Using multiple indices for biomass and apportionment estimation of Alaska groundfish stocks

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Abstract

Fish stocks in the Bering Sea, Aleutian Islands, and Gulf of Alaska are managed by the North Pacific Fisheries Management Council through a six tier system. These tiers are defined by the data availability and complexity of assessment method. In particular, Tiers 4 and 5 of this system use the area-swept biomass from bottom trawl surveys performed by the Alaska Fisheries Science Center in a random effects model to estimate total biomass from which management quantities of Acceptable Biological Catch and the Overfishing Limit are determined. In this study, we present a method in which population indices from a longline survey are also incorporated into the random effects model using the Gulf of Alaska shortraker rockfish and shortspine thornyhead stocks as examples of the development of this method. Overall, we find that estimates of biomass, as well as apportionment of biomass among sub-regions of the Gulf of Alaska, become more stable over time when random effects models incorporate longline survey population indices in addition to bottom trawl survey biomass estimates. We also show that this method can be used to evaluate spatial estimation of the catchability coefficient between the two surveys, as well as relative weighting of the longline survey index. This method may also be useful for several other Tier 5 species, as well as sub-region apportionment of biomass for Tier 3 stocks that are captured by both surveys.

Introduction

In the Fishery Management Plan (FMP) for groundfish in the Bering Sea (BS), Aleutian Islands (AI), and Gulf of Alaska (GOA) a tier system that defines the complexity of assessment methods is utilized to manage exploited fish stocks (e.g., NPFMC 2018a, NPFMC 2018b). This system has six tiers defined by data and assessment result requirements. Estimates of spawning biomass and management quantities in tier's 1-3 are provided by age-structured assessment models and are differentiated by the quality of the model's estimates of biomass, fishing mortality rates, and the their uncertainty. Exploitable biomass and management quantities in tier's 4-6 are provided by fishery-independent survey estimates of biomass (tier's 4 and 5) or fishery catch (tier 6). Specifically, in tiers 4 and 5, exploitable biomass is estimated through the use of area-swept biomass estimates that are provided by Alaska Fisheries Science Center (AFSC) bottom trawl surveys (hereon called the 'bottom trawl survey'). Historically, the estimates of exploitable biomass for tier 4 and 5 stocks or complexes in any given assessment year has been provided through various statistics and models, including a weighted (Echave and Shotwell, 2013) or unweighted (Spies et al. 2012) average of bottom trawl survey biomass, the bottom trawl survey biomass from the most recent year (Shotwell et al., 2013), or surplus production models (Spencer and Rooper 2012).

Since 1987, AFSC has conducted an annual survey to assess sablefish (*Anoplopoma fimbria*) and other species using longline gear (hereafter referred to as the 'longline survey'; Hanselman et al. 2018). While the sablefish assessment relies heavily on the longline survey, other applications of these data are for GOA Pacific cod (Barbeaux et al. 2018), and the GOA rougheye/blackspotted complex (Shotwell et al. 2017). Both of these assessments use the longline survey data to supplement the AFSC bottom trawl survey. A handful of tier 5 species are also sampled by the AFSC longline survey for which population index data are available including flatfish, rockfish, skate, and shark species. While this population index data are presented in a number of Tier 5 stock assessment reports, often they are used solely for informational purposes (e.g., Tribuzio et al. 2017) rather than estimation of exploitable biomass and management quantities. The convention is that, without a population dynamics model, the area-swept estimates of biomass from the bottom trawl survey are representative of the stock's exploitable biomass.

Due to the lack of a general and consistent method for estimating exploitable biomass across the tier 4 and 5 stock assessments, an ad-hoc working group (SAWG 2013) developed a model to account for process and observation errors. However, application of this approach to multiple indices has been limited. Consequently, we extend this random effects model to include additional index data. An important part of this extension is to provide biologically plausible area apportionments of management quantities, i.e., the Acceptable Biological Catch (ABC). This apportionment approach has also been adopted for Tiers 1-3.

In this study a method is presented that extends the current random effects model as applied to the bottom trawl survey biomass index to include the longline survey population index data as auxiliary information. Two tier 5 stocks are used as an example of the development of this method: GOA shortspine thornyhead (*Sebastolobus alascanus*) and GOA shortraker rockfish (*Sebastes borealis*).

Methods

Model description

To account for process and observation errors in survey biomass estimates we begin with:

$$\hat{B}_y = \sum_R \sum_D e^{\hat{\varepsilon}_{d,r,y}}$$

where $\hat{B}_y$ is the estimated biomass in year-y, and $\hat{\varepsilon}_{d,r,y}$ are the estimated random effects parameters. The subscripts r and d denote that the random effects parameters can be estimated by region-r and depth strata-d, as needed.

The process error component of the objective function (how much the random effects parameter estimates of biomass vary through time) is constrained by a random walk process, which here is embedded in the negative log-likelihood of the process error component as:

$$-lnL_p = \sum_{y=2}^{Y} \sum_R \frac{1}{2\pi\hat{\sigma}_{\varepsilon,r}^2} \sum_D \left(\hat{\varepsilon}_{d,r,y} - \hat{\varepsilon}_{d,r,y-1}\right)^2$$

where the subscript p denotes process error component. The random walk is constrained by the estimated process error variance parameter $\hat{\sigma}_{\varepsilon,r}^2$ (also called a hyperparameter). The subscript r denotes that this parameter can be estimated by region (attempts to estimate include depth in process error variance terms were so far infeasible without imposing more structure).

The observation error component of the objective function fits the random effects estimates of biomass to biomass from the bottom trawl survey with the lognormal distribution. The observation error component of the objective function is given by:

$$-lnL_o = \sum_Y \sum_R \sum_D \frac{1}{2} \left[ln\left(2\pi\sigma_{B,r,d,y}^2\right) + \frac{1}{\sigma_{B,r,d,y}^2} \left(\hat{\varepsilon}_{d,r,y} - lnB_{d,r,y}\right)^2 \right]$$

where the subscript o denotes that the negative log-likelihood is for the observation error component of the objective function, $B_{d,r,y}$ is the bottom trawl survey biomass in depth strata-d, region-r, and year-y, and $\sigma_{B,r,d,y}^2$ is the variance in the bottom trawl survey biomass.

The objective function that is minimized in the random effects model is the sum of the process error and observation error negative log-likelihood functions. Within the random effects model the estimated biomass that results is intended to balance variability in biomass over time (process error) and the precision of the fit to the bottom trawl survey estimates (observation error). For example, if the variance in the bottom trawl survey biomass is small, then the fit of the random effects model to the bottom trawl survey biomass will be precise and will allow for larger process error across time in the parameter estimates of biomass. Alternatively, if the variance in the bottom trawl survey biomass is large, the random effects model will fit the bottom trawl survey biomass estimates poorly and the process error will be small, thus, the changes in biomass over time will decrease.

