-scale features associated with track		-Not good for predicting intensity -Good for predicting size
Hybrid (Statistical-Dynamical)	Combinations of Statistical and Dynamical	Decay-SHIPS (statistical hurricane intensity prediction scheme) LGEM (Logistic growth equation model) -Generally the most skillful for intensity forecasting -Predict "average" behavior because rapid intensification is relatively rare; not capable of forecasting rapid change	
Consensus	Average output from other models with some		- Not models per se; combinations of other models

Type	Description	Examples	Utility and other notes
	weighting options		- Can be a simple average - Can be more complicated, where past performance is used to correct biases or optimize combinations -Consensus models generally outperform individual models that make them up -The more independent the individual models are, the better the consensus does
Ensemble	A collection of models run with slightly different initial conditions or methods of processing, presents range of possible outcomes Can be multi-model ensemble or single-model ensemble		
Single-model ensemble	Global and regional model run many times at reduced resolution with perturbed initial conditions		Current practice is to use ensemble output in a mean or average sense due to large number of ensemble members (at least 20 for global models)
Multi-model ensemble	Model suite that contains several dynamical models, less sophisticated models, and consensus models.		-Produce range of possibilities -Official forecast is manually created by forecaster based on this info -Heavily depends on experience of the forecaster -Forecasts are checked later to measure skill
Other models tangentially related	-Storm surge models -Hazard/catastrophe models		Estimates of damage and cost

Currently multiple model approaches rely on a forecaster to develop a summary forecast based on model outputs. Efforts to develop model ensemble used for probabilistic forecasts and real-time calculation of uncertainty - GOERSS Prediction of Consensus Error (GPCE, pronounced gypsy) – are underway. Within this effort, NHC will run multi-model ensembles, develop statistical estimates of the magnitude of the error of the consensus track forecast statistically predicted from model spread, develop initial and forecast intensity, forecast latitudinal and longitudinal displacements, and then adjust with regression.

To deal with uncertainty, NHC performs forecast verification, model validation, Monte Carlo simulation of wind speeds, and display a track forecast cone – known as the "cone of uncertainty".

NHC verifies ALL official TC track and intensity forecasts because it is mandated, helps reduce error, identifies critical issues for research community, and helps decision makers use info more effectively. Typically with verification they find that:

1. track forecast errors start out low, increase linearly out to day 4 or 5;
2. intensity forecast errors tend to level off at day 2 or 3
3. these errors have come down considerably since 1990
4. But, errors are highly variable from storm to storm even within a given year

Model validation also verifies predictions of all models against the official forecast. Several models are top performers that take turns at being best for a year. The track forecast cone represents track forecast errors the center of the storm, that is the storm should be inside the cone 67% of the time (which means that it will be outside 33% of the time!). The cone only predicts track, not intensity/impact. The radius of circles in cone is a function of time of forward projection.

Monte Carlo approach for wind speed probabilities is based on 1000 realistic alternative scenarios. It produces probability of winds at different locations and accounts for weakening over land. Wind thresholds (probability of hitting 64 kt, 50 kt, etc.) and timing probability are computed.

Several general conclusions were presented. Forecasts have improved greatly as quality of forecast models and input data have increased. Multi-model ensemble is the preferred approach, but there is an increasing use of single-model ensembles. The model verification program has helped to drive improvements. No matter how good the models are, there is a need for a human forecaster to make the final decision.

Leonardi

Alan Leonardi presented on Ocean Ensemble Modeling.

Leonardi outlined some general principles of ocean modeling, the need for ensemble modeling, approaches for ensemble modeling, the use of combining modeling and monitoring to assess the impacts of data on forecasts, and he presented a specific example of model ensemble utility in the Gulf of Mexico.

Generally, models can identify processes. But they can have error and bias; missed predictions are learning experience to help reduce the error and bias of future applications. With different levels of complexity in modeling tradeoffs between variance and bias, one of the goals of modeling is to find the sweet spot that minimizes overall error. Some of the challenges to modeling include: uncertainty in initial conditions, uncertainty in structural assumptions of the processes, and nonlinearities and instability in the system. A good way to deal with these challenges is using model ensembles – single model and multiple model ensembles.

