REMA: a consensus version of the random effects model for ABC apportionment and Tier 4/5 assessments

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Introduction

The random effects (RE) model was developed by the North Pacific Fisheries Management Council (NPFMC) Groundfish Plan Team's (GPT) Survey Averaging working group and has been used at the Alaska Fisheries Science Center (AFSC) since 2013 to estimate biomass in data-limited groundfish and crab stock assessments and apportion estimates of Acceptable Biological Catch (ABC) by area (Oct 2013 Joint GPT minutes). The RE model was developed and simulation tested as a way to partition observation errors from survey biomass estimates with plausible process errors related to the true (but unobserved) population biomass. In this model, the process errors are treated as random effects, where the underlying state dynamics are modeled as a random walk. The code was originally implemented in AD Model Builder (ADMB; Fournier et al. 2012, Skaug and Fournier 2013). Since its implementation, the model was modified independently by users, resulting in three primary variants (Monnahan et al. 2021):

1. The Random Effects (RE) model, which uses a single trawl survey biomass time series.
2. The Random Effects Multi-area (REM) model, which is a multivariate extension of the RE model that can fit multiple strata (e.g., area, depth) simultaneously.
3. The REM with an Additional longline survey (REMA), which was developed to include additional catch-per-unit effort (CPUE) time series data (Hulson et al. 2021).

Although the RE, REM, and REMA models share the same underlying state-space and random walk dynamics, Monnahan et al. (2021) found multiple versions of the code and several inconsistencies. Here we seek to unify these variants and improve transparency and reproducibility of applications within assessments. We present a model flexible enough to accommodate all Tier 4/5 assessments and ABC apportionment approaches. We recoded the model in Template Model Builder (TMB; Kristensen et al. 2016) and developed an R package called *rema* that is version-controlled online and includes a set of utility functions for visualizing results and conducting model comparisons. The *rema* package provides a flexible and extensible framework for users to fit RE, REM, and REMA models, and bridge tactical assessments from existing ADMB RE models.

In this document, we introduce *rema* and provide documentation for model development and methods. We demonstrate examples of comparing the ADMB and TMB versions of the model, starting with the base RE model and increasing in complexity. We demonstrate an analysis of the various zero biomass assumptions and introduce an experimental option to model the survey observations using the Tweedie distribution, a positive and continuous distribution that accepts zeros. In the section defining methods for the two-survey REMA model, we describe an error in how ADMB's SEPARABLE_FUNCTION was applied. This error affected one Tier 3 apportionment model (Gulf of Alaska [GOA] rougheye/blackspotted rockfish, Sullivan et al. 2021) and two Tier 5 assessments (GOA thornyheads, Echave et al. 2020; and GOA shortraker rockfish, Echave et al. 2021). In the section titled *A correction to the ADMB version of the two-survey REMA model,* we provide a summary of these impacts. Since observation and process errors in these types of models can be confounded, we introduce a method to estimate additional observation error in the section titled *Estimating additional observation error*. Finally, we describe the need to develop protocols for model validation for REMA models and describe an experimental implementation of one-step ahead (OSA) residuals in *rema*.

Three appendices are included at the end of the main document, one for GOA thornyheads (Appendix A), one for Bering Sea and Aleutian Islands (BSAI) shortraker rockfish (Appendix B), and the other for BSAI other rockfish (Appendix C). These appendices propose alternative models for November 2022, and should therefore be reviewed independently by the BSAI and GOA GPTs. We present these documents as appendices to reduce redundancy of methods and review. In the case of GOA thornyheads, the proposed new models were motivated by a need to correct the ADMB version of the two-survey model. In the case of BSAI shortraker and other rockfish, the proposed new models incorporate previously unused information from the NMFS longline survey and were motivated by the cessation of the Eastern Bering Sea slope bottom trawl survey in 2016.

Responses to SSC and Plan Team Comments

The Teams supported the working group's plan for moving forward, which is to:

1. *Create a consensus version of the RE model code for all Tier 4/5 assessments*
    a. *Based on REM which has several advantages and can handle the suite of cases*
    b. *Documented and version-controlled online*
2. *Encourage consistent approach to zeroes*
    a. *Explore alternative statistical approaches, e.g., delta-models, off-the shelf packages (e.g., GLMMTMB)*
    b. *Recommend that assessments note filtering of zeroes*
3. *Explorations of the preferred method for grouping multivariate models*
4. *Explore complex workflows for input variances and M approaches*
5. *Further tests of the lognormal issue*

The authors appreciate the Teams' and SSC's support and feedback. As the title suggests, Item 1, creating a consensus version of the RE model code, is the primary objective of this document. We developed an R package called *rema*, which is based on a TMB model that can handle all Tier 4/5 assessments and apportionment strategies based on the ADMB re.tpl code. As part of *rema* development, substantial progress was made on Item 2. The *rema* package allows the user to easily define and explore zero biomass assumptions through the R function that prepares model inputs. By default, *rema* defines zeros as NAs; however, the package returns a warning message stating this assumption unless it is explicitly defined. Items 2a, 3, 4, and 5 are not the focus of this document. The software listed in Item 2a will only work for the univariate RE model and any multivariate or multi-survey analogues would need to be developed from scratch in TMB. Efforts are underway to explore Items 3 and 4 using the GOA and BSAI other rockfish stock assessments as case studies in future assessment cycles. Item 5 is currently the topic of a manuscript in early prep.

The issue of how this model is used for apportionment in Tier 3 and other assessments was raised (e.g., for BSAI Atka mackerel). The Teams noted that these improvements would also apply to the apportionment applications and noted that the working-group title should probably be broadened.

We agree that the working group name should be broadened and request a name change to the random effects (or simply REMA) model working group.

Summary of the *rema* R package

The goal of the *rema* R package is to make working with the REMA model for apportionment or Tier 4/5 biomass estimation as simple as possible. The structure, naming conventions, functions, and documentation in *rema* were inspired by and modeled after the Woods Hole Assessment Model (WHAM), an open-source, state-space age-structured assessment model and R package (Miller and Stock 2020, Stock and Miller 2021).

The REMA model accepts two primary types of data: (1) a biomass survey time series (e.g. bottom trawl survey biomass), and (2) an auxiliary catch-per-unit effort (CPUE) time series. The CPUE data is generalized within *rema* and can include nominal CPUE (e.g. numbers-per-hook from a longline survey) or a summable, area-weighted index such as the NMFS longline survey relative population numbers or weights (RPNs and RPWs, respectively).

Instructions for *rema* installation and a series of vignettes can be accessed at https://afsc-assessments.github.io/rema/. There are a handful of key R functions that make up the core of *rema* and using the package can be distilled into the following five steps:

1. Read biomass or CPUE index data into R. Data can be stored and read in from .csv files, or alternatively, data can be accessed from the ADMB rwout.rep report file using read_admb_re().
2. Specify model structure and assumptions using prepare_rema_input(). This function allows users to quickly transition from a single to two survey model, specify alternative process error structures, add likelihood penalties or priors on parameters, evaluate alternative assumptions about zero biomass observations, and estimate additional observation error variance.
3. Fit the specified REMA model using fit_rema() and determine whether the model has met basic convergence criteria (e.g., Hessian is positive definite, a maximum gradient component approximately equal to zero).
4. Extract REMA model output into clean, consistently formatted data frames using tidy_rema(). The user can visualize this model output using plot_rema(), or quickly format it into tables for a report.
5. Compare alternative REMA models and conduct model selection using compare_rema_models(). Output from this function includes a table of Akaike Information Criteria (AIC) when appropriate, figures, and tidied data frames. This function also accepts model output from the ADMB version of the RE model for easy comparison to past models.

Taken together, these functions allow R users to quickly fit and compare a suite of statistical models in TMB without needing software-specific training or expertise.

Model development

Base model for a single survey and stratum

The basic REMA model can be represented as a state-space random walk model with added noise. The observation model is comprised of an index of log-transformed annual survey biomass data $ln(B_t)$ with associated standard deviations $\sigma_{ln(B_t)}$, where $\sigma_{ln(B_t)}$ is approximated using the coefficient of variation of B_t (σ_{B_t}/B_t) such that

$$\sigma_{ln(B_t)} = \sqrt{ln\left(\frac{\sigma_{B_t}{}^2}{B_t} + 1\right)}. \tag{1}$$

The measurement or observation equation, which describes the relationship between the observed survey biomass $ln(B_t)$ and the latent state variable, population biomass $ln(\hat{B}_t)$, is expressed as

$$ln(B_t) = ln(\hat{B}_t) + \epsilon_t, \text{where } \epsilon_t \sim N(0, \sigma_{ln(B_t)}^2). \tag{2}$$

The state equation and associated process error variance σ_{PE}^2 is defined as

$$ln(\hat{B}_t) = ln(\hat{B}_{t-1}) + \eta_{t-1}, \text{where } \eta_t \sim N(0, \sigma_{PE}^2), \qquad (3)$$

where the initial condition $ln(\hat{B}_1)$ is constrained by the random walk process. In the base model, the process error variance σ_{PE}^2 is the only fixed effect parameter estimated, and the unobserved population biomass $ln(\hat{B}_t)$ is estimated as a vector of random effects. The model is fit using maximum marginal likelihood estimation, where the Laplace approximation is used to approximate the marginal negative log-likelihood in both TMB and ADMB (Skaug and Fournier 2006).

The univariate versions of ADMB and TMB were compared for 58 stocks, and results showed high level of agreement between the two models (within 0.01% relative error; Figure 1). The small differences in results are attributed to the different optimizers and implementations of the Laplace approximation. A reproducible example of fitting the univariate version of the TMB model and comparing those results to ADMB is available in the [REMA basics](#) vignette.

Extending to multiple biomass survey strata

The single survey, single stratum version of the model can be extended to include one or more additional strata j from the same survey. The inclusion of multiple strata in the same model is advantageous in scenarios where the apportionment of biomass among areas is needed. This extension assumes no correlation in the observation errors among survey strata, though process error variance can be shared or estimated independently among strata.

The ADMB and TMB versions of the REMA model utilize different methods for estimating the variance of the total predicted biomass. Therefore, while strata-specific estimates of predicted biomass and associated confidence intervals will be close to identical between the ADMB and TMB versions of the model, the confidence intervals of the total predicted biomass will differ slightly (Figure 2). In the original ADMB code, the Marlow (1967) method is applied, such that the total variance σ_J^2 is approximated as

$$\sigma_J^2 = ln\left(\frac{\sum e^{2\hat{B}_j + \sigma_{\hat{B}_j}^2}\left(e^{\sigma_{\hat{B}_j}^2} - 1\right)}{\left(\sum e^{\hat{B}_j + \sigma_{\hat{B}_j}^2/2}\right)^2} + 1\right). \qquad (4)$$

In the *rema* package, the total variance is estimated using the standard delta method and can be replicated in ADMB using an sdreport_number and in TMB using the ADREPORT macro. As described in Monnahan et al. (2021), the exploration of methods for summing log-normal variables is a research topic that has potential impacts beyond the scope of this implementation of the REMA model.

A reproducible example of fitting the multivariate version of the TMB model and a comparison of results to ADMB is available in the [REMA basics](#) vignette. In this example, we also show how Akaike Information Criterion (AIC) can be used for model selection to explore the inclusion of strata-specific versus a single, shared process error variance.

Addition of an auxiliary catch per unit effort (CPUE) survey

In situations where an auxiliary biomass or catch per unit effort (CPUE) survey I_t and associated variance σ_{I_t} are available, an additional scaling parameter q can be estimated to facilitate the inclusion of the new

information into biomass predictions (Hulson et al. 2021). The predicted annual CPUE survey index $\hat{I}_t$ is calculated as

$$\hat{I}_t = qe^{\hat{B}_t},$$ (5)

and the CPUE survey observations have an additional measurement equation and likelihood component similar to the biomass survey:

$$ln(I_t) = ln(\hat{I}_t) + \epsilon_I, \text{where } \epsilon_I \sim N\left(0, \sigma^2_{ln(I_t)}\right).$$ (6)

By default, the *rema* library estimates a single q for each stratum. It also allows for user-specification of q parameters by strata, including the option to estimate a single, shared q across all strata. If the strata definitions are not the same for the biomass and CPUE surveys (e.g. biomass is estimated at a finer geographic resolution than the CPUE index), the user can define the relationship between the two surveys' strata using the q_options argument to the prepare_rema_input() function (see q_options and pointer_biomass_cpue_strata in ?prepare_rema_input). However, since the auxiliary CPUE survey index is related to unobserved population biomass at the level of the biomass survey strata, the REMA model can only accommodate scenarios where the CPUE survey strata have a coarser resolution or are equivalent to the biomass survey strata.

A reproducible example of fitting to the two-survey version of the REMA model is provided in the Fitting to an additional CPUE survey vignette. This example also describes an error in the previously used ADMB version of the REMA model, and presents several alternative models that estimate additional observation error. These topics are described in more detail in the following two sections.

A correction to the ADMB version of the two-survey REMA model

Separability, as implemented in the SEPARABLE_FUNCTION in ADMB and through automatic detection in TMB, increases the computational efficiency of the Laplace approximation by breaking complex, multivariate integrals into a product of simpler, univariate integrals (Fournier et al. 2012). In the random effects implementation of ADMB, parameters defined in the PARAMETER_SECTION of the template file cannot be used within the SEPARABLE_FUNCTION unless they are passed as arguments to the function (Skaug and Fournier 2013). In the ADMB version of REMA, the calculation of predicted CPUE (equation 5) occurred outside rather than inside the SEPARABLE_FUNCTION, and as a result, violated this rule and affected the accuracy of the Laplace approximation.

We explored this error in a simplified example of REMA in both ADMB and TMB, which is available on Github. We were able to reproduce results from the TMB version of REMA in ADMB by passing $ln(q)$ as an argument to the SEPARABLE_FUNCTION and performing the $ln(\hat{I}_t)$ calculation inside the function (Figure 3). When we used Markov Chain Monte Carlo (MCMC) methods for statistical inference instead of MLE, the results from both ADMB versions closely matched the correct version of REMA (Figure 4). A comparison of the individual negative log-likelihood (NLL) components, along with the joint and marginal NLLs, revealed that all were the same between the TMB model, correct "inside" ADMB version, and incorrect "outside" ADMB version, except the marginal NLL. Taken together, this analysis confirms there is a bug in the "outside" ADMB version, which affects the accuracy of the Laplace approximation and model results.

Currently one Tier 3 apportionment model (GOA rougheye and blackspotted rockfish) and two Tier 5 assessments (GOA thornyheads, and GOA shortraker rockfish) use the incorrect version of the ADMB REMA model. A revised GOA thornyheads model is presented in Appendix A of this report, along with

new alternate models for consideration by the GOA GPT in November 2022. Several of these alternate models estimate additional observation error, which is introduced in the next section.

Estimation of additional observation error

Based on experience gained using alternative observed index estimates (e.g., relative CPUE indices), there appears to be cases where the estimates of observation error variances for the biomass and/or CPUE survey are too low (e.g., Echave et al. 2020). That is, there is a mismatch between biologically reasonable inter-annual variability and the precision of index estimates. In these instances, the model estimates of $(\sigma_{B_{t,j}}^2 + \sigma_{I_{t,j}}^2)/\sigma_{PE}^2$ may be lower than what should be expected based on an individual species' life history traits. For example, if the ratio of observation to process error variation is low, model predictions of population biomass may exhibit high inter-annual variability. This behavior would be unexpected in a slow-growing, long-lived species, which should exhibit low inter-annual variation in biomass (i.e., low process error variance), especially in situations when fishing exploitation is low.

One approach to address this issue is to estimate additional observation error. This method is commonly implemented in Alaskan crab stock assessments (e.g., Zheng and Siddeek 2020) and has been explored in several groundfish assessment models as well. Using the biomass survey variance as an example, the extra estimated error (σ_τ) is specified as:

$$\sigma_{ln(B_t)} = \sqrt{ln\left(\frac{\sigma_{B_t}^2}{B_t} + \sigma_\tau^2 + 1\right)}. \tag{7}$$

This approach is a new method for Tier 5 stock assessments and apportionment methods at the AFSC. A reproducible example using GOA shortraker rockfish is provided in the Fitting to an additional CPUE survey vignette. In this example, the estimation of additional observation error for the biomass and CPUE survey observations resulted in a better fit by AIC than status quo approaches and has a more biologically realistic trend in predicted population biomass.