Adding additional indices

The longline survey provides and index of relative population weights (so-called RPW; Sigler 2000). Including this (or other) index to the model described above requires a scaling or catchability coefficient parameter. Including region-specific estimates from the longline survey data:

$$\widehat{RPW}_{r,y} = \hat{q}_r \sum_D e^{\hat{\varepsilon}_{d,r,y}}$$

where $\hat{q}_r$ is the catchability coefficient parameter for this gear. As above, an additional observation error component is then added to the objective function:

$$-lnL_O^L = \lambda_L \sum_Y \frac{1}{2} \left[ln\left(2\pi\sigma_{RPW,r,y}^2\right) + \frac{1}{\sigma_{RPW,r,y}^2} \left(ln\left(\widehat{RPW}_{r,y}\right) - ln\left(RPW_{r,y}\right)\right)^2 \right]$$

where $\sigma_{RPW,r,y}^2$ is the regional variance of the longline survey RPW index in year y, $RPW_{r,y}$ is the observed longline survey RPW index by region and year, and λ_L is the weighting coefficient for the longline survey RPW index.. Thus, the random effects model that includes the AFSC longline survey simply has an added observation error term. Extending this to more indices (e.g., fishery CPUE) could also be done in a similar fashion.

Case studies

Two Tier 5 stock assessments are used as an example of application of the random effects model that includes longline survey population index data: GOA shortspine thornyhead (hereon called 'shortspine') and GOA shortraker rockfish (hereon called 'shortraker'). In this study these species are used to present three aspects of development and application of the random effects model, which are:

1. Including the longline survey RPW index
2. Estimating regional catchability coefficients for the longline survey RPW index

3. Relative weighting between the bottom trawl survey biomass and longline survey RPW index data

For the shortspine case study, and the method presented here was adopted in the 2018 stock assessment (Echave and Hulson 2018). For consistency with the 2018 Stock Assessment and Fishery Evaluation (SAFE) document, the model numbering used in the stock assessment is followed. Three model scenarios were investigated in the 2018 shortspine stock assessment:

- Model 2015.1 – 2015 stock assessment random effects model with data updated through 2018
- Model 2015.1a – Model 2015.1 with bottom trawl survey biomass estimates summed for the 0-500 m depth strata within each region
- Model 2018.1 – Model 2015.1a with longline survey RPWs from 1992-2018 included as an additional population index

The shortraker case study was recommended by the authors in the 2019 stock assessment (Echave and Hulson 2019). Similar to the shortspine case, the model number convention will be consistent with the shortraker 2019 SAFE document. Three model scenarios, with three sub-scenarios, were investigated:

- Model 2017.1 – 2017 stock assessment random effects model with bottom trawl survey biomass data updated through 2019
- Model 2019.1 – Model 2017.1 with longline survey RPWs from 1992-2018 included as an additional population index
- Model 2019.2 – Model 2019.1 with catchability coefficients estimated by regions within the GOA

Three sub-scenarios of model 2019.2 were investigated that decreased the relative weight of the longline survey RPW index (i.e., decreased λ_L). These sub-scenarios were:

- Model 2019.2a – Relative weight between bottom trawl survey biomass and longline survey RPW is the same and set at 1 (same as Model 2019.2)
- Model 2019.2b – Weight of longline survey RPW index set at 0.5
- Model 2019.3c – Weight of longline survey RPW index set at 0.25

Results

In general, model scenario 2018.1 of the shortspine random effects model fit the bottom trawl survey biomass poorly compared to model 2015.1 or 2015.1a, particularly for 1990 and 2003 estimates (top panel Fig. 1). With the longline survey RPW index added, the trends are further smoothed. In most years the longline survey RPW index is fit well by model scenario 2018.1 (bottom panel Fig. 1). Interestingly, there are some periods in which the trajectories of the trawl survey biomass index and the longline survey RPW index observations conflict, in particular in the period between 2000 and 2005 and the period between 2010 and 2015.

For the regional apportionment model, including the additional index also dampens the variability of biomass estimates over time (Fig. 2). This effect trades off fitting bottom trawl survey biomass estimates (e.g., the CGOA 2003 estimates; middle panel, Fig. 2). The fit to the regional longline survey RPW index by model scenario 2018.1 was generally good (Fig. 3), with the exception of recent years in the WGOA in which estimated RPWs were lower than the observed index. As would be expected from the results of the fit to regional indices of bottom trawl survey biomass and longline survey RPW index, the regional apportionment of shortspine biomass from model scenario 2018.1 was more stable across time than the apportionment estimated by model scenario 2015.1 (Fig. 4).

Similar to the shortspine model scenarios, when the longline survey RPW index is introduced into the shortraker random effects model (model scenarios 2019.1 and 2019.2), the model fits the bottom trawl survey biomass poorer compared to the model scenario without the longline survey RPW index, 2017.1 (top panel Fig. 5). Further, because the bottom trawl survey biomass has larger uncertainty for shortraker compared to shortspine, the estimated biomass from model cases 2019.1 and 2019.2 is less sensitive to the bottom trawl survey biomass index and more influenced by the longline survey RPW index. In general, both model scenarios, 2019.1 and 2019.2, fit the longline survey RPW index well (bottom panel Fig. 5). However, when including the longline survey RPW index into model scenario 2019.1, the regional fit to the RPW index is poor (Fig. 6). Upon estimating regional specific catchability coefficients in the shortraker random effects model scenario 2019.2, the fit to the longline survey regional RPW indices is greatly improved (Fig. 6).

Reducing the relative weight of the longline survey RPW index in the shortraker random effects model resulted in an increased response to the bottom trawl survey biomass, as would be expected (Fig. 7). All in all, however, the difference in fit to the bottom trawl survey biomass when the relative weighting of the longline survey RPW index is reduced in model scenarios 2019.2a-c was minor on the regional scale (Fig. 8). This same result held for the random effects model fit to the regional longline survey RPW index (Fig. 9), with the exception of the EGOA, where there appears to be a slight data conflict between the bottom trawl survey biomass and longline survey RPW indices. For the 2019 shortraker stock assessment scenario 2019.2b was recommended as the preferred model because it increased the sensitivity of the random effects model to the bottom trawl survey biomass while still retaining influence from the longline survey RPW index (Echave and Hulson 2019). Also similar to the results when adding the longline survey RPW index to the shortspine random effects model, the apportionment of biomass among regions in the shortraker assessment was much more stable across time than the random effects model with the bottom trawl survey biomass index only (Fig. 10).

Discussion

We present an original method that introduces auxiliary population information into the random effects models used for several stock assessments at the AFSC. The method presented is a simple, flexible, and straight-forward approach for including additional population indices in the random effects model. The general result shown here was an increase in the stability of biomass estimates across time, reduced tendency for the random effects model to over-fit bottom trawl survey biomass values in some years, and more consistent regional apportionments across time. Further, using this method in the random effects model has the potential to expose data conflicts between the bottom trawl survey biomass index and the longline survey RPW index over time that can now be integrated into the estimation of management quantities. We also show, using the two case study stocks, how this method can be developed to address species-specific concerns that may arise with the implementation of the longline survey RPW index within the random effects model through the application of regional-specific catchability parameters and relative weighting between the bottom trawl and longline survey indices.