One way to create an ensemble is to change initial conditions, and rerun the same model – i.e., to use a single model with a variety of configurations. This can be done to test determinism vs non-determinism of the system. Much of this type of work began in the 1990s when Metzger et al ran a four member ocean model ensemble for longer simulations (i.e. longer than the time scale of error growth rate – in this case 1979-1996), to examine feature determinism vs non-determinism. The level of non-determinism could then be used to develop improvements to the model and data streams.

Another approach for ensemble modeling is to use multiple diverse models that are trained on the same problem. It is best to have multiple ocean forecasts, from separate model types, in most cases. Another best practice is to plot model mean and prediction variance around that mean, to demonstrate where models diverge. Typically in ocean modeling, there is a learning period, over which weights across models are optimized; then the forecast period uses those weights that have been established. Generally this will lead to better model performance. Ocean modelers use Whole Domain weighting, and 3D weighting, to allow weighting scheme to evolve to so as favor the strongest models. Leonardi noted that fisheries, with only one forecast per year, have a disadvantage, and slower learning.

Besides improving models, multiple models can be used to assess the impact of observations on forecast and improve monitoring/observations systems. When combined with data assimilation, ensembles can be used for Observing System Evaluations (OSE, removing some existing data stream), and Observing System Simulation Experiments (OSSE, for new types of data you might bring in). Basically this allows assessment of the value of certain data streams.

OSSE uses a ‘nature run’, which is the operating model. Synthetic operations then sample from this run. Then modelers use Forecast Improvement Quantitification to gauge the value of the data streams (NOAA AOML).

Leonardi noted that Gulf oil spill modeling needed multiple realizations of hydrodynamic models to get a good idea of where BP oil spill headed. However, stakeholders focused on one output of the ensemble and raised concern over one potential but unlikely scenario.

The overall summary of this presentation was that model ensembles are useful, but require a lot to produce. Ensembles are useful because they reduce error and allow evaluation of flaws of individual models. To produce model ensembles, adequate models, adequate data, and adequate diversity in models is necessary. While ocean models can be readily revised to represent a variety of ocean regions, ecosystem models are less transportable.

Neuenfeldt

Neuenfeldt presented on a specific example of MMI developed for EBFM in the Baltic Sea by an ICES working group (WKMULTBAL 2012)

Neuenfeldt gave a brief overview of the Sea ecosystem. The biology of the Baltic Sea is driven by inflow of salt water to the Baltic; this inflow has declined appreciably since the 1980s. Summer water temperatures are highly variable (2-3°C of variability across years). The Baltic Sea is a very simple ecosystem with three major fish species: cod, sprat and herring. Cod feeds on sprat and juvenile herring, and adult cod feeds upon cod juveniles. Herring feeds on sprat and cod eggs. Sprat recruitment responds to temperature; and cod recruitment seems to respond to salinity.

In this presentation, Neuenfeldt discussed using Biological Ensemble Modelling Approach (BEMA) as a tool to study the impacts of model structure and ensemble averaging on responses to climate change and fishing in the Eastern Baltic Sea. This exercise was focused on future cod stocks and was designed to answer the following questions:
- How variation between models of different complexity influence model results?
- What are the causes of variation between models (e.g., structure, methodology)?
- What is the effect of ensemble weighting and composition?
- Are general conclusions across models possible?

Neuenfeldt and colleagues used 7 different models of Eastern Baltic Sea cod: 3 single-species (2 with age structure and one without), 3 multi-species models (2 with age structure and one without), one full food-web model (with age structure for the fished species). In addition, hydrographic forcing was also modelled on cod or on interacting species, based on statistical models of environmental effect on recruitment and/or biomass. Scenarios applied to these models included 3 fishing mortality scenarios – intense, target or ban and 2 climate scenarios – past variation vs further climate change (+3.5°C SST and -0.8 psu salinity).

A large difference in responses between models without stock-recruitment relationship and with prey feedbacks on predators and those models with stock-recruitment relationship and without feedbacks was noted. The latter are also more sensitive to climate variation, such that they magnify underlying climate variation. The conclusions from the ensemble approach as a whole, depended on whether and how ensemble selection of subsets and ensemble averaging were performed.

Because of the wide range of outcomes. Neuenfeldt and colleagues opted to show the ranges of possible responses, and approach synthesis of results across models using decision tables (Figure X).