Exploration of the Tweedie distribution for zero biomass observations

The Tweedie distributions are a family of probability distributions that can be generalized to include the Gaussian, inverse Gaussian, gamma, Poisson, and compound Poisson-gamma distributions[1]. The Tweedie can be defined with three parameters, a mean (μ), power parameter (ρ), and dispersion (ϕ), where the relationship between the variance and these parameters is defined by $\sigma^2 = \phi\mu^\rho$. When ρ is bounded between 1 and 2, the Tweedie is a positive, continuous distribution that can include zero values, thus allowing it to more naturally handle survey time series with one or more zero observations. Values of ρ on these bounds are special cases of the Tweedie, where ρ=1 is equivalent to a Poisson distribution and ρ=2 is a gamma distribution. In REMA, the Tweedie is constrained between but not including 1 and 2 using a logit-transformation on ρ.

Similar to the normal distribution, observation error variances are treated as known for the Tweedie distribution in the REMA model. Using the biomass survey observation as an example, the dispersion of the biomass observation in strata j in year t is derived as

$$\phi_{B_{t,j}} = \frac{\sigma_{B_{t,j}}^2}{\left(\hat{B}_{t,j}\right)^\rho}. \tag{8}$$

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[1] https://en.wikipedia.org/wiki/Tweedie_distribution

The result is that only one additional parameter (ρ) is estimated when applying this alternative distribution. The measurement equation for the Tweedie becomes

$$B_{t,j} = \hat{B}_{t,j} + \epsilon_B, \text{where } \epsilon_B \sim Tw_\rho\left(0, \phi_{B_{t,j}}\right). \tag{9}$$

Because $\sigma_{B_{t,j}}$ is undefined when $B_{t,j}$=0, the zeros are assumed to have a CV=1.5. This assumption can be explored by the user in *rema*, for example, if the user wanted to define a CV=2.0 for zeros, they would define zeros = list(assumption = 'tweedie', options_tweedie = list(zeros_cv = 2.0)) within the prepare_rema_input() function.

A reproducible example using the Tweedie distribution for observation error can be found in the Strategies for handling zero biomass observations vignette. We use the non-shortspine thornyhead component of the BSAI other rockfish stock, which is unique in that 13 of 38 bottom trawl survey estimates are zeros. In a simplified case shown here, we compare model predictions from three alternative models that have different assumptions for zeros, including (1) treating zeros as NAs, (2) adding a small constant and CV, and (3) modeling the observed index using the Tweedie distribution (Figure 5). While the Tweedie performs well in this case, further exploration revealed that the Tweedie models can be very slow to run and often did not converge, especially in instances where the observation error variance estimates were low. It is possible that further development on estimating additional observation error variance (e.g. τ^2 in the previous section) could alleviate these convergence errors. However, in the interim, the Tweedie distribution in REMA should be considered experimental, and we do not recommend it as a viable alternative for tactical assessments at this time.

Model validation and experimental One-Step Ahead (OSA) residuals

The use of one-step ahead (OSA) residuals, also referred to as forecast residuals or prediction errors, is crucial for validation of state-space models like REMA (Thygesen et al. 2017). Instead of comparing the observed and expected values at the same time step, OSA residuals use forecasted values based on all previous observations (i.e. they exclude the observed value at the current time step from prediction). Traditional residuals (e.g. Pearson's residuals) are inappropriate for state-space models, because process error variance may be over-estimated in cases where the model is mis-specified, thus leading to artificially small residuals (see Section 3 of Thygesen et al. 2017 for an example).

Methods for calculating OSA residuals have been implemented in TMB through the TMB::oneStepPredict() function. While these methods are straightforward to implement in TMB, they are computationally demanding, and the validity (and accuracy) of the OSA residuals may vary by situation and method used. Methods to implement OSA residuals in REMA are under development and should be considered experimental. Currently REMA implements OSA residuals using the method = "cdf" option in TMB::oneStepPredict(), which has the benefit of speeding up residual calculations by saving copies of the one-step cumulative density function at each data point and thus reducing the number of calculations at each function evaluation. While OSA residuals appear to be calculated correctly for some REMA models, occasionally NaN values for residuals are returned, especially in cases with small measurement errors. One potential cause of this error may lie in the initialization of the state process within REMA and will be explored further in future versions of this package. Finally, the algorithms underpinning TMB::oneStepPredict() methods are an area of active research, and therefore this function remains in Beta mode within the TMB package and is subject to future change.

Conclusions

In response to the SSC requests, and given the importance of how the RE model is used in many NPFMC assessment documents, we have developed a unified approach that adds consistency and robustness in its application. Furthermore, we have provided a version-controlled R package with documented methods that will improve consistency, transparency in methods, and reproducibility of apportionment and Tier 4/5 assessments. We seek endorsement by the Plan Teams and SSC to adopt this updated code version for application to the NPFMC's groundfish assessments for 2022 and beyond. We recommend future research topics for the REMA model working group include model validation methods, development of priors on process error variance based on life history information[2], and continued exploration of the Tweedie distribution and other alternatives for handling zero biomass observations.

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[2] An example using the exponential smoothing model to inform the expected ratio of observation and process error variation was presented at the 2015 Lowell Wakefield Symposium by Paul Spencer and can be accessed online: https://seagrant.uaf.edu/events/2015/wakefield-data-limited/presentations/Spencer-Evaluation-Statistical-Models.pdf

99501. https://meetings.npfmc.org/CommentReview/DownloadFile?p=86098951-a0ed-4021-a4e1-95abe5a357fe.pdf&fileName=Tiers%204%20and%205%20assessment%20considerations.pdf

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Thygesen, U.H., Albertsen, C.M., Berg, C.W. et al. Validation of ecological state space models using the Laplace approximation. Environ Ecol Stat 24, 317–339 (2017). https://doi.org/10.1007/s10651-017-0372-4

Figures

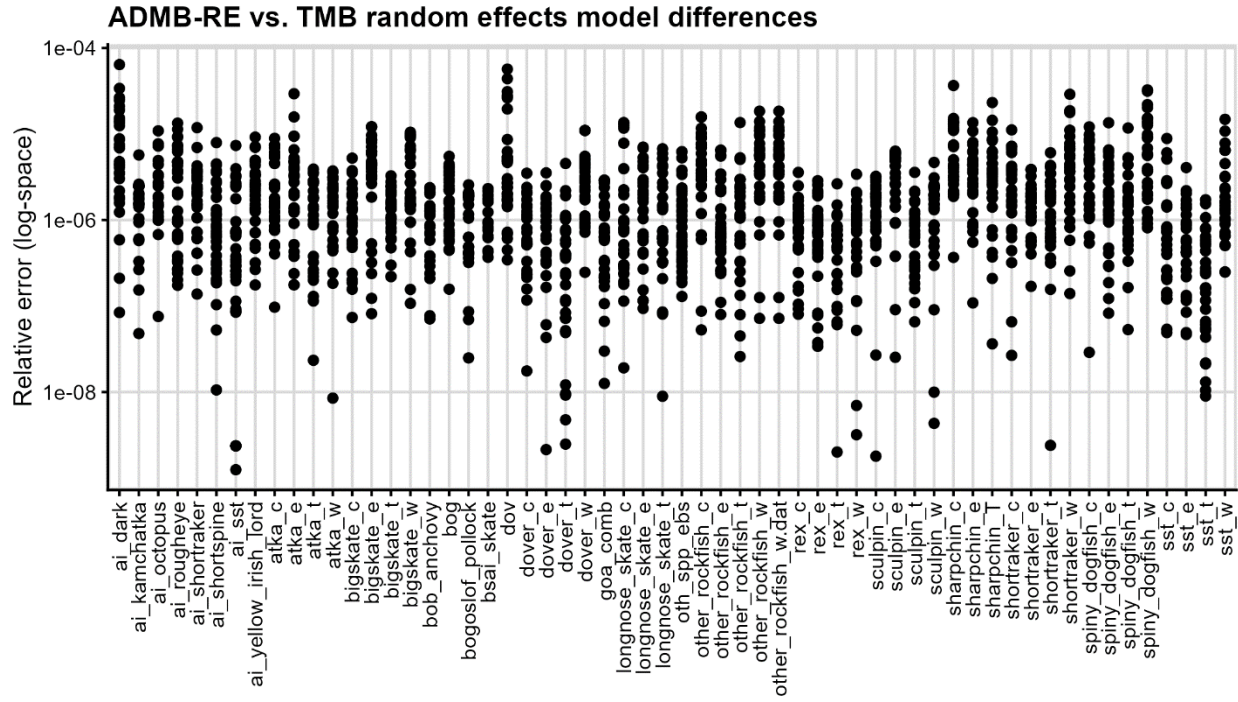**ADMB-RE vs. TMB random effects model differences**

