**The dream and the reality: meeting decision-making time frames while incorporating ecosystem and economic models into management strategy evaluation**

Jonathan J. Deroba1,\*, Sarah Gaichas1, Min-Yang Lee1, Rachel G. Feeney2, Deirdre Boelke2, Brian J. Irwin3

1Northeast Fisheries Science Center, Population Dynamics Branch,

166 Water Street, Woods Hole, Massachusetts 02543, USA

2New England Fishery Management Council

50 Water Street, Mill 2, Newburyport, MA 01950, USA

3U.S. Geological Survey, Georgia Cooperative Fish and Wildlife Research Unit, Warnell School of Forestry and Natural Resources, University of Georgia, Athens, GA 30602, USA

\*Corresponding author: [jonathan.deroba@noaa.gov](mailto:jonathan.deroba@noaa.gov), 508-495-2310 (office), 508-495-2393 (fax)

**Abstract—**

**Introduction**

Management strategy evaluation (MSE) uses simulation to evaluate the trade-offs resulting from alternative management options in the face of uncertainty (Punt et al. 2014). MSEs require time, however, for stakeholder input, data collection, and model development (Butterworth 2007; Punt et al., 2014). As such, the process can take much longer than “traditional” management time frames (Butterworth 2007). The development time is also likely to lengthen when explicit ecosystem, multi-species, or socioeconomic considerations are desired because the data and modeling needs, and subsequent uncertainties, are all greater than in a single species approach. This manuscript chronicles the development of an MSE done on a truncated timetable (~12 months) required to meet management time frames.

In January 2016, the New England Fishery Management Council (NEFMC), the political body responsible for federally managed species in the northeast US, approved the conduct of an MSE to evaluate harvest control rules (HCRs) for Atlantic herring (hereafter herring) *Clupea harengus.* The primary goal of this MSE was to evaluate the effects of alternative HCRs on the herring fishery, predators of herring, and the human environment. The MSE was also to include a public stakeholder process. The NEFMC desired to have results from the MSE ready to inform fisheries management decisions within one year, which left little time to develop the technical aspects of the MSE, especially in the context of multiple public stakeholder workshops. A particularly challenging aspect of the time frame was deciding what technical aspects of the MSE (e.g., operating models) could be compromised (i.e., perhaps not ideal from a scientific or best-practices standpoint) while ensuring the results would still accurately portray the trade-offs among objectives and remain relevant for decision-making. The objectives of this manuscript were to:

1. Evaluate the relative performance of HCRs at meeting herring fishery objectives, including those related to predators of herring, as informed by stakeholder input, and,
2. Discuss our approach to developing an MSE on a relatively truncated timetable in order to meet management time frames, and identify the lessons learned throughout the process, especially as they relate to using MSE as a tool to advance an ecosystem based approach to management (Plagányi et al., 2014).

**Methods**

**Stakeholder workshops**

Workshop #1 identified objectives, metrics, and uncertainties. See other paper for details. Here we report results for those metrics that were most responsive or likely of broad interest. Workshop #2 presented results and attempted to identify preferred performance for the metrics. This aspect is not dealt with here.

**Herring**

*Basics.—*An MSE was developed specific to Gulf of Maine – Georges Bank Atlantic herring. The MSE was a modified version of that used in Deroba (2014), and symbols were largely consistent with Deroba (2014; Table 1). The MSE was based on an age-structured simulation that considered fish from age-1 through age-8+ (age-8 and older), which is consistent with the age ranges used in the 2012 and 2015 Atlantic herring stock assessments (NEFSC 2012; Deroba 2015). The abundances at age in year one of all simulations equaled the equilibrium abundances produced by the fishing mortality rate that would reduce the population to 40% of . Abundance in each subsequent age and year was calculated assuming that fish died exponentially according to an age and year specific total instantaneous mortality rate (Table XX T1-T2).

Recruitment followed Beverton-Holt dynamics (Francis 1992; Table XX T3-T5). The variance of recruitment process errors equaled 0.36 and the degree of autocorrelation equaled 0.1, which are values consistent with recruitment estimates from a recent Atlantic herring stock assessment (Deroba 2015).

