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Retrospective analysis for New Zealand red rock lobster (*Jasus edwardsii*) stock assessment models

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Retrospective analyses are regularly carried out during stock assessments to help identify systematic biases in assessment models. A retrospective analysis involves rerunning an assessment model after removing some or all data for the most recent year, the two most recent years, and so on. It can then be evaluated whether there are systematic changes in key model outputs among successive estimates of parameters as years of data are added. When an assessment is updated with additional years of data, values from previously estimated parameters are expected to vary, but not in a systematic way.

In the present study, a retrospective analysis was performed for two case study red rock lobster (*Jasus edwardsii*) stocks (Bay of Plenty — CRA 2 and Wellington/Hawke Bay — CRA 4) to evaluate model performance in red rock lobster stock assessments that are used as a basis for management advice. The terminal 1, 2, 3, 5, and 10 years of data were removed and spawning stock biomass (*SSB*), relative *SSB*, adjusted vulnerable biomass, recruitment, selectivity, and catch per unit effort (CPUE) fits were compared. No strong systematic biases were found as new years of data were sequentially added to the assessment model for either of the stocks considered. Results indicate that the lobster stock dynamics assessment model has strong predictive power, and that the underlying assumptions of the rapid update framework (which will update estimates of rock lobster stock status on an annual basis between full stock assessments) are valid.

In 2019, Fisheries New Zealand switched from paper forms to electronic reporting to collect commercial catch and effort data. The Rock Lobster Working Group concluded that the new electronic catch and effort data are not directly comparable with the previous data collection programme and cannot yet be used to generate CPUE series. In this study, the sensitivity of estimated current stock status, population trajectories, and projections to the omission of recent years of CPUE data was also assessed.

The terminal 1, 2, 3, 5, and 10 years of CPUE data only were removed, and model outputs were compared. For both stocks, the median estimated stock status in the last year and the projected stock status were within the 90% credible intervals of the base case model, even when removing 5 years of CPUE data. The removal of terminal CPUE data did affect the median estimates of some key quantities (*SSB*, adjusted vulnerable biomass, etc.) and increased uncertainty in the projections, but the differences were not significant. The results of stock assessments missing this key input for several years can therefore still be used as a basis for management advice.

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1. INTRODUCTION

Retrospective analyses are a type of sensitivity analysis[4] regularly carried out by stock assessment working groups outside New Zealand to help identify systematic biases in stock assessments (Brooks & Legault 2016). A retrospective analysis involves rerunning the assessment model after removing all data for the most recent (terminal) year, the two most recent years, etc., and evaluating whether there are systematic changes in key model outputs such as spawning stock biomass (*SSB*), fishing mortality, and recruitment (Punt et al. 2020). When the assessment is updated with additional years of data, values from previously estimated parameters are expected to vary, but not in a systematic way. When updated parameter estimates have a systematic bias compared with earlier estimates (retrospective bias), this suggests that something may be misspecified in the model (Sinclair 1991). One example of model misspecification that can show retrospective patterns could be ignoring increased catchability over time due to continuous gains in fishing efficiency, which could produce unrealistically high abundance estimates (ICES 2002). Changes in natural mortality can also cause a retrospective pattern in sequential population analysis when they are not accounted for (Mohn 1999). Systematic biases in data collection (i.e., increasing trend in the misreporting of catch data) can also result in retrospective bias.

An assessment with strong retrospective patterns which cannot be corrected may need to be rejected (Punt et al. 2020) to avoid the provision of advice which is unreliable for management purposes. For instance, projections from models with retrospective patterns in estimated biomass may result in incorrect advice on catch levels (Deroba 2014). In the New England region of the United States, strong retrospective patterns have been observed for many species (Brooks & Legault 2016, Hurtado et al. 2015). Brooks & Legault (2016) used retrospective analysis for twelve groundfish species in the Northwest Atlantic to identify sources of bias. Projections were done with 1–7 years of recent data removed and then compared with the full times series of data from the assessment. This allowed the authors to identify a potential cause of the biased projections and to test some adjustment factors. However, there was still bias in the projections even after these adjustments. The reasons for these biases included catch misreporting and changes in natural mortality caused by increased predator populations. The important takeaway from this example is that scientists need to clearly communicate the direction and magnitude of the bias, so that managers can consider this additional uncertainty when specifying future catch limits and develop more robust control rules to achieve management objectives.

Retrospective analysis would be useful for New Zealand rock lobster fisheries in two ways: to examine the potential for biases in the assessment model and the impact of temporary suspension of the catch per unit effort (CPUE) index. Fisheries New Zealand switched from paper forms to electronic reporting of commercial catch and effort data for red rock lobster (*Jasus edwardsii*) potting in the 2019–20 fishing year. Preliminary analyses carried out in August 2020 indicated that the catches estimated by the two data collection systems differ (see appendix B of Starr 2021). As a consequence, the Rock Lobster Working Group (RLWG) agreed to temporarily suspend updating CPUE indices beginning with the 2019–20 spring/summer season. This lack of continuity is a serious problem because the CPUE time series is the primary index of abundance in rock lobster stock assessments.

The change in catch and effort reporting also led to a suspension of management procedures (MPs) that were based on offset-year CPUE. To partially address this problem a rapid assessment update framework was developed. Rapid updates rerun the base model from the previous full assessment with the additional years of data (e.g., the CRA 1 base model from 2019 with data from 2020 and 2021). Full assessment models occurring since the suspension of the CPUE series in 2019 (e.g., CRA 7 and CRA 8 in 2021) and 2021 rapid updates (CRA 1, CRA 2, CRA 3, CRA 4, and CRA 5) do not have an updated CPUE series starting in the spring/summer season of 2019. Therefore, retrospective analysis removing CPUE only will inform how the lack of this data input will affect model estimates and uncertainty.

[4] Sensitivity analysis in stock assessments can be used to investigate how a change in an observation or parameter might affect estimates and stock status conclusions.

In November 2020, Fisheries New Zealand and the New Zealand Rock Lobster Industry Council (NZ RLIC) Ltd convened a rock lobster research planning meeting to discuss information needs and research requirements to inform the assessment and management of rock lobster fisheries, including to mitigate the temporary loss of the Catch Effort Landing Return (CELR) CPUE time series. Retrospective analysis was suggested to determine the accuracy of models and associated projections with the removal of several years of past CPUE data as a way to gauge the future performance of stock assessment models and rapid updates in the absence of a CPUE abundance index. This research was considered to be a high priority by the RLWG. Therefore, this project addresses the following research questions:

1. what is the performance of the lobster stock dynamics (LSD) assessment model (Webber et al. 2018a) when subjected to retrospective analysis; and
2. how does the lack of an index of abundance (i.e., CPUE) impact population trajectories and projections?

Rock lobster stock assessments use projections to explore scenarios for catch advice and rebuilding. Thus, retrospective analyses are expected to help determine whether these projections adequately represent future stock trajectories. A retrospective analysis was carried out for two case studies (Bay of Plenty — CRA 2 and Wellington/Hawke Bay — CRA 4) to evaluate the performance of the LSD model. The CRA 2 and CRA 4 stocks (Figure 1) were selected because they are both evaluated by single region stock assessment models but have different levels of productivity. In addition, the effect of removing recent years of CPUE data on estimates of current stock status, population trajectories, and projections was investigated.

In summary, this study has two objectives:

1. perform a retrospective analysis for two case study stock assessments (CRA 2 and CRA 4) to assess the performance of the LSD stock assessment model; and
2. evaluate the sensitivity of population trajectories and projections in years where an index of abundance is not available.

A lack of systematic bias demonstrated by these retrospective analyses would build confidence that the models currently used in New Zealand to assess red rock lobster populations are adequately specified. The identification of retrospective biases on the other hand would require the adjustment of model assumptions or the application of bias adjustment factors. Finally, the sequential removal of CPUE data gives an indication of model performance in the absence of an abundance index (i.e., when relying on other input data such as length frequencies).

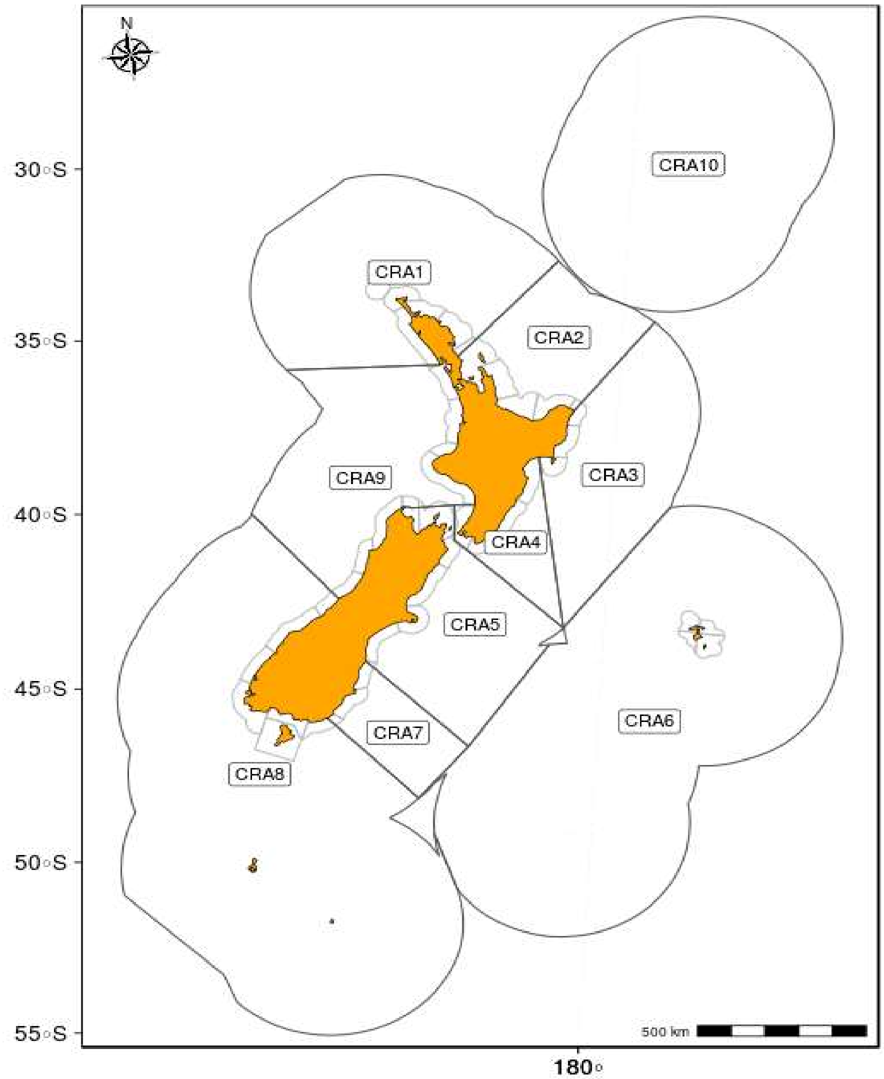

Figure 1: New Zealand red rock lobster (*Jasus edwardsii*) Quota Management Areas (QMAs).

2. METHODS

Similar methods were used to address the two objectives of this study. As the first step to address both objectives, the LSD stock assessment model was fitted to the same data sets used in the base case models of the last CRA 2 (Webber et al. 2018b) and CRA 4 (Rudd et al. 2021a) stock assessments; slight modifications were made for the CRA 4 stock assessment (see Section 2.1). [Note: Figures 1–3 are presented in the report body and Figures 4–35 are presented in Section 8. All tables are given in Section 9.]

For the first objective, which investigated retrospective patterns to test model performance, the following steps were taken:

1. fit the stock assessment model to the base case model data set, excluding the last year of data;
2. run the model and project the population with observed catch up to the final year of the base case assessment model (2018 for CRA 4 and 2016 for CRA 2. Table 1);
3. repeat steps 1 and 2, instead dropping the final 2, 3, 5, or 10 years of data (i.e., a total of five different retrospective model fits).

For the second objective, which evaluated the impacts of missing recent years of CPUE data, the steps taken were:

1. fit the stock assessment model to the base case model data sets, excluding only the CPUE data in the terminal year;
2. run the model and project the population five years into the future using the final year's catch included in the model (2018 for CRA 4 and 2016 for CRA 2, Table 1);
3. repeat steps 1 and 2, instead dropping the final 2, 3, 5, or 10 years' CPUE data (i.e., a total of five different retrospective model fits).

This produced a total of eleven maximum *a posteriori* (MAP) model runs for each CRA Quota Management Area (QMA): one base case model + five retrospective runs (dropping 1, 2, 3, 5, or 10 years) × two approaches for dropping data (all data or CPUE only). For each model run, the data were re-weighted in the standard way, aiming for a standard deviation of the normalised residual (SDNR) of 1.0 for all CPUE series and the sex ratio (Breen et al. 2003, Francis 2011). The tag data were self-weighting and the LF weight was derived using the Francis approach (Francis, 2011). Finally, samples from the posterior distribution were obtained for all 22 model runs using Markov chain Monte Carlo (MCMC) simulation.

All model runs for each objective and stock were compared using comparison plots for spawning stock biomass (*SSB*), relative *SSB*, adjusted vulnerable biomass, recruitment, fits to the CPUE, and selectivity functions. In addition, a suite of diagnostic plots was examined for each of the 22 model runs (i.e., MCMC trace plots, not presented here) to check the mixing of MCMC chains and model convergence properties.

For both study objectives (i.e., removing all data or removing CPUE data only), summary tables comparing the key model parameters for each of the 22 model runs are presented. The model parameters selected for comparison include productivity parameters (growth, natural mortality, average recruitment), maturation parameters, and fishery parameters (selectivity, vulnerability, catchability); parameter abbreviations and definitions are presented in Table 2. Key fishery indicators of interest (provided in all stock assessment documents), including relative *SSB*, adjusted vulnerable biomass, total biomass, the probabilities of being below the soft limit (20% SSB_0) and projected biomass being greater than current biomass are also presented (see Table 3 for CRA 4 and Table 4 for CRA 2).

The retrospective analysis (objective 1) would have been comparing different final years (see Table 9 and Table 10 for example), so these comparison tables were only presented when removing CPUE data (objective 2). For objective 2, all model runs had the same final year (i.e., the same terminal year in the assessment model) and only varied in the number of years of CPUE data used in the stock assessment. Therefore, the current and final years of projections are consistent and can be compared across all scenarios. The performance of each stock assessment model when conducting the retrospective analysis (objective 1) was examined based on the sensitivity of estimated model parameters (see Table 7 for example), and by visually inspecting the model estimated population time series and projections (see Figure 6 as an example), checking for systematic biases when adding new years of data.

2.1 CRA 4

The CRA 4 fishery extends from the Wairoa River in northern Hawke's Bay, southwards around Hawke's Bay, the Wairarapa and the Wellington coasts, then passing north to the Manawatu River on the Kapiti coast (Figure 2). The data used in this stock assessment were documented by Starr et al. (2021). The most recent CRA 4 stock assessment was completed in 2020 using an LSD model and assumed a single homogeneous stock across the five statistical areas (912, 913, 914, 915, and 934) (Rudd et al. 2021a).

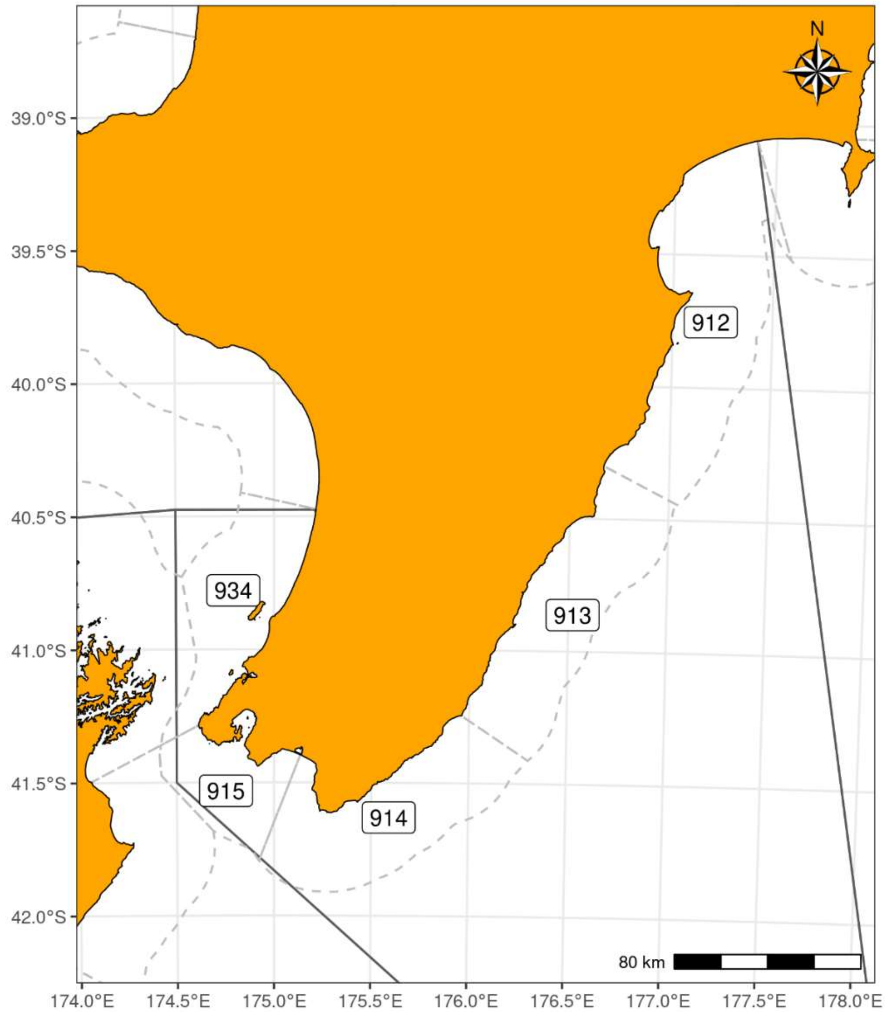

Figure 2: The CRA 4 Quota Management Area (QMA) on the southern coast of the North Island, and its statistical areas. The QMA boundaries are defined by black lines and the statistical area boundaries by grey lines.

The base case assessment model in 2020 (Rudd et al. 2021a) was fitted to standardised CPUE indices, length frequency data, sex ratio data, and tag-recapture data. Model inference for this assessment was based on MAP fits and MCMC simulations. The stock assessment estimated increasing fishing mortality from 1945 to the late 1960s, which remained high through the 1980s, resulting in a decline in estimated red rock lobster biomass in CRA 4. Since the 1990s, CRA 4 has experienced alternating periods of relatively low and high fishing mortality coupled with at least two major recruitment events, leading to oscillations in the estimated population biomass. The stock assessment model estimated that the *SSB* had generally remained above the soft limit of 20% SSB_0. Although CPUE had increased in the last two to three years of the time series, the stock assessment model estimated the population was currently at a low point in the cycle between lower and higher population biomass. Projections suggested that continued harvest at constant current catch levels would likely lead to a decline in the vulnerable biomass and *SSB*, but with no probability of dropping below the soft limit in the next five years.

Details of the base case model used in the 2020 CRA 4 stock assessment are given by Rudd et al. (2021a). The base case model for CRA 4 in 2020 was fitted to standardised CPUE indices up to autumn-winter (AW) of 2019 (spring-summer (SS) of 2019 was not available due to the changeover to electronic reporting in the 2019–20 fishing year and the apparent shifts in reporting estimated lobster catches). The first difference between the base case model presented in the assessment by Rudd et al. (2021a) and this analysis was that the 2020 base case model was rerun to the end of 2018 so that there would be a complete final year of CPUE data (Table 5). In addition, the 2020 stock assessment found that many of the models had bimodal posterior distributions for the growth model shape parameter (*Gshape*). This issue was addressed in the stock assessment by constraining the upper bound of *Gshape* to be equal to 7.5 (instead of 15). During initial runs of the present study, when removing years of all data types, the posterior distributions of *Gshape* continued to be bimodal even with the added constraint. Consequently, the *Gshape* parameter was fixed to the estimated values from the 2020 stock assessment for CRA 4, to avoid this bimodality. A summary of the changes from the base case model of the 2020 stock assessment for CRA 4 and the base case model used here are shown in Table 5. The subsequent model runs removing yearly data for CRA 4 are shown in Table 6.

2.2 CRA 2

CRA 2 extends from Te Arai Point, south of Whangarei, to East Cape at the easternmost end of the Bay of Plenty (Figure 3). This QMA includes the Hauraki Gulf, both sides of the Coromandel Peninsula, and the Bay of Plenty. The most recent stock assessment for CRA 2 was done in 2017 using the LSD model (Webber et al. 2018b). The model was fitted to standardised CPUE indices, size frequency data, sex ratio data, and tag-recapture data. Model inference for this assessment was based on MAP fits and MCMC simulations. This stock assessment estimated a stock depleted below B_R (the average vulnerable biomass from 1979 to 1981) and a low *SSB* relative to the unfished stock level (SSB_0) (Webber et al. 2018b).

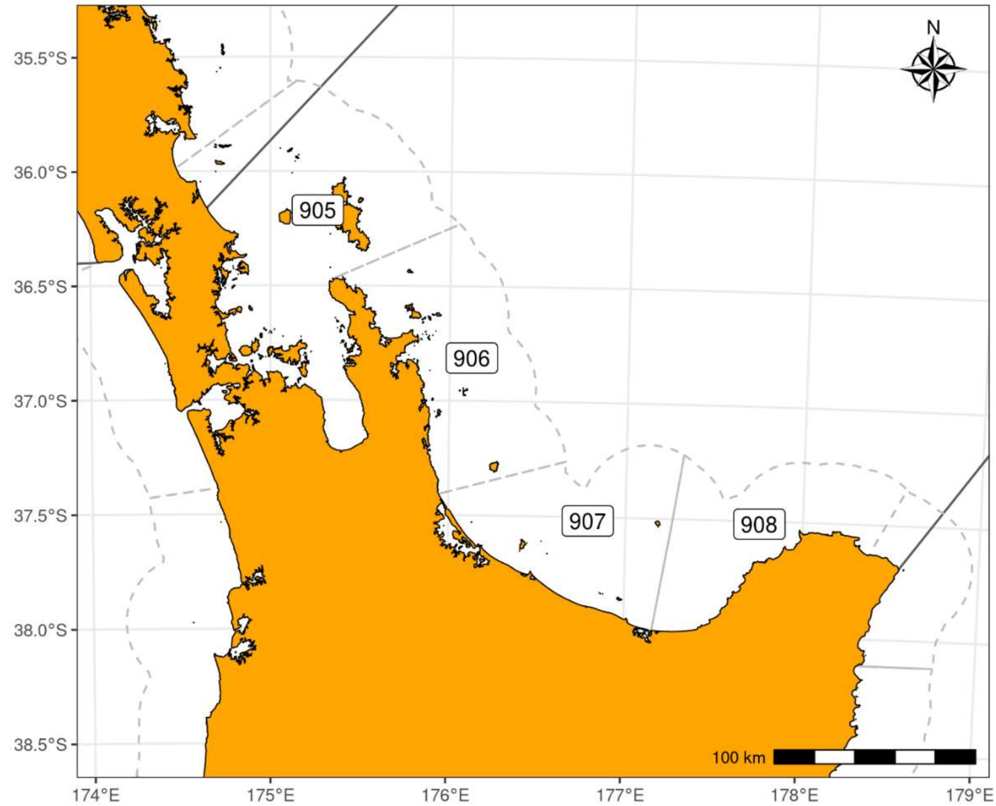

Figure 3: The CRA 2 Quota Management Area (QMA) and its statistical areas. The QMA boundaries are defined by black lines and the statistical area boundaries by grey lines.

There have been general updates to the LSD model code since the 2017 CRA 2 assessment, so the base case model was rerun with the current code for direct comparison with the retrospective scenarios. The last year of data included in this model was 2016. The subsequent model runs removing yearly data for CRA 4 are shown in Table 7.

3. CRA 4 RESULTS

3.1 Removing all data types

Retrospective patterns in *SSB* and relative *SSB* (Figure 4 to Figure 6), adjusted vulnerable biomass (Figure 7 and Figure 8), and recruitment (Figure 9) were investigated. Selectivity curves for all model runs for each of the two epochs (i.e., 1945–1992 and 1993–2015, the change in epochs being coincident with changes in escape gap regulations, Figure 10), and model fits to the CPUE (Figure 11) were also compared.

To identify retrospective patterns, systematic biases were searched for when adding new years of data. Systematic bias could, for example, be seen if the *SSB* significantly shifted up as more and more years were added to the assessment model. No strong *SSB* retrospective patterns were found for CRA 4 even though there was a slight increase in *SSB* as more years of data were added to the assessment model from 2008 to 2018. However, these shifts were not considered significant, given the overlapping credible intervals (Figure 4). When each retrospective model run was projected up to 2018 (the final year in the base case model), the LSD model was found to have good predictive power for this stock, with similar *SSB* estimates in the final year, all with overlapping posterior distributions. The only exception to this conclusion was a slight increase in the median estimate of *SSB* in 2018 when the final 10 years of data were removed and projected forward (Figure 5). However, this result was considered acceptable given the large amount of data that had been removed. In all cases, the estimated relative *SSB* in 2018 was above the soft limit of 20% SSB_0 (Figure 6).

