**Probable impacts of ageing error precision and bias on the stock assessment of Gulf of Mexico Triggerfish**

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Abstract

Introduction

Methods

Population simulation operating model

The population simulation operating model was based on the most recent assessment of Gulf of Mexico Gray Triggerfish (SEDAR 2015). The parameter values and equations governing the model are given in Tables 1 and 2, respectively. The population model runs for 94 years, with a fishing time series beginning in year 26 (years 26-94 experience fishing). The fishing time series aggregated fishing intensity values across fishing fleets from the assessment, with the shrimp fishery removed. For fishery selectivity, we searched for parameter values that roughly matched the dome-shaped selectivity from each fleet in the assessment (Figure 1, this MS; Figure 3.2.32 – SEDAR 2015).

One hundred simulation iterations were run for the population model specification, with stochasticity included using log-normal draws for recruitment deviations about a Beverton-Holt stock recruitment relationship in each year. A sampling model then sampled from that population and fishery exploitation model to simulate the data collection process.

Sampling model

Annual landings were simulated using a log-normal distribution with a standard deviation (SD) of 0.05. A fishery index was simulated using a lognormal distribution with an SD of 0.25 (Table 3). The catch age-composition available for select years throughout the time series was simulated using a multinomial distribution. Age composition data was simulated from years 26, 36, 46, 51, 56, 61, 66, 71, and consistently from year 76 to 94. The number of samples began at *n*=30 in year 26 of the model (first year with fishing), increasing by 10 each decade until year 51, and then increasing by 10 every 5 years until year 76 where it was fixed at *n*=100 for the rest of the time series. Once the true observed age composition was simulated, ageing error was included by drawing from a multinomial distribution with probabilities defined using an ageing error matrix **X** (the probabilities any specimen with true age *a* will be read as age 0, 1, …, *A*).

Ageing Error Matrix

Ageing error was simulated an ageing error matrix derived from a normal distribution with different scenarios for bias and standard deviations of ageing error at age (). The probability that an individual age will be coded age was calculated using the cumulative distribution function of the standard normal ()

Ageing error was then simulated for the observed catch at age data by drawing from a multinomial distribution with the sample size equal to the number of fish true age in the sample and the probability vector as .

Ageing Error Scenarios

We implemented four different scenarios for bias and imprecision for age reading.

1. No ageing error.
2. Constant bias with age.
3. Linear increase in bias with age.
4. Curvilinear bias relationship.

Why you chose what you chose for AE definition

Estimation model

The estimation/assessment models were identical in structure to the population operating model. They began in year 26 of the time series (first year with data). The fixed-effect parameters estimated within the model included the unfished recruitment, the recruitment SD, a natural mortality parameter, four selectivity parameters, catchability of the fishery index, and annual fully selected fishing mortality levels in each year (Table 1). Recruitment deviations in each year and those that make up the initial unfished abundance were treated as random effects. All other parameters were fixed at their true values from the operating model. The assessment models also fit the data using the same likelihoods used to generate data in the sampling model.

Experimental Design

The experimental design was a full factorial where each sampling model scenario was fit by estimation models with each of the four ageing error scenarios specified. This resulted in 16 different model fits (with 100 replicates), four of which were correctly specified.

Model Fitting

Models were fit using Template Model Builder (TMB, Kristensen et al., 2016) with recruitment deviations specified as random effects and the remainder of the fixed effect parameters identified in Table 1. TMB calculates the marginal negative log-likelihood given the fixed effect parameters using the Laplace approximation to integrate over random effects. Fixed effect parameters are estimated via minimizing the marginal negative log-likelihood within the program R using the nlminb function. Random effects and derived quantities are then predicted using empirical Bayes (Kristensen et al., [2016](javascript:;)). Starting parameter values for each simulation iteration were chosen by sampling from a uniform distribution with the bounds specified as 50% below and 50% above the true parameter value. If a model failed to converge according to a non-positive definite hessian matrix, new starting parameters were drawn and the model fit again. This process was repeated a maximum of 10 times. Standard errors of parameter estimates were extracted in addition to those of derived quantities using the generalized delta method built into TMB.

Performance Metrics

We evaluated model performance by calculating three different relative error metrics: annual spawning stock biomass, annual F-ratio, and annual B-ratio.

