SSMSE: An R package for Management Strategy Evaluation with Stock Synthesis Operating Models

Kathryn L. Doering[1¶], **Nathan R. Vaughan**[*2], **John F. Walter**[3], **Richard D. Methot**[4], **Skyler R. Sagarese**[3], **Matthew Smith**[3], **Nicholas A. Farmer**[5], **Shannon Calay**[3], **Nancie J. Cummings**[3], **Kelli F. Johnson**[6], **Kristin Marshall**[6], **Cassidy D. Peterson**[7], **Ian G. Taylor**[6], and **Chantel R. Wetzel**[6]

1 Caelum Research Corporation in support of Northwest Fisheries Science Center, National Oceanic and Atmospheric Administration, Seattle, WA **2** Vaughan Analytics in support of Southeast Fisheries Science Center, National Oceanic and Atmospheric Administration, Miami, FL **3** Southeast Fisheries Science Center, National Oceanic and Atmospheric Administration, Miami, FL **4** NOAA Senior Scientist for Stock Assessments, National Marine Fisheries Service, National Oceanic and Atmospheric Administration, Seattle, WA **5** Southeast Regional Office, National Oceanic and Atmospheric Administration, St. Petersburg, FL **6** Northwest Fisheries Science Center, National Oceanic and Atmospheric Administration, Seattle, WA **7** Southeast Fisheries Science Center, National Oceanic and Atmospheric Administration, Beaufort, NC ¶ Corresponding author

DOI: 10.21105/joss.04937

Software

- Review
- Repository
- Archive

Editor: Sebastian Benthall

Reviewers:

- @quang-huynh
- @iagomosqueira

Submitted: 29 June 2022
Published: 30 October 2023

Statement of Need

Management Strategy Evaluation (MSE) is a decision-support tool for fisheries management. MSE uses closed-loop simulation to evaluate the long-term performance of management strategies with respect to societal goals like sustainability and profits (Punt et al., 2014 ; Figure 1; Smith, 1994). Management strategies are pre-defined decision rules that can dynamically adjust management advice given an estimate of population status. In addition to specifying management actions, management strategies may specify how a stock assessment model is configured to determine the size and status of a population (Sainsbury et al., 2000).

Within MSE simulations, operating models (OMs) represent the hypothesized dynamics and relevant complexity of the system. Multiple OMs are typically generated for a single MSE to reflect different uncertainties and assess management performance under uncertainty. Developing suitable OMs requires an analyst to, at a minimum, define: the life history characteristics of the population and the fishing effort and selectivity of all fisheries affecting the population; and consider: the spatial distribution of the population and any critical environmental covariates or species interactions. OMs should be calibrated (or "conditioned") on available data to ensure that model projections are consistent with historical observations (Punt et al., 2014). Due to the many considerations, developing sufficient OMs is time-intensive.

Fortunately, the requirements for specifying OMs are largely the same as the requirements for developing a stock assessment. Due to the overlap in requirements and the millions of dollars invested in developing stock assessments (Methot, 2015), MSE approaches that build on previous stock assessment products can increase productivity (Maunder, 2014). Stock assessment models for federally managed species in the U.S. undergo substantial scrutiny during a peer review process (Brown et al., 2006; Lynch et al., 2018), and thus stock assessment models provide an excellent starting point for OMs used in MSE.

Stock Synthesis (SS3, Methot & Wetzel, 2013) is a generalized single-species population dynamics modeling platform widely used to assess marine fish populations. In the U.S., more

*Co-first author

than 220 stock assessments for federally managed populations were conducted using SS3 between 2010 and 2020 (NOAA Fisheries, 2021). The rich set of feature options in SS3 allows model parameterizations that are specific to a population. SS3 models have been used successfully as OMs in several MSEs (e.g., International Scientific Committee for Tuna and Tuna-Like Species in the North Pacific Ocean, 2019; Maunder, 2014; Sharma et al., 2020). However, in all cases, a large amount of time and effort was required to write specialized code modifying input files and model structure to implement MSE-specific simulations. The majority of this code was not reusable since it was developed with a specific MSE analysis and population in mind. While the SS3 OMs were based on existing stock assessments, in these scenarios the specific code provided little capacity building for future MSEs. Significant improvements in MSE throughput could be achieved via the development of generalized MSE software that is easily adaptable to new analyses and populations.

Existing generalized MSE tools (e.g., openMSE, Hordyk et al., 2022; FLR's mse R package, Jardim et al., 2017) have been built around custom OMs developed for use in each package. These tools provide the benefits of a generalized MSE codebase and a wide range of built-in procedures and estimation model options that are able to answer a variety of questions. However, existing generalized MSE tools offer limited capacity to use existing stock assessment products directly as OMs. These tools do support importing specifications from stock assessment model files such as SS3, but converting SS3 models to a different model format often results in some loss of model structure. For complex populations, the loss of model structure may not represent the population well. Additionally, it can be time consuming for the analyst to learn a different model format.