Fishing	Climate	Relative Cod SSB_{2100}			
		Extinct	Decrease $< SSB_{2009}$	Increase $> SSB_{1995}$	Rebuilt $> SSB_{1980s}$
Intense (F=1.08)	current	3,6	1,2,4-7	7	none
	climate change	3,4,6	1,2,4,5,7	7	none
Mngmt plan target met (F=0.3)	current	none	4,5	1-3,5-7	2-7
	climate change	none	1,2,4-6	1-3,5-7	2-5,7
Fishing ban (F=0)	current	none	1,4	1,5-7	all
	climate change	none	1,4,6	1,2,5,6	2-5,7

This decision table approach focuses on what can be said across all models. For instance, the approach suggests that regardless of model, intense fishing leads to no rebuilding under climate change.

Arkema

Katie Arkema presented on the need to collaborate and iterate with stakeholders when applying models for EBM.

Arkema presented on a case study of applying multiple modeling approaches and mapping to help stakeholders in Belize develop ecosystem management plans. In Belize, the people have a strong intuition of their natural resources needs - fishing, the role of corals and mangroves in fisheries and tourism. They also are concerned about infrastructure for tourism, aquaculture, dredging for marine transportation. About two decades ago, Belize passed a legendary legislation. This legislation identified the need for EBM and about combining expert science and local knowledge, and explicitly called for a spatially explicit coastal development plan. This was difficult to implement, because multiple ministries were involved and administration changes over time. Belize had separate regional plans but integrated for the nation

Arkema and a team from The National Capital Project worked on a collaborative project between experts and locals to design the new plan for 3 years. The science has largely been around applying a suite of models called InVEST (Integrated Valuation of Ecosystem Services) that included production functions for how changes in ecosystems lead to changes in benefits for people.

In addition to using established tools, Katie Arkema and colleagues developed additional socioeconomic tools. For example, Belize lacked good information on central tourism areas and peak tourism periods. Arkema and colleagues developed methods using used geo-coded Flickr photos. They tested the method by looking at sites identified to have large tourism interest based on Flickr photos and where tourists are going. They mapped areas with high levels of tourism and found that Belize City belonged to those areas butlacked tourism infrastructure. This enabled incorporation of information on where development might be most beneficial.

Arkema and colleagues developed the suite of models and data and used them interactively with an integrated suite of stakeholders. The process was begun by developing a list of stressors on the coastal ecosystem - marine transportation, tourism, fishing, development, agriculture, dredging, and aquaculture. They also produced lists of all the stakeholders and their roles, and objectives for the ecosystem.

Models and the list of stressors were used to help stakeholders to choose possible future zoning schemes (high development, conservation and a compromise between conservation and development). By working closely with the stakeholders, Arkema and colleagues were able to demonstrate that the compromise scenario (called targeted management) optimized the uses/stressors of the system while maintaining the essential features to ensure ecosystem productivity.

This case study illustrated that transparency is important – clearly outline data sources and assumption. Consolidating information for stakeholders was also important in getting agreement on management plans. In addition, they helped Belize develop methods for collecting important socioeconomic data and trained Belize people on tools for future use.

Arkema presented on a second case study of planning for resilient coastlines in the US.

Coastal communities in the US are at risk from a combination of rising seas and potential increases in storm intensity and frequency of storms. There are also costs of hazards to infrastructure and business. “Natural defense” (e.g., wetlands) holds promises.

Arkema and colleagues produced maps showing how many people will be at risk of climate change if natural habitats are left intact, versus if they are not. They also generated more specialized maps showing who will benefit (poor families?, people over 65 years old?, etc.). Arkema and colleagues’ study raised awareness about the role of ecosystems and “natural defense” in mitigating climate change. They found that simpler models are more helpful when diverse decisions need to be taken and that stakeholders have more confidence in those simpler models.

Gray

Steven Gray presented on the potential of using mental modeling to help with stakeholder considerations in EM.

One of the goals of LMR modeling seems to be to understand and reduce uncertainty on the ecological side of the ledger, but there is a lot of uncertainty on the human side of the equation too—social contexts, status of communities, interactions among different social sectors. Additionally, the social system affects the ecological system.