As with *SSB*, the adjusted vulnerable biomass showed an increasing trend as more years of data were added to the model, but the changes were small and again with overlapping credible intervals (Figure 7). The largest (but still not significant) difference was observed when the final 10 years of data were removed. In this case, the predictive power was lower, with a slightly higher adjusted vulnerable biomass in the recent years compared with the other model runs (Figure 8). No retrospective patterns or biases were obtained with the addition of more years of data. The higher estimated *SSB* and adjusted vulnerable biomass obtained when removing 10 years of data were driven by a higher predicted and projected recruitment (Figure 9).

The fishery selectivity for females in the first epoch (before 1993) shifted to smaller sizes as more years of data were added to the model, but those changes were not significant. No differences among model runs were observed for males or for any sex after 1993 (Figure 10). Fits to the CPUE indices are shown in Figure 11, including observed and predicted CPUE (posterior distribution) up to 2018, for all retrospective model runs. The predictive power was good because adding more years of observations did not have much effect on predicted CPUE, except for the 10-year projections (blue lines in Figure 11). Finally, Table 8 provides parameter estimates for each model run which showed no apparent retrospective patterns (i.e., model runs with very similar parameters estimates for which all credible intervals overlapped).

3.2 Removing CPUE data only

For the second objective, the potential effects of lacking CPUE indices in the most recent years were examined. The sensitivity of *SSB* and relative *SSB* (Figure 12 to Figure 14), adjusted vulnerable biomass (Figure 15 and Figure 16), and recruitment (Figure 17) were investigated. The estimated selectivity curves for each epoch from all model runs (Figure 18) and the fits to CPUE indices (Figure 19) were also compared. In general, the effects of removing the CPUE data only (i.e., instead of all observation types) were less noticeable than when all data for the year were removed (see parameter estimates in Table 9).

Removing some terminal years of CPUE data had a minimal effect on estimated *SSB*. The sensitivity of estimated current *SSB* (in 2018) increased as more years of CPUE data were removed (Figure 12). When projecting the population forward five years with the last year of observed catch (2018), the projections drifted further away from the base case model as more years of CPUE were omitted (Figure 13). However, for all the assessed scenarios, the relative *SSB* was above the soft limit of 20% SSB_0, with overlapping credible intervals for all model runs (Figure 14, Table 10, and Table 11).

As with *SSB*, estimates of vulnerable biomass drifted slightly from the base case model estimate as more years of CPUE were removed (Figure 15). When projecting the population forward five years with the last year observed catch (2018), the estimated vulnerable biomass shifted down as more years of CPUE were omitted, with the biggest jump observed when removing two or more years of the CPUE index (Figure 16). However, the predicted differences were small, and all credible intervals overlapped.

Estimated and projected recruitment were very similar among runs (Figure 17), as were the selectivity curves (Figure 18). Figure 19 shows the fit to the observed CELR CPUE data for AW and SS seasons and the predicted CPUE for the entire time series up to 2018, even for the years where the CPUE data had been removed. Estimated CPUE was comparable with the observed values, except for the model which removed the final 10 years of CPUE data (Figure 19). In general, model estimates were relatively insensitive to omitting less than the final five years of the CPUE series.

4. CRA 2 RESULTS

4.1 Removing all data types

As for CRA 4, retrospective patterns in CRA 2 model estimates, including *SSB* and relative *SSB* (Figure 20 to Figure 22), adjusted vulnerable biomass (Figure 23 and Figure 24), and recruitment (Figure 25) were investigated. Selectivity curves for all model runs for each epoch (Figure 26), model fits to CPUE (Figure 27), and parameter estimates (Table 12) were also compared.

No strong retrospective patterns in estimated *SSB* were found as more years of data were added to the assessment model (Figure 20). The evidence for potential systematic biases was even weaker than for CRA 4. Up to the final year (2016), model estimates of *SSB* were relatively insensitive to the removal of full years of data, with overlapping credible intervals when comparing scenarios. This indicates that the 2017 CRA 2 stock assessment model has strong predictive power. However, when the final 10 years of data were removed, the median projected estimate of *SSB* in 2016 was higher than in the other retrospective model runs, although with much more uncertainty (i.e., wider credible intervals, Figure 21). The relative *SSB* in 2016 from the base case model was right below the soft limit of 20% SSB_0. As more and more years of data were added to the model, the estimates of *SSB* in 2016 shifted down, but not in a systematic way (Figure 22).

As was the case for *SSB*, there were no retrospective patterns in adjusted vulnerable biomass estimates (Figure 23). The greatest difference was observed in the final model year (2016) for the projected adjusted vulnerable biomass, when the final 10 years of data were missing. Removing the last 10 years of data led to a lower predictive power, with a higher adjusted vulnerable biomass predicted in the recent years compared with all the other model runs (Figure 24). Besides this, no retrospective patterns or biases were observed when sequentially adding years of data. The higher estimates of *SSB* and adjusted vulnerable biomass when projecting 10 years of data were associated with higher predicted and projected recruitment for those last 10 years (Figure 25).

The female and male fishery selectivities in the first epoch (before 1993) shifted slightly to smaller sizes as more years of data were added to the model. No differences among model runs were observed after 1993 for any sex (Figure 26). Figure 27 shows the fits to the observed CPUE data for AW and SS seasons and the predicted CPUE up to 2016 as full years of data are removed. Sequentially removing data had minimal impact on the predicted CPUE, except for predictions when 10 years of all data had been removed. In this case, the projected population differed substantially from the observed population, with the biomass growing implausibly large. This large, predicted increase resulted from a period of good recruitment which preceded the terminal year of this model. Finally, Table 12 presents the parameter estimates for each model run. No retrospective patterns were observed, with parameter estimates being very similar across all model runs and with overlapping credible intervals.

4.2 Removing CPUE data only

For the second objective, the effect of sequentially removing only the CPUE data was explored. The presence of retrospective bias in estimates of *SSB* and relative *SSB* (Figure 28 to Figure 30), adjusted vulnerable biomass (Figure 31 and Figure 32), and recruitment (Figure 33) was investigated. The estimated selectivity curves for each epoch for all model runs (Figure 34) and fits to CPUE (Figure 35) were also compared. In general, the removal of CPUE data had minimal effect on the estimation of these parameters and quantities (see parameter estimates in Table 13).

Removing up to five years of CPUE data had minimal effect on estimated *SSB* compared with the base case model (Figure 28). When projecting the population forward five years with the last year of observed catch (2016) the projections diverged from the base case model as more years of CPUE were omitted (Figure 29). When more than two years of CPUE data were removed, the current *SSB* was estimated to be above the soft limit of 20% SSB_0 and the projections were less pessimistic than the base case model (Figure 30, Table 14).

The constant catch used in the CRA 2 projections was the catch observed in 2016, the last year in the CRA 2 stock assessment model. It is important to note that this is not the catch that was actually taken during the projected years (2017 to 2021) because catch limits were reduced from the fishing year 2018–19 onwards as a consequence of this stock falling below the soft limit. However, the catch in the final model year was used for projections to mimic the general approach used in red rock lobster stock assessments. Given this high catch used in the projections, the predictions of stock status will not have correctly mimicked the actual biomass trajectory (Table 15).

As was the case for *SSB*, the estimated adjusted vulnerable biomass was relatively insensitive to the removal of up to five years of CPUE data (Figure 31). When projecting the population five years from the last year of observed catch (2016), the estimated vulnerable biomass drifted upwards as more years of CPUE were omitted, with the biggest jump obtained when removing two or more years of the CPUE index (Figure 32). These shifts in the projections stem from changes in the recruitment estimates as the CPUE observations are removed. This effect can be seen in Figure 33, where there is a distinct upward shift in the estimated mean recruitment in the final recruitment years as CPUE data were omitted. However, the credible intervals of the projections overlap when comparing model runs (Figure 32 and Table 14).

The selectivity curves were similar, with more variability before 1993 (epoch 1, Figure 34) for both sexes. Figure 35 shows the fits to the observed CELR CPUE data for AW and SS seasons and the predicted CPUE up to 2016 as years of CPUE are excluded. For all model runs, the fits to the CPUE index were good. When removing more than one year of CPUE the estimates for the missing years were slightly higher in both seasons (Figure 35). Finally, Table 13 provides parameter estimates for each model run, revealing very similar estimates and overlapping credible intervals.

5. CONCLUSIONS

When a final year of data is omitted in a retrospective analysis, some variability in the model estimates compared with the base case model run might be expected. However, if retrospective patterns are detected when adding additional years of data, this could indicate systematic biases in the stock assessment model. This would be cause for concern since systematic biases can result in dissimilar results as assessments are updated with additional years of data. However, no significant retrospective patterns were observed for either of the examples considered (CRA 2 and CRA 4), when removing all observation types (objective 1) or CPUE indices only (objective 2).

The sensitivity of key model estimates to the removal of CPUE data were slight, and as expected increased as more years of the CPUE data were removed. However, for CRA 4 the median estimated stock status in 2019 (SSB_{2019} / SSB_0) and the projected stock status (SSB_{2023} / SSB_0) were within the 90% credible intervals of the base case model, even when removing the final 10 years of the CPUE data (Table 10). For CRA 2, the same pattern was observed, except that stock status perceptions changed as more than 2 years of CPUE were removed (Table 14). The biggest differences and uncertainties with respect to the base case model were found in the projections for both stocks. As more years of CPUE data were progressively removed, the uncertainty associated with projected *SSB* and projected adjusted vulnerable biomass increased.

This analysis suggests that the rock lobster length-based stock assessment model is robust for the case study stocks (CRA 2 and CRA 4). The retrospective analysis indicates that these stock assessment models have strong predictive power and are fit for the purpose of rapid updates used each year to update red rock lobster stock assessment models (Rudd et al. 2021a). However, performing rapid updates for more than three years without a CPUE time series becomes risky as the uncertainty and potential for introducing bias increases. This is less likely to be applicable for the full assessment models where it may be possible to develop interim abundance indices based on logbook or catch sampling data by observers.

6. ACKNOWLEDGEMENTS

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7. REFERENCES

Breen, P.A.; Kim, S.W.; Andrew, N.L. (2003). A length-based Bayesian stock assessment model for the New Zealand abalone *Haliotis iris*. *Marine and Freshwater Research 54(5)*: 619–638.

Brooks, E.N.; Legault, C.M. (2016). Retrospective forecasting — evaluating performance of stock projections for New England groundfish stocks. *Canadian Journal of Fisheries and Aquatic Sciences 73*: 935–950.

Deroba, J.J. (2014). Evaluating the Consequences of Adjusting Fish Stock Assessment Estimates of Biomass for Retrospective Patterns using Mohn's Rho. *North American Journal of Fisheries Management 34(2)*: 380–390.

Francis, R.I.C.C. (2011). Data weighting in statistical fisheries stock assessment models. *Canadian Journal of Fisheries and Aquatic Science 68(6)*: 1124–1138.

Hurtado Ferro, F.; Szuwalski, C.S.; Valero, J.L.; Anderson, S.C.; Cunningham, C.J.; Johnson, K.F.; Licandeo, R.R.; McGillaird, C.R.; Monnahan, C.C.; Muradian, M.L.; Ono, K.; Vert-pre, K.A.; Whitten, A.R.; Punt, A.E. (2015). Looking in the rear-view mirror: bias and retrospective patterns in integrated, age-structured stock assessment models. *ICES Journal of Marine Science 72*: 99–110.

ICES (2002). Report of the Working Group on Methods on fish Stock Assessments. ICES Headquarters. 3-7 December 2001. *International Council for the Exploration of the Sea*. CM 2002/D:01. 102 p.

Mohn, R. (1999). The retrospective problem in sequential population analysis: an investigation using cod fishery and simulated data. *ICES Journal of Marine Science 56*: 473–488. doi:10.1006/jmsc.1999.0481.

Punt, A.E.; Tuck, G.N.; Day, J.; Canales C.M; Cope, J.M.; de Moor, C.L.; De Oliveira, J.A.A.; Dickey-Collas, M.; Elvarsson, B.; Haltuch, M.A.; Hamel, O.S.; Hicks, A.C.; Legault, C.M., Lynch, P.D.; Wilbergm, M.J. (2020). When are model-based stock assessments rejected for use in management and what happens then? *Fisheries Research 224*: 105465.

Rudd, M.B.; Pons, M.; Roberts, J.; Webber, D.N.; Starr, P.J. (2021a). The 2020 stock assessment of rock lobsters (*Jasus edwardsii*) in CRA 4. *New Zealand Fisheries Assessment Report 2021/80*. 112 p.

Rudd, M.B.; Webber, D.N.; Starr, P.J. (2021b). Model-based reference levels for New Zealand red rock lobster (*Jasus edwardsii*). *New Zealand Fisheries Assessment Report 2021/81*. 42 p.

Sinclair, A.; Gascon, D.; Rivard, D.; Gavaris, S. (1991). Consistency of some northwest Atlantic groundfish stock assessments. *NAFO Scientific Council Studies 16*: 59–77.

Starr, P.J. (2021). Rock lobster catch and effort data: 1979–80 to 2019–20. *New Zealand Fisheries Assessment Report 2021/55*. 126 p.

Starr, P.J.; Webber, D.N.; Rudd, M.; Pons, M.; Roberts, J. (2021). Data for the 2020 stock assessment of red rock lobsters (*Jasus edwardsii*) in CRA 4. *New Zealand Fisheries Assessment Report 2021/5*6. 80 p.

Webber, D.N.; Starr, P.J.; Haist, V.; Rudd, M.B.; Edwards, C.T.T. (2018b). The 2017 stock assessment and management procedure evaluation for rock lobsters (*Jasus edwardsii*) in CRA 2. *New Zealand Fisheries Assessment Report 2018/17*. 87 p.

Webber, D.N.; Haist, V.; Starr, P.J.; Edwards, C.T.T. (2018a). A new model for the assessment of New Zealand rock lobster (*Jasus edwardsii*) stocks and an exploratory multi-area CRA 4 assessment. *New Zealand Fisheries Assessment Report 2018/53*. 111 p.

8. FIGURES

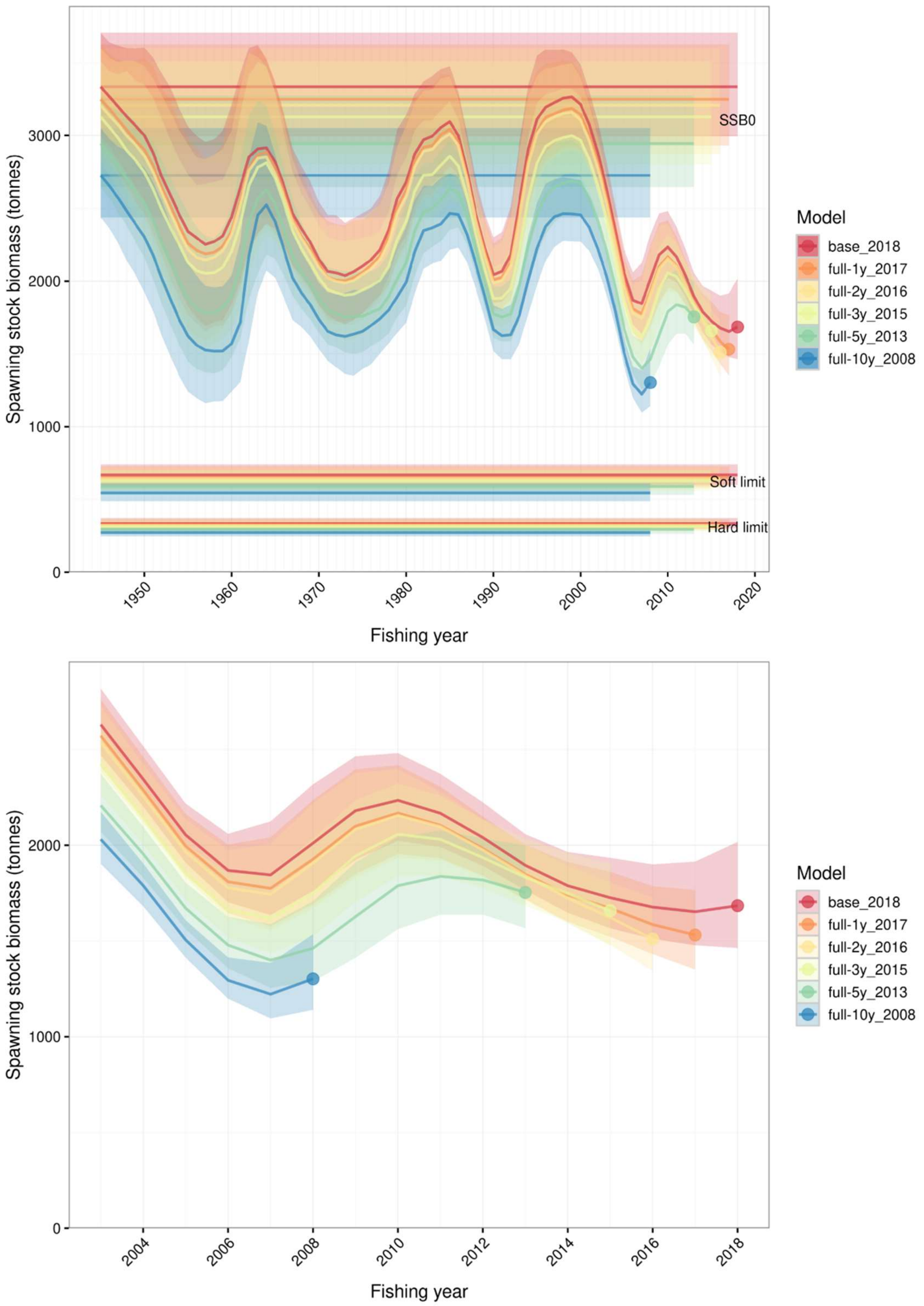


Figure 4: CRA 4 posterior distribution of spawning stock biomass (tonnes) showing the median (line) and 90% credible interval (shaded region) for the 2020 stock assessment (base_2018) and 5 retrospective model runs. The dots represent the last year of data included in the model. The top panel shows the spawning stock biomass for all model runs and years. From top to bottom, the horizontal lines and shaded regions represent SSB_0, the soft limit (20% SSB_0), and the hard limit (10% SSB_0). The lower panel shows the spawning stock biomass for all models for the last fifteen years.

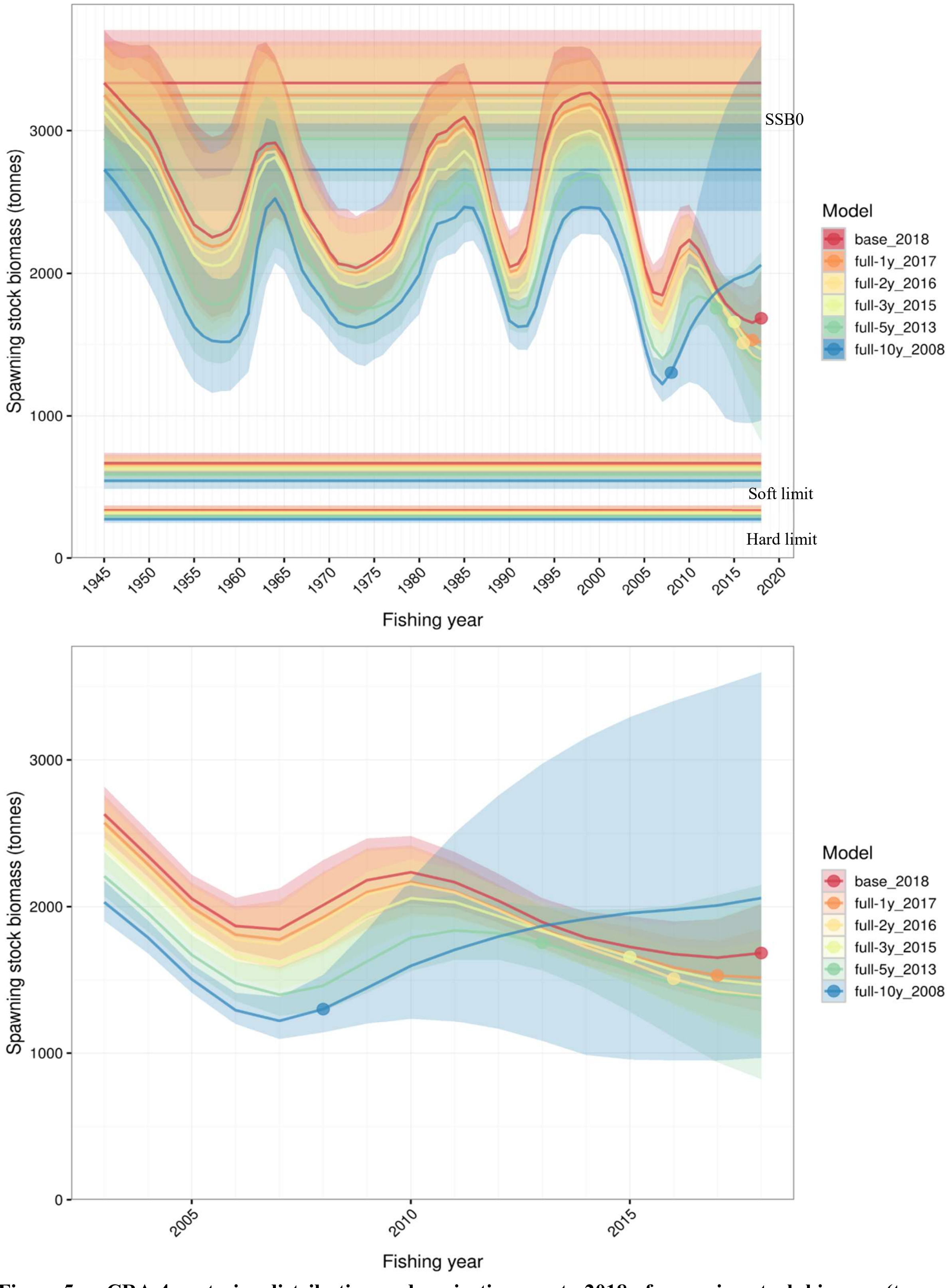


Figure 5: CRA 4 posterior distribution and projections up to 2018 of spawning stock biomass (tonnes) showing the median (line) and 90% credible interval (shaded region) for the 2020 stock assessment (base_2018) and 5 retrospective model runs. The dots represent the last year of data included in the model. The top panel shows the spawning stock biomass for all model runs and years. From top to bottom, the horizontal lines and shaded regions represent *SSB_0*, the soft limit (20% *SSB_0*), and the hard limit (10% *SSB_0*). The lower panel shows spawning stock biomass for all models for the last fifteen years.

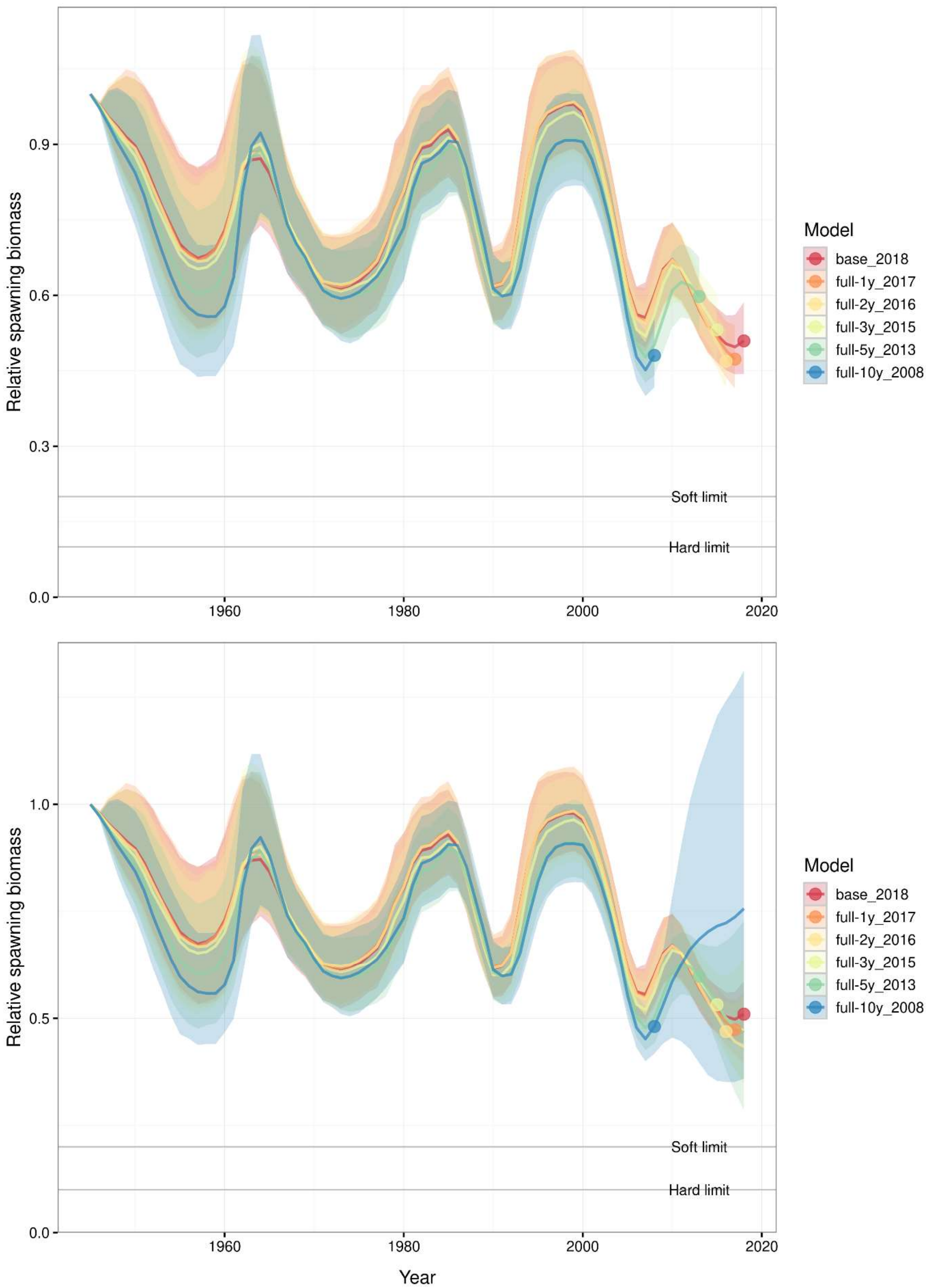


Figure 6: CRA 4 posterior distribution of relative spawning stock biomass (tonnes) showing the median (line) and 90% credible interval (shaded region) for the 2020 stock assessment (base_2018) and 5 retrospective model runs. The dots represent the last year of data included in the model. From top to bottom, the horizontal lines are the soft limit and the hard limit. The top panel shows the relative spawning stock biomass for all model runs and years. The lower panel shows the projected relative spawning stock biomass for all models up to 2018.