The primary goal of the SSMSE project was to develop a tool that can use existing SS3 models to generate OMs and then use these OMs in MSE simulations. This approach provides the advantages of allowing a wide selection of existing stock assessment models to be directly used in MSE.

Overview

SSMSE gives users flexibility in the MSE setup while reducing the amount of code that analysts write to conduct novel MSEs. SSMSE is available as an R package and employs other R dependencies developed for use with SS3 (e.g., ss3sim, Anderson et al., 2014; r4ss, Taylor et al., 2021).

Users only need a few functions to run an analysis using SSMSE (Table 1; Figure 3). The `run_SSMSE()` wrapper function runs the SSMSE simulations (Figure 2). Inputs to `run_SSMSE()` include the file names and file directories of the conditioned SS3 models to use as operating models (`OM_name_vec` and `OM_in_dir_vec`), the type of management strategy for each scenario (`MS_vec`), the number of iterations to run for each scenario (`iter_vec`), how to sample from the operating model in each scenario (`sample_struct_list`), the number of years to run the simulations (`nyrs_vec`) and how often the management strategy is run (`nyrs_assess_vec`). Helper functions for setting the variables to pass to `run_SSMSE()` are available. `run_SSMSE()` includes the option to run iterations in parallel (`run_parallel = TRUE`), reducing the time required to run simulations. Other options include the ability to use an SS3 estimation model or a custom function as a management strategy and the ability to change parameters in the OM during the projection period of the simulation. The custom function must be able to use sampling from an SS3 data file as input and output fleet-specific catches by year. After the simulations are complete, users can call the `SSMSE_summary_all()` function to compile key model values from many model folders into three summary tables. The user can then conduct further analyses and plots based on the summaries.

Five types of uncertainty that are typically captured in MSEs are process uncertainty, parameter uncertainty, model uncertainty, errors in assessments, and implementation uncertainty (Punt et al., 2014). These can all be implemented using SSMSE:

1. Process uncertainty can be accounted for by including variation in parameters in the OMs for parameters that are typically treated as fixed in stock assessments. Process uncertainty can be captured by using the `future_om_list` input to `run_SSMSE()`. This input allows users to specify time-varying trends and deviations in recruitment and other model parameter values during the simulation period.
2. Parameter uncertainty can be captured by the user creating different operating models for use in different scenarios. The helper function `develop_OMs()` generates new operating models with different specified parameter values to partially automate this process.
3. Model uncertainty includes relationships within the operating model that may not be specified correctly (e.g., uncertainty about which stock-recruitment relationship form is correct). To capture model uncertainty using SSMSE, the user could create multiple operating models (e.g., ones using two unique stock-recruitment relationship forms) to use in different scenarios.
4. Errors in assessments as defined here include specifying incorrect fixed parameter values or functional model structures in the estimation model and observational noise in data resulting in poor estimation of model parameter values (even if the assessment is correctly specified outside of those estimated parameters). Users can adjust errors in assessments by 1) specifying different fixed values and structures in different scenarios by directly changing the model files; and 2) by changing the sampling scheme through the `sample_struct_list` input to `run_SSMSE()` to adjust observation uncertainty. Assessment error is also an emergent property of the assessment model estimation algorithm itself, so the ability to run the estimation model rather than a placeholder captures this type of assessment error.
5. Implementation uncertainty happens because it is difficult to perfectly implement a theoretical management strategy. For example, fishing may continue to occur after the theoretical catch limit is caught because there is a time lag in reporting and the catch limit is exceeded before fishing can be stopped. Implementation uncertainty (also known as implementation error) can be added by specifying it in the `future_om_list` input to `run_SSMSE()`.

The source code for SSMSE is available at https://github.com/nmfs-fish-tools/SSMSE. A user manual provides more details on how to use the SSMSE tool. SSMSE can be installed from the R console using the `remotes` R package:

```
remotes::install_github("nmfs-fish-tools/SSMSE")
```

Case Study

Natural mortality (i.e., mortality not due to fishing) is a key life history characteristic that can have large effects on both population estimates and management benchmarks (e.g., Mace et al., 2021; Marty et al., 2003). Natural mortality is often assumed constant in population dynamics models because collecting informative data to estimate time-varying and/or age-varying natural mortality is difficult. However, for many populations, natural mortality likely varies in magnitude over time (e.g., Krause et al., 2020; Plagányi et al., 2022; Regular et al., 2022).