Aside from technical issues with ensemble modeling and structural uncertainty, there is also communication uncertainty, decision uncertainty, connecting with stakeholder groups. There is not a lot of empirical data on how structural uncertainty affects/relates to communication and decision uncertainty

There may be some lessons from climate modeling on how to deal with communication uncertainty in ensemble modeling - climate change case studies. Downscaled models have been used to assess the social impacts of global processes. These impacts are very hard to estimate and assess, but they are very important for decision making.

In many cases, there is probably more confusion about what is meant by the specific events being discussed than about the probabilities attached with them (e.g., US Climate Change Science Program 2009). Presence of high levels of uncertainty enables agenda-driven user groups to spin facts. There is a risk that recipients interpret what is said to them in terms of what they already know; uncertainty allows them to assert their own points and perceptions. Empirical study of peoples’ mental models is absolutely essential to properly framing results of ensemble models

The mind forms mental models of reality and uses them to make decisions. These models often underlie human behavior. This is basis by which people make predictions of changes in the external world. This has parallels to conceptual models of ecosystems. It actually implies that conceptual models should be derived by consensus if they are going to potentially inform how we interpret information. Formal models are empirical and statistical, and can be used in ensemble modeling; they are distinct from mental models, which are conceptual and informal models

Fuzzy logic cognitive mapping (FCM) is an approach that may be useful. Fuzzy logic (e.g., Delphi method, Bayesian belief networks, expert inference) has been used in some LMR management contexts. FCM is superior to these other fuzzy logic techniques because it is semi-quantitative; it is not simply a binary system, but more like the way people make choices.

FCM involves quantitatively assigning values to the amount of positive or negative influence among model components. Stakeholders define relationships between components, define influence of components on one another, and parameterize strong/medium/low and positive/negative impacts into numerical values to formalize their mental models. These models can then be translated into a matrix and calculate network metrics. Neural networks project model behavior and model system state under different scenarios. This produces structural network metrics which can be used for scenario analysis. This allows us to model how changes in behavior affect changes in decision-making

Discussion Summary

Within this session on MMI how and where to apply, workshop participants had opportunity to ask questions to the presenters after each presentation as well as two opportunities for group discussion of what could be used from the different disciplines for EM.

Important lessons from these presentations were outlined:

- It is important to have multiple models and beginning moving forward with MMI for EM The presentation by Neuenfeldt outlines a potentially good way forward.

- We do not approach model analysis with anywhere near the rigor that climate modelers do.
  This is largely due to resource constraints and availability and timing of data and models to enable rapid evaluation.

- The trust in human judgment at the forecasting stage would probably be rejected in our field.

The discussion focused on the role of the modeler/forecaster in providing forecast/assessment advice, transferability of MMI approaches from other disciplines to EM, and stakeholder considerations.

There was much discussion on the idea of a hurricane forecaster as the ultimate multi-model aggregator and developing summary advice based on the outputs of models and integrating – a forecaster in the hot seat.

The group generally agreed that the role of the modeling/assessment team was generally analogous to forecaster on the hot seat role, but with important distinctions on how assessment advice was used and the fact that LMR is two orders of magnitude slower than weather service (annual at best) because of data flows and model time steps.

Ecological modelers actually do have a very strong human dimension component because often a single-model ensemble of models is brought to the table for people to decide what is/is not plausible as the basis for making recommendations; that's all part of the small committee review process. BUT, we have a high expectation of external review—for example, assessments must be reviewed before they are used—and less of a practice of local experts giving their judgments and opinions for use as immediate advice. The review panel is not exactly the same as a forecaster but a forecaster has a time crunch if a hurricane is nearing land there is not time for a large committee and several levels of review. Also, forecasters are not making regulatory decisions, but rather providing advice for other agencies to make decisions. Ultimately a forecaster's assessment does not influence the trajectory of a hurricane; however, ecological modeler's assessments can influence the trajectory of a stock.