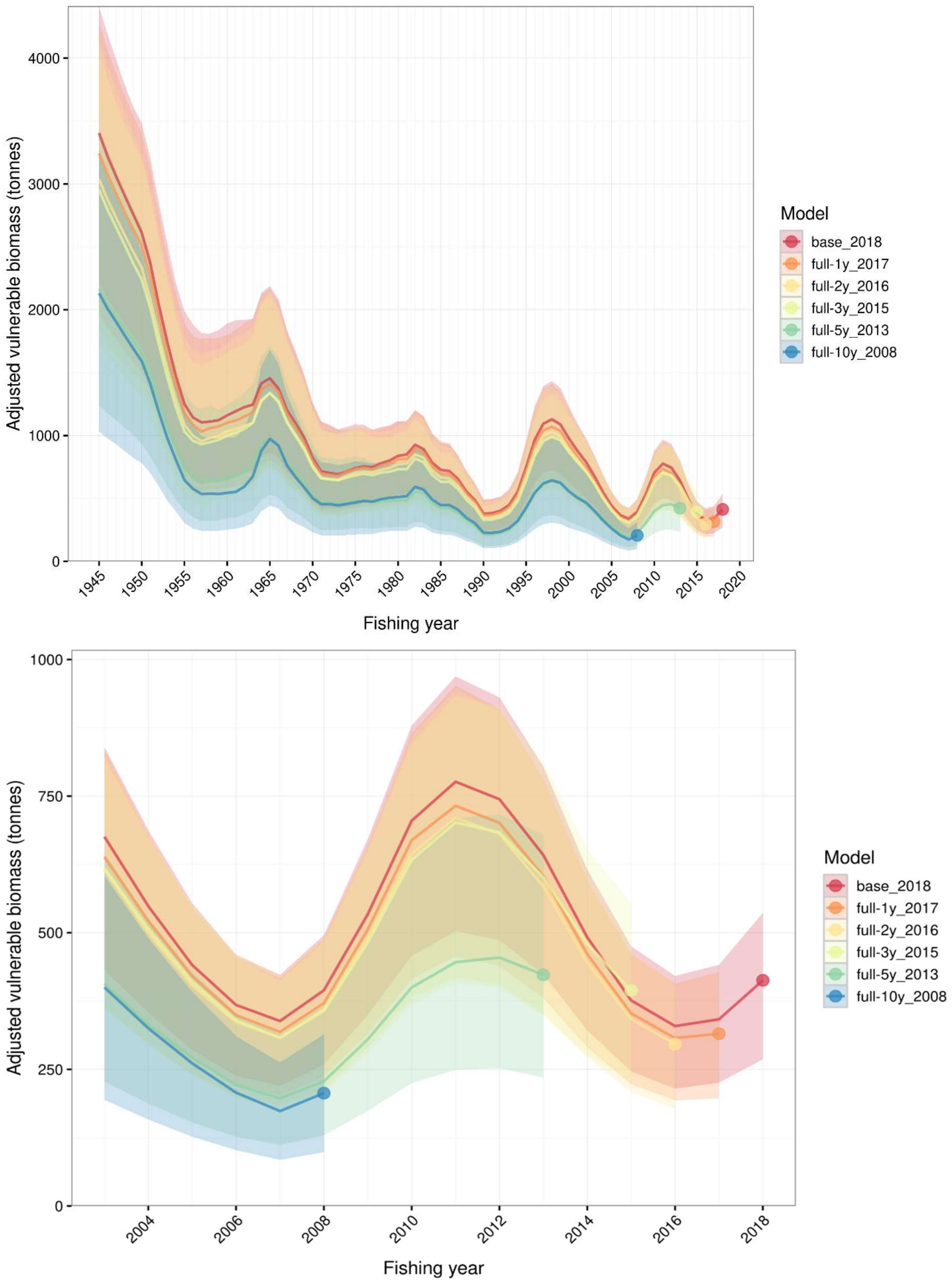


Figure 7: CRA 4 posterior distribution of adjusted vulnerable biomass (tonnes) showing the median (line) and 90% credible interval (shaded region) for the 2020 stock assessment (base_2018) and 5 retrospective model runs. The top panel shows the adjusted vulnerable biomass for all model runs and years. The lower panel shows the adjusted vulnerable biomass for all models for the last fifteen years.

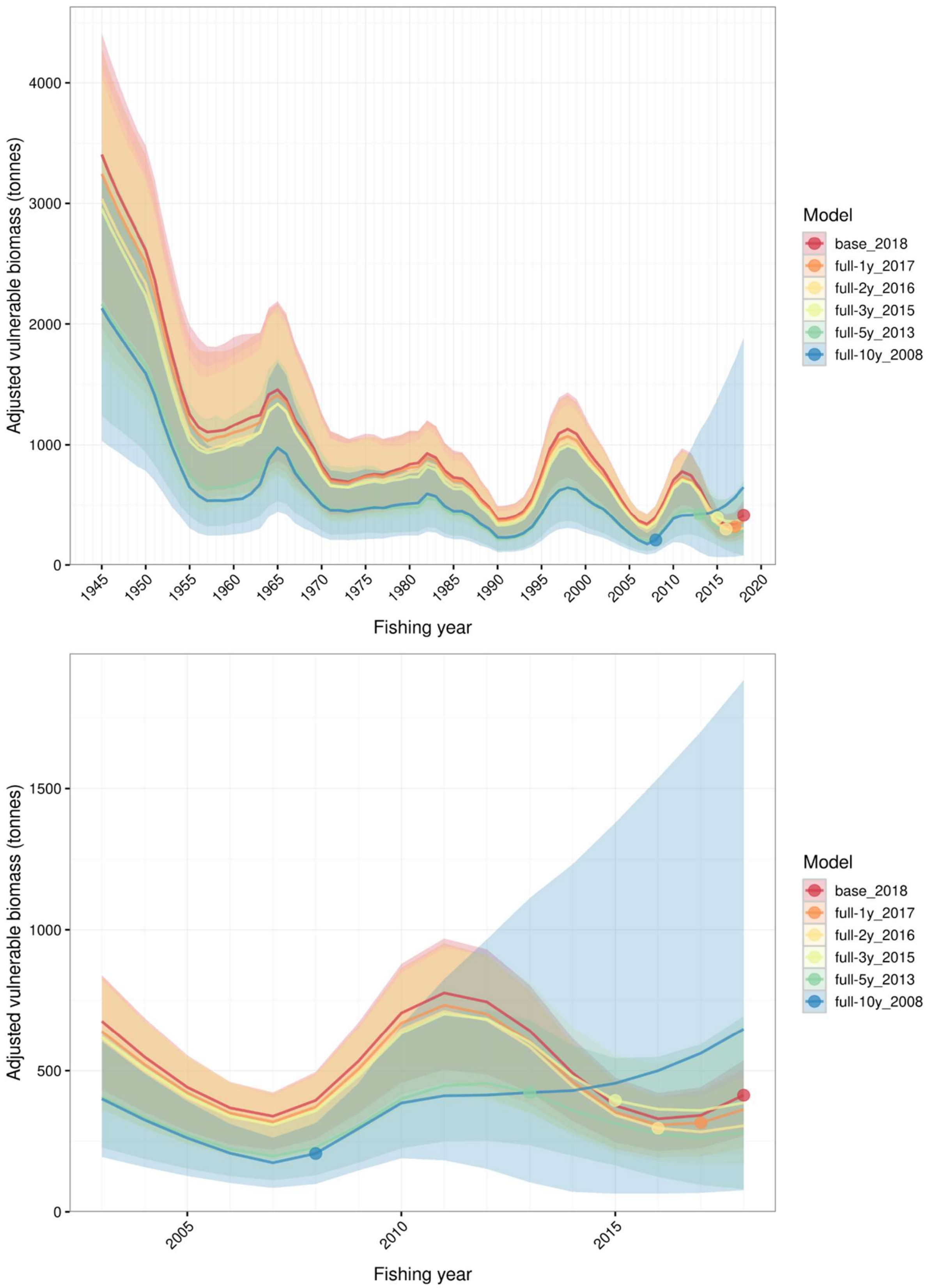


Figure 8: CRA 4 posterior distribution of adjusted vulnerable biomass (tonnes) projected up to 2018 showing the median (line) and 90% credible interval (shaded region) for the 2020 stock assessment (base_2018) and five retrospective model runs. The top panel shows the adjusted vulnerable biomass for all model runs and years, including projected years. The lower panel shows the adjusted vulnerable biomass for all models for the last fifteen years and projected years.

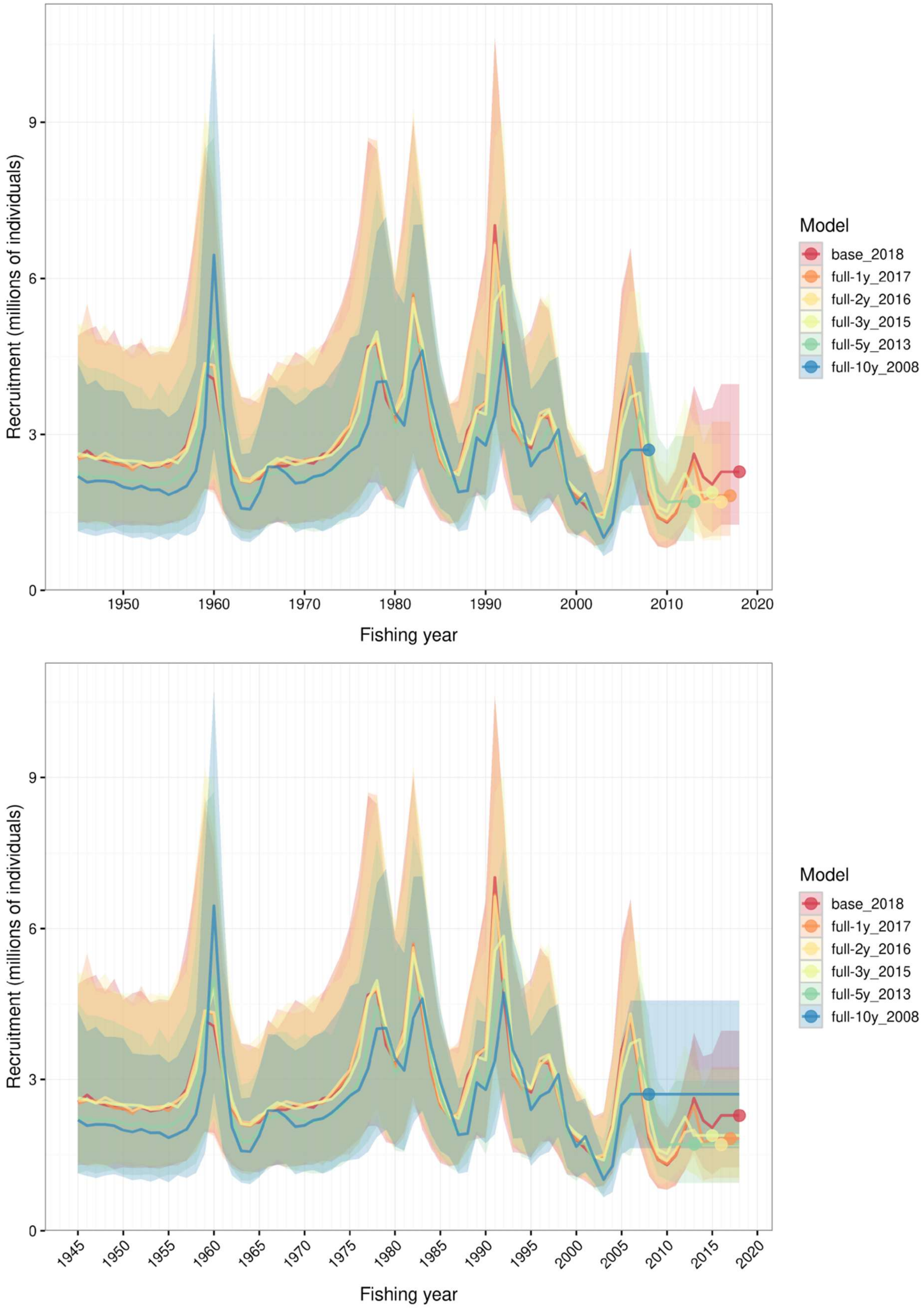


Figure 9: CRA 4 posterior distribution of recruitment showing the median (line) and 90% credible interval (shaded region) for the 2020 stock assessment (base_2018) and the retrospective runs. The top panel shows the recruitment for all model runs, and the lower panel shows projected recruitment for all model runs up to 2018.

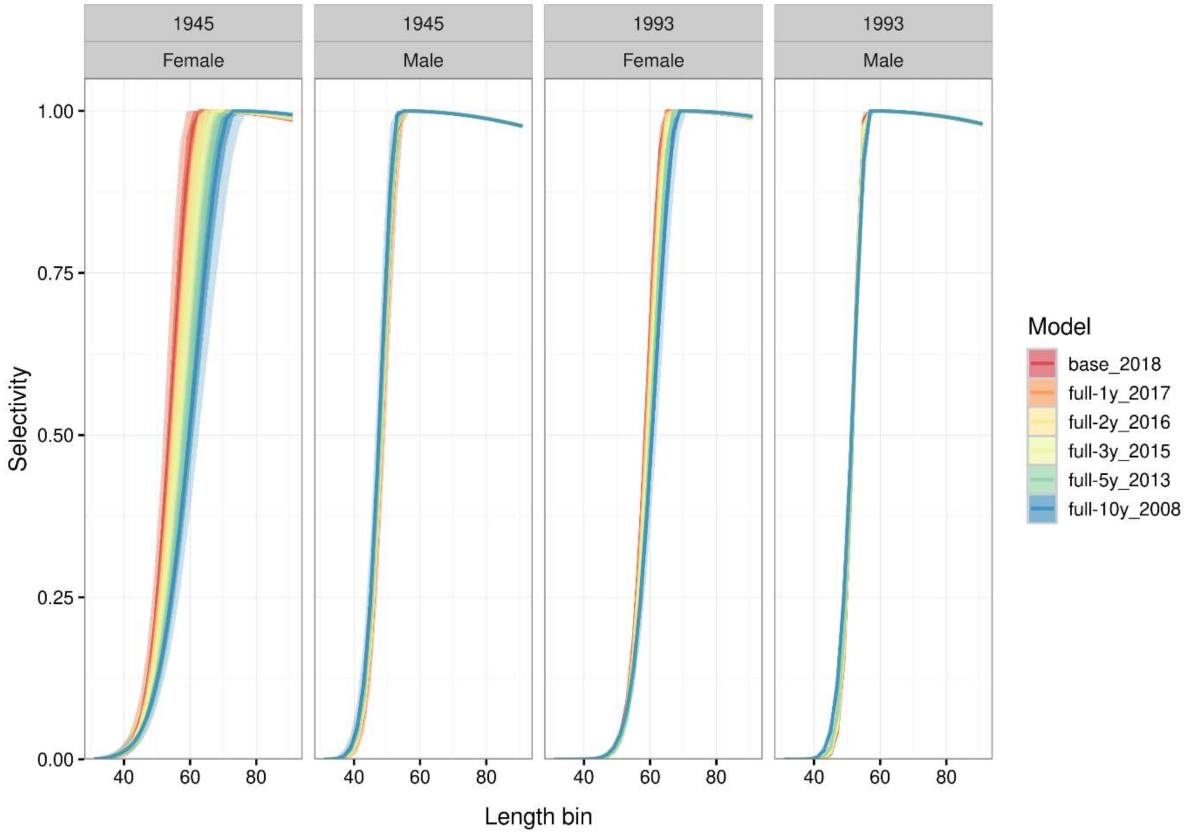


Figure 10: CRA 4 posterior distribution of selectivity by sex and epoch showing the median (line) and 90% credible interval (shaded region) for the 2020 stock assessment (base_2018) and the retrospective runs.

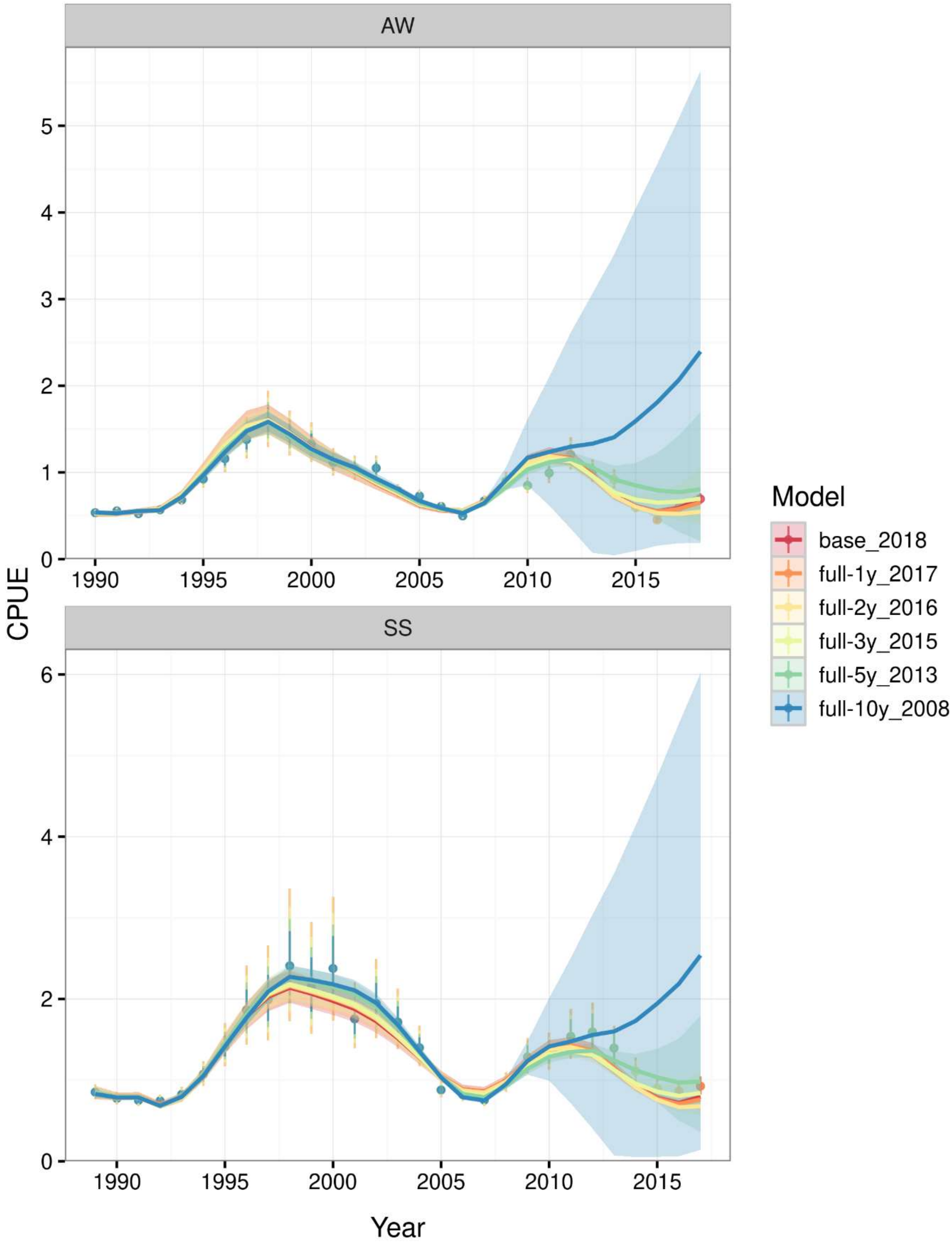


Figure 11: CRA 4 CPUE observations (points) and posterior distribution showing the median (line) and 90% credible interval (shaded region) by season (top panel: AW; bottom panel: SS) for the base case model of the 2020 stock assessment (base_2018) and the retrospective model runs.