In this case study, we used SSMSE to investigate the effects of not accounting for episodic natural mortality spikes in the estimation model (i.e., stock assessment model; Table 2) on management objectives related to catch and population size. Natural mortality spikes could occur due to periodic changes in environmental conditions that can kill fish, such as red tide (Steidinger, 2009) or upwelling-driven hypoxia (Chan et al., 2008). We assessed the performance of two distinct management strategies. We used a cod-like species as the population and one fishing fleet and one survey in both the operating and estimation models.

Because the pattern of natural mortality is uncertain, we built three OMs, each reflecting a different hypothesis of the natural mortality dynamics of the stock: 1) constant instantaneous natural mortality at 0.2 y^{-1} (per year); 2) natural mortality at 0.2 y^{-1} with a spike in natural mortality of 0.3 y^{-1} every five years; and 3) natural mortality at 0.2 y^{-1} with a spike in natural mortality of 0.4 y^{-1} every five years (Figure 4). In all OMs, process uncertainty in selectivity and recruitment was considered. One fishery length selectivity parameter was assumed to vary randomly from year to year in the simulations. In addition, annual recruitment deviations were assumed to vary randomly from year to year. Selectivity and recruitment likely vary over time (Maunder & Thorson, 2019; Sampson & Scott, 2011), so allowing random deviations was considered a more realistic characterization of uncertainty among iterations. To ensure differences in performance are due to the management strategy rather than from the use of different randomly selected selectivity parameter values and recruitment deviations, SSMSE allows for the same sets of random values to be used for each scenario by setting a seed in the `run_SSMSE()` function. We ran 100 iterations of each scenario to characterize the process uncertainty in recruitment and selectivity. The number of iterations can also be specified in the `run_SSMSE()` function.

Two management strategies were tested with each of the OMs using the built-in "EM" management strategy option in SSMSE. The "EM" management strategy uses an SS3 model to estimate population size and status (simulating a stock assessment), and the SS3 forecast file associated with the estimation model to estimate management benchmarks and set future catches consistent with the harvest controls specified by the user in the estimation model forecast file. Two management strategies with alternative target harvest rates corresponding to a Spawning Potential Ratio (SPR) of 30% or 45% (SPR_{30} and SPR_{45}, respectively) were used. The estimation model assumed constant natural mortality of 0.2 y^{-1} (i.e., matching the hypothesized base natural mortality but not accounting for episodic spikes in natural mortality included in some OMs).

The forecasting module of the SS3 estimation model estimated the management benchmarks corresponding to SPR_{30} or SPR_{45}. SPR is defined as the fraction of the fished spawning stock biomass per recruit relative to the unfished spawning biomass per recruit (Goodyear, 1993). For example, a harvest rate corresponding to SPR_{30} would lead to 30% of unfished spawning biomass per recruit (higher harvest rate), while the lower harvest rate associated with SPR_{45} would leave 45% of unfished spawning biomass per recruit (lower harvest rate). The SPR_{30} and SPR_{45} management strategies demonstrate potential tradeoffs associated with managing with less precaution by allowing more fishing in the short term (SPR_{30}) or by managing with more precaution by allowing less fishing in the short term (SPR_{45}). The assessment and associated management action happened every five years in all scenarios, so the SS3 forecast module for each scenario also generated projections of five years of catch at the fishing mortality rate corresponding to SPR_{45} or SPR_{30}. The five years of catch was then removed from the simulated population in the OM as each OM was projected forward in time until the next management strategy time step (in this case study, every five years). The simulations applied a management period of 50 years into the future.

Performance metrics quantify the goals of the management system and are used to measure the relative performance of each management strategy within the MSE. To quantify performance in the long-term, point estimates of catch by year, standard deviation of catch across years, and the spawning biomass (a measure of population size) by year were extracted from the last 25 years of the simulations and averaged for each iteration across years, then plotted by scenario. In addition, to understand the short term effects on fishing, short-term catch was calculated by extracting point estimates of catch from the first 10 years of the projection, averaging for each iteration across years, and plotting.

The R code used to set up this simulation is available at https://nmfs-fish-tools.github.io/SSMSE/manual/M-case-study-ex.html. The complete simulation may take hours or days to run, so we recommend reducing the number of iterations if running for illustrative purposes.

Iterations were excluded if any runs of the estimation model failed to converge, had a high maximum gradient (>2), or had parameters on bounds. This resulted in a maximum of six iterations (6%) excluded from any scenario.