Because of the analogies of these two roles participants were interested in 1) how forecasters transfer that individual knowledge and skill to institutional knowledge 2) how forecasters measure their improvement over time. Beven noted that there is no formal institutionalization of knowledge, though the 10 members of the forecasting team talk and share a lot. NEMoWs may be the approach for improving institutional skill among ecosystem modelers. Beven also noted that forecasters usually work in junior positions for about 10 years before moving to the hot seat. Individual improvement of forecasters over time is difficult to ascertain, because, as they are improving, models are becoming much better at compiling the terabytes of data; the data quality is much better from satellites in particular. As a forecaster Beven also uses data that are independent of the models, and that data inclusion has improved a lot. In addition, computational power also helps identify deficiencies in data, model, etc., to a much greater extent than it used to.

Participants also steered the discussion to focus on the mechanics of transferring some of these approaches for MMI to EM. Participants were concerned about the number of models needed to be used in an ensemble, the level of independence of models, what drives the improvement of models, the ability to work with and modify existing models for timely application in an ensemble approach, and the process to incorporate new models.

For many of these questions, the answers might vary on a case-by-case basis. That is, working with existing models would require an evaluation of the problem to be addressed and the suitability of existing models to address it. Case studies might help to further outline how to modify existing models.

Because Bond and Leonardi addressed the importance of independent models for multi-model ensembles, the issue of model independence was addressed. Some participants noted a long-standing concern about our discipline, namely that we do not have many flavors of models and that they are too interrelated; several that are philosophically similar (e.g., trophic interactions). Other experts might argue that something like parasitism, disease, or structural habitat is far more important determinant of a population's status. Others might say spatial processes are more important. Ensembles need to expand to include those other types of models and not just multiple variants of trophic models.

In other disciplines, when a desire or need to incorporate new models arises, the disciplines have fairly specific approaches for testing those models (e.g., running hundreds of simulation tests to evaluate model performance). They also require a learning curve on the part of users/forecasters. These testing processes may not be transferable to EM because of data issues.

In the other disciplines most of the physics are pretty well explained and understood. They try not to throw in black box parameters because they could throw other processes off kilter that lead to consistent error. An iterative process between data improvements and model improvements evolves. For example, better understanding of role of atmospheric moisture from data led to better models and measurement tools that helped incorporate that information into weather models.

Though this session was not focused on stakeholder consideration, some initial discussion on stakeholders emerged. The issues were largely centered on risk aversion/conservatism and communicating uncertainty

Generally, LMR managers and emergency managers may have different levels of risk aversion. Ecosystem modelers wondered to what extent that played a role when forecasters wrote a summary forecast. If one model suggests hurricane landfall much sooner than the others, forecasters tend to go closer to model average but may also suggest watches and warnings; they try to deal with the most likely scenario but are willing to release "but…" statements that differ from the guidance of the models. That is especially true of cases of rapid intensifications. This leads to inherent conservatism, which tends to be the case in the LMR context. This can be problematic if the outlier is actually the more accurate predictor. In this instance, where assessments or forecasts are wrong, and a learning opportunity arises.

Within the session on social and management considerations, workshop participants had opportunity to ask questions to the presenters after each presentation as well as an opportunity for group discussion of what could be used from the different disciplines for EM.

The most salient point from this discussion was a need for transparency. Transparency in model assumptions and data is necessary so that stakeholders trust the modelers and the output of the models. Withholding information can result in public backlash. The downside to transparency is that presence of high levels of uncertainty enables agenda-driven user groups to spin facts. This presents a risk that recipients interpret what is said to them in terms of what they already know or want to hear. Uncertainty allows them to assert their own points and perceptions.

Beyond general stakeholder issues, some users were concerned about how to use multiple models and present the output of these models to formal management bodies (e.g., Councils) to provide tactical advice.

One approach to building trust with stakeholders and preventing selective acceptance of model results is to work collaboratively and interactively with stakeholders during development of management objectives, model development, and model applications. This allows stakeholders to understand why a divergent result may have diverged because of model structure or initial conditions and may not be truly representative of what is likely to occur in the ecosystem. However, this level of interaction may be cost-intensive as it would require a lot of modelers' time.

Much of the group's interest was focused on the potential to use fuzzy logic cognitive mapping (FCM) as a way to develop and apply simple ecosystem models as a part of a suite of models in MMI. For MMI in a simulation context, time scale is very important; these appear to be linear production models. The results of the scenarios from FCM are based on steady states; however, model iterations can be used to show trajectories of how things in the model change through time.