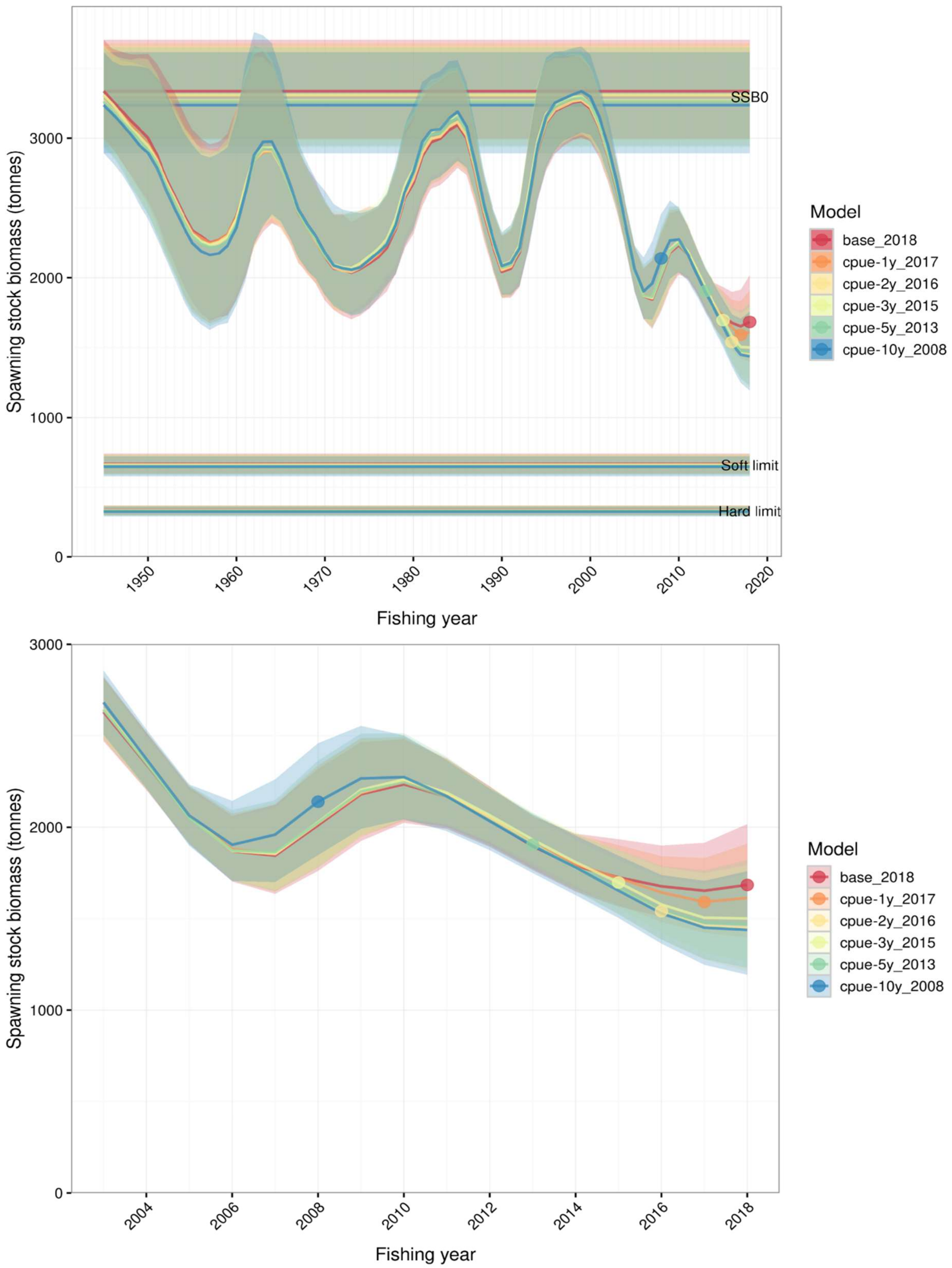
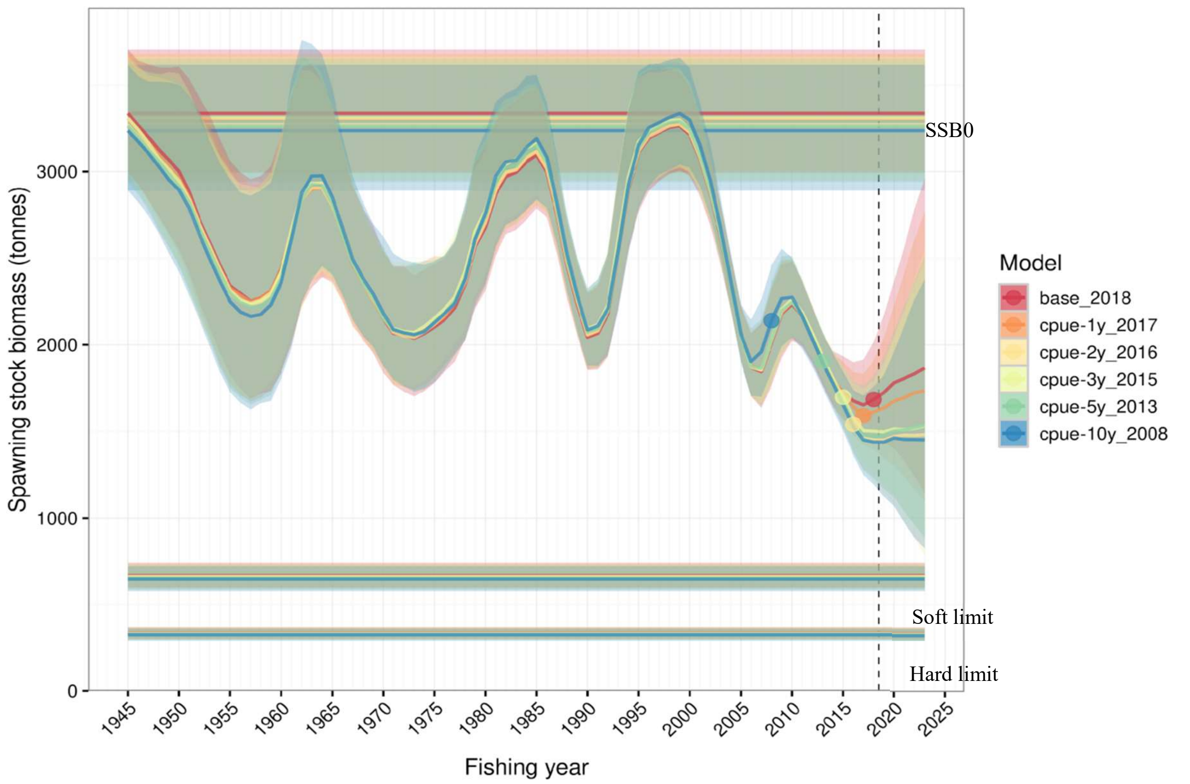


Figure 12: CRA 4 posterior distribution of spawning stock biomass (tonnes) showing the median (line) and 90% credible interval (shaded region) for the 2020 stock assessment (base_2018) and five model runs when removing only CPUE data. The dots represent the last year of CPUE included in the model. The top panel shows the spawning stock biomass for all model runs and years. From top to bottom, the horizontal lines and shaded regions represent *SSB_0*, the soft limit (20% *SSB_0*), and the hard limit (10% *SSB_0*). The lower panel shows spawning stock biomass for all models for the last fifteen years.



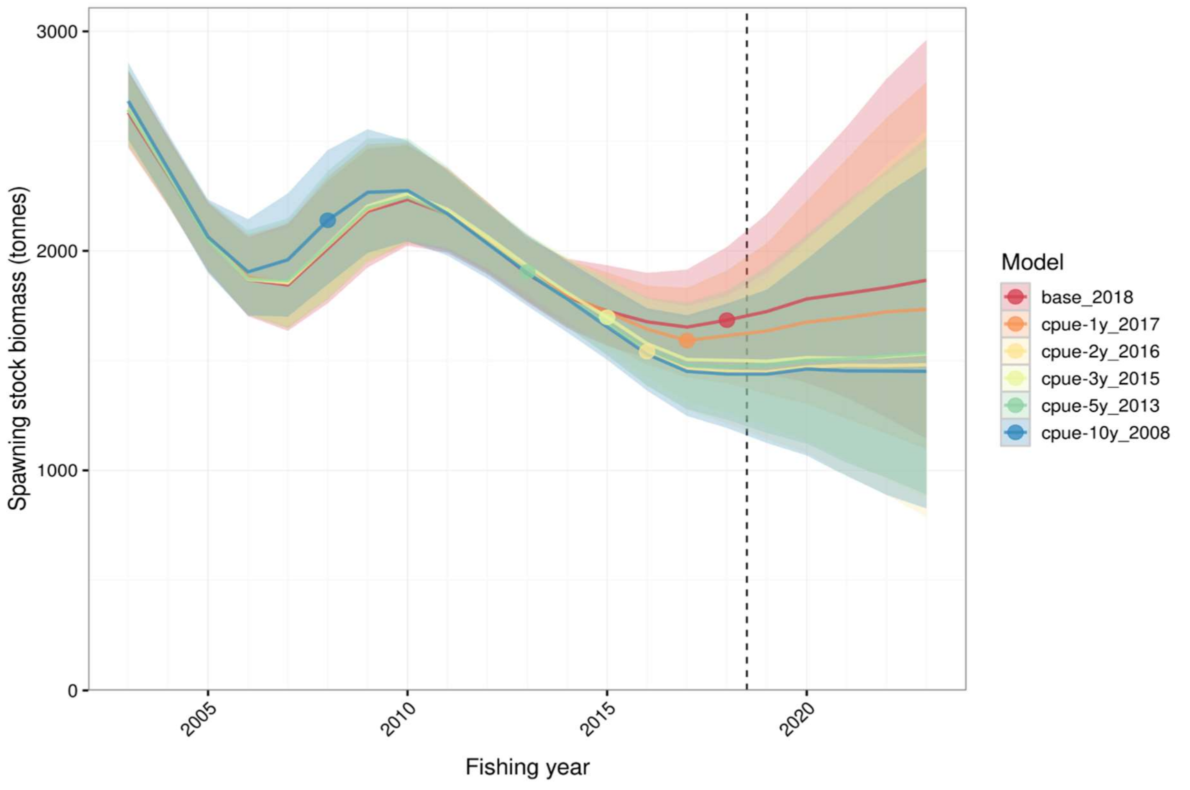


Figure 13: CRA 4 posterior distribution and projections up to 2023 of spawning stock biomass (tonnes) showing the median (line) and 90% credible interval (shaded region) for the 2020 stock assessment (base_2018) and five model runs when removing only years of CPUE data. The dots represent the last year of data included in the model. The vertical dashed lines represent the last year in the assessment model, so everything to the right of this line are projections. The top panel shows the spawning stock biomass for all model runs and years. From top to bottom, the horizontal lines and shaded regions represent *SSB_0*, the soft limit (20% *SSB_0*), and the hard limit (10% *SSB_0*). The lower panel shows spawning stock biomass for all models for the last fifteen years and projected years.

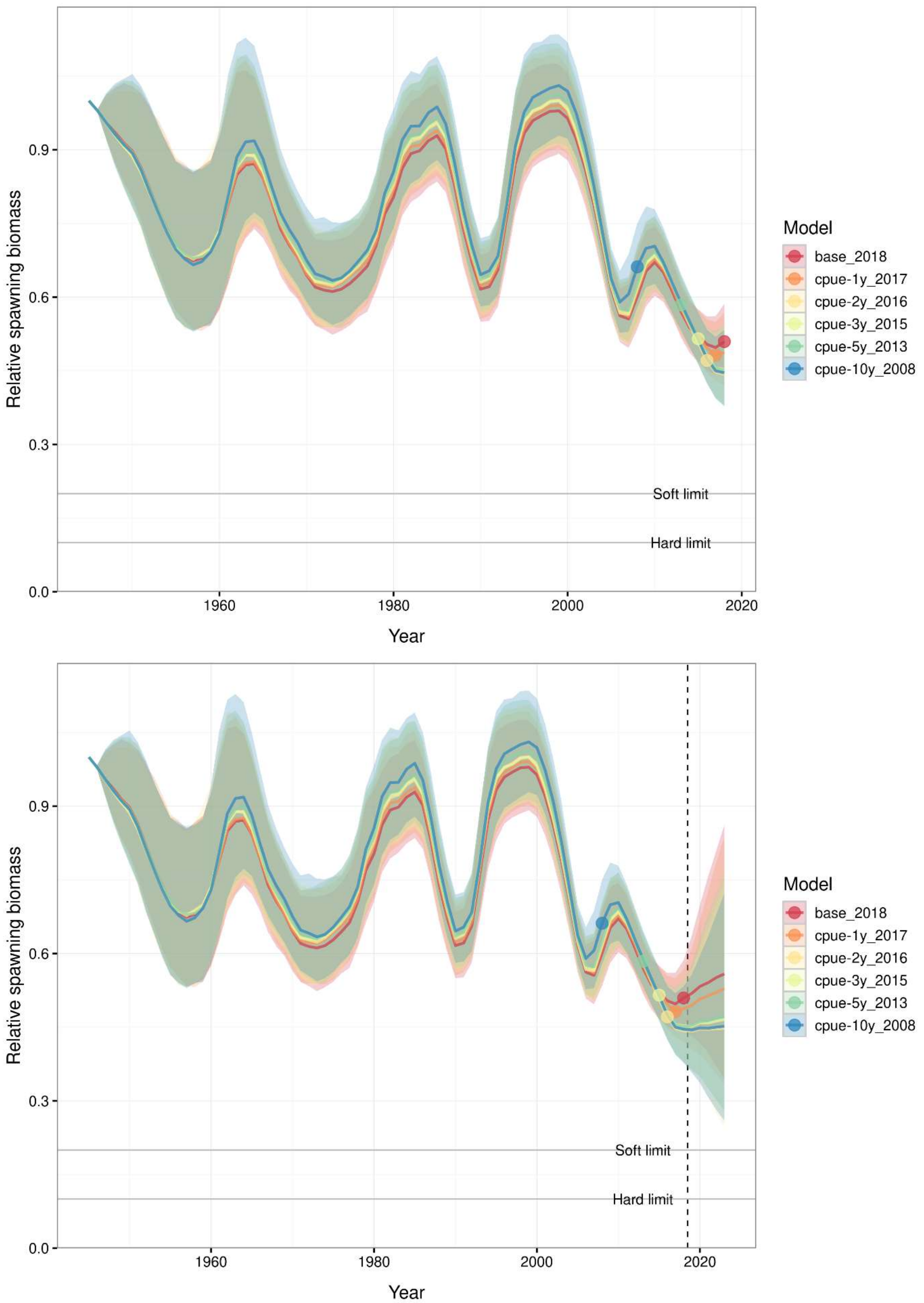


Figure 14: CRA 4 posterior distribution of relative spawning stock biomass (tonnes) showing the median (line) and 90% credible interval (shaded region) for the 2020 stock assessment (base_2018) and five model runs when removing years of CPUE data. The dots represent the last year of CPUE data included in the model. From top to bottom, the horizontal lines are the soft limit (20% SSB_0) and the hard limit (10% SSB_0). The top panel shows the relative spawning stock biomass for all model runs and years. The lower panel shows the projected relative spawning stock biomass for all models up to 2023. The vertical dashed line represents the last year in the assessment model, so everything to the right of this line are projections.

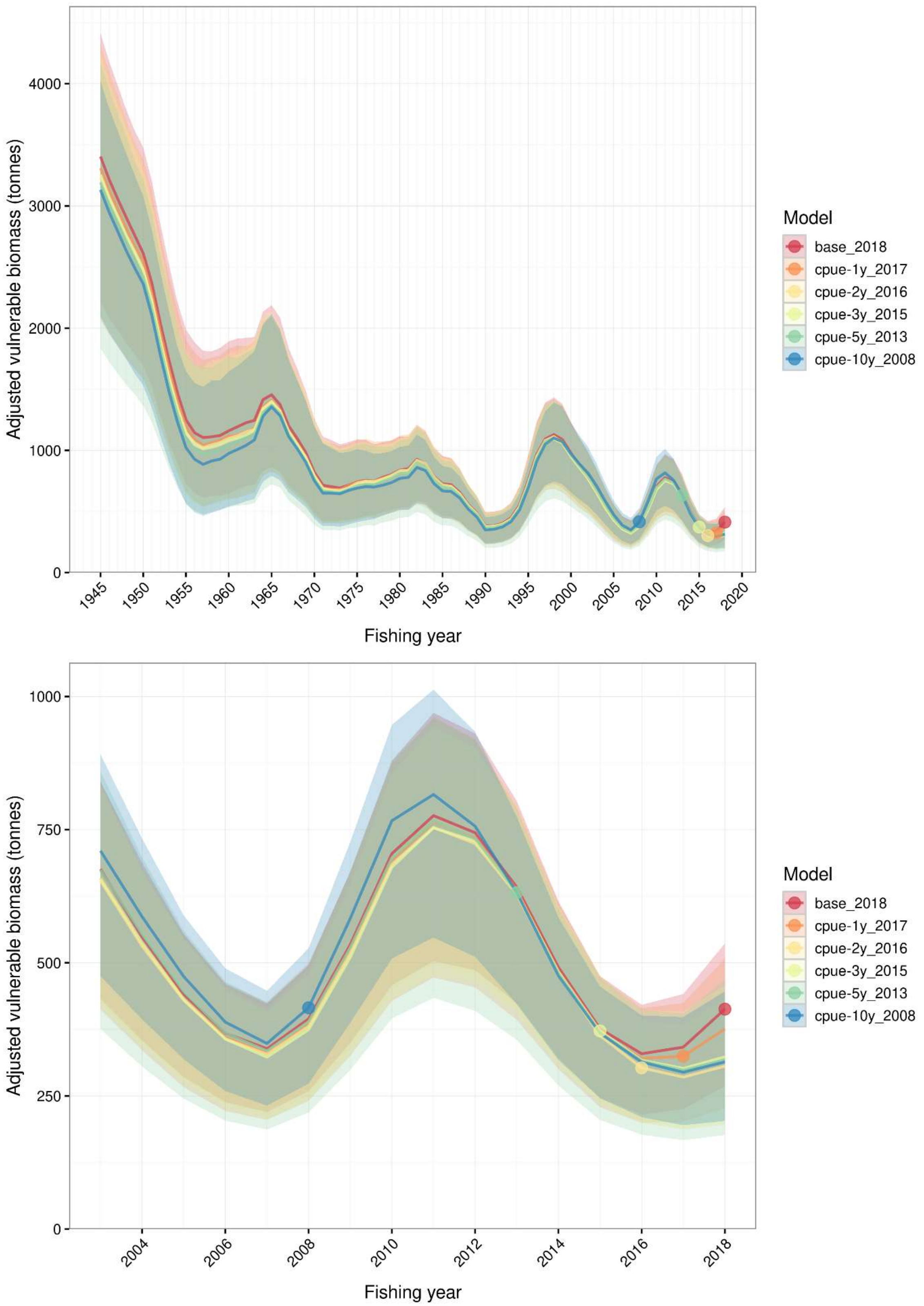


Figure 15: CRA 4 posterior distribution of adjusted vulnerable biomass (tonnes) showing the median (line) and 90% credible interval (shaded region) for the 2020 stock assessment (base_2018) and five model runs when removing years of CPUE data. The dots represent the last year of CPUE data included in the model. The top panel shows the adjusted vulnerable biomass for all model runs and years. The lower panel shows the adjusted vulnerable biomass for the last fifteen years for all models.

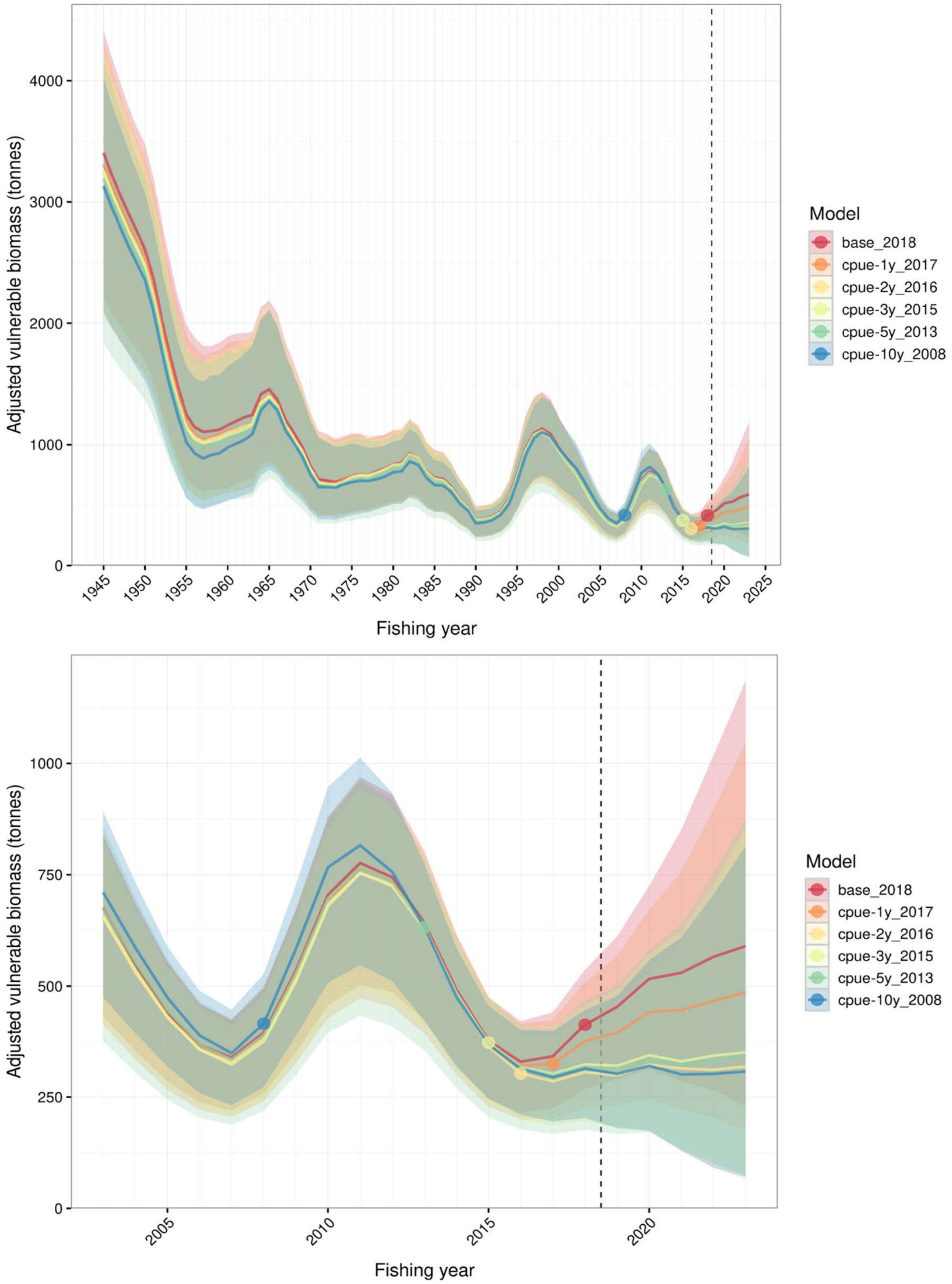
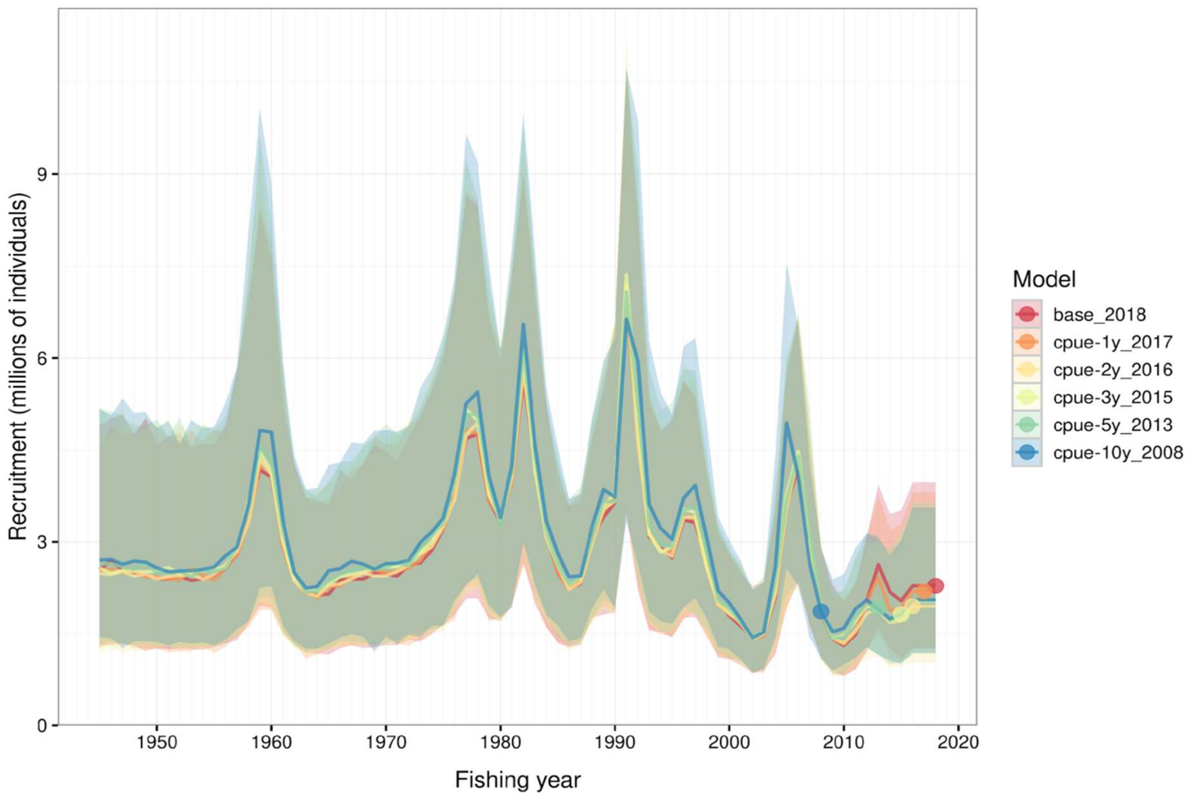


Figure 16: CRA 4 posterior distribution of adjusted vulnerable biomass (tonnes) projected up to 2023 showing the median (line) and 90% credible interval (shaded region) for the 2020 stock assessment (base_2018) and five model runs when only removing CPUE data. The dots represent the last year of CPUE data included in the model. The vertical dashed lines represent the last year in the assessment model, so everything to the right of this line are projections. The top panel shows the adjusted vulnerable biomass for all model runs and years, including projected years. The lower panel shows the adjusted vulnerable biomass for all models for the last fifteen years and projected years.