A concern that must be addressed by assessment authors before implementing this method is the potential for differences in selectivity between the bottom trawl survey and longline survey. In an age-structured assessment, differences in age- or length-based selectivity can be accounted for and explicitly defined in the estimation of spawning biomass. However, in Tier 4 and 5 stock assessments that do not use age-structured models, selectivity is not explicitly estimated. In these cases the assessment scientist must evaluate whether this method would be appropriate for their stock. For the two example stocks presented here, the assessment authors evaluated the differences in length compositions from the bottom trawl survey and longline survey. While there were minor differences, the authors of these assessments deemed that these differences were not substantial enough to cause concern using this method. We also

demonstrate with the shortraker example, that potential differences in catchability (which is the combination of availability and selectivity) across space can be identified and estimated.

The method presented in this study could easily be extended to assess other Tier 5 species that are sampled by longline gear as well as aid in the estimation of apportionment for Tier 3 species that include multiple population indices within the assessment. The Tier 3 species that use longline survey data for which this method could be used for apportionment include sablefish (Hanselman et al. 2018), GOA Pacific cod (Barbeaux et al. 2018), and the GOA rougheye and blackspotted complex (Shotwell et al. 2017). An interesting application of this method for Tier 3 stock assessments is the potential to develop a prior on the catchability coefficient estimated by the random effects model using the selectivity and numbers-at-age estimated in the age-structured assessment for these stocks. This prior would then overcome the concern of differing selectivities between the bottom trawl survey and longline survey. GOA arrowtooth flounder (Spies and Palsson 2017) and GOA Dover sole (McGilliard and Palsson 2015) are additional Tier 3 flatfish stocks that are captured by the longline survey for which this method may be applicable. Other Tier 5 stock assessments at AFSC for which this method could be evaluated are the GOA shark complex (specifically for spiny dogfish, Tribuzio et al. 2015) and the GOA skate complex (Ormseth 2017), both of which may also have auxiliary population index data available from the International Pacific Halibut Commission longline survey.

The results we present provide strong rationale for incorporating additional population index data, such as longline survey RPW data, into the random effects model currently being used to assess stocks at the AFSC. We recommend that the methods presented in this study be considered by those assessment scientists whose stocks are candidates. This is a simple and flexible way to incorporate the best scientific information available, which is a mandate of the Magnuson-Stevens Fisheries Conservation and Management Act. Other promising methods that combine bottom trawl data with longline survey data, such as spatio-temporal models (Thorson et al. 2015), are also in development. However, we recommend that, until spatio-temporal methods are fully developed, the method presented in this study should be considered by assessment scientists at AFSC.

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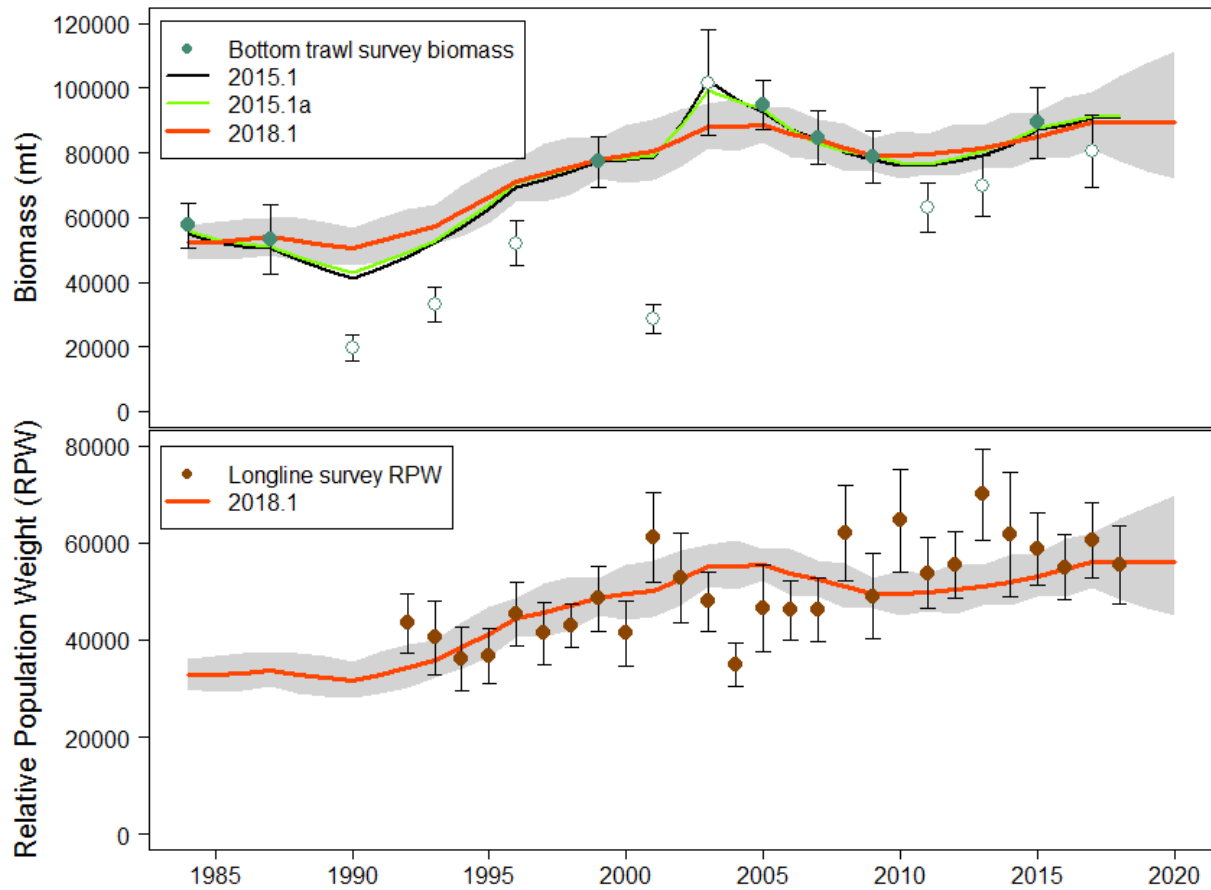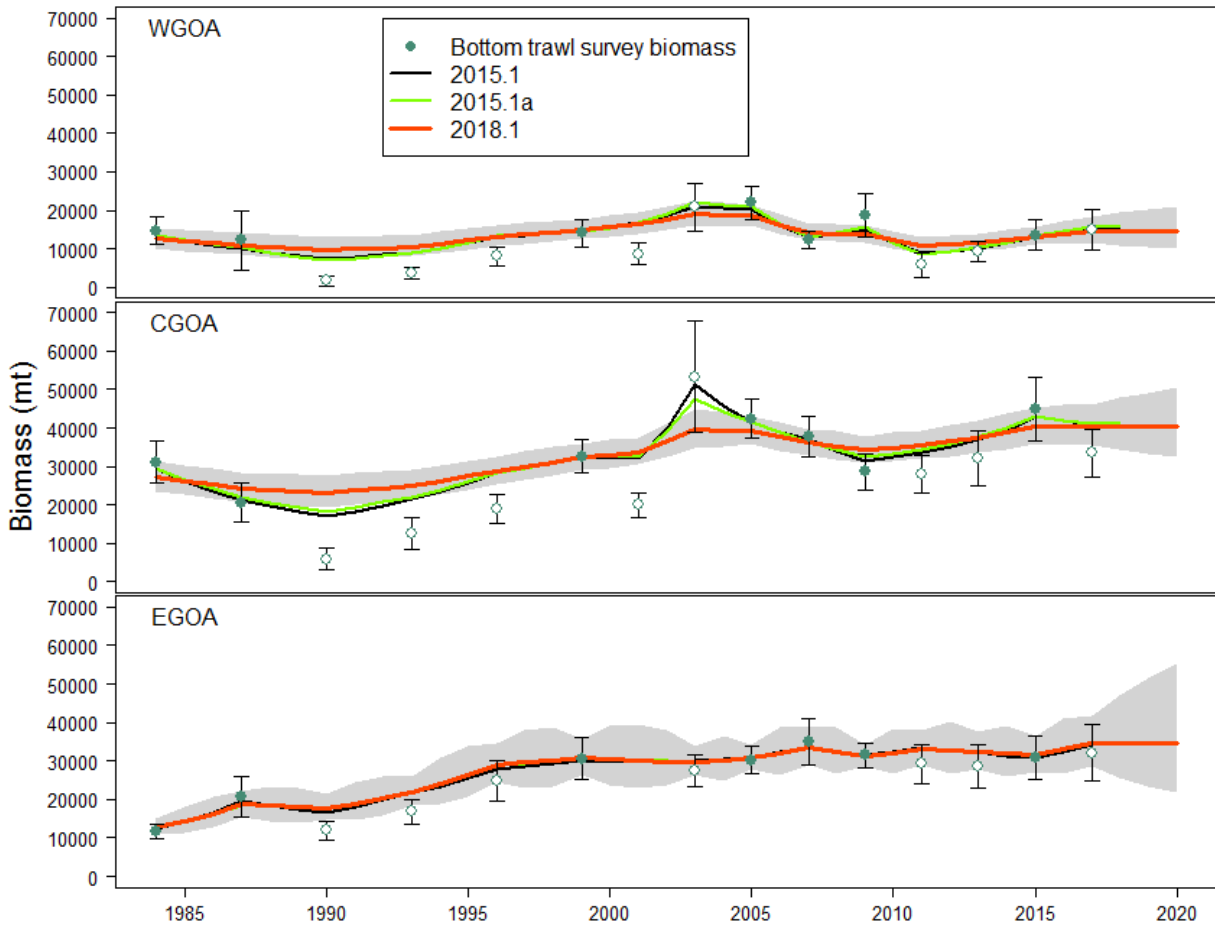
Figures