Figure 1. The relative error between predicted log-biomass in the ADMB-RE and TMB versions of the univariate random effects model for 58 example stocks, where each data point represents an annual model prediction for a given stock. The *y*-axis has been transformed to log-space for ease of visualization. These examples do not include zeroes.
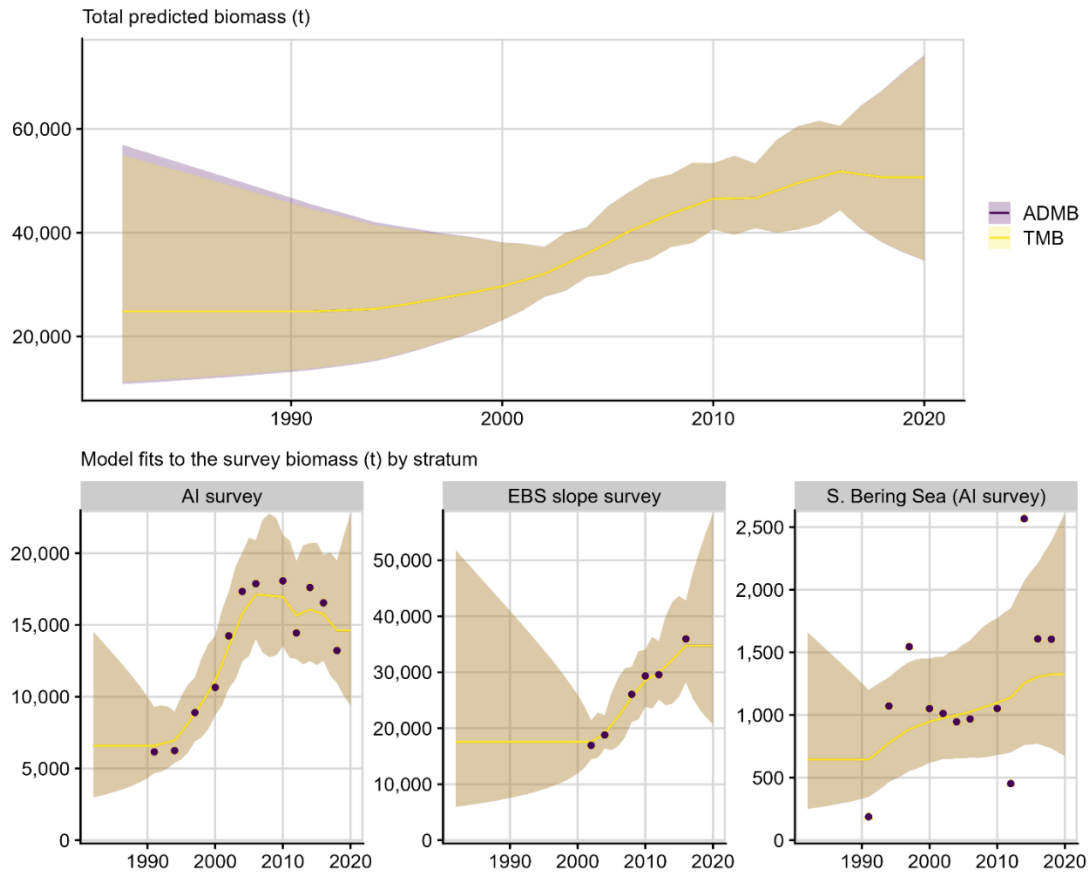
Figure 2. A comparison of ADMB and TMB total predicted biomass (top panel) and model fits to the survey biomass estimates by stratum for the Bering Sea and Aleutian Islands shortspine thornyhead stock. The shaded regions represent the 95% confidence intervals for the model predictions. Although results are close to identical when compared by stratum, the confidence intervals for the total predicted biomass differ slightly because the ADMB model used the Marlow method for the variance of the total biomass.
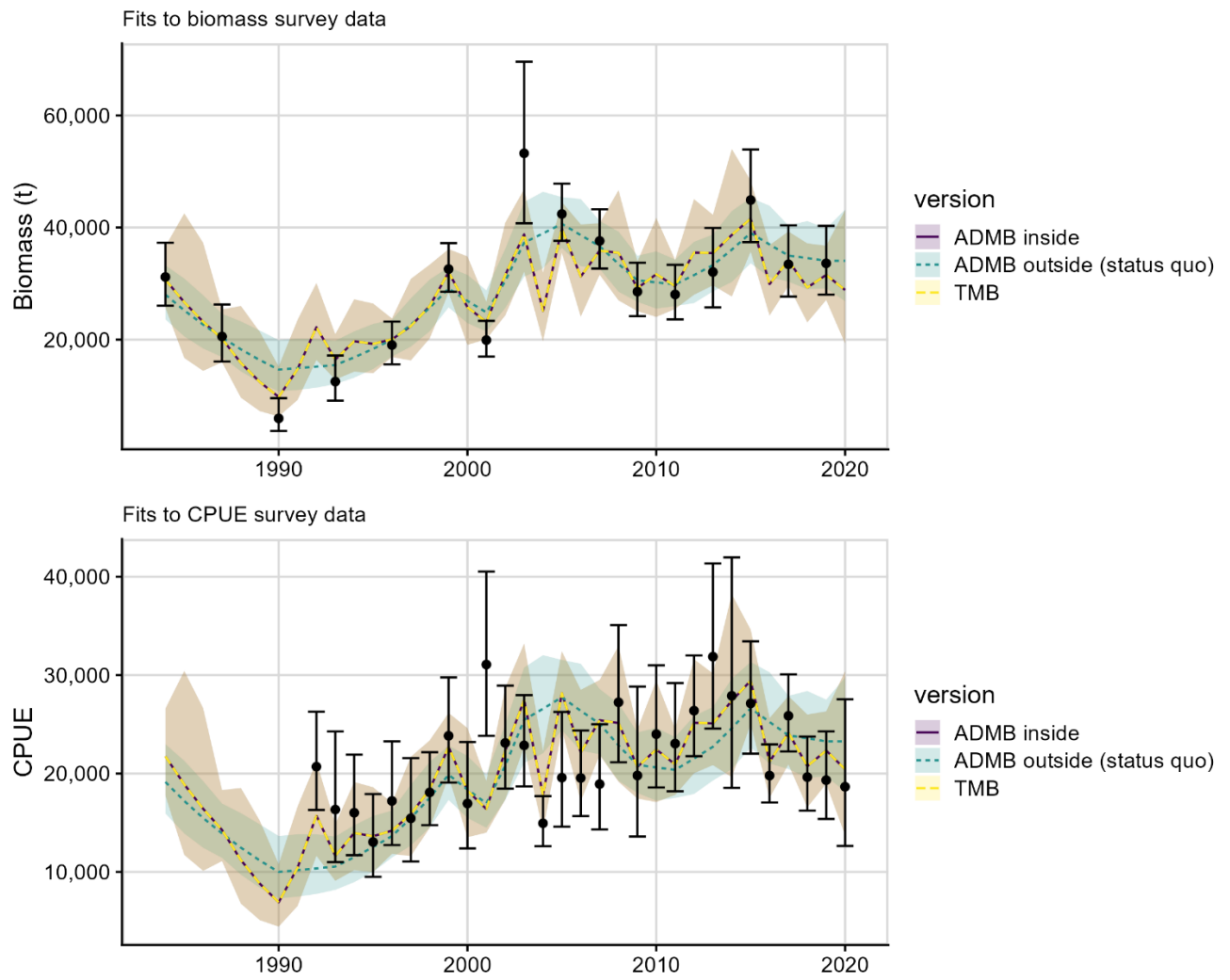
Figure 3. A comparison of model fits to biomass and CPUE survey data using the "ADMB inside", "ADMB outside," and TMB models. Predicted CPUE is correctly defined inside the SEPARABLE_FUNCTION in the "ADMB inside" model, and incorrectly defined outside of the SEPARABLE_FUNCTION in the status quo ADMB "outside model."
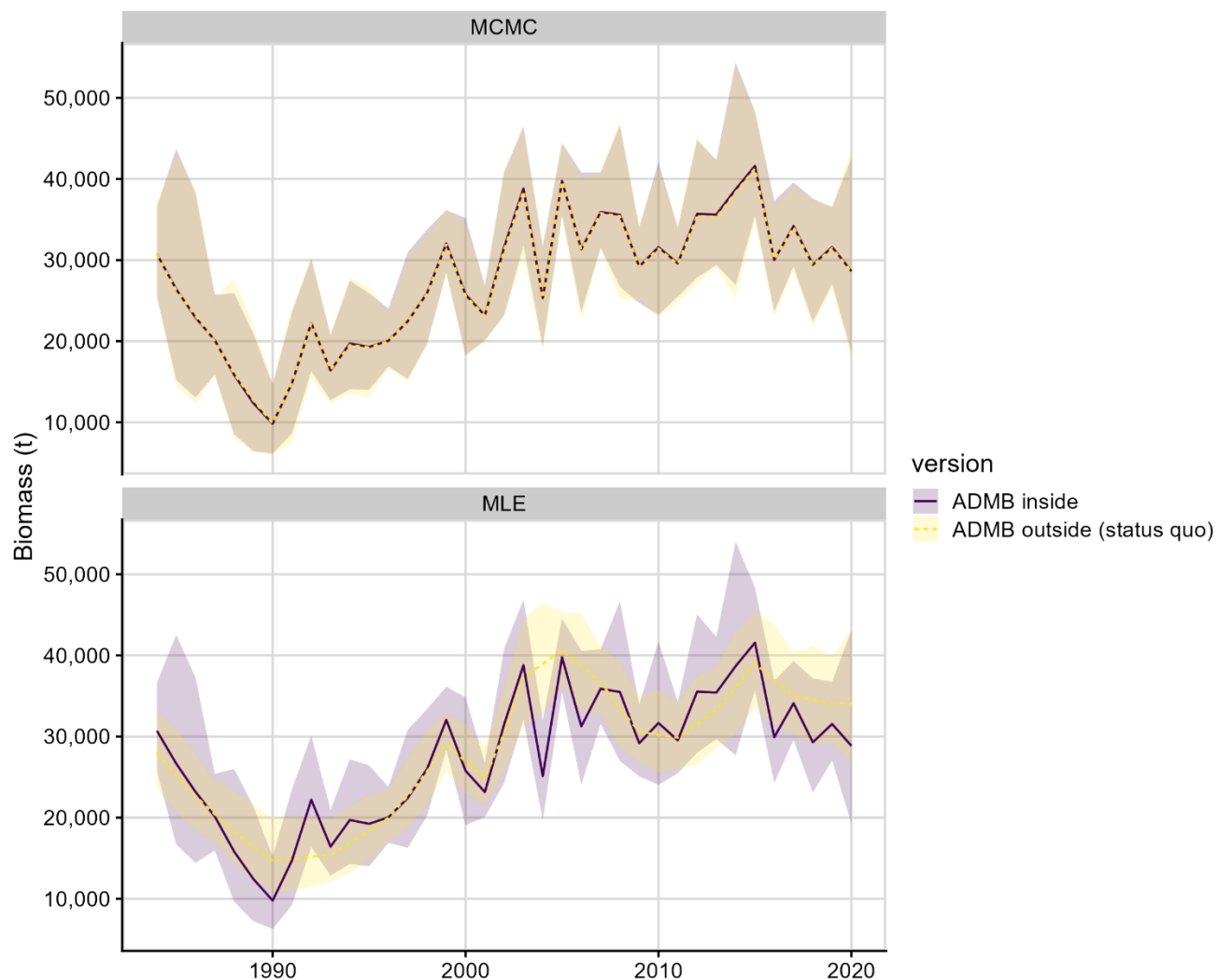
Figure 4. A comparison of "ADMB inside" and "ADMB outside" model predicted biomass using Markov Chain Monte Carlo (MCMC) methods and Maximum Likelihood Estimation (MLE). Predicted CPUE is correctly defined inside the SEPARABLE_FUNCTION in the "ADMB inside" model, and incorrectly defined outside of the SEPARABLE_FUNCTION in the status quo ADMB "outside model." With MCMC the Laplace approximation is not used and so the separable distinction is irrelevant.
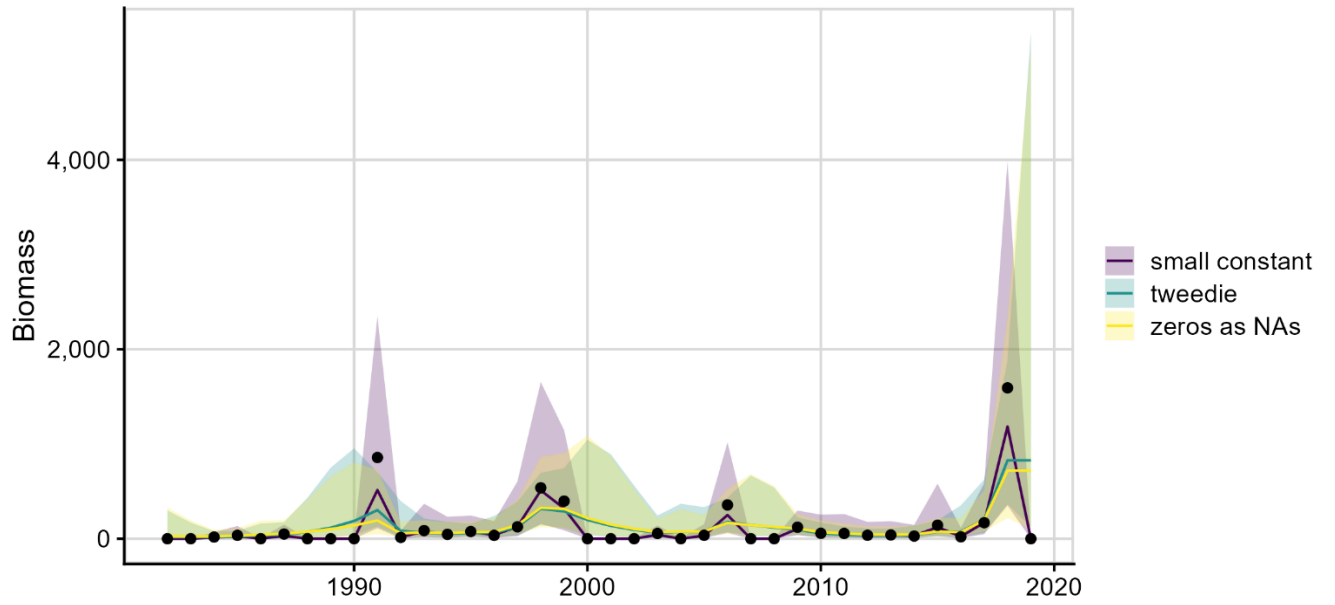
Figure 5. A comparison of model fits to the non-shortspine thornyhead other rockfish trawl survey biomass in the eastern Bering Sea using three different assumptions about how to treat zero biomass observations: 1) zeros as NAs, (2) adding a small constant = 0.1 with a CV = 3.0, and (3) modeled using the Tweedie distribution.

Appendix A: Alternative models for the GOA thornyheads stock complex in 2022

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September 2022

Executive summary

Gulf of Alaska (GOA) thornyheads (*Sebastolobus* species) are assessed on a biennial schedule in even years and managed as a Tier 5 stock. The assumed natural mortality for thornyheads (M=0.03) is used to inform harvest recommendations for Tier 5 stocks, where $F_{OFL}=M$ and $F_{ABC}=0.75M$. Biomass is estimated using a two-survey random effects (REMA) model fit to the GOA bottom trawl and NMFS longline survey data (Hulson et al. 2021). Here we present a correction to current assessment methodology and propose alternative models for consideration in November 2022.

Changes in the input data

For the full assessment in November 2022, we recommend the following changes to input data:

1) The time series of NMFS longline survey (LLS) relative population weights (RPWs) will be updated for 2021 and 2022. The 2022 LLS RPWs are not ready for September 2022, so this document only includes data through 2021. New geographic area sizes and variance calculations were implemented in the longline database in 2021, which resulted in small changes to the longline survey time series, primarily in the eastern GOA (Table A-1).
2) Addition of the 2021 GOA bottom trawl survey (BTS; Table A-2).

Changes in the assessment methodology

For the full assessment in November 2022, we recommend a correction to the assessment model based on an error in the implementation of the SEPARABLE_FUNCTION in AD Model Builder (ADMB; Fournier et al. 2012, Skaug and Fournier 2013) as described in the main document in the section titled *A correction to the ADMB version of the two-survey REMA model*. We present the corrected version of the two-survey random effects (REMA) model fit in Template Model Builder (TMB; Kristensen et al. 2016) and propose three alternative models that estimate additional observation error. Models not fit in ADMB were fit in TMB using the new *rema* R package and rely on methods introduced in the main document of this report (https://afsc-assessments.github.io/rema/).

The models presented use the following naming conventions:

1) **Model 18**: The accepted model in the last full assessment (Echave et al. 2020) as implemented in 2020 using the multivariate, two-survey version of the random effects (REMA) model fit in ADMB. An error was found in this model code, which impacted biomass predictions.

2) **Model 22.1.a 2020 data**: Corrected two-survey version of Model 18 fit using TMB with the same data and model assumptions as Model 18.

3) **Model 22.1.b 2021 data**: Same as Model 22.1.a but with updated data through 2021 (includes the 2021 BTS biomass estimate and updated time series of LLS RPWs; Tables A-1 and A-2).

4) **Model 22.2.a**: Same as Model 22.1.b and estimates additional observation error for the BTS biomass data using equation 7 of the main document.

5) **Model 22.2.b**: Same as Model 22.1.b and estimates additional observation error for the LLS RPWs using equation 7 of the main document.

6) **Model 22.2.c**: Same as Model 22.1.b and estimates additional observation error for both the BTS and LLS data using equation 7 of the main document.

7) **Model 22.3**: Same as Model 22.1.b but drops the LLS RPWs and only fits to the BTS biomass.

These models were evaluated based on biological realism and a visual examination of fits to the data. When applicable, we use Akaike Information Criteria (AIC) to inform model selection.

Summary of results

The model correction resulted in a 14.4% decrease in estimates of 2020 biomass, OFL, and maximum permissible ABC (max ABC):

Model	Year	Biomass (t)	OFL (t)	max ABC (t)
Model 18	2020	86,802	2,604	1,953
Model 22.1.a	2020	74,296	2,229	1,672

When data were updated through 2021 (where Model 22.1.b is the same as Model 22.1.a but with updated data), alternative models resulted in the following estimates of 2022 biomass, OFL, and maximum permissible ABC (max ABC), with the author-preferred model highlighted in bold:

Model	Year	Biomass (t)	OFL (t)	max ABC (t)
Model 22.1.b	2022	65,631	1,969	1,477
Model 22.2.a	2022	63,241	1,897	1,423
Model 22.2.b	2022	74,108	2,223	1,667
Model 22.2.c	**2022**	**71,584**	**2,148**	**1,611**
Model 22.3	2022	81,061	2,432	1,824

The corrected Model 22.1.b with updated data resulted in further declines in biomass as a result of recent declines in the GOA BTS and LLS abundance indices. Trawl survey biomass declined 5.9, 13.8, and 21.8% in the eastern GOA (EGOA), central GOA (CGOA), and western GOA (WGOA), respectively between 2019 and 2021 (Table A-2). Similarly, LLS RPWs declined 16.7, 12.5, and 16.7% in the EGOA, CGOA, and WGOA, respectively, between 2020 and 2021 (Table A-1). These declines were moderated or reversed by estimating additional observation error in the BTS and/or LLS indices (Model 22.2 series) or by removing the LLS index entirely (Model 22.3). **The author-preferred model is Model 22.2.c, which uses the corrected two-survey REMA model and estimates additional observation error for the GOA BTS and LLS indices.** Model 22.2.c resulted in the most biologically realistic biomass trajectory and was the best-fitting model by AIC (Table A-3).

The alternative models resulted in the following biomass apportionment by management area:

Model	Year	EGOA	CGOA	WGOA
Model 18	2020	35.4%	46.6%	18.0%
Model 22.1.a	2020	30.6%	45.6%	23.8%
Model 22.1.b	2022	32.0%	46.4%	21.6%
Model 22.2.a	2022	30.9%	47.1%	22.1%
Model 22.2.b	2022	34.2%	44.8%	21.0%
Model 22.2.c	**2022**	**32.6%**	**46.1%**	**21.2%**
Model 22.3	2022	34.7%	45.3%	19.9%

When comparing the effect of updated data on the corrected model (Model 22.1.a uses data through 2020 and Model 22.1.b uses data through 2021), there was a small shift in biomass and apportionment ratios towards the EGOA. These changes are attributed to recent declines in the BTS and LLS abundance indices, especially in the WGOA. The author-preferred Model 22.2.c resulted in negligible changes to apportionment ratios when compared to the corrected model with updated data, Model 22.1.b.

Analytic approach

Model structure

The GOA thornyheads assessment model uses the two-survey version of the random effects model (REMA; Hulson et al. 2021) fit to the GOA BTS biomass and LLS RPWs (Echave et al. 2020). The GOA BTS did not sample in all depth strata in all years; the 1996 and 2001 surveys did not survey the depths >500 m, and the 2003, 2011, 2013, 2017, and 2019 surveys did not survey depths >700 m (Echave et al. 2020). Additionally, the GOA BTS did not sample the EGOA in 2001. In order to appropriately model data gaps, BTS biomass estimates are stratified by management area (EGOA, CGOA, and WGOA) and depth strata (0-500 m, 501-700 m, and 701-1000 m), resulting in nine total biomass survey strata (Table A-2). The LLS RPWs are stratified by management area (EGOA, CGOA, WGOA; Table A-1). All versions of the REMA model presented here estimate three process error parameters, one for each management area (Echave et al. 2020; equations 1-4 in the main document). In the two-survey versions of the model, an additional parameter (q) is estimated, which scales the LLS RPWs to population biomass (Echave et al. 2020; equations 5-6 in the main document).

During the development of the REMA model in TMB, an error in the implementation of the SEPARABLE_FUNCTION in ADMB was discovered. This error is discussed in the main document in the section titled *A correction to the ADMB version of the two-survey REMA model*. In short, the specification of predicted RPWs outside the SEPARABLE_FUNCTION violated guidelines in the ADMB manual that state parameters must be passed as arguments into the SEPARABLE_FUNCTION when using the parameters directly or indirectly through derived quantities (Fournier et al. 2012, Skaug and Fournier 2013). Although this version of the model produces results that suggest model convergence (i.e., a maximum gradient component approximately equal to the zero, a positive definite Hessian), the SEPARABLE_FUNCTION propagates to the Laplace approximation of the marginal negative log-likelihood and thus model results are invalid.

We present the corrected version of the two survey random effects (REMA) model (Models 22.1.a and 22.1.b) and propose alternative models that estimate additional observation error (Models 22.2.a, 22.2.b, and 22.2.c; equation 7 in the main document) or omit the LLS RPWs entirely (Model 22.3). All new models were fit in TMB using the new *rema* R package and rely on methods described in the main document of this report (https://afsc-assessments.github.io/rema/). Model selection was conducted using a visual examination of model fits and evaluation of model suitability based on the biological realism of resulting biomass trajectories. When applicable (i.e., when models were fit to the same data), we used AIC to inform model selection, where a reduction in AIC by ≥ 2 lends statistical support to the inclusion of new parameters.