Appendix A – Agenda

Day 1		
8:30 -9:00	Plenary	Welcome, Introduction, Layout plans for NEMoW 3. Overview and Welcome (**Jason Link**)
9:00-10:00	Plenary	Report on current efforts underway or planned at NMFS centers/labs/offices (**TOR 4**).
9:00		AKFSC
9:15		NWFSC
9:30		SWFSC
9:45		PIFSC
10:00-10:15	Break	Coffee break*
10:15-11:00	Plenary	Report on current efforts underway or planned at NMFS centers/labs/offices (**TOR 4**).
10:15		NEFSC
10:30		NCBO
10:45		SEFSC
11:00 -12:00	Breakout 1	Outline and review precursor steps (determine the purpose for using multiple model inference in ecosystem assessment and outlining the capabilities and limitations of the models to be used for inference) (**TOR 1**) and summarize center efforts (**TOR 4**)
12:00-1:00		Lunch break**
1:00-2:00	Plenary	Report out on precursor steps from the breakout groups.
2:00 - 3:00	Plenary	Outline and review the mechanics of multiple model inference (**TOR 2**). Perspective from atmospheric/climate modeling. Focus on model ensembles. Presentation from Invited Speaker (**Nick Bond**).
3:00-3:15	Break	Coffee break
3:15 -4:15	Plenary	Outline and review the mechanics of multiple model inference (**TOR 2**). Perspective from weather/hurricane modeling. Focus on model ensembles. Presentation from invited speaker (**John Beven**).
4:15-5:00	Plenary	Group discussion of how to apply climate and weather approaches to living marine resource (LMR) management.
5:00		Adjourn
6:30		Seattle Aquarium Event more details from Phil Levin

Day 2		
8:30 -9:00	Plenary	Recap previous day. Layout plans for day 2.
9:00-10:00	Plenary	Outline and review the mechanics of multiple model inference (**TOR 2**). Perspective from oceanic and atmospheric modeling and potential applications to marine ecosystems. Focus on model ensembles. Presentation from Invited Speaker (**Alan Leonardi**).
10:00-10:15	Break	Coffee break
10:15-11:15	Plenary	Outline and review the mechanics of multiple model inference (**TOR 2**). Perspective from other systems. Focus on linking models.

		Presentation from invited speaker (**Stefan Neunefeldt**).
11:15 -12:00	Breakout 2	Outline and review the mechanics of multiple model inference (e.g., linking models, model ensembles) (**TOR 2**). Capture best practices for employing MMI (**TOR 5**).
12:00-1:00		Lunch break
1:00-2:00	Plenary	Breakout groups report on practices from presenters that can be implemented for NMFS LMR management.
2:00 - 3:00	Plenary	Management implications and review case studies (**TOR 3**). Focus on policy implications. Presentation from invited speaker (**Katie Arkema**).
3:00-3:15		Coffee break
3:15 -4:15	Plenary	Management implications and review case studies (**TOR 3**). Focus on policy implications. Presentation from invited speaker (**Steven Gray**).
4:15-5:00	Breakout 3	Identify practices for incorporating social and policy considerations that can be implemented for NMFS LMR management (**TOR 3**).
5:00		Adjourn

Day 3		
8:30 -9:00	Plenary	Recap previous day. Layout plans for day 3.
9:00-10:00	Plenary	Breakout groups report on practices for incorporating social and policy considerations that can be implemented for NMFS LMR management. (**TOR 3**)
10:00-10:15	Break	Coffee break
10:15-11:15	Breakout 4	Discuss best practices for employing multiple model inference (**TOR 5**).
11:15 -12:00	Plenary	Report out on general recommendations for moving forward with NMFS Ecosystem Modeling.
12:00-1:00		Lunch break
1:00-1:30	Plenary	Quick list of future NEMoWs and NEMoW workgroups (**TOR 6**).
1:30- 2:30	Breakout 5	Discuss general recommendations for moving forward with multiple model inference in NMFS Ecosystem Modeling in the regions (**TOR 6**).
2:30-2:45	Break	Coffee break
2:45 -3:45	Plenary	Report out on general recommendations for moving forward with multiple model inference in NMFS Ecosystem Modeling.
3:45-4:00	Plenary	Wrap-up.
4:00		Adjourn.