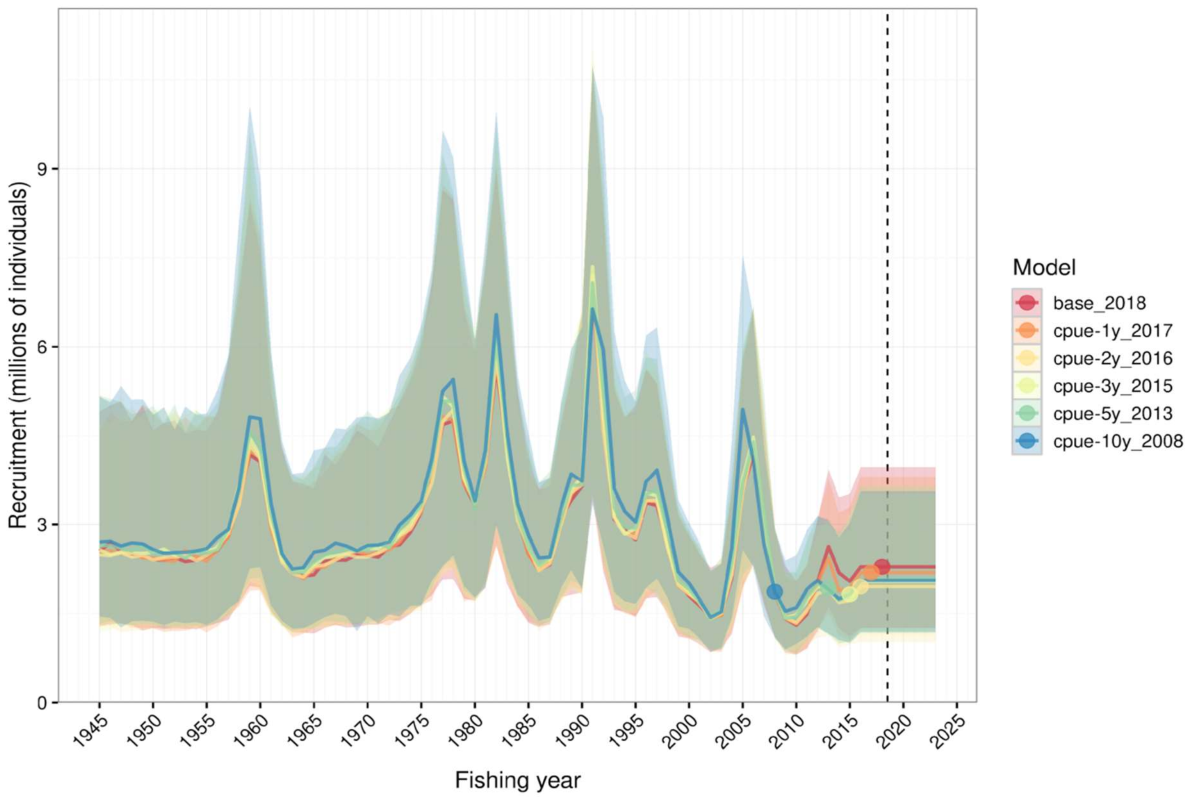


Figure 17: CRA 4 posterior distribution of recruitment showing the median (line) and 90% credible interval (shaded region) for the 2020 stock assessment (base_2018) and the model runs when removing CPUE data. The top panel shows the recruitment for all model runs, and the lower panel shows projected recruitment for all model runs up to 2023. The dots represent the last year of CPUE data included in the model. The vertical dashed line represents the last year in the assessment model, so everything to the right of this line are projections.

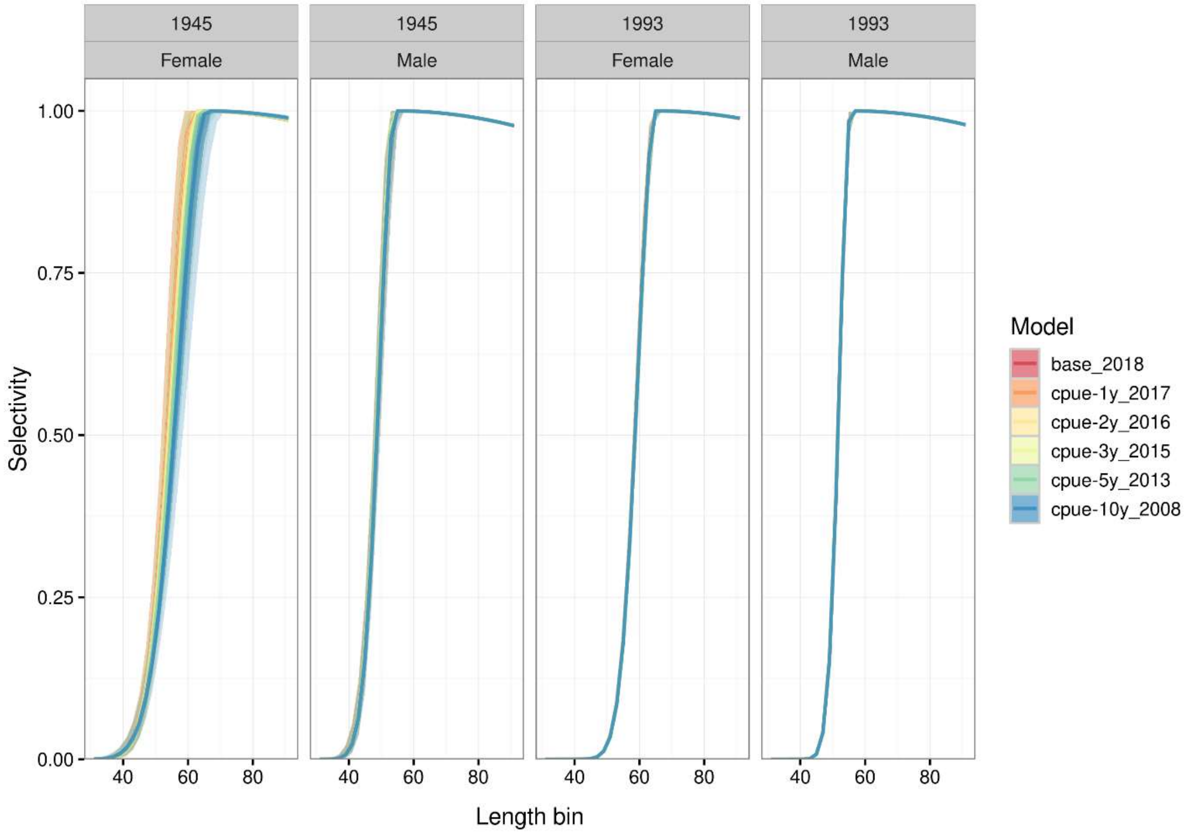


Figure 18: CRA 4 posterior distribution of selectivity by sex and epoch showing the median (line) and 90% credible interval (shaded region) for the 2020 stock assessment (base_2018) and the model runs when removing years of CPUE data.

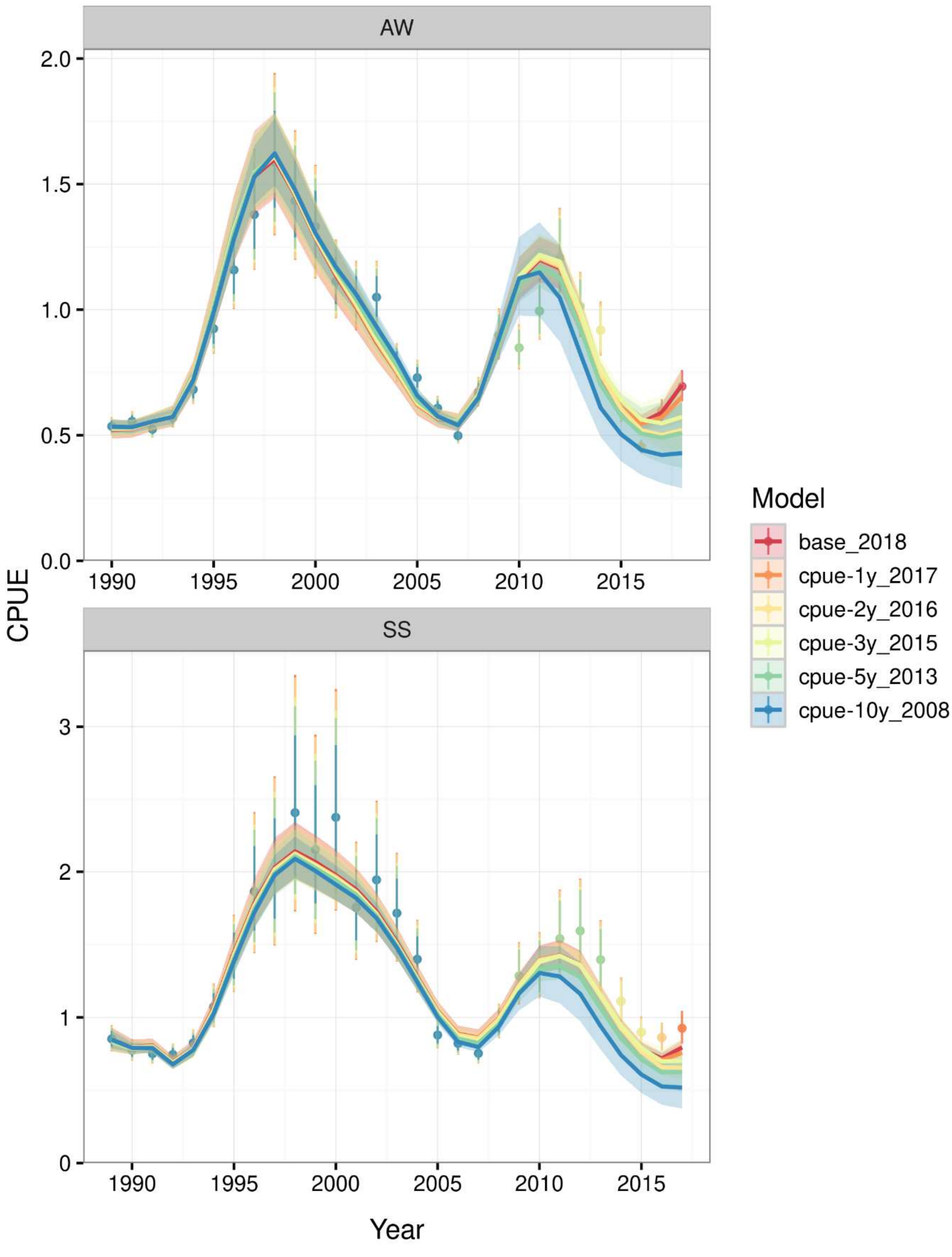
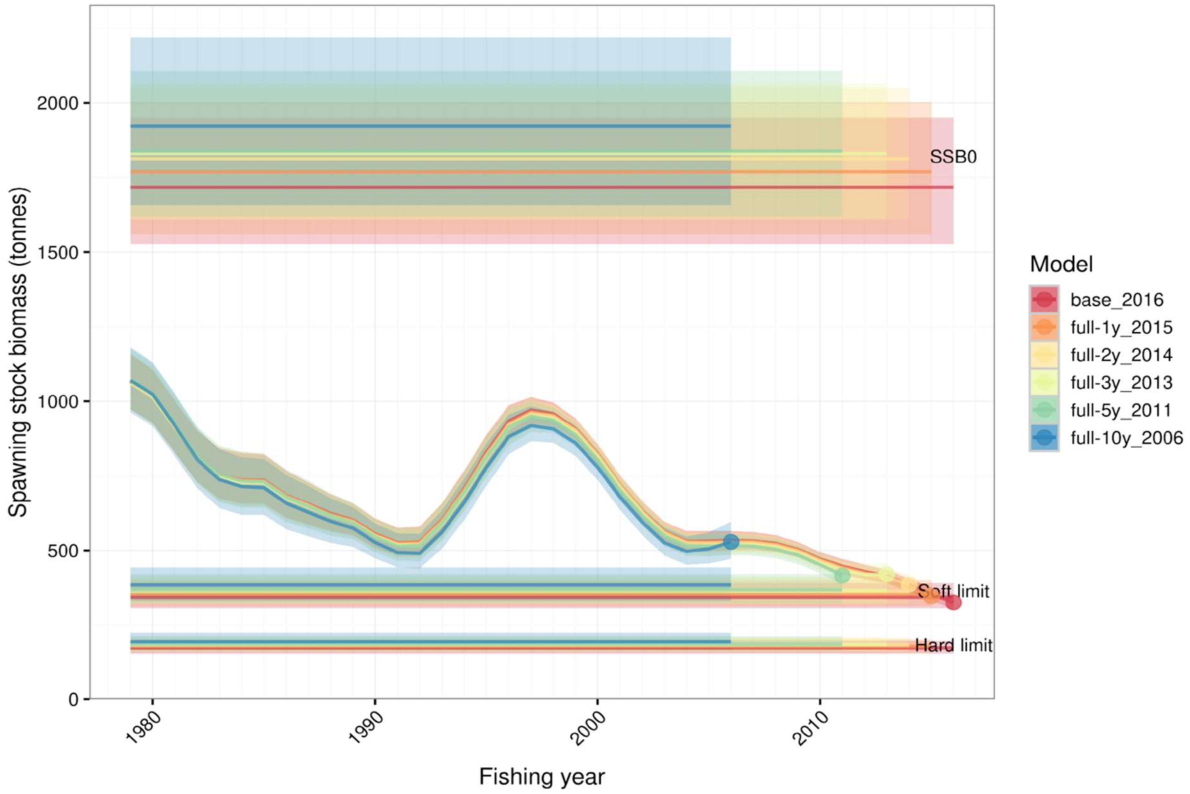


Figure 19: CRA 4 CPUE observations (points) and posterior distribution showing the median (line) and 90% credible interval (shaded region) by season (top panel: AW; bottom panel: SS) for the 2020 stock assessment (base_2018) and the model runs when removing years of CPUE data.



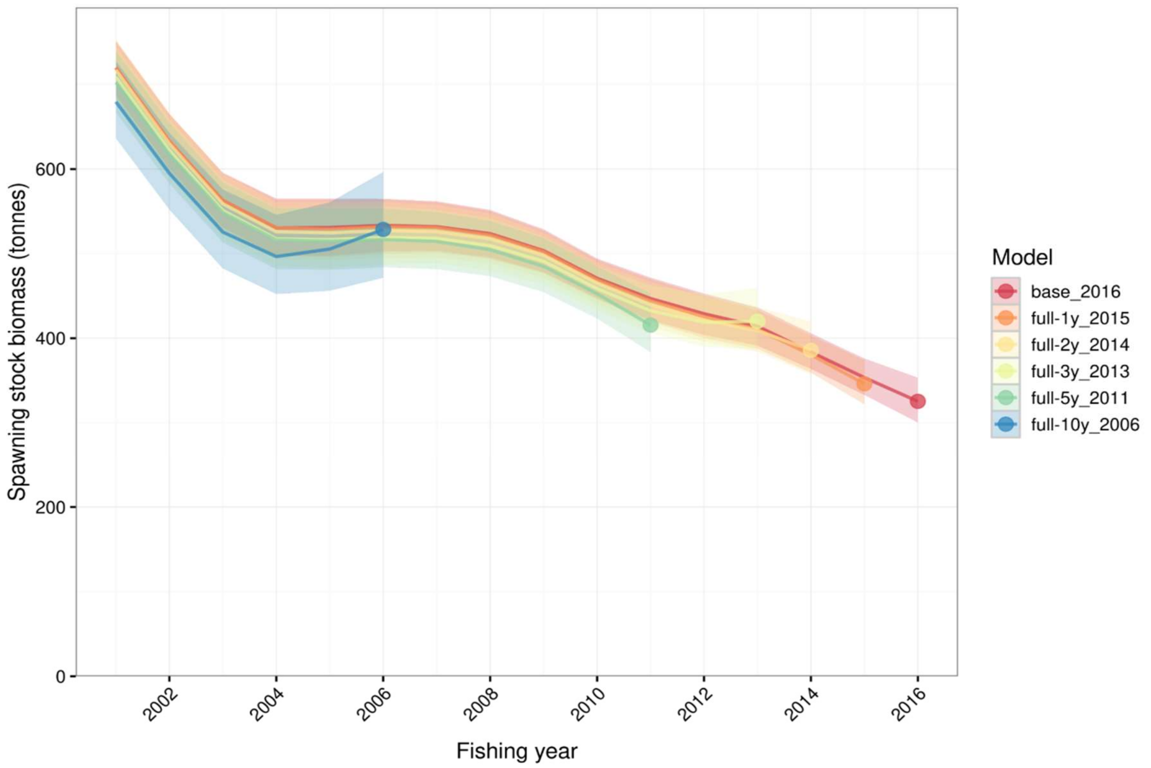


Figure 20: CRA 2 posterior distribution of spawning stock biomass (tonnes) showing the median (line) and 90% credible interval (shaded region) for the 2017 stock assessment (base_2016) and five retrospective model runs. The dots represent the last year of data included in the model. The top panel shows the spawning stock biomass for all model runs and years. From top to bottom, the horizontal lines and shaded regions represent SSB_0, the soft limit (20% SSB_0), and the hard limit (10% SSB_0). The lower panel shows the spawning stock biomass for all models for the last fifteen years.

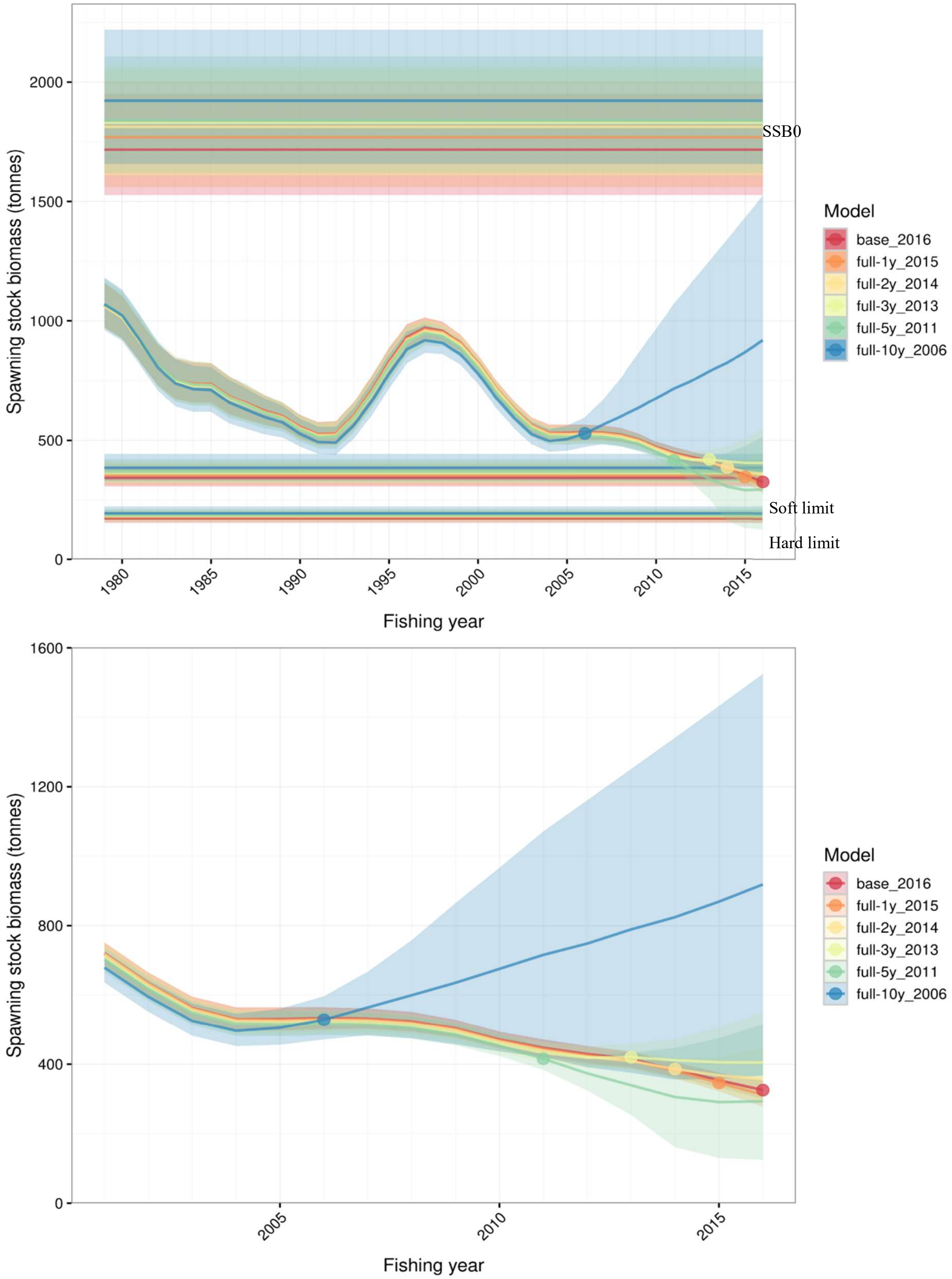


Figure 21: CRA 2 posterior distribution and projections up to 2016 of spawning stock biomass (tonnes) showing the median (line) and 90% credible interval (shaded region) for the 2017 stock assessment (base_2016) and five retrospective model runs. The dots represent the last year of data included in the model. The top panel shows the spawning stock biomass for all model runs and years. From top to bottom, the horizontal lines and shaded regions represent SSB_0, the soft limit (20% SSB_0), and the hard limit (10% SSB_0). The lower panel shows spawning stock biomass for all models for the last fifteen years.

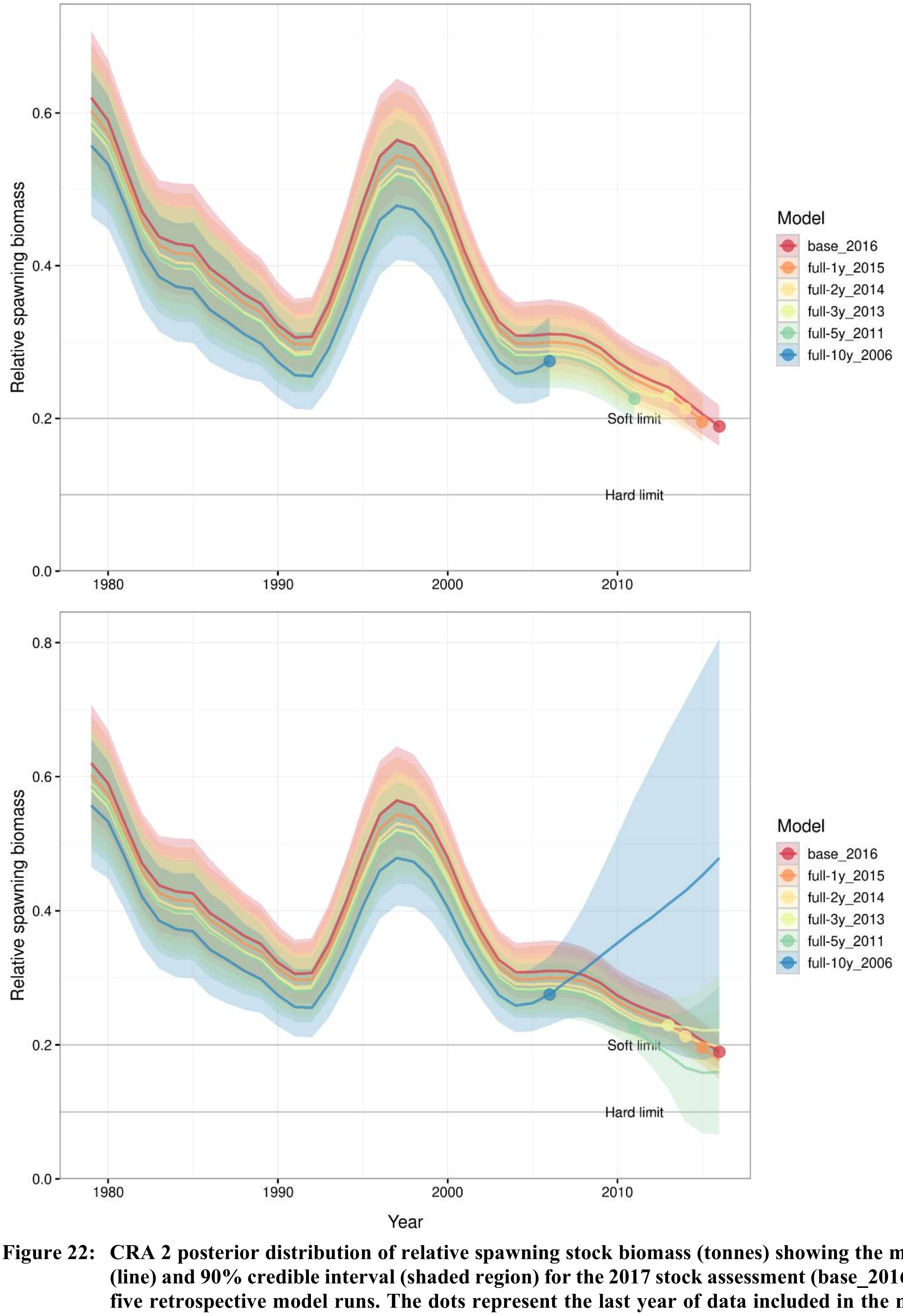
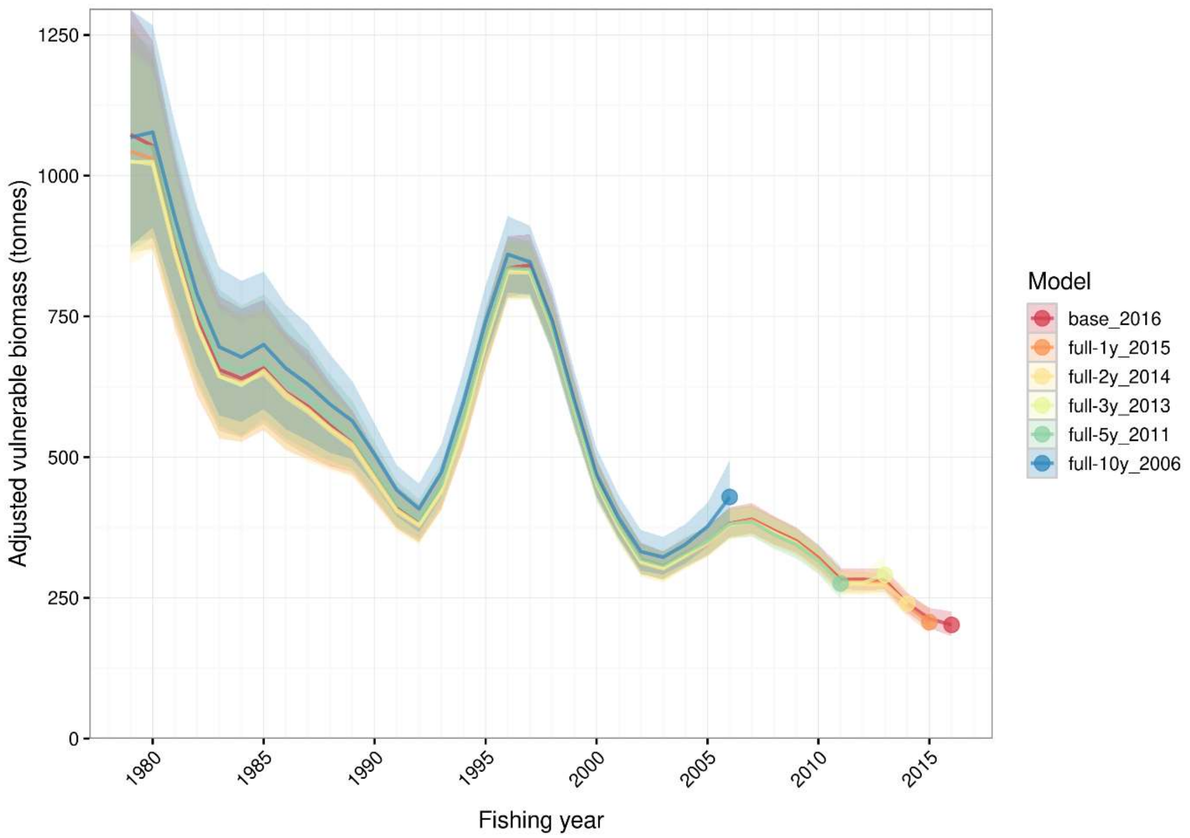


Figure 22: CRA 2 posterior distribution of relative spawning stock biomass (tonnes) showing the median (line) and 90% credible interval (shaded region) for the 2017 stock assessment (base_2016) and five retrospective model runs. The dots represent the last year of data included in the model. From top to bottom, the horizontal lines are the soft limit and the hard limit. The top panel shows the relative spawning stock biomass for all model runs and years. The lower panel shows the projected relative spawning stock biomass for all models up to 2016.