Results

Comparison of Model 18 to the corrected Model 22.1.a

Model 18, the status quo version of the two-survey model with the error in the ADMB code, resulted in a much smoother biomass trajectory (i.e., lower process error variation) when compared to the correctly-specified version of the model (Model 22.1.a; Figure A-1). For Model 22.1.a, this result was attributed to the high precision (i.e., low observation error) of BTS biomass and LLS RPW estimates (Tables A-1 and A-2), which in turn produced large estimates of process error variance and allowed the model predictions to closely track inter-annual variability in the survey data (Table A-4, Figure A-1). The REMA model's over-emphasis on noisy survey data is undesirable for long-lived species like thornyheads. First, we show the impact of data updates, then we present alternative models in later sections.

Impact of data updates: Model 22.1.a and Model 22.1.b

As described in the *Changes in the input data* section, the LLS RPW estimates were updated in the longline survey database in 2021, and new 2021 GOA BTS biomass and 2021 LLS RPW data points were added to the model (Tables A-1 and A-2). Although the model structures are identical, for clarity we identified this as a minor model change, where Model 22.1.a uses the same data as the 2020 assessment and Model 22.1.b uses the updated data.

The updated LLS RPW time series had negligible impacts on the predicted biomass trajectories between 1984 and 2020 (Figure A-2, Table A-5). The small increase in the total predicted biomass over time was attributed to a slight increase in the geographic area size assumed in the EGOA in the LLS RPW calculations (C. Rodgveller, AFSC, personal communication, September 2021). However, between 2020 and 2022 model predictions diverge significantly due to recent declines in abundance index data (Figure A-2). Between 2019 and 2021, the BTS biomass estimates declined 5.9, 13.8, and 21.8% in EGOA, CGOA, and WGOA, respectively (Table A-2). Between 2020 and 2021, the LLS RPWs declined 16.7, 12.5, and 16.7% in the EGOA, CGOA, and WGOA, respectively (Table A-1). The consistent declines in both survey indices in all management areas resulted in an overall 11.7% decrease in the 2022 model estimate of total biomass between Model 22.1.a and Model 22.1.b (Figure A-2).

Comparison of Model 22.1.b to new alternative models

The biomass trajectories in Model 22.1.b are highly variable and closely track the noise in the BTS and LLS observations (Figure A-3). This result is attributed to the relatively high precision of the BTS biomass and LLS RPW estimates, which leads to an over-emphasis on the data and high estimates of process error variance (Table A-4). These results are biologically unrealistic for *Sebastolobus* species, which are notably long-lived fish that should exhibit low variability in population biomass. In response to these findings, we developed several alternative models that estimate additional observation error for the BTS biomass index (Model 22.2.a), LLS RPW index (Model 22.2.b), and both the biomass and RPW indices (Model 22.2.c). For comparison, we also present a final model that removes the LLS RPW entirely and only fits to the BTS biomass (Model 22.3).

The inclusion of additional observation error parameters for the BTS biomass and LLS RPW indices resulted in a substantial decrease in the marginal negative log-likelihood (i.e., the objective function) and smoother biomass trajectories that fit the data well without over-fitting to the noisy survey observations (Table A-3, Figure A-3). The best-fitting model by AIC was Model 22.2.c, which also produced the smoothest, and thus most biologically realistic, biomass trajectory (Table A-3, Figure A-3). Model 22.2.c parameter estimates show that the REMA model effectively balances the tradeoff between observation and process error when allowed to estimate additional observation error for the survey abundance indices (Table A-4).

As expected, Model 22.3 closely tracks the BTS biomass survey observations (Figure A-4). A comparison of process error variance parameter estimates between Model 22.3 and Model 22.2.c suggest that process error may be over-estimated in Model 22.3, especially in the CGOA and WGOA (Table A-4). Additionally, Model 22.3 does not adequately capture recent reductions in both survey abundance indices, which suggests the LLS RPWs provide important information on thornyheads that should not be excluded from the model (Figure A-4).

Recommendations for November 2022

For November 2022, we recommend omitting Model 18 due to the error in the ADMB code and replacing it with a suite of corrected models coded in TMB using the *rema* R library. We plan to present Model 22.1 (dropping the 'b' with the formal inclusion of all new data in 2022), Models 22.2.a, 22.2.b, 22.2.c, and Model 22.3, because they represent a logical model progression and transition from the previous model (Figure A-5, Table A-5). **Our preferred model for November 2022 is Model 22.2.c, because it resulted in the most biologically realistic predicted biomass trajectory and was the best-fitting model by AIC (Table A-3)**. We caution against reverting back to the single-survey model (Model 22.3), because the LLS appears to contribute meaningful abundance trend information to the model that the BTS may be missing (Figures A-3, A-4, and A-5). Additionally, the use of two fishery-independent time series provides a buffer in the event of future changes to survey effort.

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Tables

Table A-1. A summary of changes in the NMFS longline survey relative population weights (RPWs) and associated coefficient of variations (CVs) between the 2020 assessment (old) and present (new) by management area (EGOA = eastern Gulf of Alaska, CGOA = central Gulf of Alaska, WGOA = western Gulf of Alaska).

Management area	Year	New RPWs	Old RPWs	Percent change	New RPW CV	Old RPW CV	Percent change
EGOA	1992	11,508	11,343	1.5	0.092	0.093	-1.2
EGOA	1993	16,280	15,854	2.7	0.087	0.089	-2.4
EGOA	1994	11,420	11,230	1.7	0.097	0.099	-1.5
EGOA	1995	15,391	15,093	2.0	0.095	0.096	-1.6
EGOA	1996	17,773	17,489	1.6	0.091	0.092	-1.4
EGOA	1997	20,537	20,182	1.8	0.082	0.083	-1.7
EGOA	1998	17,280	17,150	0.8	0.058	0.058	-0.7
EGOA	1999	18,512	18,358	0.8	0.102	0.102	-0.8
EGOA	2000	18,619	18,403	1.2	0.100	0.101	-1.1
EGOA	2001	23,071	22,734	1.5	0.075	0.076	-1.3
EGOA	2002	16,872	16,572	1.8	0.083	0.084	-1.8
EGOA	2003	16,468	16,232	1.5	0.087	0.088	-1.4
EGOA	2004	12,631	12,434	1.6	0.107	0.109	-1.4
EGOA	2005	17,418	17,091	1.9	0.098	0.099	-1.5
EGOA	2006	19,307	19,105	1.1	0.090	0.091	-1.0
EGOA	2007	19,878	19,614	1.3	0.065	0.066	-1.2
EGOA	2008	25,211	24,940	1.1	0.104	0.105	-1.1
EGOA	2009	18,339	17,956	2.1	0.080	0.081	-2.1
EGOA	2010	26,361	26,107	1.0	0.090	0.091	-0.8
EGOA	2011	21,823	21,548	1.3	0.074	0.075	-0.9
EGOA	2012	22,553	22,202	1.6	0.092	0.093	-1.5
EGOA	2013	26,493	26,037	1.8	0.058	0.059	-1.3
EGOA	2014	21,839	21,471	1.7	0.093	0.095	-1.5
EGOA	2015	19,669	19,354	1.6	0.076	0.076	-1.0
EGOA	2016	22,031	21,765	1.2	0.093	0.094	-1.2
EGOA	2017	21,605	21,255	1.6	0.115	0.117	-1.6
EGOA	2018	22,453	22,285	0.8	0.085	0.086	-0.6
EGOA	2019	18,684	18,488	1.1	0.050	0.051	-1.2
EGOA	2020	13,300	12,930	2.9	0.062	0.064	-2.7
EGOA	2021	11,081	NA	NA	0.059	NA	NA
CGOA	1992	20,697	20,697	0.0	0.123	0.123	0.0
CGOA	1993	16,337	16,337	0.0	0.206	0.206	0.0
CGOA	1994	16,017	16,017	0.0	0.162	0.162	0.0
CGOA	1995	13,043	13,043	0.0	0.164	0.164	0.0
CGOA	1996	17,215	17,215	0.0	0.156	0.156	0.0
CGOA	1997	15,449	15,449	0.0	0.173	0.173	0.0
CGOA	1998	18,083	18,083	0.0	0.104	0.104	0.0
CGOA	1999	23,834	23,834	0.0	0.114	0.114	0.0
CGOA	2000	16,954	16,954	0.0	0.162	0.162	0.0
CGOA	2001	31,076	31,076	0.0	0.137	0.137	0.0
CGOA	2002	23,109	23,109	0.0	0.115	0.115	0.0
CGOA	2003	22,861	22,861	0.0	0.103	0.103	0.0
CGOA	2004	14,944	14,944	0.0	0.087	0.087	0.0
CGOA	2005	19,580	19,580	0.0	0.151	0.151	0.0
CGOA	2006	19,550	19,550	0.0	0.113	0.113	0.0
CGOA	2007	18,925	18,925	0.0	0.144	0.144	0.0
CGOA	2008	27,239	27,239	0.0	0.130	0.130	0.0
CGOA	2009	19,802	19,802	0.0	0.195	0.195	0.0
CGOA	2010	24,000	24,000	0.0	0.132	0.132	0.0

Management area	Year	New RPWs	Old RPWs	Percent change	New RPW CV	Old RPW CV	Percent change
CGOA	2011	23,041	23,041	0.0	0.122	0.122	0.0
CGOA	2012	26,388	26,388	0.0	0.099	0.099	0.0
CGOA	2013	31,873	31,873	0.0	0.134	0.134	0.0
CGOA	2014	27,897	27,897	0.0	0.213	0.213	0.0
CGOA	2015	27,130	27,130	0.0	0.107	0.107	0.0
CGOA	2016	19,793	19,793	0.0	0.076	0.076	0.0
CGOA	2017	25,866	25,866	0.0	0.077	0.077	0.0
CGOA	2018	19,637	19,637	0.0	0.097	0.097	0.0
CGOA	2019	19,329	19,329	0.0	0.117	0.117	0.0
CGOA	2020	18,657	18,657	0.0	0.203	0.203	0.0
CGOA	2021	16,328	NA	NA	0.104	NA	NA
WGOA	1992	11,390	11,390	0.0	0.122	0.122	0.0
WGOA	1993	8,308	8,308	0.0	0.146	0.146	0.0
WGOA	1994	8,849	8,849	0.0	0.198	0.198	0.0
WGOA	1995	8,585	8,585	0.0	0.143	0.143	0.0
WGOA	1996	10,650	10,650	0.0	0.122	0.122	0.0
WGOA	1997	5,721	5,721	0.0	0.113	0.113	0.0
WGOA	1998	7,712	7,712	0.0	0.101	0.101	0.0
WGOA	1999	6,309	6,309	0.0	0.148	0.148	0.0
WGOA	2000	6,043	6,043	0.0	0.158	0.158	0.0
WGOA	2001	7,352	7,352	0.0	0.176	0.176	0.0
WGOA	2002	13,157	13,157	0.0	0.282	0.282	0.0
WGOA	2003	8,807	8,807	0.0	0.178	0.178	0.0
WGOA	2004	7,566	7,566	0.0	0.164	0.164	0.0
WGOA	2005	9,922	9,922	0.0	0.306	0.306	0.0
WGOA	2006	7,514	7,514	0.0	0.170	0.170	0.0
WGOA	2007	7,676	7,677	0.0	0.204	0.204	0.0
WGOA	2008	9,943	9,943	0.0	0.233	0.233	0.0
WGOA	2009	11,290	11,290	0.0	0.155	0.155	0.0
WGOA	2010	14,504	14,504	0.0	0.254	0.254	0.0
WGOA	2011	9,208	9,208	0.0	0.210	0.210	0.0
WGOA	2012	6,860	6,860	0.0	0.168	0.168	0.0
WGOA	2013	12,085	12,085	0.0	0.116	0.116	0.0
WGOA	2014	12,420	12,420	0.0	0.155	0.155	0.0
WGOA	2015	12,389	12,389	0.0	0.159	0.159	0.0
WGOA	2016	13,473	13,473	0.0	0.170	0.170	0.0
WGOA	2017	13,429	13,429	0.0	0.177	0.177	0.0
WGOA	2018	13,652	13,652	0.0	0.223	0.223	0.0
WGOA	2019	18,104	18,104	0.0	0.285	0.285	0.0
WGOA	2020	9,469	9,469	0.0	0.158	0.158	0.0
WGOA	2021	7,885	NA	NA	0.093	NA	NA

Table A-2. Time series of Gulf of Alaska bottom trawl survey biomass estimates (with coefficients of variation; CVs in parentheses) for all management area (EGOA = eastern Gulf of Alaska, CGOA = central Gulf of Alaska, WGOA = western Gulf of Alaska) and depth strata combinations.

Year	EGOA (0-500 m)	EGOA (501-700 m)	EGOA (701-1000 m)	CGOA (0-500 m)	CGOA (501-700 m)	CGOA (701-1000 m)	WGOA (0-500 m)	WGOA (501-700 m)	WGOA (701-1000 m)
1984	7,332 (0.131)	3,639 (0.103)	814 (0.100)	20,174 (0.120)	4,002 (0.160)	6,996 (0.199)	9,511 (0.147)	3,053 (0.233)	2,024 (0.460)
1985	NA	NA	NA	NA	NA	NA	NA	NA	NA
1986	NA	NA	NA	NA	NA	NA	NA	NA	NA
1987	15,395 (0.122)	5,218 (0.361)	NA	12,544 (0.164)	4,588 (0.202)	3,422 (0.389)	9,296 (0.407)	2,317 (0.517)	577 (0.090)
1988	NA	NA	NA	NA	NA	NA	NA	NA	NA
1989	NA	NA	NA	NA	NA	NA	NA	NA	NA
1990	11,996 (0.105)	NA	NA	5,941 (0.250)	NA	NA	1,679 (0.401)	NA	NA
1991	NA	NA	NA	NA	NA	NA	NA	NA	NA
1992	NA	NA	NA	NA	NA	NA	NA	NA	NA
1993	16,800 (0.096)	NA	NA	12,509 (0.164)	NA	NA	3,706 (0.222)	NA	NA
1994	NA	NA	NA	NA	NA	NA	NA	NA	NA
1995	NA	NA	NA	NA	NA	NA	NA	NA	NA
1996	24,910 (0.108)	NA	NA	19,030 (0.102)	NA	NA	8,043 (0.150)	NA	NA
1997	NA	NA	NA	NA	NA	NA	NA	NA	NA
1998	NA	NA	NA	NA	NA	NA	NA	NA	NA
1999	25,890 (0.102)	2,838 (0.214)	1,922 (0.344)	22,935 (0.085)	6,725 (0.141)	2,930 (0.153)	7,029 (0.232)	5,389 (0.153)	1,679 (0.100)
2000	NA	NA	NA	NA	NA	NA	NA	NA	NA
2001	NA	NA	NA	19,908 (0.082)	NA	NA	8,753 (0.171)	NA	NA
2002	NA	NA	NA	NA	NA	NA	NA	NA	NA
2003	22,393 (0.079)	5,011 (0.235)	NA	42,787 (0.141)	10,462 (0.413)	NA	15,035 (0.176)	5,887 (0.290)	NA
2004	NA	NA	NA	NA	NA	NA	NA	NA	NA
2005	22,729 (0.065)	5,108 (0.176)	2,408 (0.256)	27,429 (0.068)	6,728 (0.124)	8,262 (0.197)	12,351 (0.163)	6,377 (0.080)	3,277 (0.239)
2006	NA	NA	NA	NA	NA	NA	NA	NA	NA
2007	25,818 (0.110)	4,858 (0.203)	4,241 (0.191)	20,910 (0.091)	8,962 (0.176)	7,736 (0.145)	7,619 (0.140)	2,590 (0.145)	1,943 (0.096)
2008	NA	NA	NA	NA	NA	NA	NA	NA	NA
2009	19,809 (0.067)	6,820 (0.139)	4,821 (0.092)	19,722 (0.088)	5,365 (0.225)	3,469 (0.361)	12,464 (0.207)	5,605 (0.222)	719 (0.549)
2010	NA	NA	NA	NA	NA	NA	NA	NA	NA
2011	24,971 (0.099)	4,334 (0.184)	NA	21,172 (0.109)	6,884 (0.134)	NA	3,546 (0.163)	2,272 (0.664)	NA

Year	EGOA (0-500 m)	EGOA (501-700 m)	EGOA (701-1000 m)	CGOA (0-500 m)	CGOA (501-700 m)	CGOA (701-1000 m)	WGOA (0-500 m)	WGOA (501-700 m)	WGOA (701-1000 m)
2012	NA	NA	NA	NA	NA	NA	NA	NA	NA
2013	25,031 (0.113)	3,569 (0.121)	NA	23,868 (0.123)	8,196 (0.262)	NA	6,476 (0.203)	2,739 (0.085)	NA
2014	NA	NA	NA	NA	NA	NA	NA	NA	NA
2015	22,743 (0.114)	4,374 (0.302)	3,686 (0.091)	33,026 (0.125)	4,666 (0.126)	7,214 (0.091)	9,653 (0.163)	2,733 (0.195)	1,147 (0.986)
2016	NA	NA	NA	NA	NA	NA	NA	NA	NA
2017	27,820 (0.132)	4,301 (0.150)	NA	28,591 (0.110)	4,844 (0.172)	NA	12,196 (0.201)	2,740 (0.387)	NA
2018	NA	NA	NA	NA	NA	NA	NA	NA	NA
2019	22,253 (0.138)	3,827 (0.176)	NA	27,598 (0.107)	6,015 (0.177)	NA	10,785 (0.135)	7,992 (0.480)	NA
2020	NA	NA	NA	NA	NA	NA	NA	NA	NA
2021	19,104 (0.103)	5,443 (0.230)	NA	21,385 (0.139)	7,600 (0.191)	NA	10,424 (0.369)	4,269 (0.201)	NA

Table A-3. Model selection results for candidate models that use the two-survey random effects model (REMA) fit to new data through 2021. Model 22.1.b is the corrected version of the status quo Model 18 with updated data through 2021, and Models 22.2.a, 22.2.b, and 22.2.c are Model 22.1.a but estimate additional observation error for the bottom trawl survey, longline survey, or both surveys, respectively. Model 22.2.c is the author-preferred model.

