Challenge and Opportunity for Fisheries Stock Assessment in Changing Environments

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Fisheries Management System and Sources of Error /Variation

Fulton et al. 2011. Fish and Fisheries 12 2-17
Large Uncertainties in Stock Assessment
Lack of understanding

- Biology
- Fishing
- Data, sampling process
- Ecosystem

- Climate changes
- Regime shift
- Changes in management

Problematic perception of stock status?

Poor management
Objectives of Fisheries Management

- Make management decision based on best available information and science
- Precautionary approach
✓ Best Available Science
✓ Precautionary Approach

Figure 2: Relationship between OFL, ABC, ACL and ACT

Definition Framework: OFL ≥ ABC ≥ ACL

- Overfishing Limit → Corresponds with MSY
- Acceptable Biological Catch
- Annual Catch Limit
- Annual Catch Target

- ABC may not exceed OFL. The distance between the OFL and ABC depends on how scientific uncertainty is accounted for in the ABC control rule.
- AMs prevent the ACL from being exceeded and correct or mitigate overages of the ACL if they occur. ACTs are recommended in the system of accountability measures so that ACL is not exceeded.
A general framework of developing tools for ecosystem-based fisheries management (cited from Smith et al. 2007)
Model classification of the types of multispecies ecological models (cited from Whipple et al. 2000).
Fig. 1: Schematic of the integrated GoM/GB model system

Developed by Dr. Changshen Chen in SMAST UMASSD
Differences from the long-term average global ocean heat content (1955-2006) in the top 700 meters of the ocean.

Data: Global Ocean Heat Content from the National Oceanographic Data Center
Ocean heat content over time

700 meters (2,300 feet)
700-2,000 meters (6,600 feet)

Johnson et al. 2018
Ocean heat content in the upper ocean (from the sea surface to a depth of 700 meters) for 2017 relative to the 1993–2017 baseline

Johnson et al. 2018
Global mean temperature near-term projections relative to 1986–2005

- Observations
- Historical (41 models)
- RCP 2.6 (32 models)
- RCP 4.5 (41 models)
- RCP 6.0 (25 models)
- RCP 8.5 (39 models)

Temperature anomaly [°C]

Historical - RCPs
Over past 40 yrs:

- 60% major fish stocks have shifted distributions poleward (1 mile yr\(^{-1}\)) and/or deeper (0.8 ft yr\(^{-1}\)).

- Species shifting at different rates (25-200 miles poleward)

- Also changes in abundance, phenology, species assemblages

- Implications to stock monitoring & assessment?

Source: Nye JA et al. (2009), Hare et al. (2010)
Stock assessment in changing environments

**Challenges**

- More dynamic ecosystems
- Unknown adaptation and changes in fish life history
- Possible changes in movement, distribution, and fishing fleet dynamics
- Changes in prey-predator dynamics
- Unknown monitoring program performance
- Questionable data, assumptions, and models
- INCREASED UNCERTAINTIES

**Opportunities**

- Evaluate existing monitoring programs
- Develop new modeling tools for evaluating spatio-temporal dynamics of fish populations
- Include environmental/ecological drivers in stock assessment
- better understand dynamics of coupled human-natural system
- Improve quantification of the uncertainty
- Develop ecosystem-based fisheries monitoring and assessment
HMS Stock assessment in changing environments

Challenges

- Changes in migration, distribution and species composition (and bycatch)
- Changes in overlapping t-RFMOs and national jurisdictions
- t-RFMOs decision-making difficult in the face of increased uncertainty
- Increased complexity in stock assessment
- Increased difficulty to communicate science to stakeholders
- Reduced assessment effectiveness

Opportunities

- Develop new technology to better monitor spatio-temporal dynamics of HMS
- Include environmental/ecological drivers to reduce uncertainties in HMS stock assessment
- Operationalize ecosystem-based fisheries monitoring and assessment
- Improve science-management dialogues
- Establish a sustained dialogue across t-RFMOs and national experts for collaborative stock assessment
Ecosystem drivers were only considered for 24 of the 1200 marine fish stocks examined.
The current assessment of fish stocks focuses on harvest rates and spawning stock biomass and often do not incorporate environmental variability.
Approaches used to incorporate environmental drivers in stock assessment:

- Use environmental variables to standardize CPUE
- Link environmental variable(s) to key life history processes (e.g., movement, recruitment, and/or growth)
- Use time-period-specific and/or area-specific life history parameters in stock assessment (time/space blocks)
Use environmental variables to standardize CPUE

• Widely used in HMS stock assessment (Erisman et al. 2011).