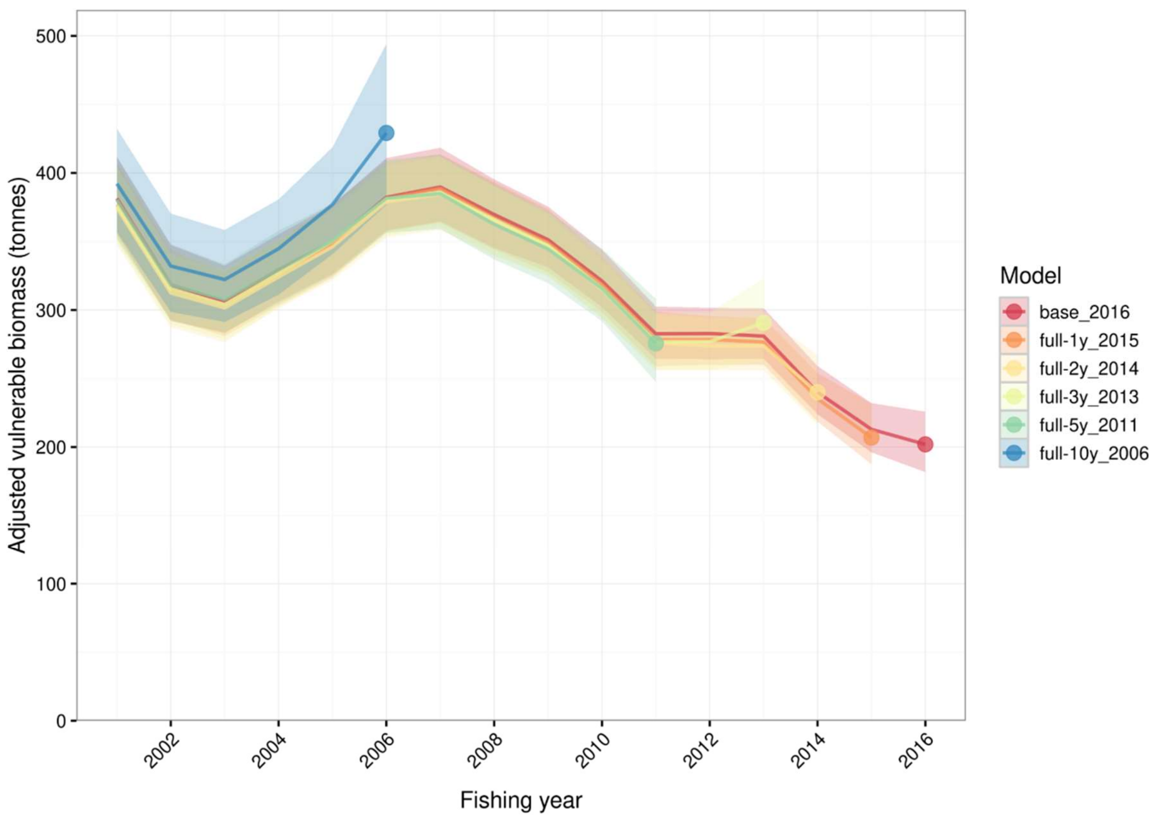


Figure 23: CRA 2 posterior distribution of adjusted vulnerable biomass (tonnes) showing the median (line) and 90% credible interval (shaded region) for the 2017 stock assessment (base_2016) and five retrospective model runs. The top panel shows the adjusted vulnerable biomass for all model runs and years. The lower panel shows the adjusted vulnerable biomass for all models for the last fifteen years.

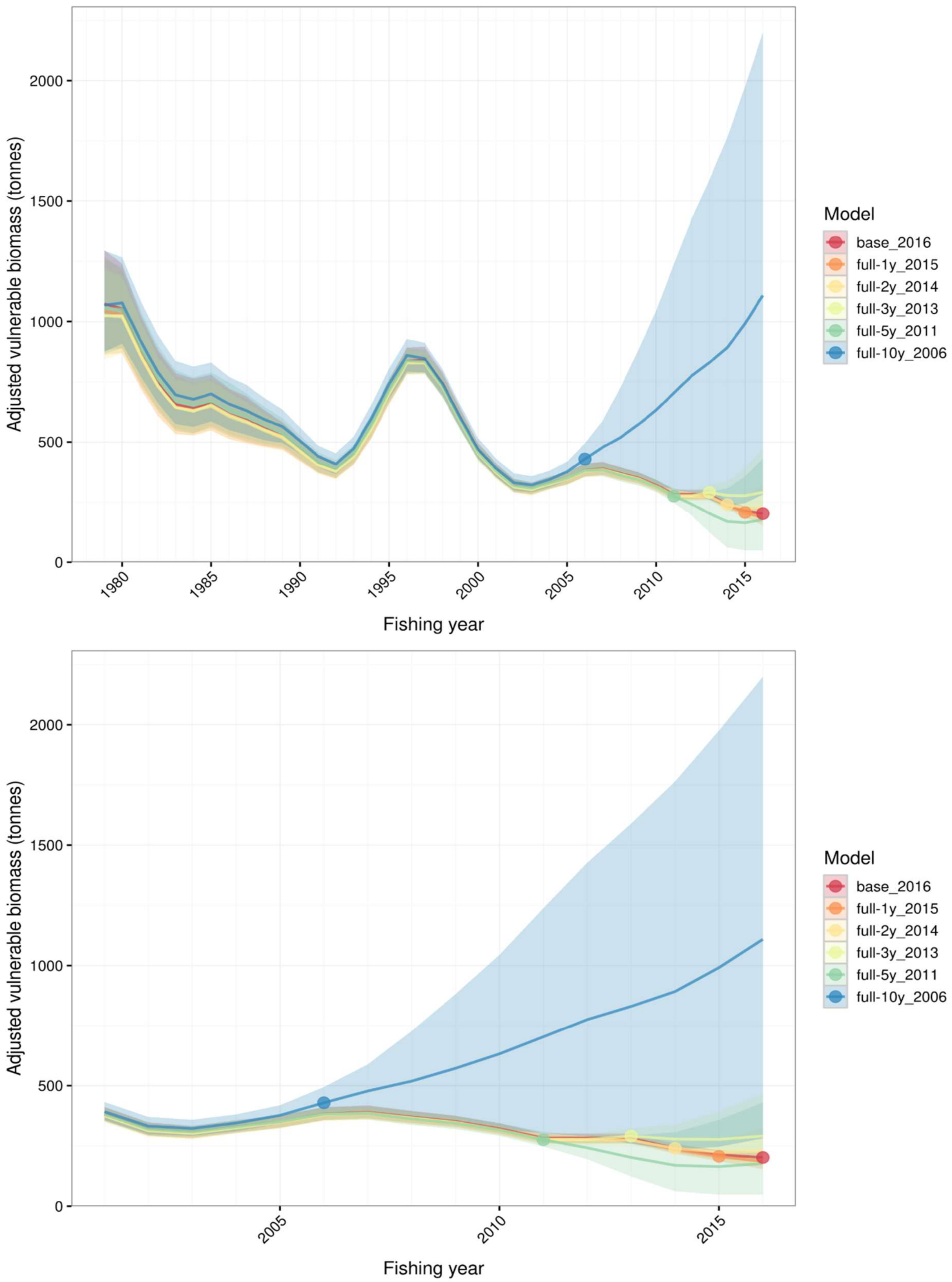


Figure 24: CRA 2 posterior distribution of adjusted vulnerable biomass (tonnes) projected up to 2016 showing the median (line) and 90% credible interval (shaded region) for the 2017 stock assessment (base_2016) and five retrospective model runs. The top panel shows the adjusted vulnerable biomass for all model runs and years, including projected years. The lower panel shows the adjusted vulnerable biomass for all models for the last fifteen years and projected years.

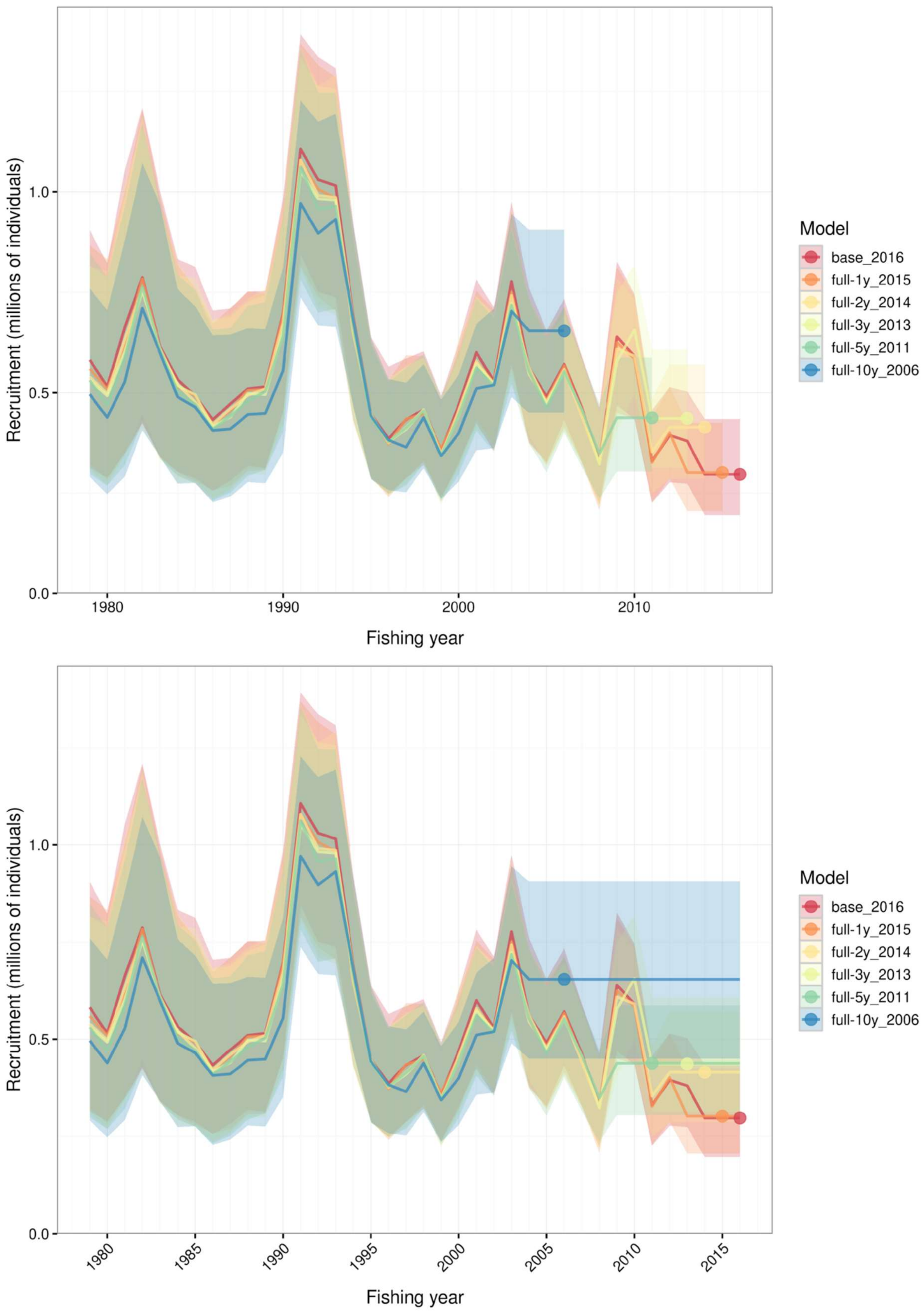


Figure 25: CRA 2 posterior distribution of recruitment showing the median (line) and 90% credible interval (shaded region) for the 2017 stock assessment (base_2016) and the retrospective runs. The top panel shows the recruitment for all model runs, and the lower panel shows projected recruitment for all model runs up to 2016.

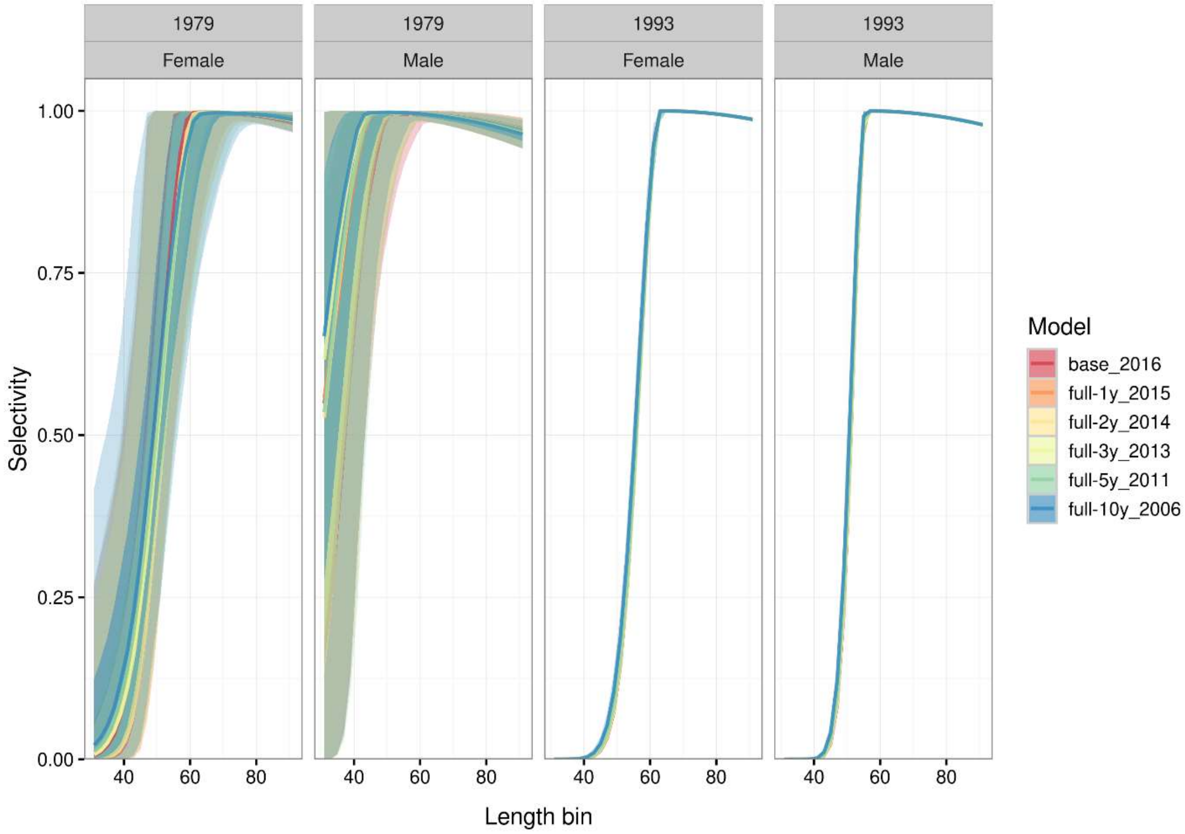


Figure 26: CRA 2 posterior distribution of selectivity by sex and epoch showing the median (line) and 90% credible interval (shaded region) for the 2017 stock assessment (base_2016) and the retrospective runs.

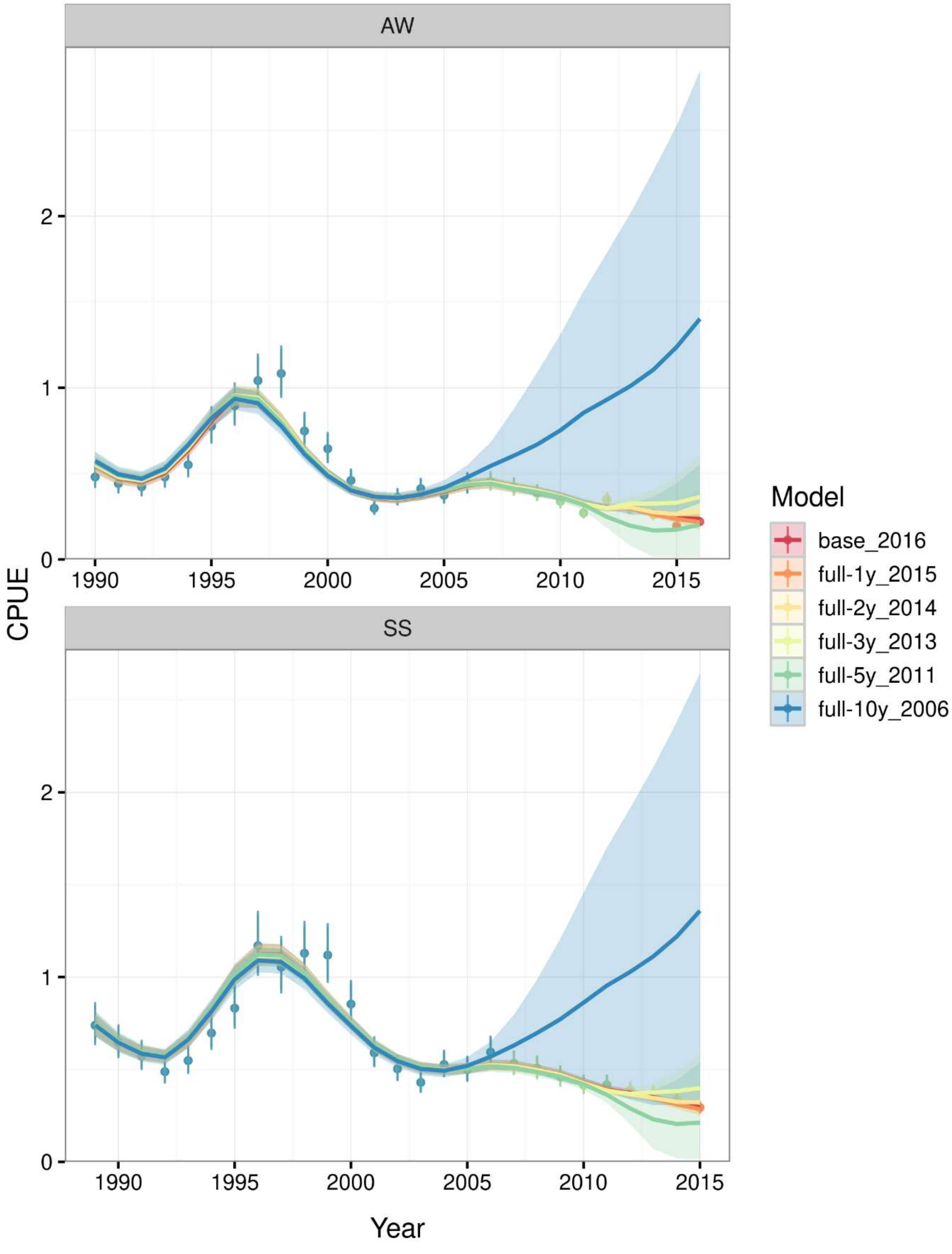


Figure 27: CRA 2 CPUE observations (points) and posterior distribution showing the median (line) and 90% credible interval (shaded region) by season (top panel: AW; bottom panel: SS) for the 2017 stock assessment (base_2016) and the retrospective model runs.

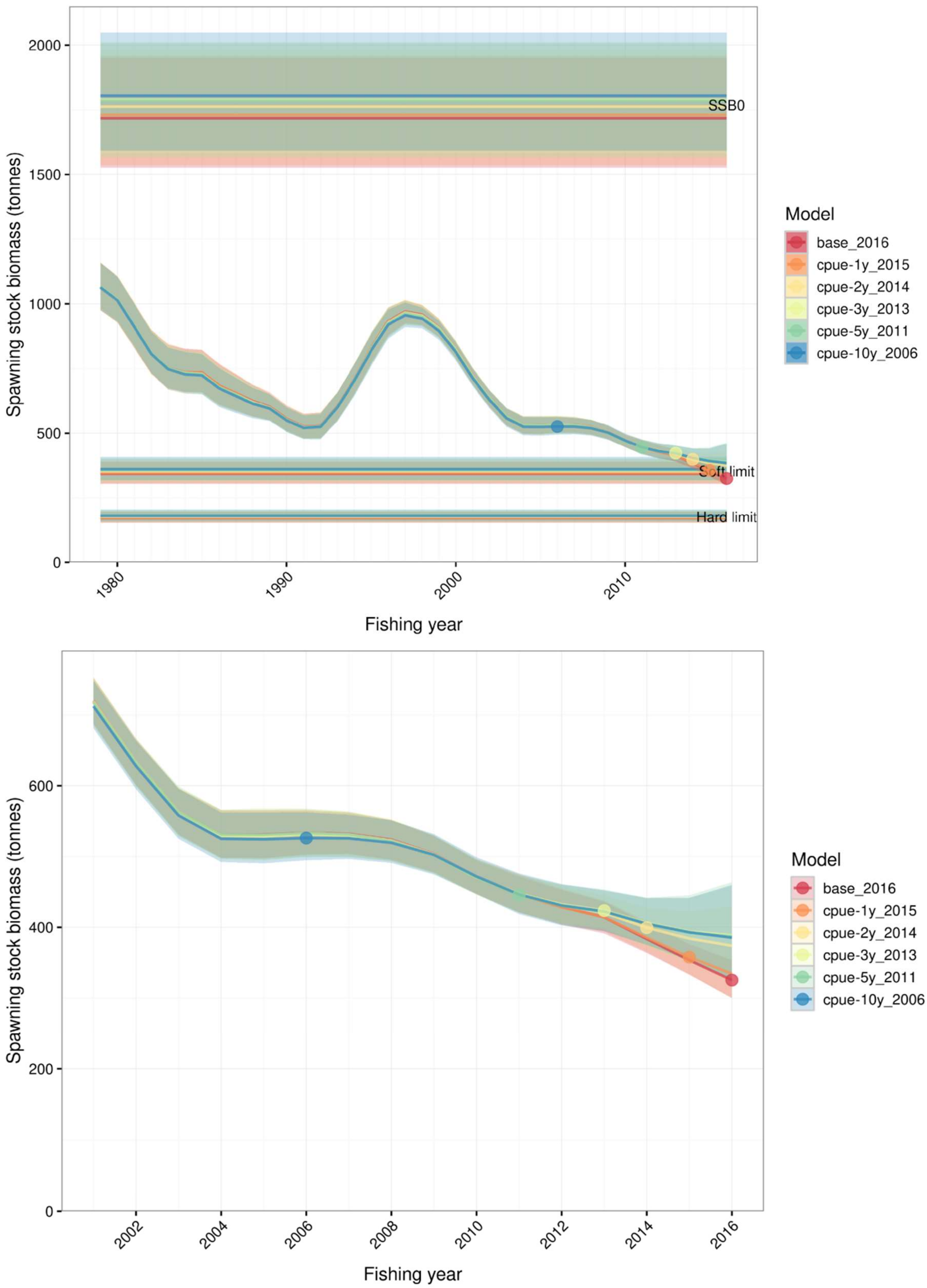


Figure 28: CRA 2 posterior distribution of spawning stock biomass (tonnes) showing the median (line) and 90% credible interval (shaded region) for the 2017 stock assessment (base_2016) and five model runs when removing only CPUE data. The dots represent the last year of CPUE included in the model. The top panel shows the spawning stock biomass for all model runs and years. From top to bottom, the horizontal lines and shaded regions represent SSB_0, the soft limit (20% SSB_0), and the hard limit (10% SSB_0). The lower panel shows spawning stock biomass for all models for the last fifteen years.