Model	Objective function	Number of parameters	AIC	Δ AIC
Model 22.2.c	52.3	6	116.7	0
Model 22.2.b	57.1	5	124.3	7.6
Model 22.2.a	60.1	5	130.2	13.5
Model 22.1.b	68.6	4	145.2	28.5

Table A-4. Parameter estimates and their associated standard errors (SEs) and 95% confidence intervals for the candidate random effects models. All values have been transformed to an arithmetic scale for ease of interpretation. Note that Model 18 has an error in the AD Model Builder code that was corrected in Model 22.1.a using the same data as presented in the 2020 stock assessment. Model 22.1.b is Model 22.1.a with updated data through 2021, Models 22.2.a, 22.2.b, and 22.2.c are Model 22.1.a but estimate additional observation error for the bottom trawl survey, longline survey, or both surveys, respectively, and Model 22.3 omits the longline survey and only fits to the bottom trawl survey. Model 22.2.c is the author-preferred model.

Model	Parameter	Estimate	SE	LCI	UCI
Model 18	CGOA process error	0.070	0.015	0.046	0.107
	EGOA process error	0.176	0.031	0.125	0.248
	WGOA process error	0.106	0.021	0.072	0.156
	Scaling parameter (q)	0.615	0.007	0.601	0.629
Model 22.1.a	CGOA process error	0.214	0.045	0.142	0.323
	EGOA process error	0.188	0.029	0.139	0.253
	WGOA process error	0.359	0.056	0.264	0.487
	Scaling parameter (q)	0.603	0.015	0.575	0.632
Model 22.1.b	CGOA process error	0.214	0.043	0.144	0.318
	EGOA process error	0.192	0.029	0.143	0.258
	WGOA process error	0.358	0.054	0.266	0.481
	Scaling parameter (q)	0.595	0.014	0.568	0.624
Model 22.2.a	CGOA process error	0.145	0.041	0.083	0.253
	EGOA process error	0.180	0.029	0.132	0.246
	WGOA process error	0.269	0.057	0.178	0.408
	Scaling parameter (q)	0.605	0.021	0.564	0.648
	Extra BTS biomass observation error	0.224	0.039	0.157	0.313
Model 22.2.b	CGOA process error	0.150	0.032	0.099	0.228
	EGOA process error	0.147	0.025	0.105	0.204
	WGOA process error	0.318	0.055	0.227	0.445
	Scaling parameter (q)	0.602	0.018	0.568	0.637
	Extra LLS RPW observation error	0.151	0.025	0.107	0.208
Model 22.2.c	CGOA process error	0.082	0.031	0.039	0.173
	EGOA process error	0.130	0.028	0.086	0.198
	WGOA process error	0.193	0.098	0.071	0.522
	Scaling parameter (q)	0.616	0.026	0.568	0.669
	Extra BTS biomass observation error	0.229	0.059	0.136	0.370
	Extra LLS RPW observation error	0.136	0.026	0.093	0.195
Model 22.3	CGOA process error	0.171	0.034	0.117	0.252
	EGOA process error	0.145	0.026	0.102	0.205
	WGOA process error	0.302	0.055	0.211	0.431

Table A-5. Total predicted biomass for the candidate random effects models. Note that Model 18 has an error in the AD Model Builder code that was corrected in Model 22.1.a using the same data as presented in the 2020 stock assessment. Model 22.1.b is Model 22.1.a with updated data through 2021, Models 22.2.a, 22.2.b, and 22.2.c are Model 22.1.a but estimate additional observation error for the bottom trawl survey, longline survey, or both surveys, respectively, and Model 22.3 omits the longline survey and only fits to the bottom trawl survey. Model 22.2.c is the author-preferred model.

| Year	Model 18	Model 22.1.a	Model 22.1.b	Model 22.2.a	Model 22.2.b	Model 22.2.c	Model 22.3
1984	52,206	56,198	56,230	54,260	55,668	53,732	55,647
1985	52,483	54,179	54,289	53,693	53,993	53,752	53,350
1986	53,175	53,039	53,238	53,428	52,990	53,907	51,789
1987	54,339	52,777	53,079	53,467	52,659	54,198	50,952
1988	53,112	50,764	51,147	53,169	50,841	54,233	47,939
1989	51,975	49,772	50,251	53,324	49,751	54,446	45,490
1990	50,926	49,752	50,344	53,936	49,338	54,834	43,497
1991	53,010	56,750	57,546	58,884	54,477	57,596	46,394
1992	55,269	65,266	66,309	64,538	60,438	60,573	49,589
1993	57,718	63,577	64,760	65,044	61,108	61,991	53,113
1994	61,758	61,428	62,463	62,334	62,899	63,105	58,202
1995	66,213	64,948	66,130	65,912	66,717	66,076	64,029
1996	71,129	73,697	74,777	72,159	72,981	69,896	70,711
1997	73,302	70,994	72,358	71,980	71,833	70,783	72,883
1998	75,580	71,881	72,906	72,250	73,725	72,188	75,183
1999	77,967	76,767	77,398	76,633	76,746	74,438	77,619
2000	79,038	75,191	76,258	77,778	76,394	75,978	78,355
2001	80,234	83,901	85,318	86,642	80,064	79,331	79,317
2002	83,711	84,356	85,606	82,381	85,428	79,655	87,943
2003	87,585	87,739	88,598	80,111	91,061	79,916	98,710
2004	87,818	69,974	70,757	69,720	82,888	77,229	95,649
2005	88,116	87,603	88,101	78,243	89,604	80,203	93,155
2006	85,879	80,462	81,458	78,928	83,671	80,393	87,164
2007	84,171	82,010	82,781	81,699	82,589	81,937	82,673
2008	81,561	90,274	91,519	89,953	85,019	85,198	80,526
2009	79,254	83,219	83,784	86,471	82,832	85,559	79,044
2010	79,332	91,981	93,288	93,652	85,428	87,686	76,884
2011	79,883	85,616	86,607	88,548	82,837	86,168	76,245
2012	80,769	92,149	93,654	93,621	87,000	88,371	78,173
2013	81,819	100,122	101,625	102,365	90,681	91,121	80,490
2014	83,297	98,683	100,157	98,674	93,543	91,450	83,685
2015	85,005	94,830	95,786	93,986	93,063	90,281	87,622
2016	87,164	91,877	93,081	92,591	93,573	90,373	88,906
2017	89,442	97,322	97,719	95,103	94,622	89,575	90,384
2018	88,069	92,100	92,705	90,651	91,091	86,532	88,622
2019	86,802	88,005	87,212	83,231	87,131	81,798	87,170
2020	86,802	74,296	72,121	70,206	78,137	75,266	83,950
2021	86,802	74,296	65,631	63,241	74,108	71,584	81,061
2022	86,802	74,296	65,631	63,241	74,108	71,584	81,061

Figures
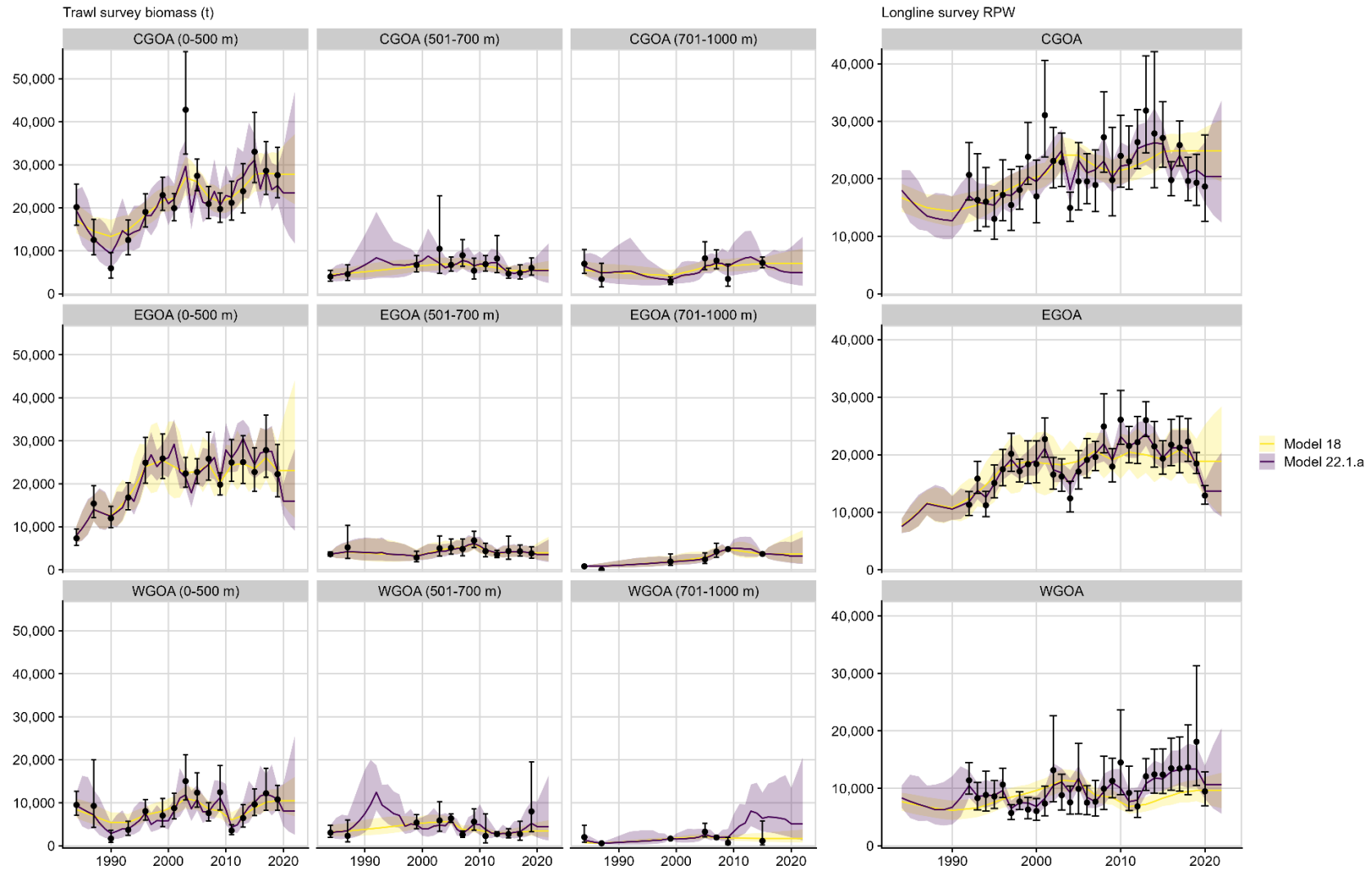
Figure A-1. Two-survey random effects (REMA) model fits to the GOA bottom trawl survey biomass and longline survey relative population weights (RPWs), where the points are observations and the lines with shaded regions are the model predictions and 95% confidence intervals. Results are shown for Models 18 (the status quo ADMB model with the error in the SEPARABLE function) and 22.1.b (the corrected two-survey REMA fit in TMB with 2020 assessment data).
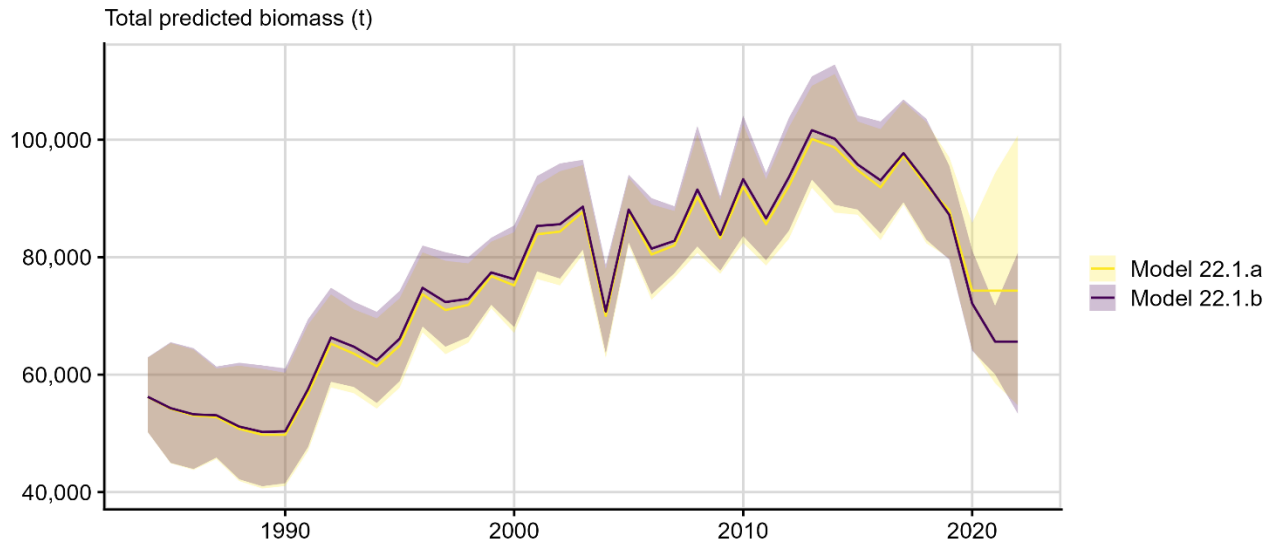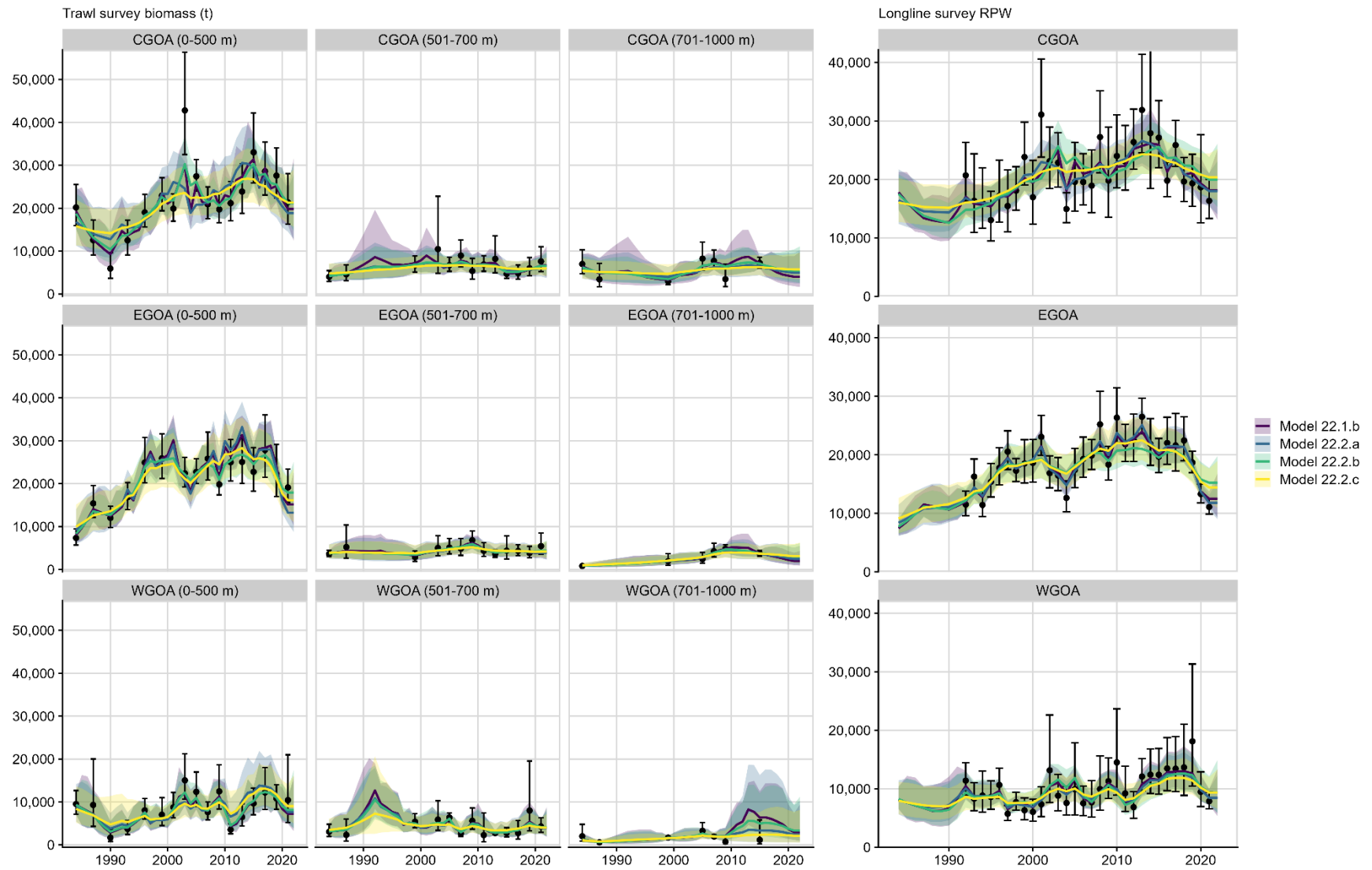
Total predicted biomass (t)