*Assessment Error.—*A stock assessment was approximated (i.e., assessment errors) similar to Punt et al. (2008) and Deroba (2014). Assessment error was modeled as a year-specific lognormal random deviation common to all ages, with first-order autocorrelation and a term that created the option to include bias (Table XX T6-T7). The variance of assessment errors equaled 0.05 and autocorrelation equaled 0.7. Rho allowed for the inclusion of bias in the assessed value of abundance (see below; Deroba 2014). Assessed spawning stock biomass was calculated similarly to except with replaced with (Table XX T5), and assessed total biomass was calculated as the sum across ages of the product of and .

*Operating Models.—*The stakeholder workshops identified uncertainties about herring life history traits and stock assessment, and the effect of some of these uncertainties on harvest control rule performance was evaluated by simulating the control rules for each of eight operating models (Table 2; Figures 1-2). The uncertainties addressed by the eight operating models included: Atlantic herring natural mortality and recruitment , Atlantic herring weight-at-age, and possible bias in the stock assessment beyond the unbiased measurement error .

The specific values used in the operating models for each of the uncertainties were premised on data used in recent stock assessments or estimates from fits of stock assessment models (Deroba 2015). Natural mortality in recent stock assessments has varied among ages and years, with being higher during 1996-2014 than in previous years (NEFSC 2012; Deroba 2015). Natural mortality, however, has also been identified as an uncertainty in the stock assessments and sensitivity runs have been conducted without higher during 1996-2014, such that was constant among years (NEFSC 2012; Deroba 2015). To capture uncertainty in in the MSE, operating models were run with either relatively high or low (Table 2; Figure 1). Relatively high values equaled the age-specific natural mortality rates used for the years 1996-2014 in the stock assessment. Relatively low values in the MSE equaled the age-specific natural mortality rates used for the years 1965-1995 in the stock assessment. In the MSE, was always time invariant.

Uncertainty in estimates of stock-recruit parameters were represented in the MSE by using the parameters estimated by stock assessments fit with and without the higher during 1996-2014. Stock assessment fits with higher during 1996-2014 produced estimates of steepness and unfished *SSB* that were lower than in stock assessment fits without higher during 1996-2014 (Table 3; Figure 1). Thus, operating models with relatively high always had relatively low steepness and unfished *SSB*, and the opposite held with relatively low (Table 2).

Uncertainty in Atlantic herring size-at-age was accounted for by having operating models with either fast or slow growth (i.e., weights-at-age; Table 2; Figure 3). Atlantic herring weight-at-age generally declined from the mid-1980s through the mid-1990s, and has been relatively stable since. Reasons for the decline are speculative and no causal relationships have been established. Thus, fast growth operating models had weights-at-age that equaled the January 1 weights-at-age from the most recent stock assessment averaged over the years 1976-1985, while the slow growth operating models averaged over the years 2005-2014 (Deroba 2015). In the MSE, weight-at-age was always time invariant.

Differences in , stock-recruit parameters, and weights-at-age led to differences in unfished and *MSY* reference points among operating models (Table 3). The effect of and stock-recruit parameters was larger than the effect of differences in weight-at-age (Table 3).

To address concerns about possible stock assessment bias, operating models with and without a positive bias were included. In operating models without bias, and the only assessment error was that caused by the unbiased measurement errors . In operating models with bias, , which was based on the degree of retrospective pattern in *SSB* from the most recent stock assessment (Deroba 2015).

*Harvest Control Rules.—*Several basic control rules were evaluated, including a biomass based control rule (Katsukawa 2004), a constant catch rule, and a conditional constant catch rule (Figure 3; Clark and Hare 2004; Deroba and Bence 2012). The biomass based control rule was defined by three parameters: the proportion () of that dictates the maximum desired fishing mortality rate , an upper *SSB* threshold (*SSBup*), and a lower *SSB* threshold (*SSBlow*). The equaled the maximum when was above the upper threshold, declined linearly between the upper and lower thresholds, and equaled zero below the lower threshold:

The was then used to set a quota in year + 1 (Table XX T8). equaled times , and was time and simulation invariant selectivity at age equal to the values for the mobile gear fishery reported in Deroba (2015; Table 1). was used to set a quota in the following year to approximate the practice of using projections based on an assessment using data through year – 1 to set quotas in the following year(s). Furthermore, although was set using, the quota was based on because the fishery selects some immature ages. The fully selected fishing mortality rate that would remove the quota from the true population was found using Newton-Raphson iterations.