We found that managing the stock with more precaution in the face of episodic natural mortality spikes resulted in both higher long-term catch and less variability in catch (Figure 5). However, managing the stock with more precaution comes at the cost of less short-term catch. These results were true regardless if natural mortality was correctly captured within the management strategy (within the estimation model) or not.

Within the same management strategy, scenarios with higher spikes of natural mortality that were unaccounted for had slightly lower average catch, slightly higher catch variability, and slightly lower spawning biomass. In the short term, catch was similar regardless of the size of the natural mortality spikes in the OM. Although there were some consequences for not accounting for spikes in natural mortality, the performance metrics demonstrate that the choice of management strategy rather than capturing natural mortality correctly (or not) leads to a larger difference in performance.

The result that managing with more precaution results in higher long-term yields and less variability in yields is not surprising given that the level of spawning biomass that results in maximum sustainable yield is closer to SPR_{45} than to SPR_{30} for these populations. Harford et al. (2018) used a custom-built MSE and found that managing with more precaution in the face of episodic natural mortality spikes resulted in lower probabilities of overfishing and being overfished, but at the expense of lower catches. Here with only a few lines of code, SSMSE demonstrates similar findings, providing a powerful tool for rapidly conducting MSEs from existing SS3 stock assessment applications.

Summary

SSMSE is a generalizable tool for stock assessment scientists and MSE practitioners. It allows SS3 models to be used directly as OMs (and optionally as estimation models) within MSEs. We expect that SSMSE will greatly advance the capacity to conduct MSEs. As SS3 is one of the most widely used stock assessment platforms, adding MSE capacity means that any existing SS3 model could be the basis for MSE simulations with less effort and code. This will allow practitioners to more readily evaluate a wide range of research questions and potential management actions.

Acknowledgements

Thanks to Desiree Tommasi and Owen Hamel for providing comments that greatly improved this manuscript; Robert Wildermuth and Peter Kuriyama for their extensive testing of SSMSE; Matthew Damiano, Allan Hicks, and Huihua Lee for early discussions regarding MSE and the development of SSMSE; and Corrine Bassin and Christine Stawitz for their support in setting up the repository and documentation. KD and NV acknowledge funding for this project was provided through a NOAA Magnuson Stevens Act development grant.

Tables

Table 1. Functions that users can call in SSMSE.

Function	Description
`run_SSMSE()`	Run the MSE simulations
`SSMSE_summary_all()`	Summarize MSE output
`create_sample_struct()`	Helper function to create a list for future sampling from a model to use as input in `run_SSMSE()`

Function	Description
`create_future_om_list()`	Helper function that provides examples of the structure for the `future_om_list` input to `run_SSMSE()`
`develop_OMs()`	Helper function to turn one OM into many
`run_EM()`	Run an SS3 estimation model (uses `run_ss_model()`)
`run_ss_model()`	Run an SS3 model
`get_bin()`	Get location of the SS3 binary
`parse_MS()`	Run the management strategy and get catch by fleet for the projections. A function to reference for setting up custom management strategies.
`plot_index_sampling()`	Create diagnostic plot to compare the sampled index values to the OM expected values and original OM conditioning index data
`plot_comp_sampling()`	Create diagnostic plot to compare the sampled composition values to the OM expected values and original OM conditioning composition data.

Table 2. Details about the steps in the case study. See Figure 2 for a general schematic of steps.

General step	Details for case study	Differences across scenarios?	Differences across iterations within a scenario?
Create OM	Use OMs that differ in their assumed natural mortality values across scenarios; recruitment deviations and fishery selectivity pattern differ across iterations within scenarios	Yes	Yes
Sample data from OM	Use sampling scheme: survey index and age composition every 5 years, length composition from the fishery every 5 years. Use same sample size as in the original model the OM is derived from	No	No

General step	Details for case study	Differences across scenarios?	Differences across iterations within a scenario?
Run estimation method	Use SS3 estimation models	No	No
Use management actions to project n years of catch	Use the forecast modules from the SS3 models to project catch 5 years, managing either for SPR_{30} or SPR_{45}	Yes	No
Update OM with n years of catch	$n = 5$	No	No
Sample n years of data	$n = 5$	No	No

Figures

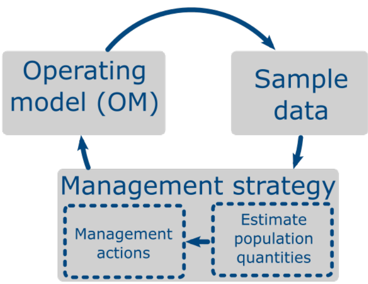

Figure 1: The main components of MSE simulations. The operating model (OM) represents the hypothesized dynamics. From the OM, data can be sampled (in the sample data step) and passed to the management strategy. The management strategy is run and usually influences the OM (e.g., the management strategy may remove a certain amount of catch from the OM) as the OM is projected forward in time. The management strategy can be subdivided into a step that estimates the population quantities (often using an estimation method) and a step that simulates management actions (including error in implementing the management actions).