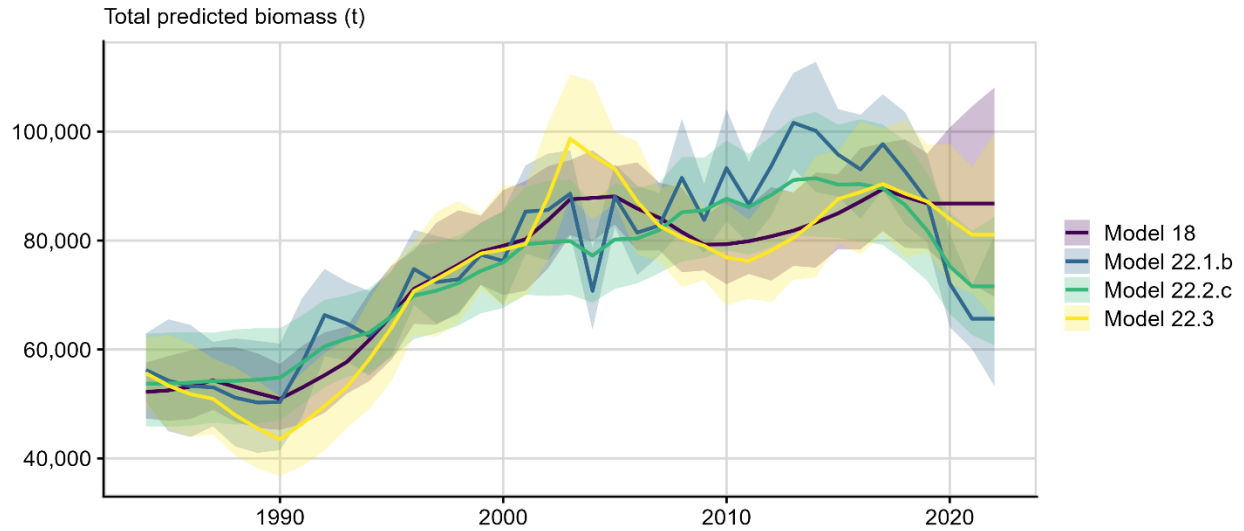
Figure A-2. Two-survey random effects (REMA) model predictions of total biomass with 95% confidence intervals. Results are shown for Models 22.1.a (the corrected two-survey REMA with 2020 assessment data) and 22.1.b (Model 22.1.a with updated data through 2021).

Figure A-3. Two-survey random effects (REMA) model fits to the GOA bottom trawl survey (BTS) biomass and longline survey (LLS) relative population weights (RPWs), where the points are observations and the lines with shaded regions are the model predictions and 95% confidence intervals. Results are shown for Model 22.1.b (the corrected two-survey REMA fit in TMB with 2020 assessment data), Model 22.2.a (extra BTS observation error estimated), Model 22.2.b (extra LLS observation error estimated), and Model 22.2.c (extra BTS and LLS observation error estimated). Model 22.2.c is the author-preferred model.
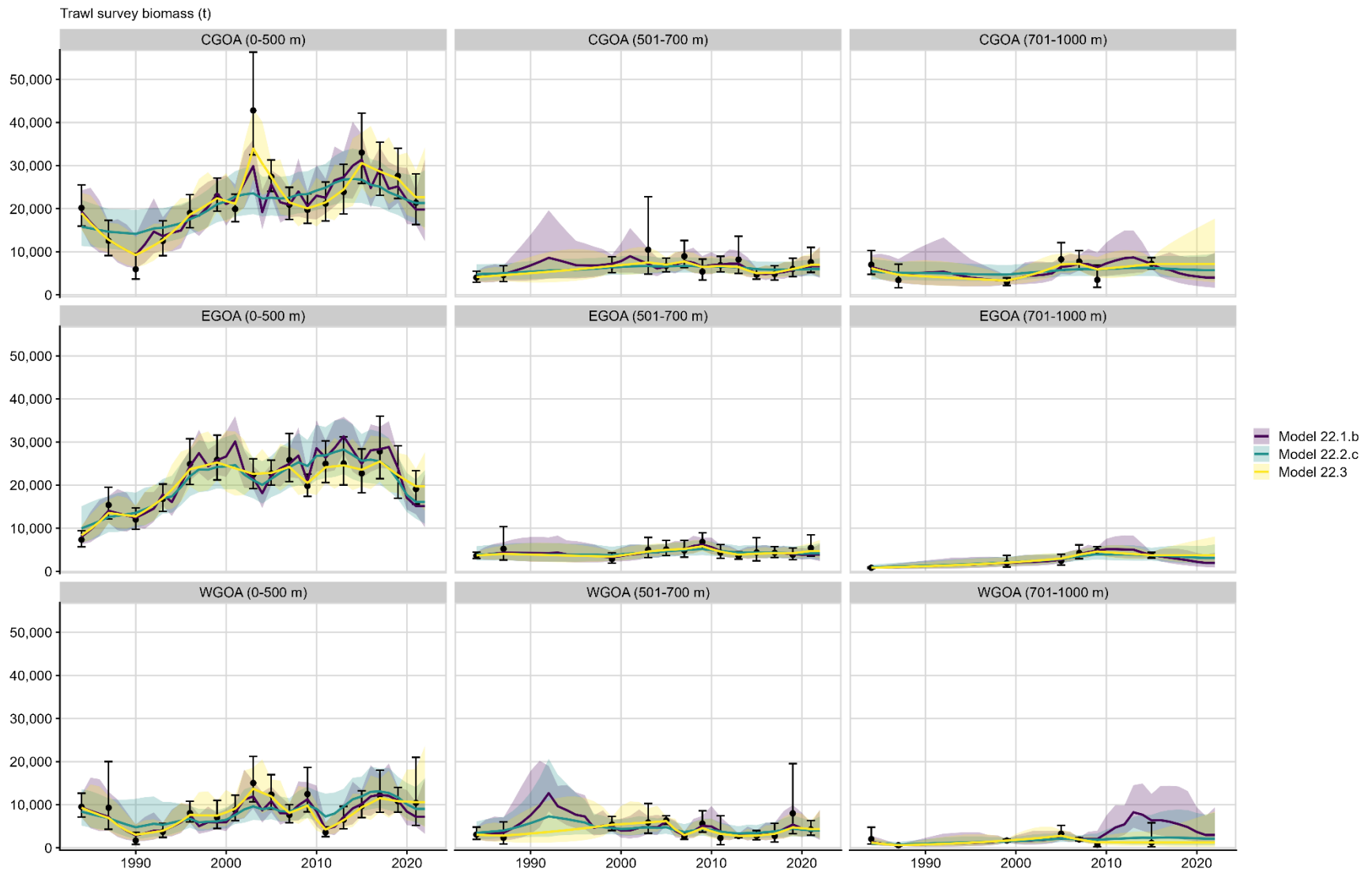
Figure A-4. One and two-survey random effects (REMA) model fits to the GOA bottom trawl survey (BTS) biomass estimates, where the points are observations and the lines with shaded regions are the model predictions and 95% confidence intervals. Results are shown for Model 22.1.b (the corrected two-survey REMA fit in TMB with 2020 assessment data), Model 22.2.c (extra BTS and longline survey observation error estimated), and Model 22.3 (only fits to the BTS data). Model 22.2.c is the author-preferred model.

Figure A-5. One and two-survey random effects (REMA) model predictions of total biomass with 95% confidence intervals. Results are shown for Models 18 (the status quo ADMB model with the error in the SEPARABLE function), Model 22.1.b (the corrected two-survey REMA fit in TMB with 2020 assessment data), Model 22.2.c (extra bottom trawl and longline survey observation error estimated), and Model 22.3 (only fits to the bottom trawl survey data). Model 22.2.c is the author-preferred model.

Appendix B: Alternative models for BSAI shortraker rockfish in 2022

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September 2022

Executive summary

Bering Sea and Aleutian Islands (BSAI) shortraker rockfish (*Sebastes borealis*) are managed as a Tier 5 stock and assessed in even years to coincide with the Aleutian Islands (AI) groundfish trawl survey (Shotwell et al. 2020). The assumed natural mortality for shortraker rockfish (*M*=0.03) is used to inform harvest recommendations for Tier 5 stocks, where $F_{OFL}=M$ and $F_{ABC}=0.75M$. Biomass is estimated using a random effects (RE) model fit to the bottom trawl survey (BTS) data.

In recent years, concerns have been raised about the lack of abundance information for shortraker rockfish and other species in the eastern Bering Sea (EBS) slope region following the cessation of the EBS slope BTS in 2016 (Shotwell et al. 2020, Sullivan et al. 2020). In response, we developed a suite of alternative models that address these concerns through the inclusion of the NMFS longline survey (LLS) relative population weights (RPWs) in the eastern Bering Sea (EBS) slope region.

Changes in the input data

For the full assessment in November 2022, we propose the following changes to input data:

1) A new time series of LLS RPWs in the EBS slope region for 1997-2021 (available in odd years; Table B-1). Although a 2019 and 2021 RPW are available, we only fit to data through 2018 for ease of comparison with the last full assessment (Shotwell et al. 2020).
2) The 2022 AI BTS biomass estimate is not ready for September 2022, so this document only includes BTS through 2018. The 2020 AI BTS was cancelled due to the COVID-19 pandemic.

Changes in the assessment methodology

We present the base model plus three alternative models that bridge the current model to a multivariate version of the RE model in Template Model Builder (TMB; Kristensen et al. 2016) using the new *rema* R package (https://afsc-assessments.github.io/rema/). For November 2022, we recommend a new model that uses the multi-survey version of the random effects (REMA) model and fits to AI BTS biomass (in both the AI and southern Bering Sea regions), EBS slope BTS biomass, and LLS RPWs in the EBS slope region.

The models presented use the following naming conventions:
1) **Model 18**: The accepted model in the last full assessment (Shotwell et al. 2020) as implemented in 2018 and 2020 using the univariate version of the RE model fit separately to the AI, southern Bering Sea (SBS, sampled by the AI BTS), and EBS slope.

2) **Model 18.a**: Bridged Model 18 to TMB using the *rema* R package.

3) **Model 18.b**: Model 18 fit in TMB but using the multivariate version of the random effects (REM) model, where the three regions are fit simultaneously with a separate process error parameter in each region.

4) **Model 22**: Multi-survey (AI BTS, EBS slope BTS, and LLS) version of the REMA model, which has the same configuration as Model 18.b but also fits to the LLS RPWs in the EBS slope region.

Summary of results

The alternative models result in the following estimates of biomass, OFL, and maximum permissible ABC (max ABC), with the author-preferred model highlighted in bold:

Model	Year	Biomass (t)	OFL (t)	max ABC (t)	Percent change from Model 18
Model 18	2018	24,055	722	541	--
Model 18.a	2018	24,055	722	541	0%
Model 18.b	2018	24,055	722	541	0%
Model 22	**2018**	**23,968**	**719**	**539**	**-0.4%**

Model 22 produced a negligible (<1%) decrease in total predicted biomass and estimated OFLs and ABCs when compared to Model 18 and it's TMB and multivariate equivalents, Model 18.a and Model 18.b. **The author-preferred model is Model 22, because it is informed by recent abundance trends in the EBS slope region using LLS RPWs.** The BSAI shortraker rockfish stock assessment does not apportion biomass and ABC by management area (Shotwell et al. 2020).

Analytic approach

Model structure

Biomass in the shortraker rockfish assessment is estimated using the univariate version of the random effects (RE) model, where a single model is run for each survey and stratum combination (Model 18; Shotwell et al. 2020). There are two surveys, the AI BTS and EBS slope BTS. The AI BTS is stratified by region, the AI (eastern, central, and western AI combined) and southern Bering Sea (SBS). The EBS slope BTS is treated as a single stratum. Process error is estimated independently for the three strata, AI, SBS, and EBS slope.

Transition to TMB and to the multivariate random effects (REM) model

An alternative to fitting multiple univariate RE models is to fit all strata simultaneously using the multivariate version of the RE model (REM). In order to transition to the REM model, we first bridged the status quo ADMB Model 18 to TMB using the new *rema* R library (Model 18.a). We then fit the same data using the REM model (Model 18.b) and compared the resulting fits to the data and parameter estimates (Table B-2, Figure B-1). In the multivariate approach, one can assume strata-specific process error, or alternatively, share process error across multiple strata. We maintained the current structure of the model by estimating strata-specific parameters in Model 18.b. A more detailed description of these methods are provided in the *Extending to multiple biomass survey strata* section of the main document.

Addition of the NMFS longline survey (LLS) Relative Population Weights (RPWs)

The inclusion of LLS RPWs for shortraker rockfish in the EBS slope region was prompted by concerns over the cessation of the EBS slope BTS in 2016 (e.g., Shotwell et al. 2020, Monnahan et al. 2021). We recommend including the EBS slope LLS RPWs to inform abundance trend information in recent years, thus reducing reliance on the 2016 estimate of biomass in that region (Table B-1). The LLS is conducted biennially along the EBS slope, and shortraker rockfish are considered to be well-sampled by the gear (Echave et al. 2019, Hulson et al. 2021). The potential use of LLS RPWs in the AI was explored; however, we do not recommend using the AI RPWs at this time due to a mismatch in the spatial extent and resolution of the AI BTS and LLS.

Methods for including the additional LLS RPW index into the model are described in the *Model development* section of the main document and in Hulson et al. (2021). Alternative models that estimate additional observation error for the BTS biomass or LLS RPW data (i.e., using equation 7 in the main document) were explored during model development. These models either exhibited convergence issues (e.g., hitting parameter bounds) or were not statistically supported using Akaike Information Criteria for model selection. We therefore do not present results for these more complex models.