Figure 1. -- Fit of GOA Shortspine thornyhead random effects model scenarios to AFSC bottom trawl survey biomass (top panel) and longline survey RPW (bottom panel) population indices. The whiskers surrounding the bottom trawl survey biomass and longline survey RPW represent the 95% confidence intervals for the indices, and the shaded region (light gray) represents the 95% confidence interval in the biomass estimates from model scenario 2018.1. Open circles in the plots of bottom trawl survey biomass represent years in which certain regions or depth strata (or both) were not sampled.

Figure 2. -- Fit of GOA Shortspine thoryhead random effects model scenarios to the AFSC bottom trawl survey biomass by region (denoted in the upper left hand corner of each panel). The whiskers surrounding the bottom trawl survey biomass index represent the 95% confidence intervals, and the shaded region (light gray) represents the 95% confidence interval in the biomass estimates from model scenario 2018.1. Open circles in the plots of bottom trawl survey biomass represent years in which certain regions or depth strata (or both) were not sampled.
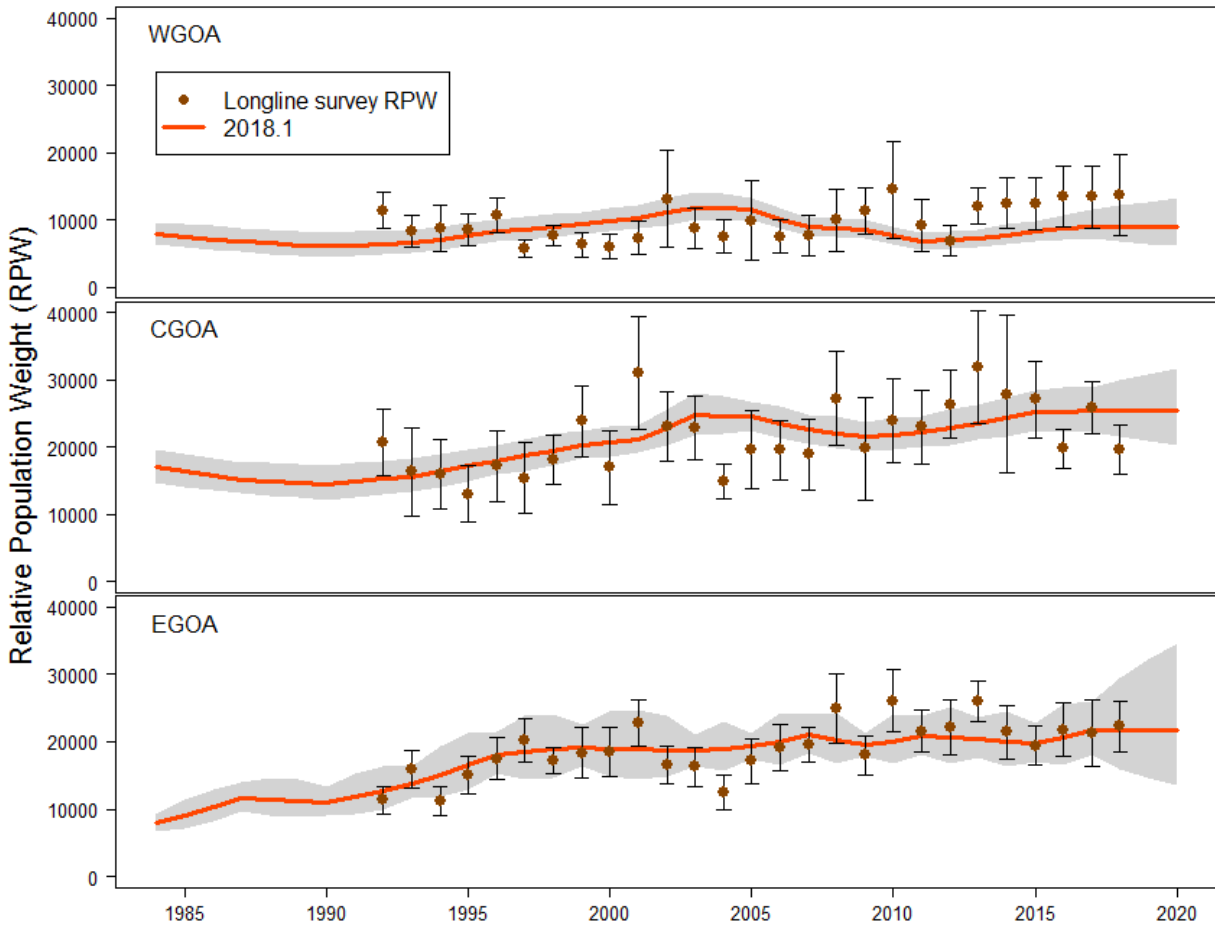
Figure 3. -- Fit of GOA Shortspine thoryhead random effects model scenarios to the AFSC longline survey RPW index by region (denoted in the upper left hand corner of each panel). The whiskers surrounding the longline survey RPW index represent the 95% confidence intervals, and the shaded region (light gray) represents the 95% confidence interval in the RPW estimates from model scenario 2018.1.
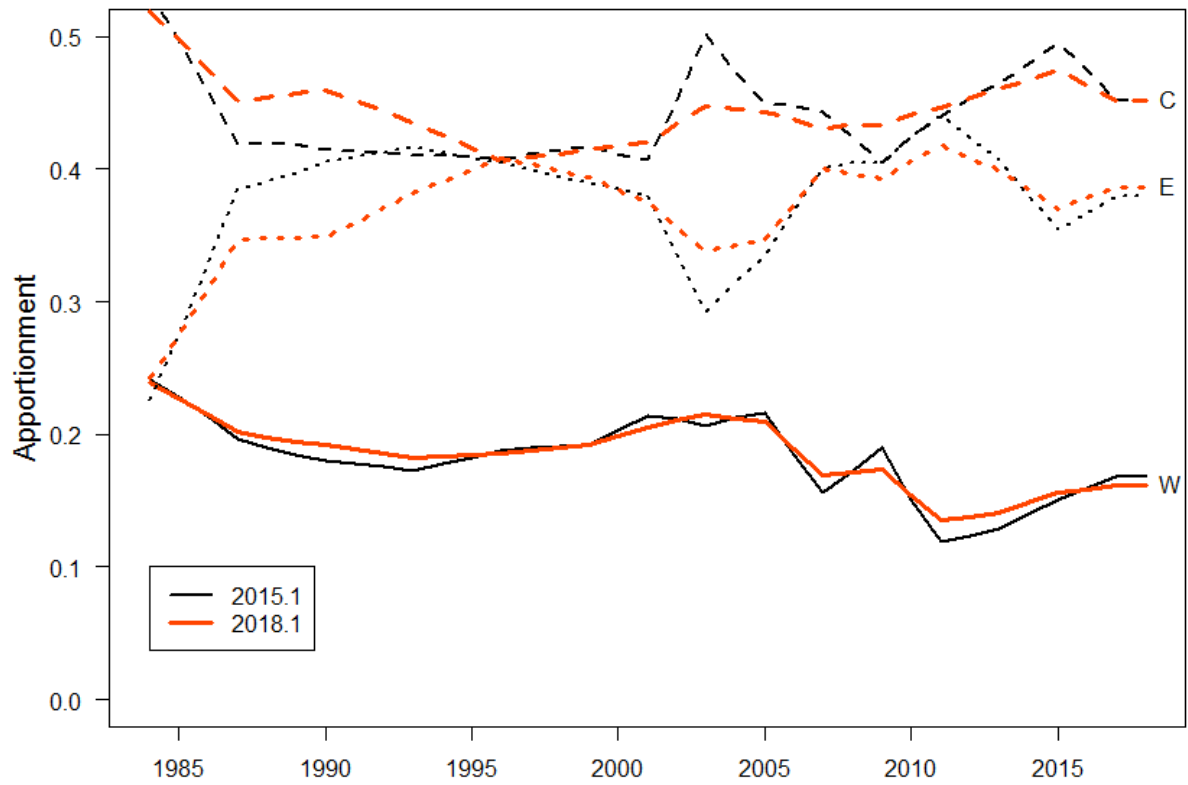