• Changes in fisheries spatial dynamics
  ✓ Hyperstability: overfishing to go undetected
  ✓ Hyperdepletion: foregone yields (van der Lee 2012)

Critical to understand gear dynamics and environmental influences for analyzing CPUE data.

Biased estimates of relative abundance if important environmental covariates are excluded in CPUE standardization (Bigelow and Maunder 2007)
Link environmental variable(s) to key life history processes (e.g., movement, recruitment, and/or growth)

\[ N_{t+1} = GSN_t + R_t \]

climatic-driven recruitment models

\[ R_t = \frac{aSSB_t}{\beta + SSB_t} e^{\Sigma_i \theta_i E_{i,t} e^{Rdev_t}} \]

Tanaka et al. In revision
$$N_{t+1} = GSN_t + R_t$$

Model-based approach to complement survey-based abundance index.

Environment-dependent modeled fish density field

Tanaka et al. In revision
\[ N_{t+1} = GSN_t + R_t \]

Growth transition matrices accounting for changing phenology.

Winter & Spring

\[
\begin{array}{ccccc}
1.0 & 0.0 & 0.0 & 0.0 & 0.0 \\
0.0 & 1.0 & 0.0 & 0.0 & 0.0 \\
0.0 & 0.0 & 0.0 & 0.0 & 0.0 \\
0.0 & 0.0 & 0.0 & 1.0 & 0.0 \\
0.0 & 0.0 & 0.0 & 0.0 & 1.0 \\
\end{array}
\]

Summer & Fall

\[
\begin{array}{ccccc}
0.1 & 0.5 & 0.4 & 0.0 & 0.0 \\
0.0 & 0.0 & 0.4 & 0.5 & 0.1 \\
0.0 & 0.0 & 0.0 & 0.2 & 0.6 \\
0.0 & 0.0 & 0.0 & 0.1 & 0.1 \\
0.0 & 0.0 & 0.0 & 0.0 & 0.1 \\
\end{array}
\]
Improving assessment of *Pandalus* stocks using a seasonal, size-structured assessment model with environmental variables. Part I: Model description and application

Jie Cao, Yong Chen, and R. Anne Richards

**Abstract:** *Pandalus* species display the following features that make it difficult to apply traditional age-based stock assessment models: (i) difficulty of determining age in the absence of hard parts retained through the molt; (ii) sex change in which individuals mature first as males and then transform to females; and (iii) potentially strong influence of environmental conditions on recruitment population dynamics. In this context, we propose a seasonal, size-structured assessment model dedicated to stock assessment of hermaphroditic *Pandalidae*. The modeling framework incorporates a submodel for changes of length at sex transformation and functions to incorporate environmental effects on recruitment dynamics. The model can be directly fitted to length-structured data, overcoming the length to age conversion problem. The model has a seasonal time step that allows it to account for seasonal variations in biological processes and fishing patterns. The model provides stock assessment outputs, such as fishing mortality and stock biomass estimates, and sex-specific abundance-at-length. The model is applied to the exploited shrimp stock of *Pandalus borealis* in the Gulf of Maine as an example of its utility. The model proposed in this study is flexible and parameterized can be applied to many other exploited stocks.
Use time-period-specific and/or area-specific life history parameters in stock assessment (time/space blocks)

- Need to identify time blocks/areas within which fish productivity/life history is more or less stable
North Pacific Neon Flying Squid Fishery

15-19 °C in August
14-18 °C in September
10-13 °C in October
12-15 °C in November

21-25 °C from January to May

A stock assessment for *Illex argentinus* in Southwest Atlantic using an environmentally dependent surplus production model

WANG Jintao1,5,4, CHEN Xinjun1,2,3,5*, Kevin W. Staples4, CHEN Yong4,1

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5 Collaborative Innovation Center for National Distant-water Fisheries, Shanghai 201306, China

Received 25 June 2016; accepted 14 February 2017

Bower and Ichii 2005
Chen and Tian 2005
Four surplus production models were proposed:

Assume SSTs have no effects on $K$ and $r$

\[
\log(B_{i+1}) | K, \sigma^2 = \log(K) + u_i
\]

\[
\log(B_{i+1}) | B_{i-1}, K, r, \sigma^2 = \\
= \log \left\{ B_{i-1} + rB_{i-1} \left( 1 - \frac{B_{i-1}}{K} \right) - C_{i-1} \right\} + u_i
\]  (3)

Assume SSTs on the spawning grounds have effects on parameter $K$

\[
\log(B_{i+1}) | K, \sigma^2 = \log(K) + u_i
\]

\[
\log(B_{i+1}) | B_{i-1}, K, r, \sigma^2 = \\
= \log \left\{ B_{i-1} + rB_{i-1} \left( 1 - \frac{B_{i-1}}{PS_{i-1}K} \right) - C_{i-1} \right\} + u_i
\]  (4)