Results

Bridging from ADMB to TMB and to the multivariate version of the random effects model (REM)

Models 18, 18.a, and 18.b resulted in nearly identical fits to the BTS biomass data and parameter estimates (Table B-2, Figure B-1). The REM model is preferred over the univariate RE model approach, because the total number of models fit is reduced from three to one. This approach also lends itself to easy estimation of variance for total predicted log-biomass using the delta method in TMB.

Impact of adding the longline survey relative population weights

The addition of the shortraker rockfish LLS RPWs in the EBS slope region had minimal impact on model results in 2018, the last time the assessment model was updated (Shotwell et al. 2020). Estimates of process error slightly increased in the EBS slope region, resulting in a slightly more variable biomass trajectory (Table B-2, Figure B-3). As shown in the ABC summary table in the Executive summary, Model 22 resulted in an approximately 0.4% decrease in biomass relative to Models 18, 18.a, and 18.b.

Recommendations for November 2022

For November 2022, we recommend transitioning to the TMB version of the model using the *rema* R library. Model 22, which includes the LLS RPW index in the EBS slope region, is the author-preferred model, because it uses the most current data on shortraker available and reduces our reliance on the 2016 EBS slope BTS biomass estimate. Although adding this new data source does not change our current understanding of shortraker abundance on the EBS slope, it is an improved model and enhances the ability to inform future trends in the EBS slope region.

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Tables

Table B-1. NMFS longline survey (LLS) relative population weights (RPWs) with estimated coefficients of variation (CV) for the shortraker rockfish in the eastern Bering Sea (EBS) slope region.

Year	EBS slope
1997	12,478 (0.341)
1998	NA
1999	29,202 (0.414)
2000	NA
2001	21,571 (0.363)
2002	NA
2003	74,645 (0.465)
2004	NA
2005	14,453 (0.394)
2006	NA
2007	20,088 (0.403)
2008	NA
2009	7,513 (0.285)
2010	NA
2011	27,065 (0.584)
2012	NA
2013	12,588 (0.243)
2014	NA
2015	19,316 (0.190)
2016	NA
2017	23,006 (0.480)
2018	NA
2019	34,046 (0.472)
2020	NA
2021	18,660 (0.345)

Table B-2. Parameter estimates and their associated standard errors (SEs) and 95% confidence intervals for the new random effects models. All values have been transformed to an arithmetic scale for ease of interpretation. Model 18.a is the status quo univariate random effects (RE) model fit in Template Model Builder (TMB), Model 18.b is the same model but fit simultaneously using the multivariate random effects (REM) model, and Model 22 is Model 18.b which also fits to the longline survey in the eastern Bering Sea slope.

| Model	Parameter	Estimate	SE	LCI	UCI
Model 18.a	AI process error	0.148	0.104	0.037	0.587
Model 18.a	EBS Slope process error	0.195	0.137	0.049	0.775
Model 18.a	SBS process error	1.135	0.297	0.679	1.897
Model 18.b	AI process error	0.148	0.104	0.037	0.587
Model 18.b	EBS Slope process error	0.195	0.137	0.049	0.775
Model 18.b	SBS process error	1.135	0.297	0.679	1.897
Model 22	AI process error	0.148	0.104	0.037	0.587
Model 22	EBS Slope process error	0.331	0.240	0.080	1.372
Model 22	SBS process error	1.135	0.297	0.679	1.897
Model 22	Scaling parameter (q)	3.624	0.732	2.438	5.385

Figures

Figure B-1. Random effects (RE) model fits to biomass estimates from the Aleutian Islands combined (eastern, central, western) bottom trawl survey (AI), the eastern Bering Sea (EBS) Slope bottom trawl survey, and the southern Bering Sea portion of the AI bottom trawl survey (SBS). Biomass data with assumed 95% confidence intervals are shown with black points and error bars, and model predictions with 95% confidence intervals are shown using solid lines and shaded areas. Results are shown for Model 18 (the status quo univariate ADMB model), Model 18.a (same as Model 18 but fit in TMB), and Model 18.b (same as Model 18 but fit in TMB using the multivariate version of the random effects model; REM).
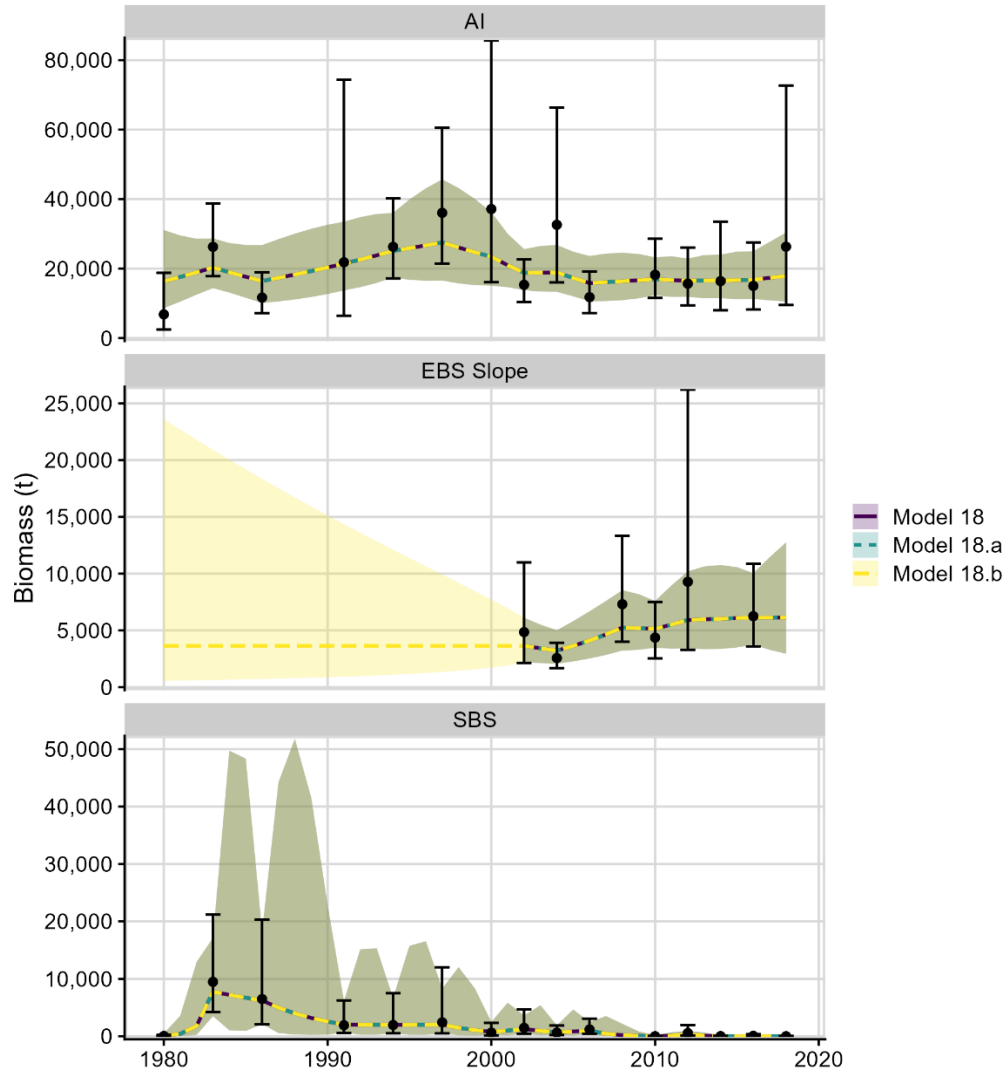
Figure B-2. Random effects (RE) model fits to biomass estimates form the Aleutian Islands combined (eastern, central, western) bottom trawl survey (AI), the eastern Bering Sea (EBS) Slope bottom trawl survey, and the southern Bering Sea portion of the AI bottom trawl survey (SBS) (top three figures), and the longline survey (LLS) relative population weights (RPWs; bottom figure). Biomass and RPW data with assumed 95% confidence intervals are shown with black points and error bars, and model predictions with 95% confidence intervals are shown using solid lines and shaded areas. Results are shown for Model 18.b (status quo Model 18 but fit in TMB using the multivariate version of the random effects model; REM) and Model 22 (Model 18.b with additional fit to LLS RPWs in the EBS slope).
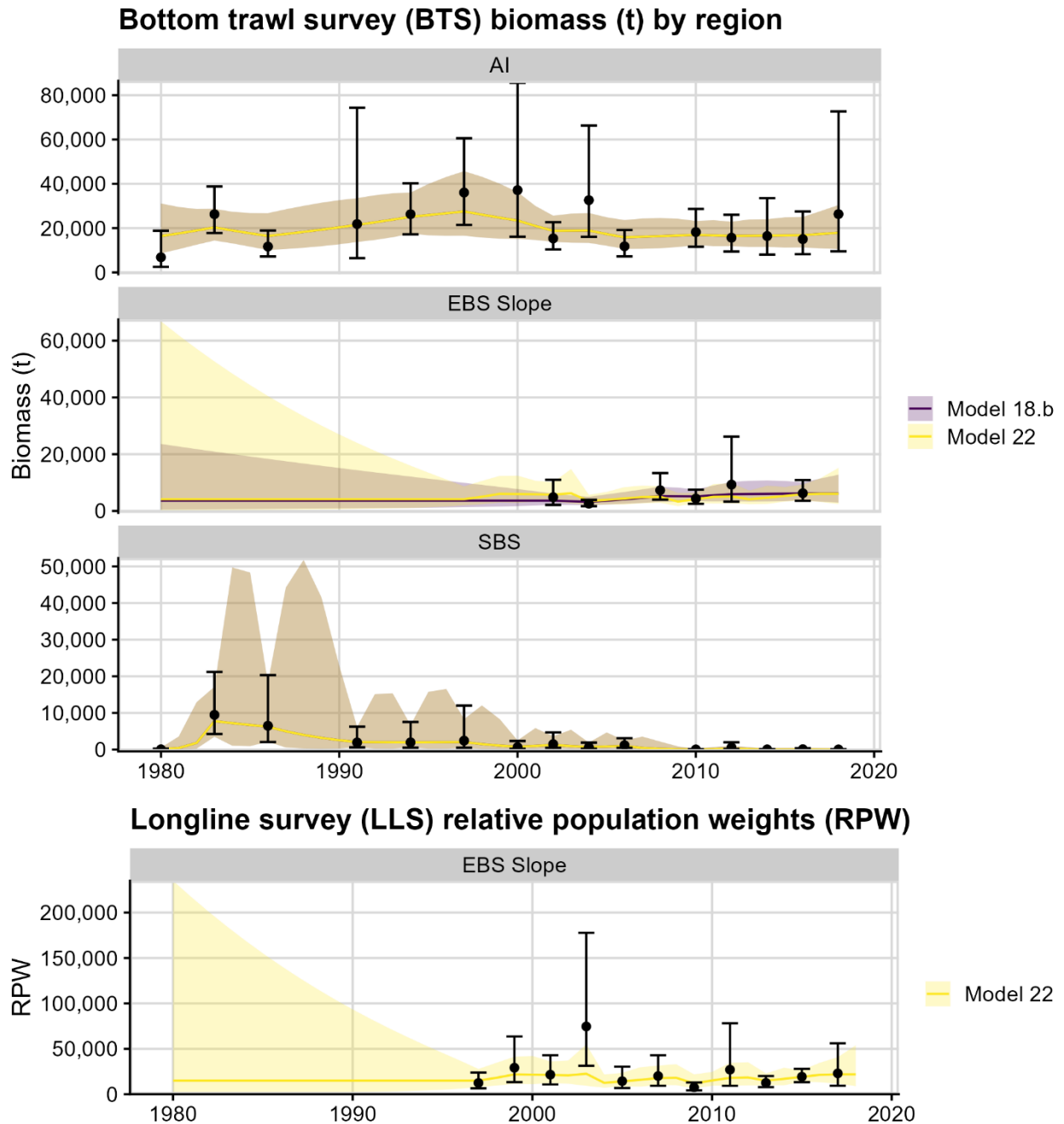
Appendix C: Alternative models for the BSAI other rockfish stock complex in 2022

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Executive summary

The Bering Sea/Aleutian Islands (BSAI) other rockfish complex is currently managed in Tier 5 and is assessed on even years to coincide with the Aleutian Islands (AI) groundfish trawl survey. The other rockfish complex is assessed in two parts: (1) shortspine thornyhead (SST, *Sebastolobus alascanus*), which comprise approximately 95% of the estimated total other rockfish exploitable biomass; and (2) the remaining "non-SST" species, which are dominated by dusky rockfish (*Sebastes variabilis*) but include at least eleven other *Sebastes* and *Sebastolobus* species.

In recent years, concerns have been raised about the lack of abundance information for SST and other species in the Eastern Bering Sea (EBS) slope region following the cessation of the EBS slope bottom trawl survey in 2016 (Shotwell et al. 2020, Sullivan et al. 2020). In response, we developed a suite of alternative models that address these concerns by including the NMFS longline survey (LLS) relative population weights (RPWs) in the eastern Bering Sea (EBS) slope region.

Changes in the input data

For the full assessment in November 2022, we propose the following changes to input data:

1) The addition of the NMFS longline survey relative population weights (RPWs) for SST on the EBS slope, 1997-2021 (Table 1). Although a 2021 RPW is available, here we only fit to data through 2020 for ease of comparison with the last full assessment (Sullivan et al. 2020).
2) The new 2021 EBS shelf BTS biomass estimate for non-SST. For September 2022, we only fit to data through 2020 for ease of comparison with the last full assessment.
3) The 2022 Aleutian Islands (AI) BTS biomass estimate will be available in November 2022. The 2020 AI BTS was cancelled due to the COVID-19 pandemic, so this document only includes AI BTS for SST and non-SST through 2018.

Changes in the assessment methodology

For the full assessment in November 2022, we propose one new model for consideration in addition a bridged version of the status quo model fit in Template Model Builder (TMB; Kristensen et al. 2016). Models were implemented using the new *rema* R package and rely on methods introduced in the main document of this report. The new models only affect SST on the EBS slope, where we fit to both the EBS slope BTS and the NMFS longline survey RPWs.

The models presented are as follows:

1) **Model 20**: The accepted model in the last full assessment as implemented in 2020 using BTS biomass estimates multivariate version of the random effects (REM) model in AD Model Builder (ADMB; Fournier et al. 2012). Two separate models are fit, one for SST and one for non-SST. The SST model has three strata (AI, EBS slope, southern Bering Sea; SBS), and the non-SST model has four strata (AI, EBS shelf, EBS slope, SBS). Both models share process error across strata (Sullivan et al. 2020).
2) **Model 20.a**: Bridged Model 20 to TMB using the *rema* R package.

3) **Model 22**: Same as Model 20.a and also fits to the EBS slope LLS RPWs for SST. The non-SST model is the same as Model 20.a.

Summary of results

For Tier 5 stocks, F_{OFL} and F_{ABC} are defined as M and $0.75M$, respectively. The acceptable biological catch (ABC) is obtained by multiplying F_{ABC} by the estimated biomass, and the overfishing level (OFL) is obtained by multiplying F_{OFL} by the estimated biomass. The estimated natural mortality differs between SST (0.03) and the remaining non-SST species in the other rockfish complex (0.09); therefore, ABC and OFL, and thus F_{OFL} and F_{ABC}, are calculated separately for SST and non-SST. Apportionments between the AI and the EBS are based on survey biomass estimates in those regions.

The alternative models result in the following estimates of biomass, OFL, and maximum permissible ABC (max ABC), with the author-preferred model highlighted in bold:

Model	Year	Biomass (t)	OFL (t)	max ABC (t)	Percent change in biomass from Model 20	Percent change in OFL/ABC from Model 20
Model 20	2020	53,248	1,751	1,313	--	--
Model 20.a	2020	53,364	1,758	1,318	0.22%	0.41%
Model 22	**2020**	**55,793**	**1,831**	**1,373**	**4.78%**	**4.58%**

The alternative models resulted in the following apportionment of max ABC by management area:

Model	AI	EBS
Model 20	30.0%	70.0%
Model 20.a	29.8%	70.2%
Model 22	**28.0%**	**72.0%**

Model 22 produced a small (<5%) increase in total predicted biomass and estimated OFLs and ABCs when compared to Model 20 and it's TMB equivalent, Model 20.1. **The author-preferred model is Model 22, because it is informed by recent abundance trends in that region.** Model 22 resulted in a small (2%) shift in apportioned biomass from the AI to EBS).