Several variations of the biomass based rule were also evaluated. These variations included applying the control rule annually, using the same quota for three year blocks such that the control rule is applied every fourth year (i.e., ), using the same quota for 5 year blocks, and using the same quota for three year blocks but restricting the change in the quota to 15% in either direction when the control rule was reapplied in the fourth year. Thus, four variants of the biomass based control rule were evaluated: 1) annual application, 2) three year blocks, 3) five year blocks, and 4) 3 year blocks with a 15% restriction.

For each biomass based control rule variant, a range of values for the three parameters defining the control rule were evaluated. The proportion () of that dictates the maximum desired fishing mortality rate was varied from 0.1 to 1.0 in increments of 0.1, while the upper and lower *SSB* threshold parameters (*SSBup*, *SSBlow*) were varied from 0.0 to 4 but with inconsistent increments (i.e., 0.0, 0.1, 0.3, 0.5, 0.7, 0.9, 1.0, 1.1, 1.3, 1.5, 1.7, 2.0, 2.5, 3, 3.5, 4). The full factorial of combinations for the three biomass based control rule parameters produced 1,360 shapes (note *SSBlow* must be < *SSBup*) and each of these shapes was evaluated for each of the four biomass based control rule variants described above.

The constant catch control rule is defined by one parameter, a desired constant catch (i.e., quota) amount (Figure 3). The constant catch amounts were varied from 0.1 to 1.0 in increments of 0.1.

The conditional constant catch rule used a constant desired catch amount unless removing that desired catch from the assessed biomass caused the fully selected fishing mortality rate to exceed a pre-determined maximum, in which case the desired catch was set to the value produced by applying the maximum fully selected fishing mortality rate to the assessed biomass (Figure 3). Thus, the conditional constant catch rule has two policy parameters: a desired constant catch amount, and a maximum fishing mortality rate. The constant catch amounts were varied from 0.1 to 1.0 in increments of 0.1, while the maximum fishing mortality rate equaled 0. 5. When the maximum fishing mortality rate portion the conditional constant catch rule was invoked, a quota was set in the same manner as when in the biomass based control rule described above.

*Implementation Error.—*Implementation errors were also included in a similar way as in Punt et al. (2008) and Deroba and Bence (2012), as year-specific lognormal random deviations (Table XX T9). The variance of implementation errors equaled 0.001.

*Performance metrics.—*For each combination of control rule shape and operating model, 100 simulations were conducted, each for 150 years. Preliminary simulations suggested that this number of simulations and years was sufficient for results to be insensitive to starting conditions and short-term dynamics caused by auto-correlated processes. Median *SSB*, ,, yield, , biomass of herring dying due to , and the proportion of the herring population comprised of age-1 fish over the last 50 years of each simulation were recorded as performance metrics. Additional performance metrics included the proportion of the last 50 years of each simulation with *SSB* < , *SSB* < (i.e., proportion of the last 50 years that are overfished), *SSB* < , *SSB* < , fully-selected (i.e., proportion of the last 50 years that overfishing occurred), and (i.e., proportion of the last 50 years that the fishery was closed). Interannual variation in yield (*IAV*) was also recorded over the last 50 years of each simulation (Table XX T10). These performance metrics were highlighted to be of interest at the stakeholder workshops.

Two types of two-dimensional tradeoff plots for some pairs of performance metrics were used to graphically summarize results. 1) For comparing large numbers of control rule shapes, tradeoff plots were generated for individual operating models and were based on the median among simulations, such that each control rule shape was represented by a single point. These types of plots were generally used to introduce the broad topic of tradeoffs, convey the extent of performance that each general control rule could achieve, and to highlight the pairs of metrics with relatively strong tradeoffs. While focusing on a single operating model and relying solely on the median ignores variation in results, simultaneously plotting the range of performance among operating models with multiple percentiles for thousands of control rule shapes was ineffectual. 2) For comparing relatively few control rule shapes (e.g., < ~6), tradeoff plots were generated using shaded areas that ranged from the 25th to the 75th percentile of each performance metric among all the operating models for each control rule shape. These types of plots were generally used to introduce the concept of “robustness”, i.e., that some control rule shapes are more certain to produce a given result or tradeoff than other control rule shapes. These two types of tradeoff plots are presented in separate Results sections below.