Assume SSTs on the feeding grounds have effects on parameter $r$

\[
\log(B_{i+1}) | K, \sigma^2 = \log(K) + u_i
\]

\[
\log(B_{i+1}) | B_{i-1}, K, r, \sigma^2 = \\
= \log \left\{ B_{i-1} + Pf_{i-1}rB_{i-1} \left( 1 - \frac{B_{i-1}}{K} \right) - C_{i-1} \right\} + u_i
\]  (5)

Assume SSTs on the spawning grounds have effects on $K$ and SSTs on the feeding grounds have effects on $r$

\[
\log(B_{i+1}) | K, \sigma^2 = \log(K) + u_i
\]

\[
\log(B_{i+1}) | B_{i-1}, K, r, \sigma^2 = \\
= \log \left\{ B_{i-1} + Pf_{i-1}rB_{i-1} \left( 1 - \frac{B_{i-1}}{PS_{i-1}K} \right) - C_{i-1} \right\} + u_i
\]  (6)

Wang et al., 2017
Table 4. – Summary of the estimates of parameters with the bootstrapped ML method from 1500 runs of bootstrap simulation for CPUE and catch data observed from 2003 to 2013 for *O. bartramii*. For each bootstrap run, mean square error (MSE) was calculated.

<table>
<thead>
<tr>
<th>Models</th>
<th>Statistic</th>
<th>r</th>
<th>K</th>
<th>q</th>
<th>MSE</th>
<th>AIC</th>
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<td></td>
<td>Median</td>
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<td>106</td>
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<td>0.45</td>
<td>30.26</td>
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<td>SP</td>
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<td>45%</td>
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<td>33%</td>
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<tr>
<td></td>
<td>5&lt;sup&gt;th&lt;/sup&gt;%</td>
<td>0.22</td>
<td>42</td>
<td>0.01</td>
<td>0.38</td>
<td>25.38</td>
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<tr>
<td></td>
<td>95&lt;sup&gt;th&lt;/sup&gt;%</td>
<td>2.707</td>
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<td>0.09</td>
<td>0.96</td>
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<td>Ps-EDSP</td>
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<td>0.027</td>
<td>0.43</td>
<td>25.32</td>
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<td></td>
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<td>0.031</td>
<td>0.49</td>
<td>27.47</td>
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<tr>
<td></td>
<td>CV</td>
<td>52%</td>
<td>38%</td>
<td>64%</td>
<td>30%</td>
<td>29%</td>
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<tr>
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<td>5&lt;sup&gt;th&lt;/sup&gt;%</td>
<td>0.214</td>
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<td>0.38</td>
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<tr>
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<td>0.03</td>
<td>0.45</td>
<td>34.53</td>
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<tr>
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<td>45%</td>
<td>71%</td>
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<td>31%</td>
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<tr>
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<td>Ps-Pf-EDSP</td>
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<tr>
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<td>Mean</td>
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<td>0.032</td>
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<tr>
<td></td>
<td>CV</td>
<td>56%</td>
<td>42%</td>
<td>68%</td>
<td>32%</td>
<td>32%</td>
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<td>1.226</td>
<td>261</td>
<td>0.076</td>
<td>0.93</td>
<td>39.93</td>
</tr>
</tbody>
</table>
Fig. 6. – Development of the *O. bartramii* fishery from 2003 to 2013. A, based on the PS model; B, based on the Ps-EDSP model. Triangle represents the biomass status of the first year (2003) of study; square represents the biomass status of the last year (2013).
Develop a framework to incorporate environmental variability into assessment

Qualitative modeling approach

Statistical modeling approach

Population modeling approach
American lobster fishery

American lobster supports the most valuable fishery in the United States worth over **666 million USD** in 2016. Gulf of Maine/Georges Bank accounted for ~97% of total landings (ACCSP 2017).
Changing environment

Global sea surface temperature trends ($^\circ$ yr$^{-1}$) over the period 2004-2013. (Pershing et al. 2015)

Time series of bottom temperature (blue) and surface temperature (orange) within Gulf of Maine. (Kleisner et al. 2016)
Changing environment

IPCC 5th assessment ensemble model projections in Northeast Continental Shelf under RCP 8.5

Surface temperature

Bottom temperature

NOAA ESRL 2016
Qualitative modeling approach
Evaluate the impact of climate variability on lobster habitat quality.