Analytic approach

Model structure

Biomass in the BSAI other rockfish assessment is estimated using the multivariate version of the random effects (REM) model, where a single model is fit to multiple strata (i.e., multiple areas or surveys) simultaneously (Model 20). Two REM models are fit (one for SST and non-SST), and biomass for each species group is stratified by survey and Fishery Management Plan (FMP; i.e., BS and AI). The SST biomass is estimated with three strata, where the AI BTS is split into two strata, the AI (eastern, central, and western AI combined) and southern Bering Sea (SBS), and the EBS slope BTS is treated as a single stratum. The non-SST biomass is estimated using four strata, where the AI BTS biomass is split into the AI and SBS, and the EBS slope and shelf BTS biomass are estimated as unique strata. There are no SST on the EBS shelf, therefore the EBS shelf survey data is not used for that component of the stock. Process error is shared across all strata for both species groups.

Zero biomass observations

The EBS shelf survey frequently does not catch non-SST, and 14 out of 39 survey years are zero biomass observations. Consistent with past assessments, we assume these zeros are failed surveys and treat them as NAs in the model. Alternative approaches to handling zeros were analyzed in the section titled *Exploration of the Tweedie distribution for zero biomass observations* of the main document, and a reproducible example focusing on non-SST on the EBS shelf is available in the *rema* R library's [Strategies for handling zero biomass observations](#) vignette.

Addition of the NMFS longline survey (LLS) Relative Population Weights (RPWs)

The inclusion of LLS RPWs for SST in the EBS slope region was prompted by concerns over the cessation of the EBS slope BTS in 2016 (e.g., Sullivan et al. 2020, Monnahan et al. 2021), coupled with declining biomass trends in the Gulf of Alaska (GOA) SST stock (Appendix A). Biomass of SST in the EBS slope region is currently estimated to be 65% of the entire BSAI other rockfish stock (Sullivan et al. 2020). We recommend including the EBS slope LLS RPWs to inform abundance trend information in recent years, thus reducing reliance on the 2016 estimate of biomass in that region. The LLS is conducted biennially along the EBS slope, and SST are considered to be well-sampled by the gear (Echave et al. 2018, Hulson et al. 2021). The potential use of LLS RPWs in the AI was explored; however, we do not recommend using the AI RPWs at this time due to a mismatch in the spatial extent and resolution of the AI BTS and LLS.

Methods for including the additional LLS RPW index into the model are described in the *Model development* section of the main document and in Hulson et al. (2021). Alternative models that estimate additional observation error for the BTS biomass or LLS RPW data (i.e., using equation 7 in the main document) were explored during model development. These models either exhibited convergence issues (e.g., hitting parameter bounds) or were not statistically supported using Akaike Information Criteria for model selection. We therefore do not present results for these more complex models.

Results

Bridging from ADMB to TMB and to the multivariate version of the random effects model

For both SST and non-SST components of the stock, the differences between the ADMB (Model 20) and TMB (Model 20.a) versions of the model were negligible (<0.1% for total predicted biomass in all years; Figures C-1 and C-2; Table C-2). These small changes were attributed to differences in the optimization algorithms and implementation of the Laplace approximation in ADMB versus TMB. Although point estimates were roughly equivalent in Models 20 and 20.a, there were noticeable differences in the estimated 95% confidence intervals for stratum-specific and total predicted biomass (Figures C-1 and C-2). These changes were the result of different methods used to estimate the variance of summed log-biomass in the ADMB and TMB versions of the REM model. Specifically, the ADMB version of the REM model uses the Marlow method, whereas the TMB model uses the standard delta method. More details about variance estimation methods and model bridging from ADMB to TMB are available in the *Model development* section of the main document.

Impact of adding the EBS Slope longline survey (LLS) relative population weights (RPW)

During overlapping years, the LLS and BTS indices are highly positively correlated, consistently tracking the increase in SST abundance in the early 2000s up through the cessation of the EBS slope BTS in 2016 (Figure C-3). The 2015 LLS RPW and 2016 BTS biomass estimates were the maximum values in both time series, and in recent years the LLS RPWs has showed steady declines (Table C-1, Figure C-3).

Estimates of process error were higher in Model 22, which generated more variability in the predicted biomass trajectory through time (Table C-2). Despite declines in RPWs in recent years, the addition of the SST LLS RPWs in the EBS slope region had minimal impact on model results for 2020 and the overall biomass trajectory (Table C-2, Figure C-3). As shown in the ABC summary table in the Executive summary, Model 22 resulted in an approximately 5% increase in biomass relative to Models 20 and 20.a.

Recommendations for November 2022

For November 2022, we recommend transitioning to the TMB version of the model using the *rema* R library. The inclusion of the LLS RPW index uses the most current data on SST abundance in the EBS slope region, and therefore, Model 22 is the author-preferred model. Although adding this new data source does not change our current understanding of SST abundance on the EBS slope, recent declines in the RPWs and declines in the SST stock in the GOA, suggest there may be continued changes to the dynamics of this stock (Appendix A; Echave et al. 2020).

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Tables

Table C-1. NMFS longline survey (LLS) relative population weights (RPWs) with estimated coefficients of variation (CV) for the shortspine thornyhead in the eastern Bering Sea (EBS) slope region.

Year	EBS Slope
1996	NA
1997	12,110 (0.23)
1998	NA
1999	4,192 (0.12)
2000	NA
2001	9,444 (0.24)
2002	NA
2003	11,050 (0.27)
2004	NA
2005	13,503 (0.15)
2006	NA
2007	13,135 (0.28)
2008	NA
2009	16,118 (0.22)
2010	NA
2011	28,630 (0.17)
2012	NA
2013	24,760 (0.09)
2014	NA
2015	31,782 (0.14)
2016	NA
2017	28,295 (0.14)
2018	NA
2019	26,073 (0.16)
2020	NA
2021	25,497 (0.18)

Table C-2. Parameter estimates and their associated standard errors (SEs) and 95% confidence intervals for the candidate random effects models. All values have been transformed to an arithmetic scale for ease of interpretation. The models are fit separately by species group, including shortspine thornyhead (SST) and all non-SST species. Model 20 is the status quo multivariate random effects (REM) model fit in AD Model Builder, Model 20.a is the same REM model but fit in Template Model Builder, and Model 22 is Model 20.a fit to an additional index (REMA), the longline survey in the eastern Bering Sea slope region for SST only. Note that for non-SST, there is no difference between Models 20.a and 22.

Species group	Model	Parameter	Estimate	SE	LCI	UCI
non-SST	Model 20	Process error	0.701	0.130	0.488	1.007
non-SST	Model 20.a	Process error	0.738	0.126	0.529	1.031
non-SST	Model 22	Process error	0.738	0.126	0.529	1.031
SST	Model 20	Process error	0.121	0.029	0.076	0.193
SST	Model 20.a	Process error	0.128	0.027	0.084	0.195
SST	Model 22	Process error	0.176	0.033	0.121	0.255
SST	Model 22	Scaling parameter (q)	0.705	0.064	0.589	0.843

Figures

Shortspine thornyhead (SST)

Model fits to bottom trawl survey biomass (t) by region
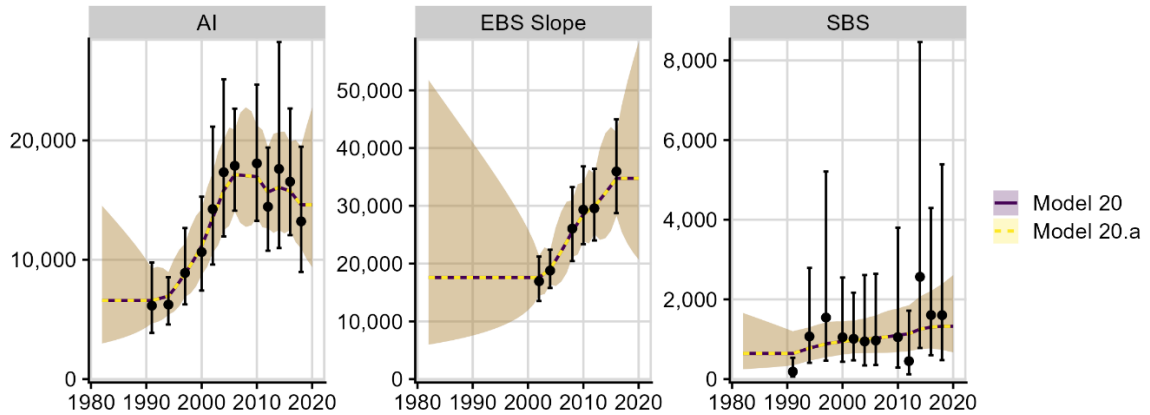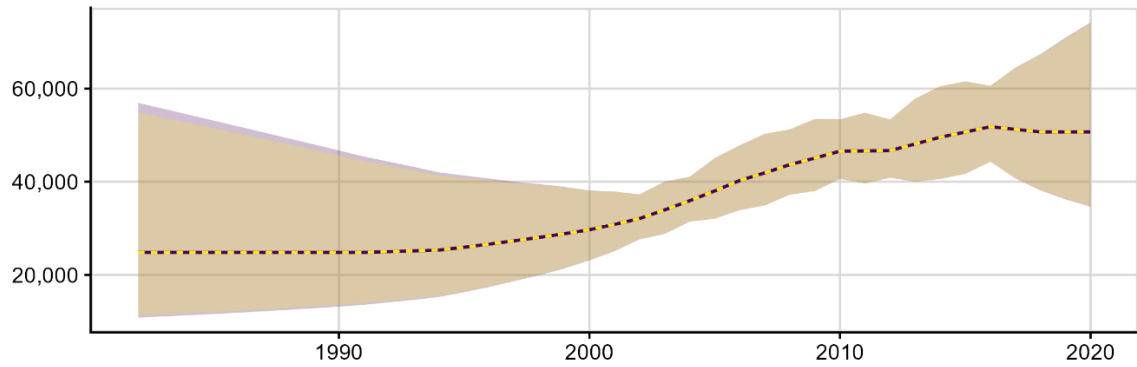

Total predicted biomass (t)

Figure C-1. Model fits by survey region (top) and total predicted biomass for shortspine thornyhead (SST). Results are show for Model 20, the status quo multivariate random effects (REM) model fit in AD Model Builder, and Model 20.a, the same REM model but fit in Template Model Builder.
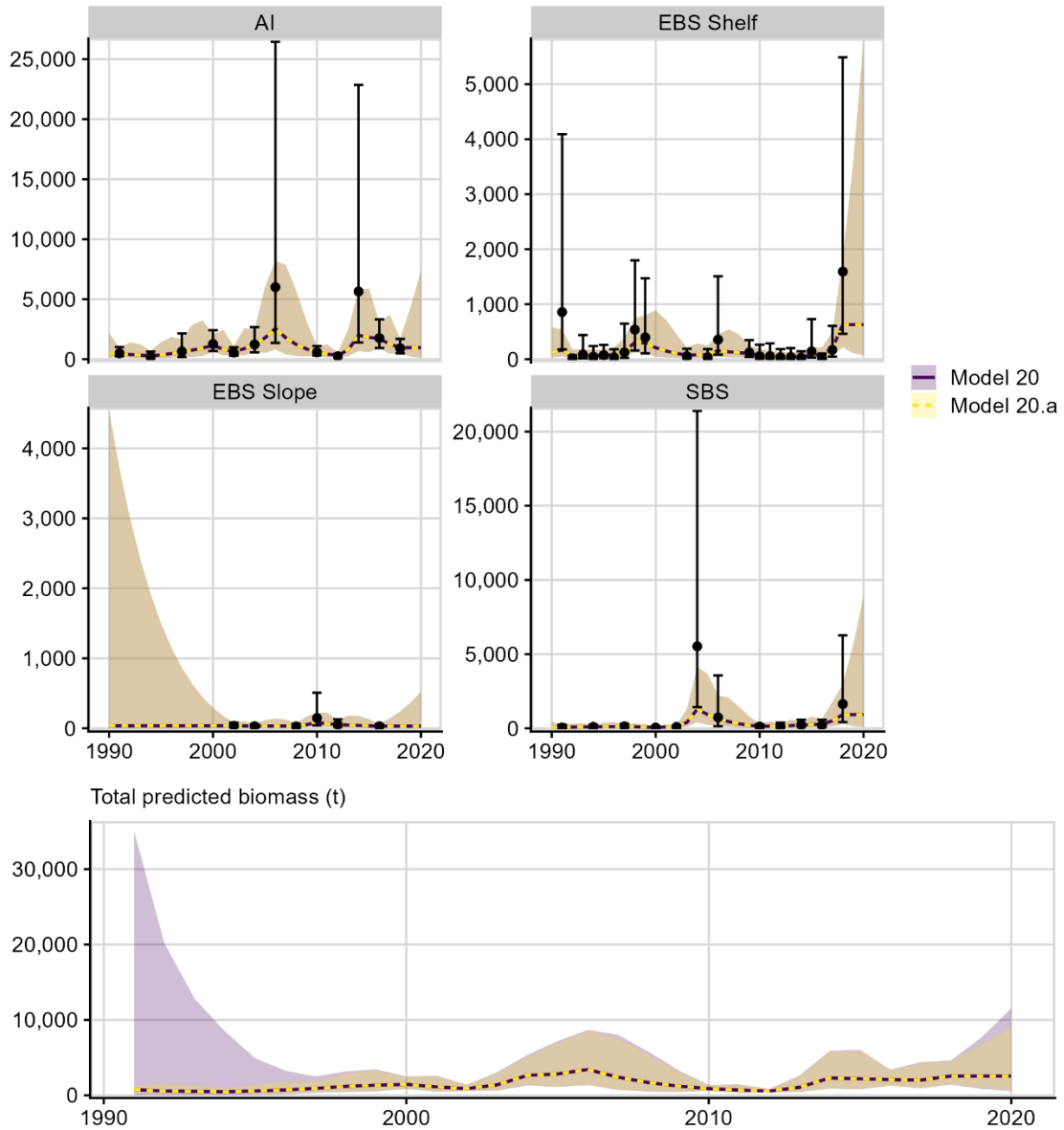
Figure C-2. Model fits by survey region (top) and total predicted biomass for all species in the other rockfish complex except shortspine thornyhead (SST). Results are show for Model 20, the status quo multivariate random effects (REM) model fit in AD Model Builder, and Model 20.a, the same REM model but fit in Template Model Builder.
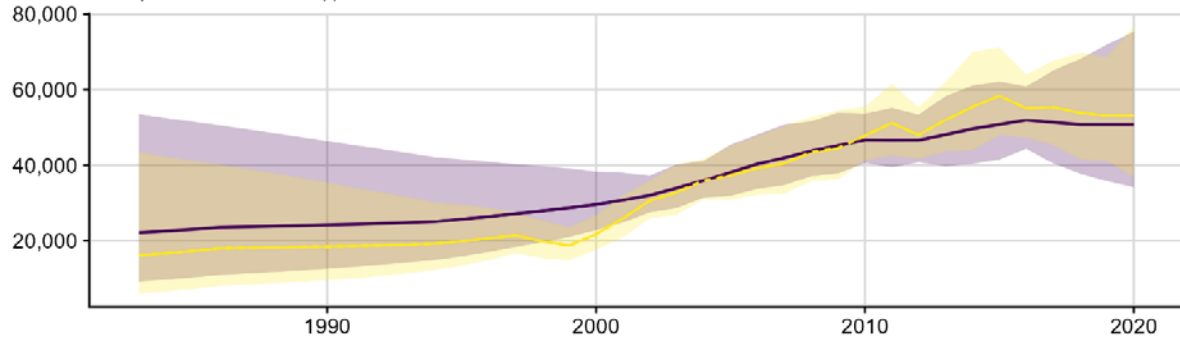
Figure C-3. Model fits to the bottom trawl survey by survey region (top), fits to the EBS slope longline survey relative population weights (RPWs; middle), and total predicted biomass for shortspine thornyhead (SST; bottom). Results are show for Model 20.a, the status quo multivariate random effects (REM) model fit in Template Model Builder, and the Model 22, which also fits to the EBS slope RPWs.