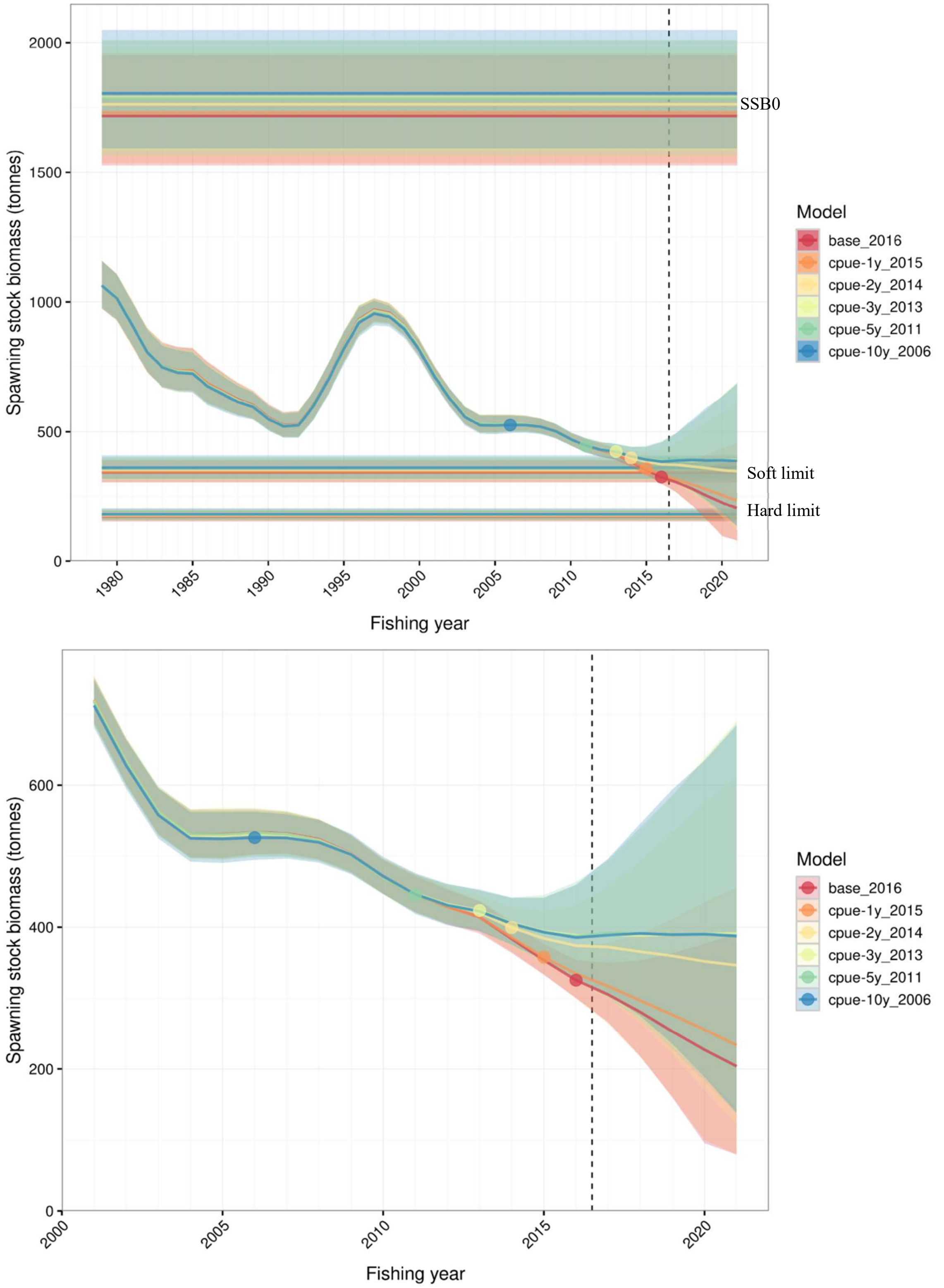


Figure 29: CRA 2 posterior distribution and projections up to 2021 of spawning stock biomass (tonnes) showing the median (line) and 90% credible interval (shaded region) for the 2017 stock assessment (base_2016) and five model runs when removing only years of CPUE data. The dots represent the last year of data included in the model. The vertical dashed lines represent the last year in the assessment model, so everything to the right of this line are projections. The top panel shows the spawning stock biomass for all model runs and years. From top to bottom, the horizontal lines and shaded regions represent SSB_0, the soft limit (20% SSB_0), and the hard limit (10% SSB_0). The lower panel shows spawning stock biomass for all models for the last fifteen years and projected years.

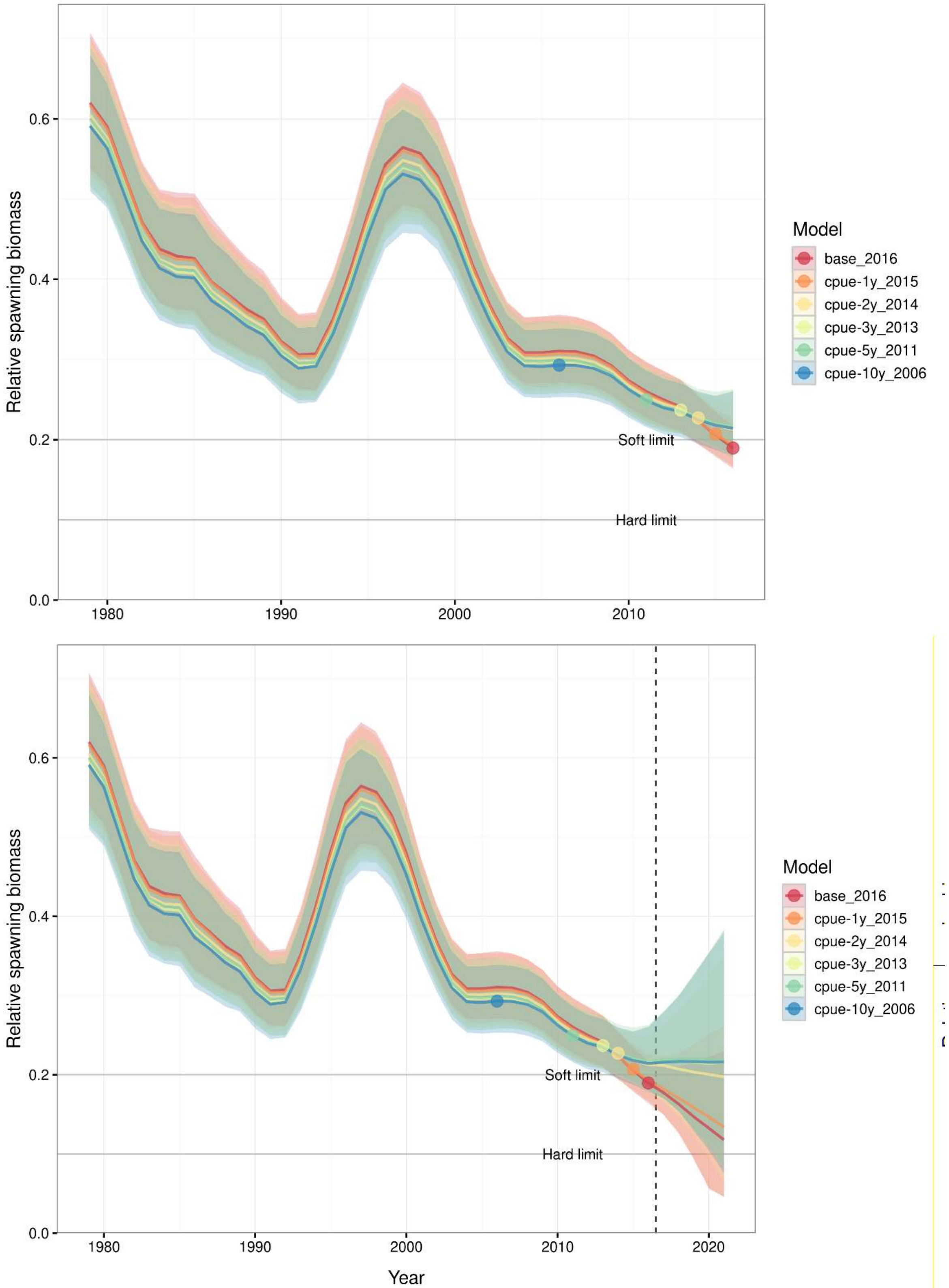
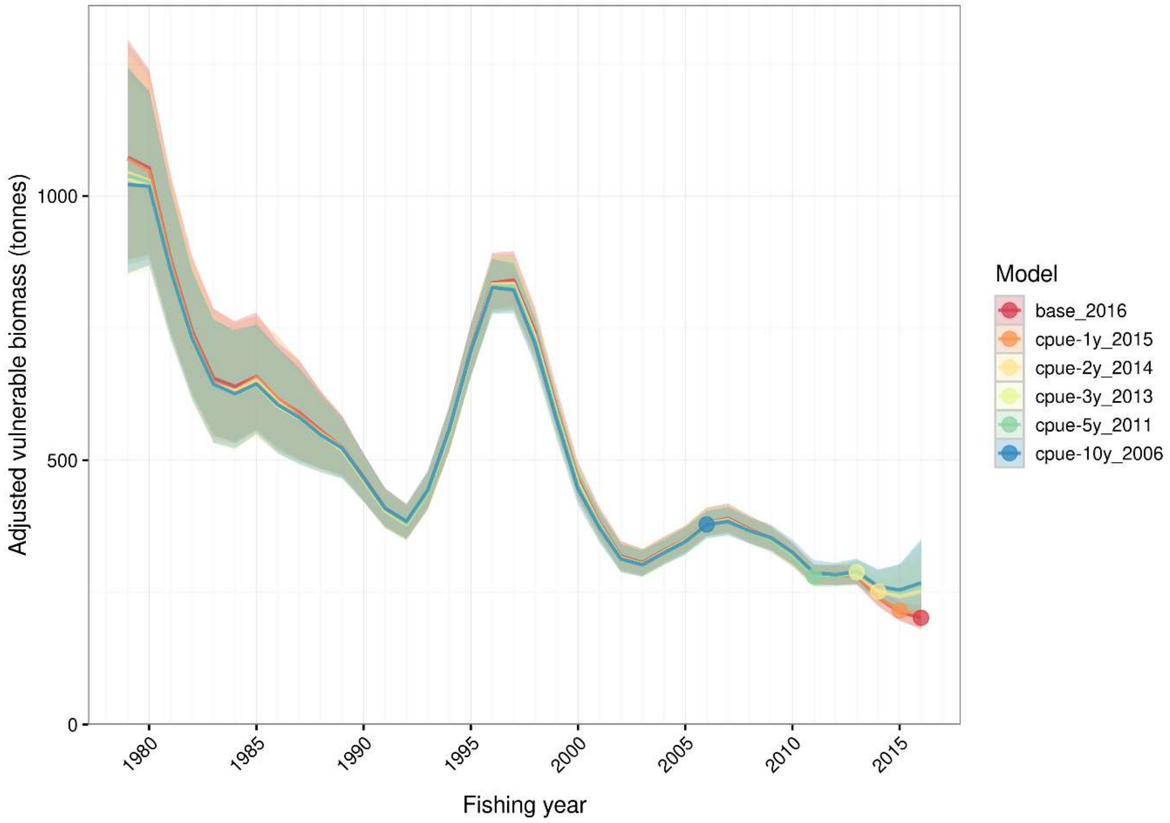


Figure 30: CRA 2 posterior distribution of relative spawning stock biomass (tonnes) showing the median (line) and 90% credible interval (shaded region) for the 2017 stock assessment (base_2016) and five model runs when removing years of CPUE data. The dots represent the last year of CPUE data included in the model. From top to bottom, the horizontal lines are the soft limit and the hard limit. The top panel shows the relative spawning stock biomass for all model runs and years. The lower panel shows the projected relative spawning stock biomass for all models up to 2021. The vertical dashed line represents the last year in the assessment model, so everything to the right of this line are projections.



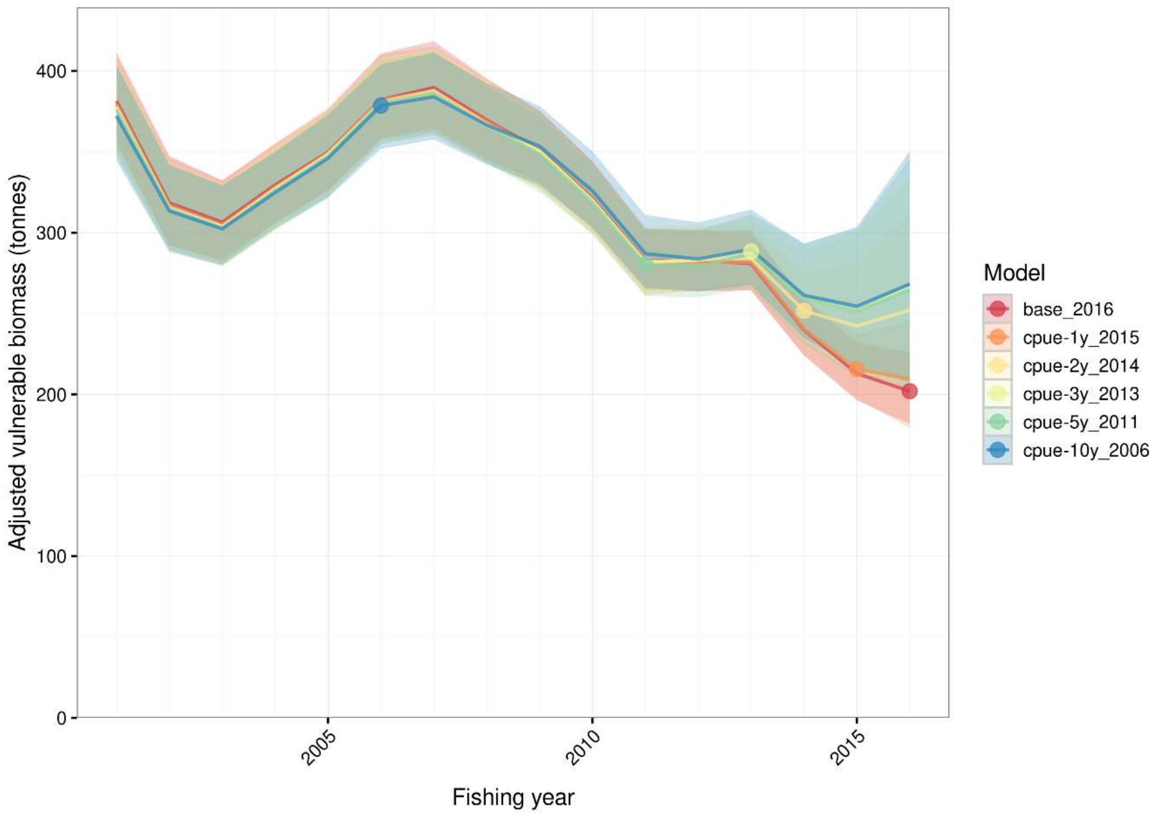


Figure 31: CRA 2 posterior distribution of adjusted vulnerable biomass (tonnes) showing the median (line) and 90% credible interval (shaded region) for the 2017 stock assessment (base_2016) and five model runs when removing years of CPUE data. The dots represent the last year of CPUE data included in the model. The top panel shows the adjusted vulnerable biomass for all model runs and years. The lower panel shows the adjusted vulnerable biomass for the last fifteen years for all models.

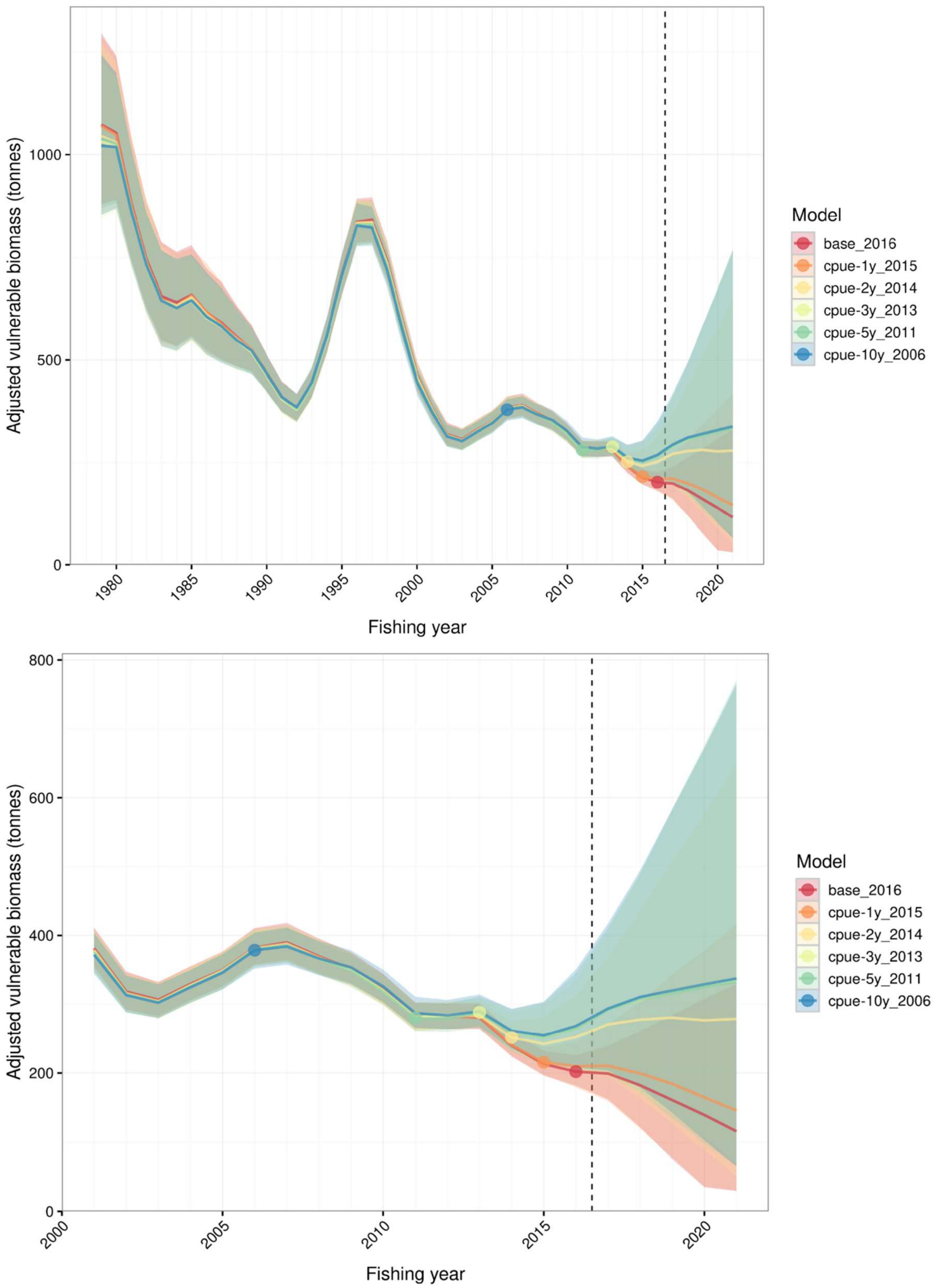


Figure 32: CRA 2 posterior distribution of adjusted vulnerable biomass (tonnes) projected up to 2021 showing the median (line) and 90% credible interval (shaded region) for the 2017 stock assessment (base_2016) and five model runs when only removing CPUE data. The dots represent the last year of CPUE data included in the model. The vertical dashed lines represent the last year in the assessment model, so everything to the right of this line are projections. The top panel shows the adjusted vulnerable biomass for all model runs and years, including projected years. The lower panel shows the adjusted vulnerable biomass for all models for the last fifteen years and projected years.

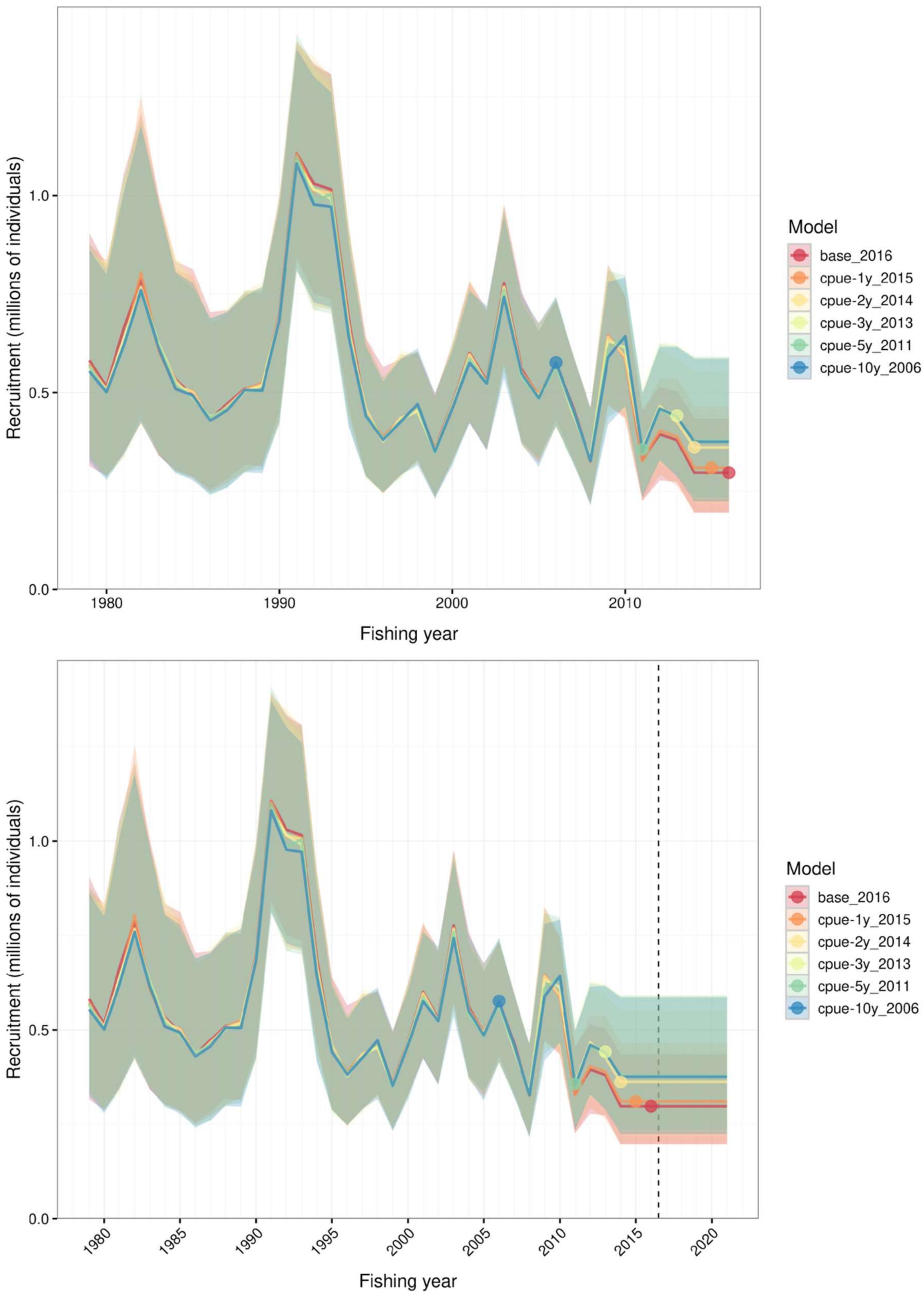


Figure 33: CRA 2 posterior distribution of recruitment showing the median (line) and 90% credible interval (shaded region) for the 2017 stock assessment (base_2016) and the model runs when removing CPUE data. The top panel shows the recruitment for all model runs, and the lower panel shows projected recruitment for all model runs up to 2021. The dots represent the last year of CPUE data included in the model. The vertical dashed line represents the last year in the assessment model, so everything to the right of this line are projections.