F-ratio was defined as the fishing mortality estimated in the model divided by the estimated fishing mortality at maximum sustainable yield. Similarly, B-ratio was defined as the annual estimated biomass divided by the biomass at maximum sustainable yield estimated by the model.

Results

Convergence

Model convergence rates varied between the scenarios, with all correctly specified scenarios resulting in convergence rates greater than 90% (Table 3). The lowest convergence rates occurred with sampling models fit with estimation models that assumed ageing error had a linear bias with age. Outside of the correctly specified scenario for linear bias, the convergence rates were 41, 14, and 19% for EMs fit to sampling models without ageing error, with a constant bias, and with a curvilinear bias. All other scenarios had convergence rates above 70%.

Performance Metrics

The correctly specified scenarios were all approximately unbiased in each performance metric (diagonal panels, Figures 2-4). The one slight exception to this is the linear ageing bias estimation model, which had a slight positive bias in SSB and F-ratio (although unbiased in B-ratio).

*SSB*

When there was no ageing error in the data, assuming ageing error had a constant bias or a linear bias led to positive biases in annual SSB, although the former became more unbiased through time and the latter less biased (Figure 2). The model that assumed there was a curvilinear bias resulted in very little bias in annual SSB.

When the data had a constant bias in age reading, assuming there was no ageing error or curvilinear error led to negative biases in SSB on the order of 25%. The model that assumed a linear bias in age reading was approximately unbiased although had very low convergence.

When there was a linear bias in age reading, assuming no ageing error or curvilinear error led to a negative bias in SSB at the end on the time series, on the order of ~10%. Estimation models that assumed a constant bias in age reading at age resulted in positive bias in SSB on the order of 10-15%.

When there was a curvilinear bias in age reading, assuming no ageing error in the estimation model led to approximately unbiased SSB at the end of the time series. The estimation models that assumed a constant or a linear bias in age reading led to positive biases in annual SSB on the order of 20-30%.

*F-ratio*

When there was no ageing error in the data, assuming ageing error had a constant bias or a linear bias led to consistent biases in annual F-ratio (although in opposite directions, on the order of -25 and +50%, Figure 3). The model that assumed there was a curvilinear bias also resulted in bias in F-ratio however less so on the order of +10%.

When the data had a constant bias in age reading, assuming no ageing error or a curvilinear ageing bias led to a positive bias in Fratio on the order of ~10-20%. The estimation models that assumed a linear bias in age reading had very low convergence although of those that did converge, the median F-ratios were approximately unbiased.

When there was a linear bias in age reading, assuming no ageing error, constant bias, or curvilinear bias each led to positive biases in F-ratios, on the orders of 25%, 10%, and 20%, respectively.

When there was a curvilinear bias in age reading, assuming no ageing error or linear bias led to positive biases in F-ratio, on the orders of 15 and 50% (although low convergence for linear bias EM). When the estimation model assumed a constant bias in age reading, the F-ratio was unbiased.

*B-ratio*

When there was no ageing error in the data, assuming there was a constant bias in age reading led to a positively biased B-ratio, which became more biased as the time series went on. The estimation models that assumed a linear bias in age reading were positively biased at the beginning of the time series in B-ratio however negatively biased at the end of the time series. The estimation models that assumed a curvilinear bias in age reading were negatively biased at the beginning of the time series however approximately unbiased in the final year.

When the data had a constant bias in age reading, assuming no ageing error or curvilinear error led to minor negative biases in B-ratio in the terminal year. When the estimation model assumed a linear bias in age reading, a positive bias in B-ratio resulted.

When there was a linear bias in age reading, assuming no ageing error or curvilinear error led to negative biased in B-ratio at the end of the time series on the order of 10-15%. The estimation model that assumed a constant bias at age was approximately unbiased in B-ratio.

When there was a curvilinear bias in age reading, assuming no ageing error led to a negative bias in B-ratio in the terminal year on the order of 10%. Estimation models that assumed a constant bias in age reading were approximately unbiased in B-ratio in the terminal year. The estimation models that assumed linear bias in age reading had very low convergence rates but of those that converged, had a negative bias in B-ratio at the terminal end of the time series on the order of 10%.

Discussion

Curvilinear seems to be the least worst outcome.