Figure 4. -- Apportionment between regions in the GOA as estimated by different scenarios of the GOA shortspine thornyhead random effects model. Model results for scenario 2015.1 are shown in black; results for scenario 2018.1 are in red. Regional apportionment areas are: W – WGOA, C – CGOA, and E – EGOA.
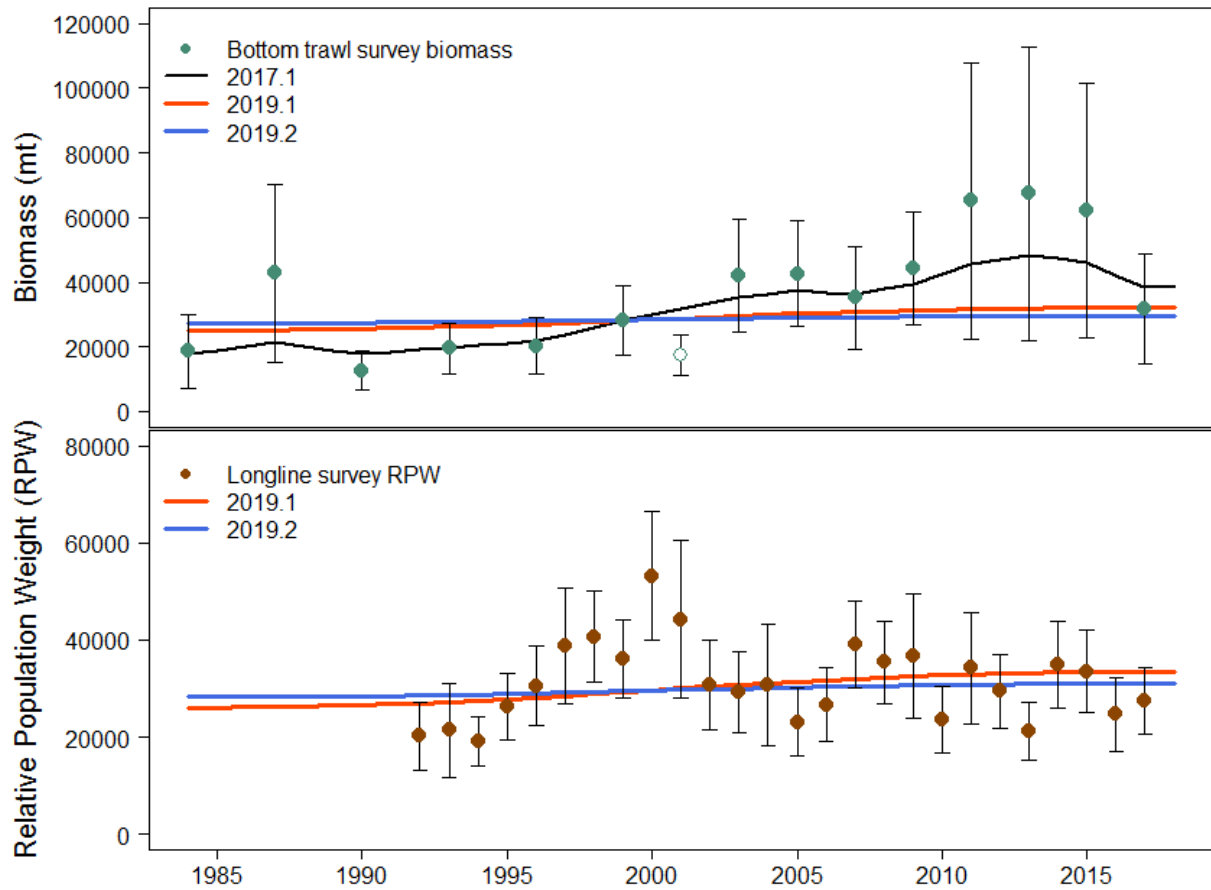
Figure 5. -- Fit of GOA Shortraker rockfish random effects model scenarios 2017.1, 2019.1, and 2019.2 to AFSC bottom trawl survey biomass (top panel) and longline survey RPW (bottom panel) population indices. The whiskers surrounding the bottom trawl survey biomass and longline survey RPW represent the 95% confidence intervals for the indices. Open circles in the plots of bottom trawl survey biomass represent years in which certain regions or depth strata (or both) were not sampled.
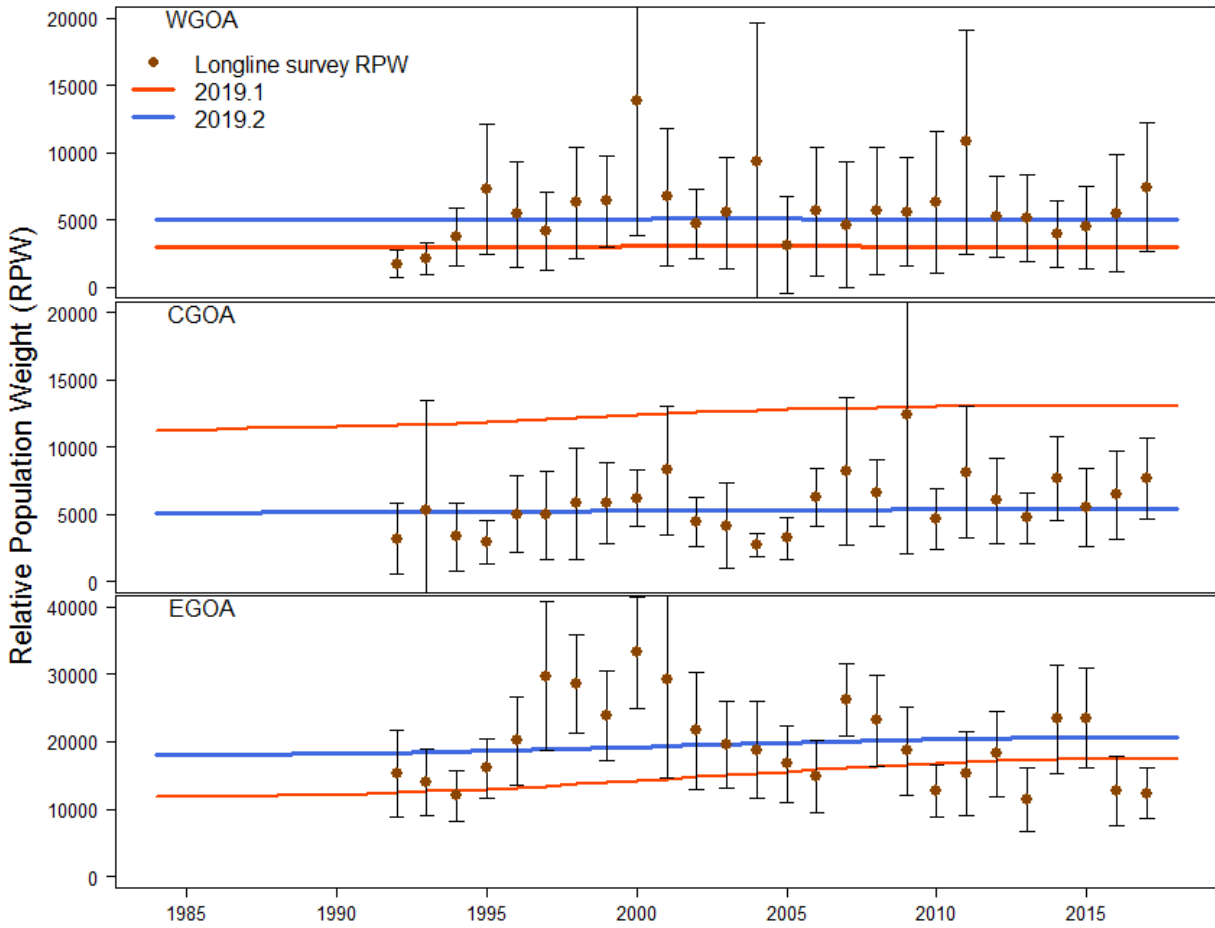