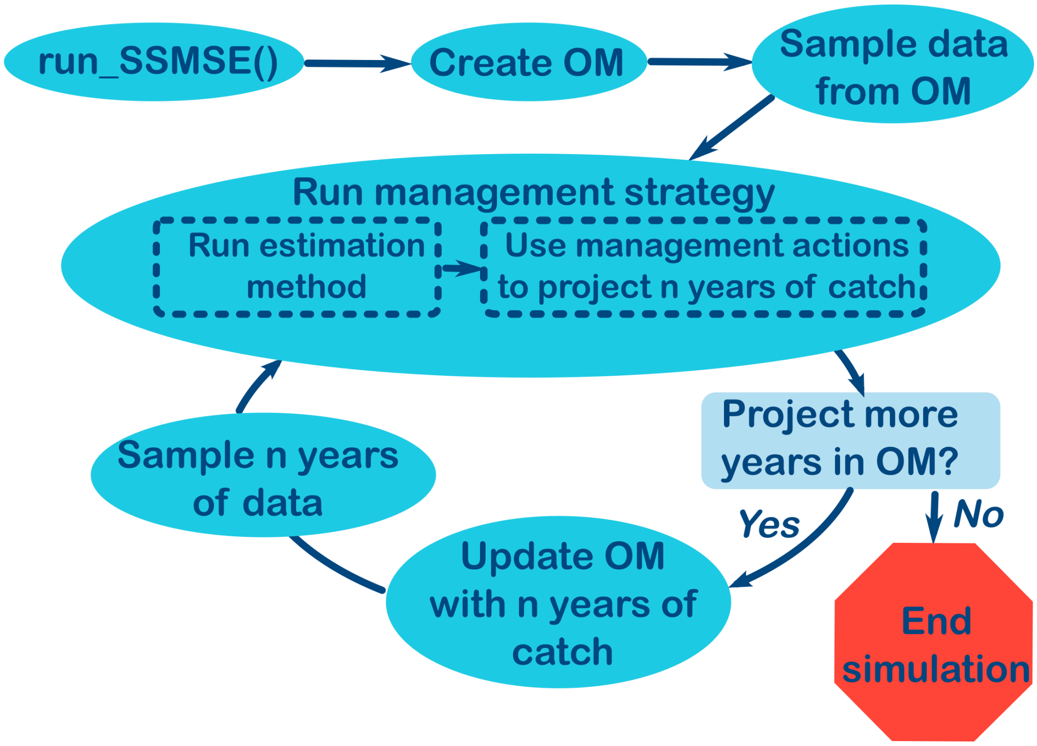

Figure 2: Schematic illustrating the steps within the `run_SSMSE()` function. Note for simplicity, this diagram only shows steps for a single iteration, even though multiple iterations and/or scenarios could be called through `run_SSMSE()`.