**Top:** Spatial distribution of the median habitat suitability index (HSI) over 1978-2013 in the coastal waters of Maine and New Hampshire for American lobster.

**Bottom:** Changes in HSI over the same time period. Darker red indicates change toward higher habitat suitability at higher magnitude.

Tanaka & Chen 2016
Statistical modeling approach
Evaluate the impacts of climatic variability on lobster distribution

Spatiotemporal lobster distribution dynamics forced by mesoscale climatic variability.

Potential climate-induced range shifts.

Tanaka et al. In press
\[ N_{t+1} = GSN_t + R_t \]

Climate-driven recruitment models

\[ R_t = \frac{\alpha SSB_t}{\beta + SSB_t} e^{\sum_i \theta_i E_{i,t} \sigma Rdev_t} \]

Temporal change in the proportion of the study area with suitable climate for lobster recruit (CL 53-63 mm; top) and spawning stock biomass (CL > 60 mm; bottom)
Changes in environment (HSI) not considered

Changes in environment (HSI) considered
Changes in environment (HSI) not considered

Changes in environment (HSI) considered
Changes in environment (HSI) not considered

Mohn = 0.52

Changes in environment (HSI) considered

Mohn = 0.31
Mohn = 0.51
Changes in environment (HSI) not considered

Mohn = 0.36
Changes in environment (HSI) considered
Climate vulnerability and resilience in the most valuable North American fishery

Arnault Le Bris¹,², Katherine E. Mills³, Richard A. Wahle⁴, Yong Chen⁵, Michael A. Alexander⁶, Andrew J. Allyn⁷, Justin G. Schuetz⁸, James D. Scott⁹, and Andrew J. Pershing⁸

¹Gulf of Maine Research Institute, Portland, ME 04101; ²School of Marine Sciences, University of Maine, Orono, ME 04469; ³National Oceanic and Atmospheric Administration, Earth System Research Laboratory, Boulder, CO 80305; and ⁴Cooperative Institute for Research in Environmental Sciences, University of Colorado, Boulder, CO 80309

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Managing natural resources in an era of increasing climate impacts requires accounting for the synergistic effects of climate, ecosystem changes, and harvesting on resource productivity. Coincident with recent exceptional warming of the northwest Atlantic Ocean and removal of large predatory fish, the American lobster has become the most valuable fishery resource in North America. Using a model that links ocean temperature, predator density, and fishing to population productivity, we show that harvester-driven conservation efforts to protect large lobsters prepared the Gulf of Maine lobster fishery to capitalize on favorable ecosystem conditions, resulting in the record-breaking landings recently observed in the region. In the species' range, has increased dramatically, while the fishery at the warmer southern edge in SNE has effectively collapsed (11). The exceptional warming rate in the northwest Atlantic, well above the global average (12), may have contributed to these divergent trajectories (13) (Fig. 1). Warming waters have been associated with decreased juvenile habitat (14, 15) and increased prevalence of epizootic shell disease (16) in the southern region, and with expanded juvenile habitat in the north (17, 18). These environmental changes have been accompanied by the decline of large-bodied predators in the GoM, which may have added to the regional differences in population trajectories (17, 19).
Hindcast of abundance of American lobster across three temperature and management scenarios (A) Gulf of Maine stock (B) Southern New England stock.

The blue lines show model hindcast with observed temperatures and actual management plans.

Yellow lines show model hindcast with constant temperature set at the average of the 1984-1999 time period (first half of temperature time series).

Red lines show model hindcast with observed temperatures but inversed management strategies between the two stocks.

Le Bris et al. 2018
Summary

In light of the great complexity of natural systems and large environmental variability, appropriate incorporation of environmental drivers in stock assessment can reduce the uncertainty and help develop assessment and management strategies more robust to the gradual and abrupt environmental changes.
Winter is not the same without shrimp. Since 1938, Maine fishermen have spent the cold months from December through March working the icy waters, hauling in nets filled with small, tender, dark pink shrimp: *Pandalus borealis*, northern shrimp. Fishing historically took place statewide by hundreds of boats. Maine
Challenges and opportunities abound in fisheries assessment in a changing environment.
Acknowledgement

Kisei Tanaka (UM), Jie Cao (UM), Larry Jacobson (NOAA NEFSC), Burton Shank (NOAA NEFSC), Andy Pershing (GMRI), Arnault Le Bris (MUN), Rick Wahle (UM), Andy Thomas (UM), James Thorson (NOAA NWFSC), Anne Richards (NOAA NEFSC), Jui-han Chang (NOAA NEFSC), Carl Wilson (ME DMR), Kathleen Reardon (ME DMR), and Sam Truesdell (GMRI)
Thanks! Question?