Figure 6. -- Fit to regional AFSC longline survey RPW indices with GOA Shortraker rockfish random effects model scenarios 2019.1 and 2019.2. The whiskers surrounding the longline survey RPW represent the 95% confidence intervals for the index.
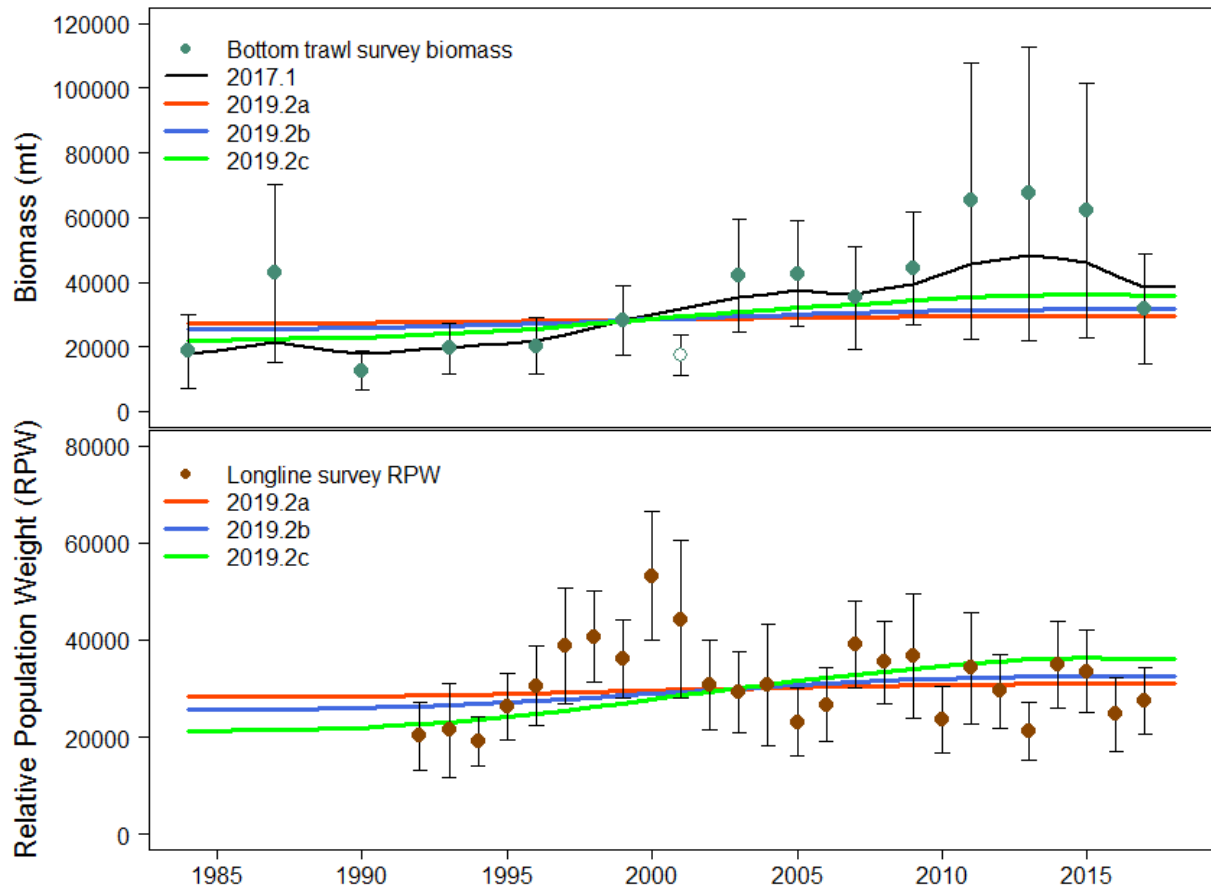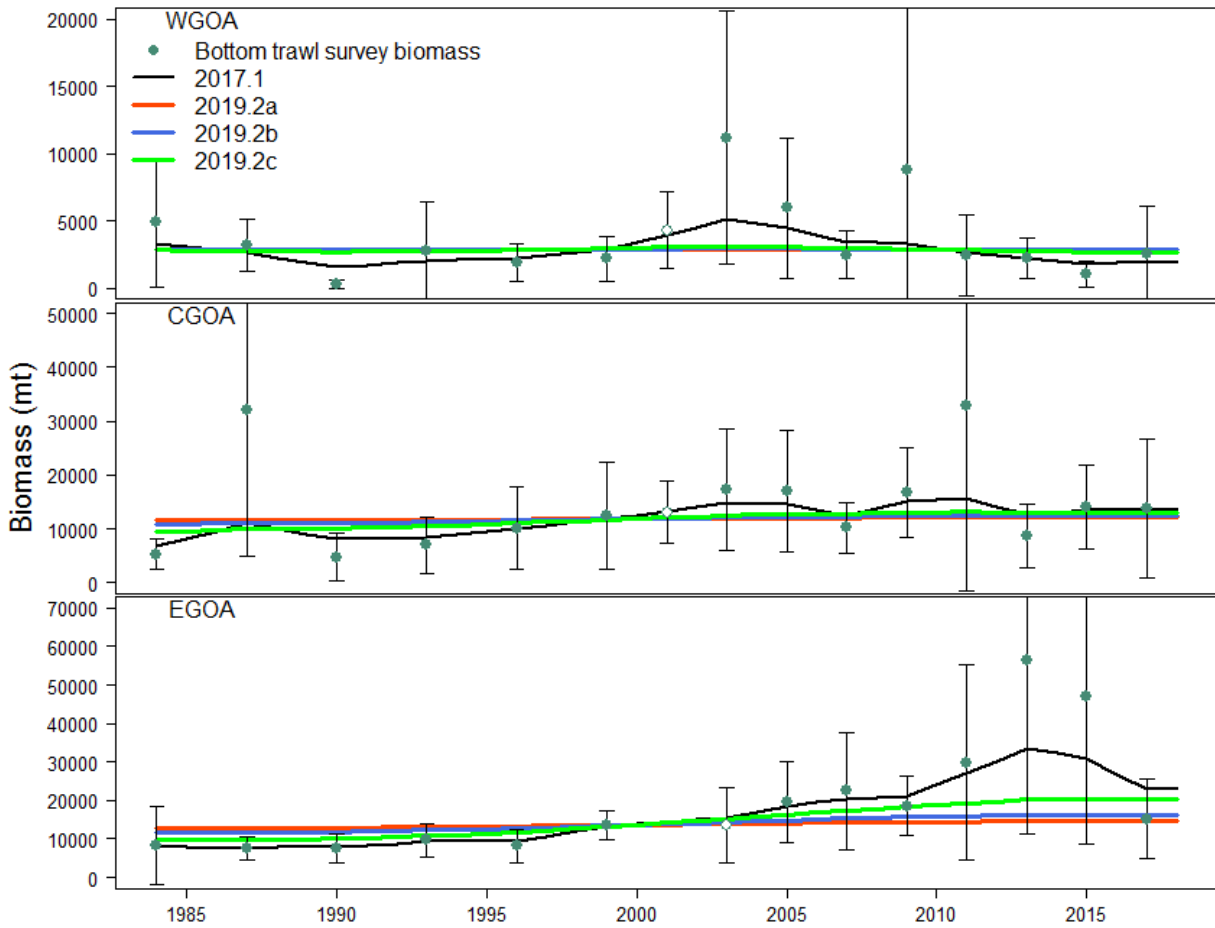
Figure 7. -- Fit of GOA Shortraker rockfish random effects model scenarios 2017.1 and 2019.2a-c to AFSC bottom trawl survey biomass (top panel) and longline survey RPW (bottom panel) population indices. The whiskers surrounding the bottom trawl survey biomass and longline survey RPW represent the 95% confidence intervals for the indices. Open circles in the plots of bottom trawl survey biomass represent years in which certain regions or depth strata (or both) were not sampled.