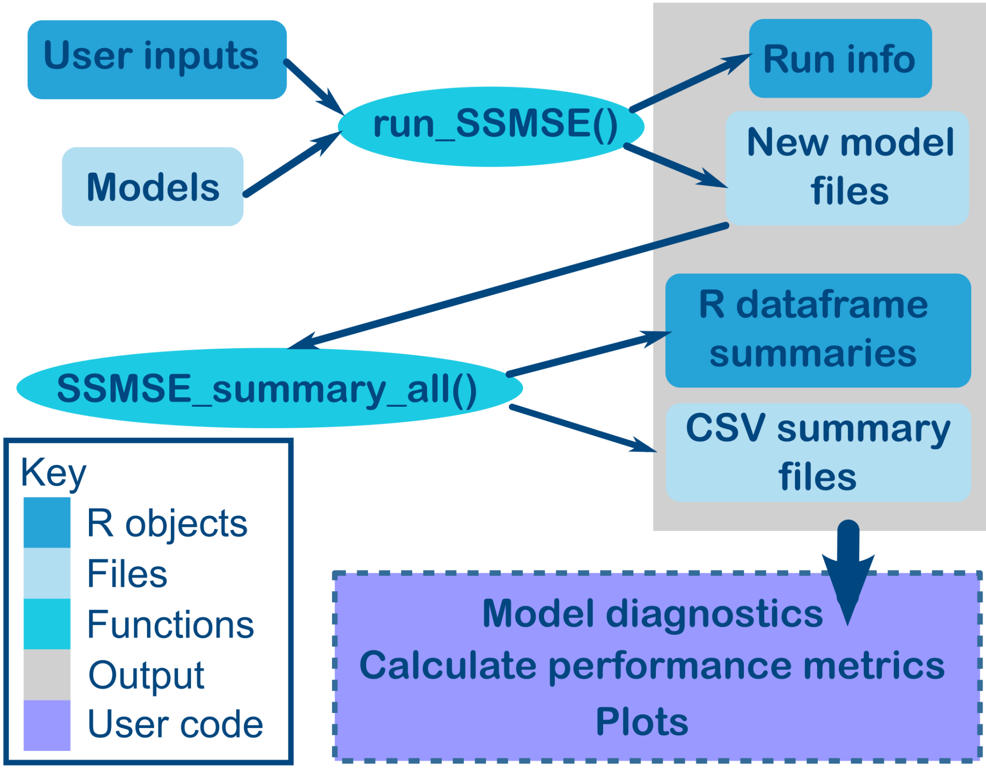

Figure 3: Diagram illustrating a basic workflow for using SSMSE. This diagram shows the functions (ovals) in addition to input and output objects (rounded rectangles) and the steps for which users will write their own code (rectangle enclosed by dashed line). Note that the helper functions `create_sample_struct()` and `create_future_om_list()` may be used to assemble components of the "user inputs."

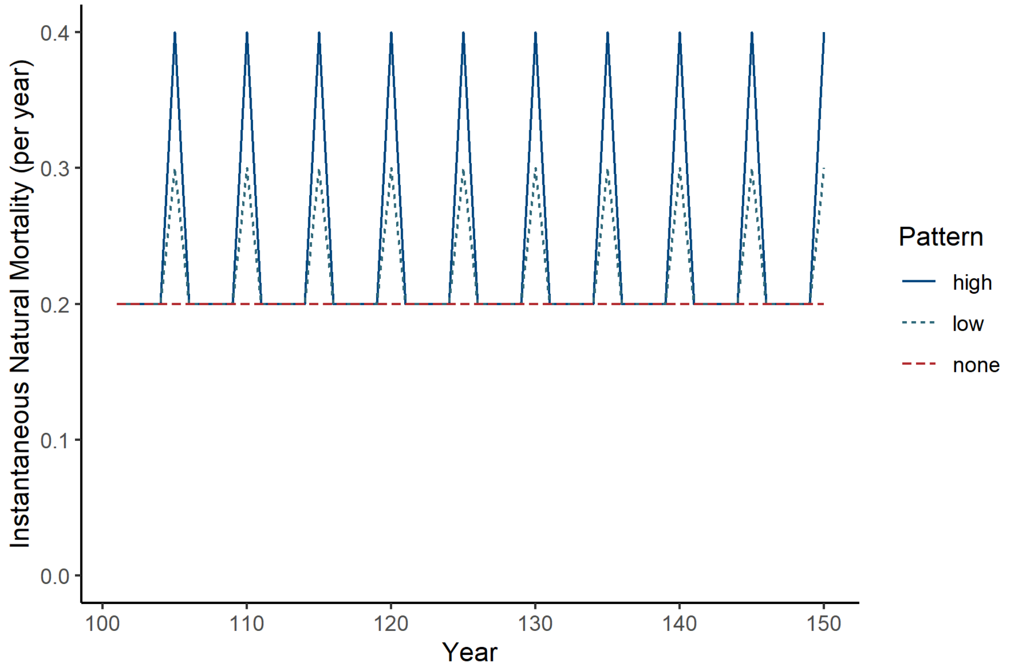

Figure 4: Natural mortality patterns in the case study OMs through the simulation years (years 101-150). The EMs assumed constant natural mortality equivalent to the pattern labeled "none."