Appendix B – Participants List

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Appendix D – Breakout Group Questions for TOR and Summary Discussion

Session 1 (Day 1 - 11:00-12:00) TOR 1 & 4

What are the typical management objectives for your ecosystem models?

How many of your ecosystem models are used operationally, either tactically or strategically (or contextually)?

Would any of these applications benefit from multiple model inference (MMI)?

<u>Secondary</u>

Approximately how many fishery stock assessments, protected species assessments, habitat assessments, aquaculture sitings, and ecosystem assessments are executed at your Center each year?

Each of those assessment processes uses a model. How many *ecosystem models* (and which ones) does your Center use/develop to support these assessment efforts?

Session 2 (Day 2 - 11:15-12:00) TOR 2 & 5

What are the main methods and tools for executing MMI?

From other disciplines and examples, summarize how MMI have been employed and used.

From plenary speakers and Center experiences, are there specific tools/methods that appear most promising?

<u>Secondary</u>

What are the best methods to explore MMI assumptions and divergence in results?

What are the best methods to combine MMI results?

Session 3 (Day 2 - 4:15-5:00) TOR 3

How would MMI change the way that advice is given, compared to a single model?

What is the appropriate guidance to provide to the LMR assessment scientific review process (e.g. SRG or SSC) regarding when to use "single best" model (and output) versus ensemble models (and outputs)?

What are the best methods to communicate MMI assumptions and divergence in results?

Secondary

Discuss the policy and sociological considerations when using different models that may have divergent results.

Session 4 (Day 3 - 10:15-11:15) TOR 5

What are the potential benefits and drawbacks to MMI in a living marine resource (LMR) context? Consider the mechanics of MMI and potential management implications.

Is there a set of conditions that would be most amenable to MMI?

From session 2, are there are any best practices for MMI use or adoption that particularly merit highlighting?

Secondary

Do we need to revisit the development of a national ecosystem model toolbox?

What are the pros and cons of developing general operational capacity (NOAA support of capacity) versus models built for purpose (funding specific to an issue)

Session 5 (Day 3 - 1:30-2:30) TOR 6

Should we consider employing MMI in a LMR context?

If so, what are the main recommendations for use of MMI in a LMR context?

What are some key topics for future NEMoWs? And should we alter the format of future NEMoWs?

Appendix E – Glossary of Frequently Used Abbreviations

AFSC: NMFS Alaska Fisheries Science Center
BEMA: Biological Ensemble Modeling Approach
BMA: Bayesian Model Averaging
BRP: biological reference point
CWA: Clean Water Act
CZMA: Coastal Zone Management Act
EAF: ecosystem approach to fisheries
EBM: ecosystem-based management
EM: ecosystem modeling (covering the full range from minimal realistic models, multispecies and extended stock assessment models, bulk biomass (network and aggregate) and full system (ecosystem and biophysical) models.
ESA: Endangered Species Act
IEA: Integrated ecosystem assessment
LME: large marine ecosystem
LMRs: living marine resources
MMI: multiple model inference
MMPA: Marine Mammal Protection Act
MS: multi-species
MSA: Magnuson-Stevens Act
MSE: management strategy evaluation
NCBO: NOAA/NMFS/HC/Chesapeake Bay Office
NEFSC: NMFS Northeast Fisheries Science Center
NEMoW: National Ecosystem Modeling Workshop
NEPA: National Environmental Protection Act
NMFS: National Marine Fisheries Service
NOAA: National Oceanic and Atmospheric Administration
NHAW: National Habitat Assessment Workshop
NSAW: National Stock Assessment Workshop
NWFSC: NMFS Northwest Fisheries Science Center
OSEs: Observing System Evaluations; evaluations used in physical oceanography, which involve the systematic with-holding of observations from assimilating systems to quantify the degradation of the system's performance when those observations are neglected.
OSSEs: Operating System Simulation Experiments; modeling experiments that are used in physical oceanography to evaluate the impact of new/proposed observing systems on operational forecasts.
PIFSC: NMFS Pacific Islands Fisheries Science Center
ROMS: Regional Ocean Modeling System
SEFSC: Southeast Fisheries Science Center
SWFSC: NMFS Southwest Fisheries Science Center
TOR: Term of reference