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Figure 8. -- Fit of GOA Shortraker rockfish random effects model scenarios 2017.1 and 2019.2a-c to AFSC bottom trawl survey biomass (top panel) and longline survey RPW (bottom panel) population indices. The whiskers surrounding the bottom trawl survey biomass and longline survey RPW represent the 95% confidence intervals for the indices. Open circles in the plots of bottom trawl survey biomass represent years in which certain regions or depth strata (or both) were not sampled.
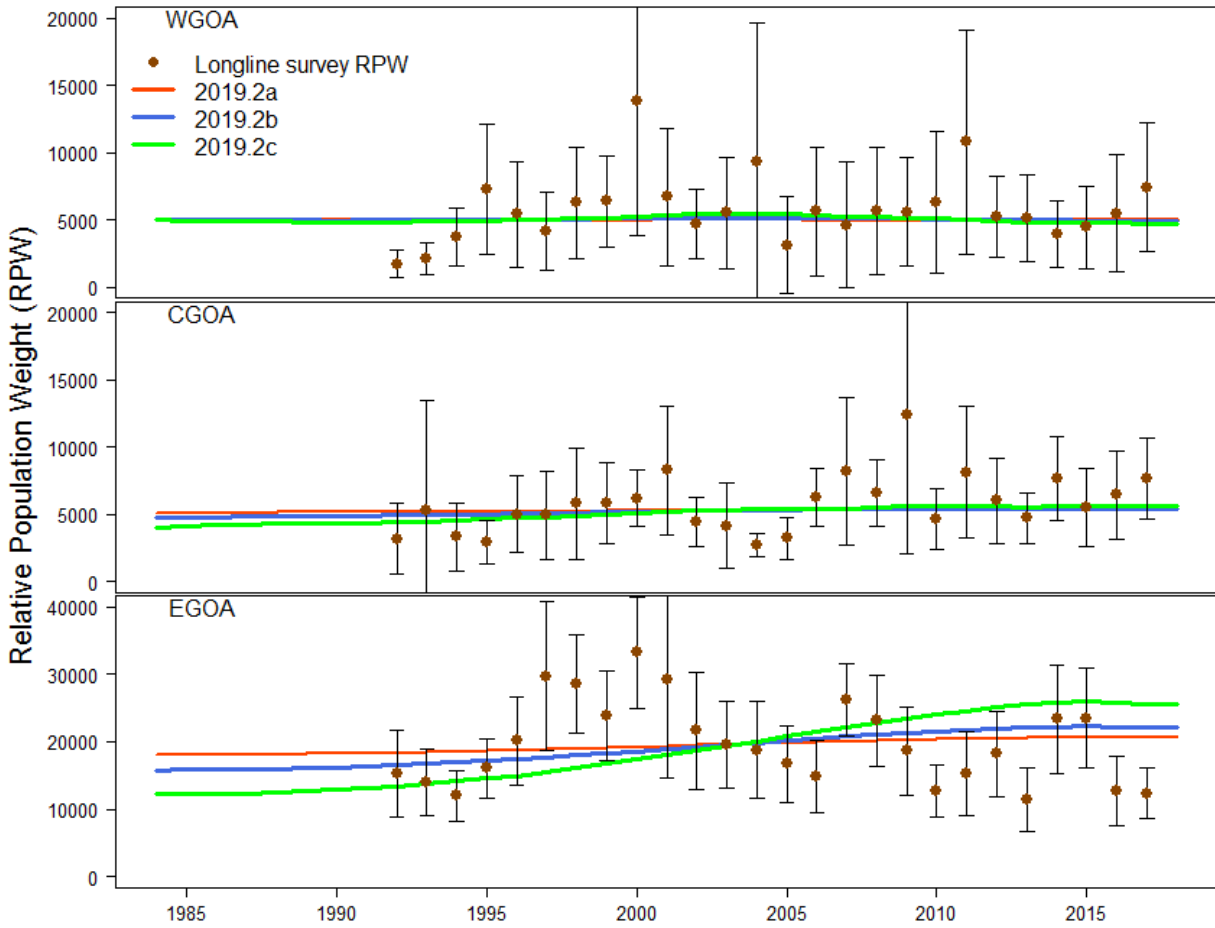
Figure 9. -- Fit to regional AFSC longline survey RPW indices with GOA Shortraker rockfish random effects model scenarios 2019.2a-c. The whiskers surrounding the longline survey RPW represent the 95% confidence intervals for the index.
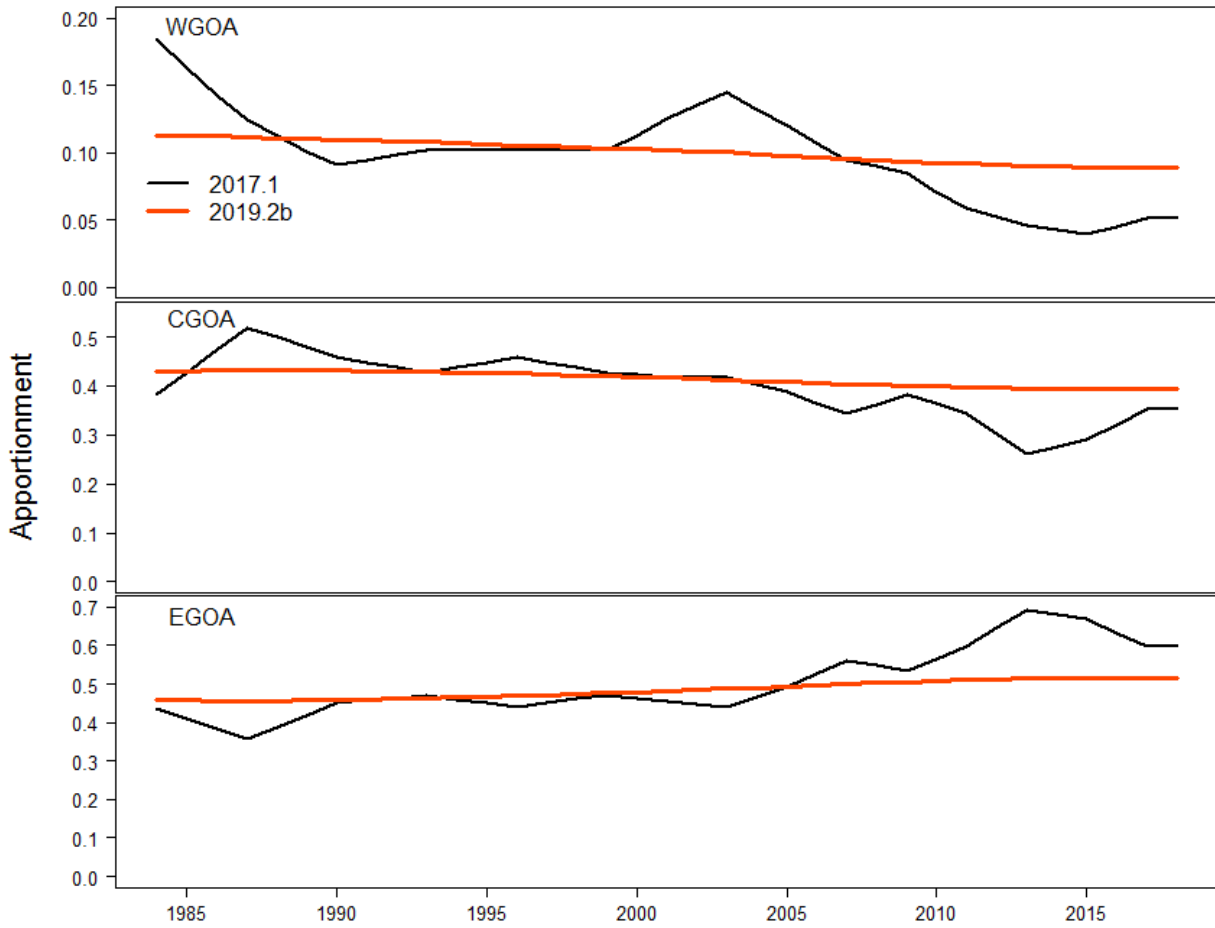
Figure 10. -- Apportionment between regions in the GOA as estimated by the GOA Shortraker rockfish random effects model scenarios 2017.1 and 2019.2b.