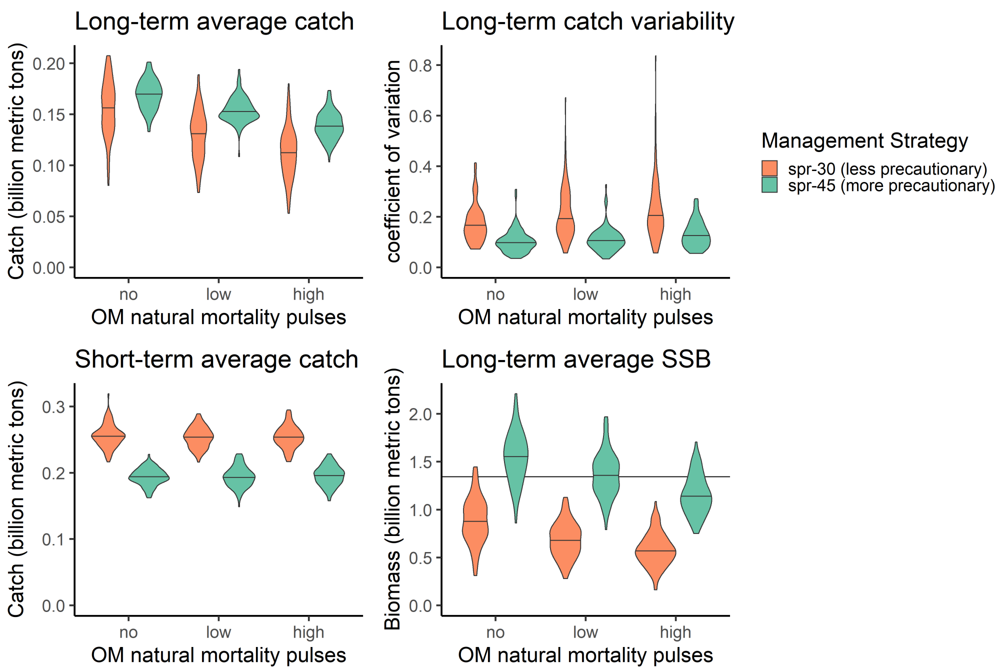

Figure 5: Performance metrics from the case study. Each plot shows a different performance metric. Each violin represents the distribution of the metric from a different scenario. Colors of the violins correspond to which management strategy was used in the scenario. The horizontal lines within each violin represent the median. For the plot in the bottom right corner, SSB means spawning biomass and the horizontal line outside of the violins represents the spawning biomass at the maximum sustainable yield.

References

Anderson, S. C., Monnahan, C. C., Johnson, K. F., Ono, K., & Valero, J. L. (2014). ss3sim: An R package for fisheries stock assessment simulation with Stock Synthesis. *PLOS ONE*, *9*(4), e92725. https://doi.org/10.1371/journal.pone.0092725

Brown, S. K., Shivlani, M., Die, D., Sampson, D. B., & Ting, T. A. (2006). The Center for Independent Experts: The national external peer review program of NOAA's National Marine Fisheries Service. *Fisheries*, *31*(12), 590–600. https://doi.org/10.1577/1548-8446(2006)31%5B590:TCFIE%5D2.0.CO;2

Chan, F., Barth, J. A., Lubchenco, J., Kirincich, A., Weeks, H., Peterson, W. T., & Menge, B. A. (2008). Emergence of anoxia in the California Current Large Marine Ecosystem. *Science*, *319*(5865), 920–920. https://doi.org/10.1126/science.1149016

Goodyear, C. P. (1993). Spawning stock biomass per recruit in fisheries management: Foundation and current use. *Canadian Special Publication of Fisheries and Aquatic Sciences*, *120*, 67–81.

Harford, W. J., Grüss, A., Schirripa, M. J., Sagarese, S. R., Bryan, M., & Karnauskas, M. (2018). Handle with care: Establishing catch limits for fish stocks experiencing episodic natural mortality events. *Fisheries*, *43*(10), 463–471. https://doi.org/10.1002/fsh.10131

Hordyk, A., Huynh, Q., & Carruthers, T. (2022). *openMSE: Easily install and load the 'openMSE' packages*. https://openmse.com/

International Scientific Committee for Tuna and Tuna-Like Species in the North Pacific Ocean. (2019). *Report for the first north Pacific albacore Management Strategy Evaluation* (p. 157) [Annex 12]. http://isc.fra.go.jp/pdf/ISC19/ISC19_ANNEX12_Report_First_North_Pacific_Albacore_MSE.pdf

Jardim, J., Scott, F., Mosqueira, I., Citores, L., Devine, J., Fischer, S., Ibaibarriaga, L., Mannini, A., Millar, C., Miller, D., Minto, C., De Oliveira, J., Osio, G., Urtizberea, A., Vasilakopoulos, P., & Kell, L. (2017). *Assessment for All initiative (a4a) - Workshop on development of MSE algorithms with R/FLR/a4a. KJ-NA-28705-EN-N*. https://doi.org/10.2760/18924

Krause, J. R., Hightower, J. E., Poland, S. J., & Buckel, J. A. (2020). An integrated tagging and catch-curve model reveals high and seasonally-varying natural mortality for a fish population at low stock biomass. *Fisheries Research*, *232*, 105725. https://doi.org/10.1016/j.fishres.2020.105725

Lynch, P. D., Methot, R. D., & Link, J. S. (2018). *Implementing a next generation stock assessment enterprise: An update to the NOAA Fisheries Stock Assessment Improvement Plan* [NOAA Technical Memorandum NMFS-F/SPO-183]. U.S. Department of Commerce. https://doi.org/10.7755/TMSPO.183