**Predators**

OMs

**Performance metrics**

Herring

Predators

Economic –

There are many economic methods that can inform ecosystem approaches to fisheries management. Flaaten and Stollery (1996) and Brown, Berger, and Ikiara (2005) examine the bioeconomics of predator-prey interactions. Edwards et al. (2004); Jin et al. (2016) illustrate a “reduced form” portfolio approach. Jin et al. (2003, 2012) link regional economic models to ecosystem models. Tschirhart (2000); Finnoff and Tschirhart (2003) link structural economic models of constrained optimization to ecosystem models.

Two economic models were recently developed that focused on herring in the Northeast United States. Kirkley et al. (2011) use a static input-output model to simulate the effects of changes in herring quotas and predator biomass levels on many sectors of the New England economy, through the intermediary of the extractive herring sector. The authors take an optimization approach: herring landings are selected to maximize output. The model is static, so changes in commercial herring removals cannot impact predators (through changes in herring biomass). The authors also assume constant prices for herring are assumed; this assumption is relaxed later in this section. Finally, the Kirkley et al. (2011) analysis suggested that (a) the effects of changes in herring catch are mostly confined to the herring fishery and (b) the effects of dramatic changes in the herring fishery on other segments of the economy (in percentage terms) are smaller than miniscule. Because of these two reasons, and the fact that the first stakeholder workshop did not put forth objectives related to other parts of the economy, an IO style model was not developed further. Lehuta et al. (2013) also construct an coupled economic model of herring. We do some different stuff; but we also borrow some stuff. We don’t explicitly model the lobster fishery. We don’t have zero economic profits.

The economic sub-model converts Yield from the biological component into Gross and Net Operating Revenues. An econometric model of prices as a function of previous prices and landings is estimated; the results of this model are used to predict prices as a function of landings in the simulation model (Appendix Table or Table of Parameters). Following Lehuta et al (2013), we assume that an unlimited quantity of menhaden is available as a perfect substitute at a backstop price.

There are two fleets, purse seine and trawl, that are have the ability to catch 30 and 70% of the yield respectively. The trawl fleet has a higher marginal cost of fishing (Appendix Table or Table of Parameters). The fishery yield acts as a constraint (upper bound) on the landings of both fleets. If a fleet is unconstrained, then it makes zero net profits (it will fish until it is unprofitable to do so, the point at which price is equal to marginal cost). If a fleet is constrained by regulations, then positive net profits are possible. Gross Revenues are simply yield multiplied by price. Net operating Revenues subtract out the variable operating costs (not including labor or fixed costs). Because the price of herring decreases when landings are high, there is a level of landings above which increases actually decrease Gross or Net revenues.

An additional performance metric, stationarity, is used to assess the stability of net revenues over the terminal period. For each simulation, we perform an econometric test of stationarity (Dickey and Fuller, 1979). We classify a simulation as stationary if we reject the null at the 10% significance level. We then compute the number of simulation (out of 100) that are stationary for each of the 8 operating models and 5,460 control rules. This classification may be too knife-edged. Many methods have been used in the fields of meta-analysis and bioinformatics to combine the results of independent experiments (Folks, 1984; Rice, 1990; Whitlock,

2005). We therefore use a weighted Z-score method to combine these trials (Whitlock 2005).

Not built in yet: Supporting regressions for prices. Supporting tables for costs.

**Results**

See outline

**Discussion**

See outline

* Ecosystem based approaches are also being increasingly considered for fisheries management, and MSEs have subsequently included more environmental and climate forcing, multi-species interactions, and economic considerations (Dichmont et al., 2008; A’mar et al., 2010; Punt et al., 2014). More specifically, explicit consideration of how harvest control rules (HCR) for prey species (i.e., forage fish) affect predators has also been suggested (Cury et al., 2011; Pikitch et al., 2012; ADD Hilborn rebuttal as relevant).
* Fishery management must, among other things, incorporate multiple objectives, promote legitimacy by reflecting accepted norms, and have low and equitably distributed transactions costs (Hanna, 1999). User participation in decision-making is a way to increase regulatory legitimacy, although the right amount of user participation requires balancing of costs and benefits (Hanna, 1995). The MSE also included a stakeholder process that solicited goals, objectives, and information from any interested member of the public. User participation can be a double-edged sword: meetings typically attract participants with the most extreme views (Osborne et al., 2000; Turner and Weninger, 2005).

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