Mace, M. M., Doering, K. L., Wilberg, M. J., Larimer, A., Marenghi, F., Sharov, A., & Tarnowski, M. (2021). Spatial population dynamics of eastern oyster in the Chesapeake Bay, Maryland. *Fisheries Research*, *237*, 105854. https://doi.org/10.1016/j.fishres.2020.105854

Marty, G. D., Quinn, T. J., Carpenter, G., Meyers, T. R., & Willits, N. H. (2003). Role of disease in abundance of a Pacific herring (*Clupea pallasi*) population. *Canadian Journal of Fisheries and Aquatic Sciences*, *60*(10), 1258–1265. https://doi.org/10.1139/f03-109

Maunder, M. N. (2014). *Management Strategy Evaluation (MSE) implementation in Stock Synthesis: Application to Pacific bluefin tuna* [Document SAC-05-10b]. Inter-American Tropical Tuna Commission. https://www.iattc.org/Meetings/Meetings2014/SAC-05/Docs/_English/SAC-05-10b_Management-Strategy-Evaluation.pdf

Maunder, M. N., & Thorson, J. T. (2019). Modeling temporal variation in recruitment in fisheries stock assessment: A review of theory and practice. *Fisheries Research*, *217*, 71–86.

https://doi.org/10.1016/j.fishres.2018.12.014

Methot, R. D. (Ed.). (2015). *Prioritizing fish stock assessments* (p. 31) [NOAA Technical Memorandum NMFS-F/SPO-152]. U.S. Department of Commerce. https://repository.library.noaa.gov/view/noaa/12874

Methot, R. D., & Wetzel, C. R. (2013). Stock Synthesis: A biological and statistical framework for fish stock assessment and fishery management. *Fisheries Research*, *142*, 86–99. https://doi.org/10.1016/j.fishres.2012.10.012

NOAA Fisheries. (2021). *Stock SMART data records*. www.st.nmfs.noaa.gov/stocksmart

Plagányi, É. E., Blamey, L. K., Rogers, J. G. D., & Tulloch, V. J. D. (2022). Playing the detective: Using multispecies approaches to estimate natural mortality rates. *Fisheries Research*, *249*, 106229. https://doi.org/10.1016/j.fishres.2022.106229

Punt, A. E., Butterworth, D. S., Moor, C. L. de, De Oliveira, J. A., & Haddon, M. (2014). Management Strategy Evaluation: Best practices. *Fish and Fisheries*, *17*(2), 303–334. https://doi.org/10.1111/faf.12104

Regular, P. M., Buren, A. D., Dwyer, K. S., Cadigan, N. G., Gregory, R. S., Koen-Alonso, M., Rideout, R. M., Robertson, G. J., Robertson, M. D., Stenson, G. B., Wheeland, L. J., & Zhang, F. (2022). Indexing starvation mortality to assess its role in the population regulation of Northern cod. *Fisheries Research*, *247*, 106180. https://doi.org/10.1016/j.fishres.2021.106180

Sainsbury, K. J., Punt, A. E., & Smith, A. D. (2000). Design of operational management strategies for achieving fishery ecosystem objectives. *ICES Journal of Marine Science*, *57*(3), 731–741. https://doi.org/10.1006/jmsc.2000.0737

Sampson, D. B., & Scott, R. D. (2011). An exploration of the shapes and stability of population–selection curves. *Fish and Fisheries*, *13*(1), 89–104. https://doi.org/10.1111/j.1467-2979.2011.00417.x

Sharma, R., Levontin, P., Kitakado, T., Kell, L., Mosqueira, I., Kimoto, A., Scott, R., Minte-Vera, C., De Bruyn, P., Ye, Y., & others. (2020). Operating model design in tuna Regional Fishery Management Organizations: Current practice, issues and implications. *Fish and Fisheries*, *21*(5), 940–961. https://doi.org/10.1111/faf.12480

Smith, A. (1994). Management Strategy Evaluation: The light on the hill. *Population Dynamics for Fisheries Management*, 249–253.

Steidinger, K. A. (2009). Historical perspective on *Karenia brevis* red tide research in the Gulf of Mexico. *Harmful Algae*, *8*(4), 549–561. https://doi.org/10.1016/j.hal.2008.11.009

Taylor, I. G., Doering, K. L., Johnson, K. F., Wetzel, C. R., & Stewart, I. J. (2021). Beyond visualizing catch-at-age models: Lessons learned from the r4ss package about software to support stock assessments. *Fisheries Research*, *239*, 105924. https://doi.org/10.1016/j.fishres.2021.105924