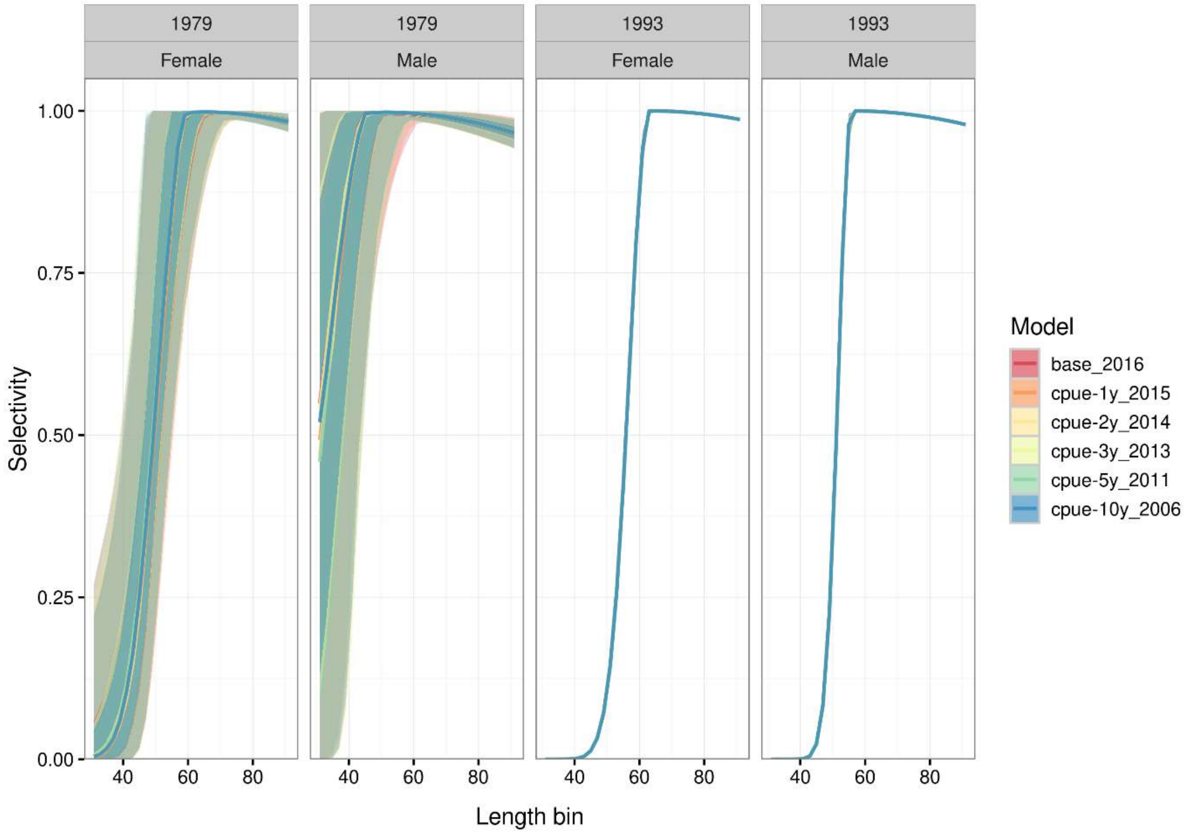


Figure 34: CRA 2 posterior distribution of selectivity by sex and epoch showing the median (line) and 90% credible interval (shaded region) for the 2017 stock assessment (base_2016) and the model runs when removing years of CPUE data.

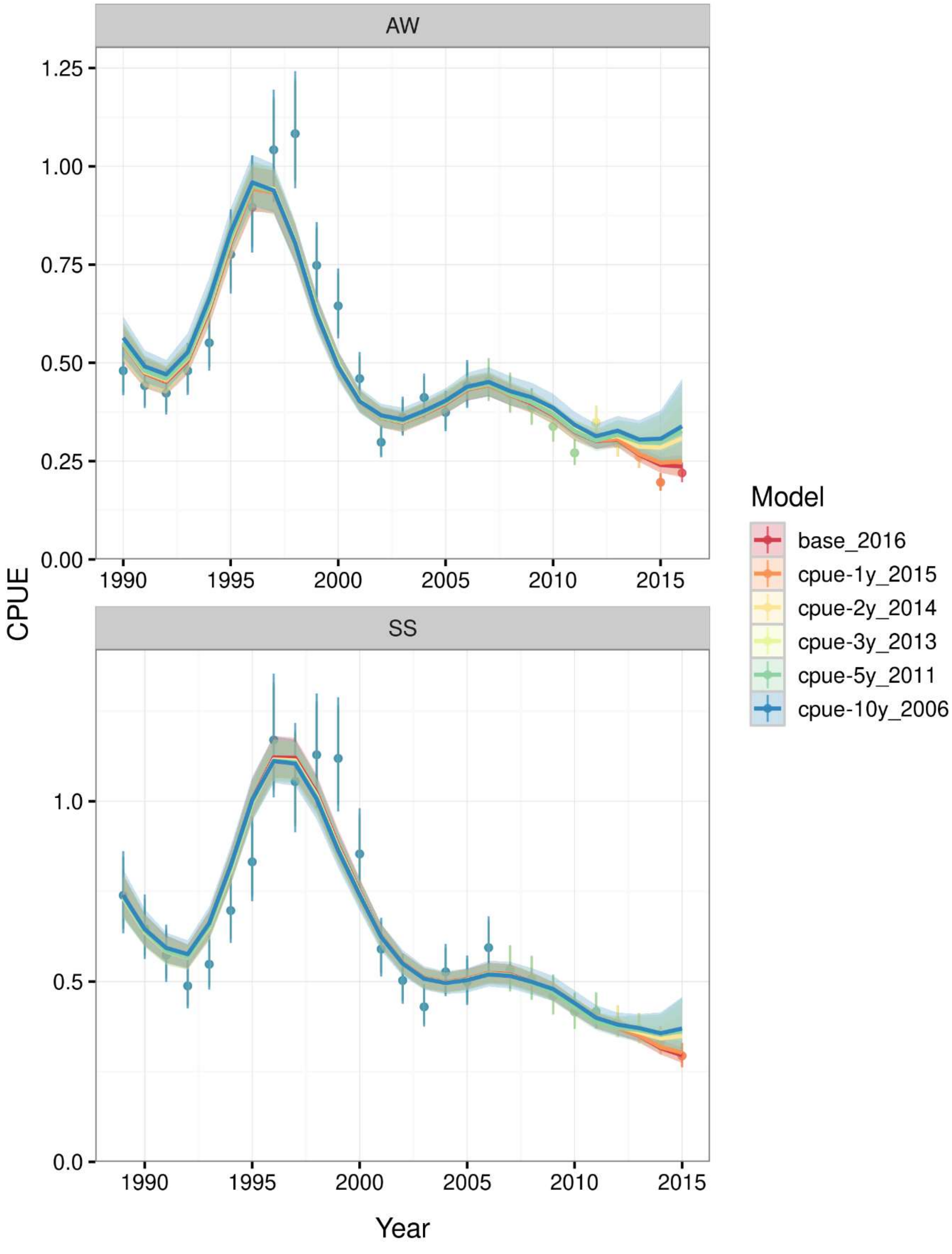


Figure 35: CRA 2 CPUE observations (points) and posterior distribution showing the median (line) and 90% credible interval (shaded region) by season (top panel: AW; bottom panel: SS) for the 2017 stock assessment (base_2016) and the model runs when removing years of CPUE data.

9. TABLES

Table 1: Yearly total observed catch (metric tonnes) used for projections.

Stock	Year	Observed Catch
CRA 4	2009	352
	2010	506
	2011	569
	2012	581
	2013	601
	2014	556
	2015	512
	2016	453
	2017	370
	2018	402
CRA 2	2007	354
	2008	350
	2009	343
	2010	326
	2011	329
	2012	332
	2013	329
	2014	287
	2015	256
	2016	222

Table 2: Definitions of parameters and derived quantities discussed in the text, figures, and tables. CR = Catch Rate; FSU = Fisheries Statistics Unit; CELR = Catch Effort Landing Return.

Parameters	Definition
R_0	initial numbers recruiting
M	instantaneous rate of natural mortality
Rdevs	annual recruitment deviations
sigmaR	standard deviation of *Rdevs*
qCR	catchability coefficient (relationship between the vulnerable biomass and CR series)
qFSU	catchability coefficient (relationship between the vulnerable biomass and FSU CPUE series)
qCELR	catchability coefficient (relationship between the vulnerable biomass and CELR CPUE series)
Mat50	size where 50% of immature females become mature
Mat95add	difference between *Mat50* and the size at which 95% of immature females become mature
Galpha	annual growth increment at 50 mm TW
Gbeta	annual growth increment at 80 mm TW
Gdiff	the ratio of *Gbeta* to *Galpha*
Gshape	parameter for shape of growth curve: 1 implies von Bertalanffy straight line; >1 implies a concave upwards curve
GCV	standard deviation of growth-at-size divided by growth-at-size
Gobs	standard deviation of observation error for tag-recaptures
SelLH	shape of the left-hand limb of the selectivity curve (as if it were a standard deviation)
SelM	size at maximum selectivity
vuln	relative vulnerability by sex and season
qdrift	additive change in catchability coefficient each year
U_0	initial exploitation rate (first year is in equilibrium using this estimate)
Gdd	density-dependent growth parameter

Table 3: Reference points, performance indicators, and stock status probabilities for the base case CRA 4 stock assessment. These quantities are only shown for the CPUE retrospective analysis (objective 2).

Type	Description
Reference Points	
B_0	beginning of season AW adjusted vulnerable biomass before fishing (1945)
SSB_0	female AW spawning stock biomass before fishing (1945)
B_{0TOT}	equilibrium total biomass
B_{0now}	equilibrium adjusted vulnerable biomass using mean 2007–2017 recruitment
SSB_{0now}	equilibrium female spawning biomass using mean 2007–2017 recruitment
$B_{0TOTNOW}$	equilibrium total biomass using mean 2007-2017 recruitment
B_{MIN}	the lowest beginning AW adjusted vulnerable biomass in the series
B_{2019}	beginning of season AW adjusted vulnerable biomass for 2019
B_{2023}	beginning of season AW adjusted vulnerable biomass for 2023
B_R	reference level in terms of AW adjusted vulnerable biomass (Rudd et al. 2021b)
SSB_{2019}	female spawning stock biomass at beginning of 2019 AW season
SSB_{2023}	female spawning stock biomass at beginning of 2023 AW season
$B_{2019TOT}$	beginning of season AW total biomass for 2019
$B_{2023TOT}$	beginning of season AW total biomass for 2023
$CPUE_{2018}$	AW CPUE at beginning of 2018 (in kg/potlift)
$CPUE_{2023}$	AW CPUE at beginning of 2023 (in kg/potlift)
H_{2018}	total handling mortality for 2018 (tonnes)
H_{2022}	total handling mortality for 2022 (tonnes)
Performance indicators	
B_{2019} / B_0	ratio of B_{2019} to B_0
B_{2023} / B_0	ratio of B_{2023} to B_0
B_{2019} / B_{0now}	ratio of B_{2019} to B_{0now}
B_{2023} / B_{0now}	ratio of B_{2023} to B_{0now}
B_{2023} / B_{2019}	ratio of B_{2023} to B_{2019}
SSB_{2019}/SSB_0	ratio of SSB_{2019} to SSB_0
SSB_{2023} / SSB_0	ratio of SSB_{2023} to SSB_0
SSB_{2019} / SSB_{0now}	ratio of SSB_{2019} to SSB_{0now}
SSB_{2023} / SSB_{0now}	ratio of SSB_{2023} to SSB_{0now}
SSB_{2023} / SSB_{2019}	ratio of SSB_{2023} to SSB_{2019}
$B_{2019TOT} / B_{0TOT}$	ratio of $B_{2019TOT}$ to B_{0TOT}
$B_{2019TOT} / B_{0TOTNOW}$	ratio of $B_{2019TOT}$ to $B_{0TOTNOW}$
$B_{2023TOT} / B_{0TOT}$	ratio of $B_{2023TOT}$ to B_{0TOT}
$B_{2023TOT} / B_{0TOTNOW}$	ratio of $B_{2023TOT}$ to $B_{0TOTNOW}$
$B_{2023TOT} / B_{2019TOT}$	ratio of $B_{2023TOT}$ to $B_{2019TOT}$
Probabilities	
$P(B_{2019} > B_{MIN})$	probability B_{2019} is greater than B_{MIN}
$P(SSB_{2019} < 20\% \ SSB_0)$	probability SSB_{2019} is less than $20\% SSB_0$
$P(SSB_{2019} < 10\% \ SSB_0)$	probability SSB_{2019} is less than $10\% SSB_0$
$P(SSB_{2019} < 20\% \ SSB_{0now})$	probability SSB_{2019} is less than $20\% SSB_{0NOW}$
$P(SSB_{2019} < 10\% \ SSB_{0now})$	probability SSB_{2019} is less than $10\% SSB_{0NOW}$
$P(SSB_{2023} < 20\% \ SSB_0)$	probability SSB_{2023} is less than $20\% SSB_0$
$P(SSB_{2023} < 10\% \ SSB_0)$	probability SSB_{2023} is less than $10\% SSB_0$
$P(SSB_{2023} < 20\% \ SSB_{0now})$	probability SSB_{2023} is less than $20\% SSB_{0NOW}$
$P(SSB_{2023} < 10\% \ SSB_{0now})$	probability SSB_{2023} is less than $10\% SSB_{0NOW}$
$P(B_{2023} > B_{2019})$	probability B_{2023} is greater than B_{2019}
$P(SSB_{2023} > SSB_{2019})$	probability SSB_{2023} is greater than SSB_{2019}
$P(B_{2023TOT} > B_{2019TOT})$	probability $Btot_{2023}$ is greater than $Btot_{2019}$

Table 4: Reference points, performance indicators, and stock status probabilities for the base case CRA 2 stock assessment. These quantities are only shown for the CPUE retrospective analysis (objective 2).

Type	Description
Reference Points	
B_0	beginning of season AW adjusted vulnerable biomass before fishing (1945)
SSB_0	female AW spawning stock biomass before fishing (1945)
B_{0TOT}	equilibrium total biomass
B_{0now}	equilibrium adjusted vulnerable biomass using mean 2005–2015 recruitment
SSB_{0now}	equilibrium female spawning biomass using mean 2005–2015 recruitment
$B_{0TOTNOW}$	equilibrium total biomass using mean 2005-2015 recruitment
B_{MIN}	the lowest beginning AW adjusted vulnerable biomass in the series
B_{2017}	beginning of season AW adjusted vulnerable biomass for 2017
B_{2021}	beginning of season AW adjusted vulnerable biomass for 2021
B_R	reference level in terms of AW adjusted vulnerable biomass (Rudd et al. 2021b)
SSB_{2017}	female spawning stock biomass at beginning of 2017 AW season
SSB_{2021}	female spawning stock biomass at beginning of 2021 AW season
$B_{2017TOT}$	beginning of season AW total biomass for 2017
$B_{2021TOT}$	beginning of season AW total biomass for 2021
$CPUE_{2016}$	AW CPUE at beginning of 2016 (in kg/potlift)
$CPUE_{2021}$	AW CPUE at beginning of 2021 (in kg/potlift)
H_{2016}	total handling mortality for 2016 (tonnes)
H_{2020}	total handling mortality for 2020 (tonnes)
Performance indicators	
B_{2017} / B_0	ratio of B_{2017} to B_0
B_{2021} / B_0	ratio of B_{2021} to B_0
B_{2017} / B_{0now}	ratio of B_{2017} to B_{0now}
B_{2021} / B_{0now}	ratio of B_{2021} to B_{0now}
B_{2021} / B_{2017}	ratio of B_{2021} to B_{2019}
SSB_{2017}/SSB_0	ratio of SSB_{2017} to SSB_0
SSB_{2021} / SSB_0	ratio of SSB_{2021} to SSB_0
SSB_{2017} / SSB_{0now}	ratio of SSB_{2017} to SSB_{0now}
SSB_{2021} / SSB_{0now}	ratio of SSB_{2021} to SSB_{0now}
SSB_{2021} / SSB_{2017}	ratio of SSB_{2021} to SSB_{2017}
$B_{2017TOT} / B_{0TOT}$	ratio of $B_{2017TOT}$ to B_{0TOT}
$B_{2017TOT} / B_{0TOTNOW}$	ratio of $B_{2017TOT}$ to $B_{0TOTNOW}$
$B_{2021TOT} / B_{0TOT}$	ratio of $B_{2021TOT}$ to B_{0TOT}
$B_{2021TOT} / B_{0TOTNOW}$	ratio of $B_{2021TOT}$ to $B_{0TOTNOW}$
$B_{2021TOT} / B_{2017TOT}$	ratio of $B_{2021TOT}$ to $B_{2017TOT}$
Probabilities	
P($B_{2017} > B_{MIN}$)	probability B_{2017} is greater than B_{MIN}
P($SSB_{2017} < 20\% \, SSB_0$)	probability SSB_{2017} is less than 20%SSB_0
P($SSB_{2017} < 10\% \, SSB_0$)	probability SSB_{2017} is less than 10%SSB_0
P($SSB_{2017} < 20\% \, SSB_{0now}$)	probability SSB_{2017} is less than 20%SSB_{0NOW}
P($SSB_{2017} < 10\% \, SSB_{0now}$)	probability SSB_{2017} is less than 10%SSB_{0NOW}
P($SSB_{2021} < 20\% \, SSB_0$)	probability SSB_{2021} is less than 20%SSB_0
P($SSB_{2021} < 10\% \, SSB_0$)	probability SSB_{2021} is less than 10%SSB_0
P($SSB_{2021} < 20\% \, SSB_{0now}$)	probability SSB_{2021} is less than 20%SSB_{0NOW}
P($SSB_{2021} < 10\% \, SSB_{0now}$)	probability SSB_{2021} is less than 10%SSB_{0NOW}
P($B_{2021} > B_{2017}$)	probability B_{2021} is greater than B_{2017}
P($SSB_{2021} > SSB_{2017}$)	probability SSB_{2021} is greater than SSB_{2017}
P($B_{2021TOT} > B_{2017TOT}$)	probability $Btot_{2021}$ is greater than $Btot_{2017}$

Table 5: CRA 4 model changes from base case model in 2020 assessment (Rudd et al. 2021a).

Changes	Base case 2020 assessment	Base case retrospective analysis	Reason
Last model year	2019	2018	To have full year of CPUE
Growth shape parameter	Estimated, upper bound at 7.5 for some models to address bimodality	Fixed to 2020 base case model posterior median (6.382, 5.468)	Bimodality was not thoroughly addressed by Gshape upper bound adjustment, needs more work

Table 6: CRA 4 model runs. The year included in the name of each model is the last year of data included in the model.

Model run name	Description
Base_2018	Base case model, last year included 2018
Full-1y_2017	Removing 1 full year of all datasets
Full-2y_2016	Removing 2 full years of all datasets
Full-3y_2015	Removing 3 full years of all datasets
Full-5y_2013	Removing 5 full years of all datasets
Full-10y_2008	Removing 10 full years of all datasets
cpue-1y_2017	Removing 1 year of CPUE data
cpue-2y_2016	Removing 2 years of CPUE data
cpue-3y_2015	Removing 3 years of CPUE data
cpue-5y_2013	Removing 5 years of CPUE data
cpue-10y_2008	Removing 10 years of CPUE data

Table 7: CRA 2 model runs. The year included in the name of each model is the last year of data included in the model.

Model run name	Description
Base_2016	Base case model, last year included 2016
Full-1y_2015	Removing 1 full year of all datasets
Full-2y_2014	Removing 2 full years of all datasets
Full-3y_2013	Removing 3 full years of all datasets
Full-5y_2011	Removing 5 full years of all datasets
Full-10y_2006	Removing 10 full years of all datasets
cpue-1y_2015	Removing 1 year of CPUE data
cpue-2y_2014	Removing 2 years of CPUE data
cpue-3y_2013	Removing 3 years of CPUE data
cpue-5y_2011	Removing 5 years of CPUE data
cpue-10y_2006	Removing 10 years of CPUE data

Table 8: CRA 4 stock assessment parameter estimates: MCMC runs for base case and retrospective runs. Growth increment values in mm TW and R_0 in numbers.

	Base_2018			full-1y_2017			full-2y_2016			full-3y_2015			full-5y_2013			full-10y_2008		
	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%
R_0	2406000	2865000	3517000	2340000	2848000	3487000	2462000	2909000	3545000	2485000	2960000	3571000	2220000	2649000	3207000	2174000	2599000	3089000
M	0.203	0.227	0.254	0.204	0.229	0.258	0.210	0.235	0.263	0.218	0.245	0.274	0.212	0.237	0.265	0.227	0.253	0.284
qCR	0.047	0.075	0.130	0.047	0.077	0.145	0.049	0.082	0.154	0.050	0.083	0.157	0.064	0.116	0.225	0.069	0.127	0.286
qFSU	0.001	0.002	0.002	0.001	0.002	0.002	0.001	0.002	0.003	0.001	0.002	0.003	0.002	0.003	0.005	0.002	0.002	0.005
qCELR	0.001	0.002	0.003	0.001	0.002	0.003	0.001	0.002	0.003	0.002	0.002	0.004	0.002	0.003	0.006	0.002	0.003	0.007
mat50	38.02	41.70	43.64	38.00	41.69	43.66	37.12	41.50	43.68	37.31	41.47	43.66	36.46	41.27	43.39	36.73	41.01	43.05
qdrift	-0.005	0.003	0.011	-0.005	0.005	0.013	-0.007	0.003	0.012	-0.012	-0.002	0.008	-0.011	-0.001	0.008	-0.003	0.011	0.025
Galpha males	2.582	2.680	2.771	2.615	2.713	2.816	2.632	2.732	2.837	2.732	2.840	2.949	2.912	3.034	3.163	3.163	3.322	3.469
Gbeta males	2.089	2.306	2.521	2.074	2.308	2.541	2.050	2.284	2.521	2.032	2.267	2.514	2.033	2.316	2.598	2.128	2.457	2.784
GCV males	0.683	0.718	0.752	0.674	0.707	0.743	0.669	0.704	0.741	0.654	0.690	0.726	0.612	0.651	0.692	0.579	0.625	0.673
Galpha females	1.877	2.035	2.208	1.888	2.056	2.242	1.907	2.071	2.253	1.968	2.160	2.333	2.007	2.189	2.385	2.226	2.424	2.658
Gbeta females	1.107	1.236	1.368	1.133	1.255	1.393	1.146	1.269	1.412	1.151	1.291	1.432	1.247	1.387	1.533	1.259	1.404	1.568
GCV females	1.161	1.276	1.400	1.138	1.258	1.392	1.128	1.243	1.365	1.089	1.205	1.333	1.006	1.131	1.255	0.887	0.987	1.102
Stdobs	0.445	0.492	0.544	0.452	0.497	0.551	0.453	0.498	0.546	0.460	0.511	0.572	0.666	0.747	0.824	0.742	0.832	0.916
vuln1	0.529	0.806	0.983	0.482	0.783	0.979	0.445	0.743	0.971	0.427	0.728	0.963	0.283	0.508	0.812	0.254	0.533	0.806
vuln2	0.438	0.665	0.817	0.400	0.644	0.807	0.373	0.615	0.805	0.348	0.602	0.782	0.239	0.423	0.664	0.213	0.443	0.669
vuln3	0.404	0.597	0.786	0.402	0.609	0.832	0.392	0.637	0.882	0.425	0.688	0.933	0.386	0.648	0.946	0.381	0.705	0.971
vuln4	0.248	0.370	0.494	0.243	0.373	0.508	0.238	0.392	0.543	0.274	0.438	0.601	0.240	0.401	0.588	0.266	0.490	0.680

	Base_2018			full-1y_2017			full-2y_2016			full-3y_2015			full-5y_2013			full-10y_2008		
	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%
SelL males < 1993	4.808	5.782	6.993	4.753	5.765	7.031	4.752	5.759	7.050	4.910	5.894	7.120	5.026	6.020	7.156	4.960	5.992	7.203
SelM males < 1993	6.771	8.733	11.460	7.070	9.137	11.790	7.246	9.311	12.160	7.915	10.670	13.910	9.501	11.720	14.280	10.640	12.960	15.650
SelL females < 1993	3.796	4.023	4.269	3.892	4.131	4.380	3.961	4.216	4.490	4.064	4.368	4.669	4.482	4.774	5.132	5.124	5.595	6.147
SelM females < 1993	5.938	6.352	6.806	5.983	6.408	6.898	6.115	6.587	7.099	6.317	6.829	7.396	6.689	7.170	7.751	7.565	8.224	9.090
SelL males >= 1993	52.65	54.24	56.12	52.51	54.14	56.06	52.42	54.13	56.04	52.44	54.10	56.08	52.42	54.04	55.67	51.87	53.60	55.25
SelM males >= 1993	58.89	62.58	67.49	59.49	63.50	68.54	59.97	64.07	69.66	61.74	67.08	72.97	65.82	70.34	74.96	68.14	72.76	77.88
SelL females >= 1993	55.21	55.60	56.03	55.28	55.75	56.18	55.32	55.79	56.28	55.42	55.91	56.44	55.88	56.41	56.96	56.13	56.90	57.82
SelM females >= 1993	64.08	64.92	65.89	64.19	65.14	66.12	64.59	65.62	66.79	65.07	66.24	67.53	66.13	67.24	68.65	67.12	68.79	71.04

Table 9: CRA 4 stock assessment parameter estimates: MCMC runs for base case and model runs when removing years of CPUE data. Growth increment values in mm TW and R0 in numbers (continued next page).

	Base_2018			cpue-1y_2017			cpue-2y_2016			cpue-3y_2015			cpue-5y_2013			cpue-10y_2008		
	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%
R_0	2406000	2865000	3517000	2396000	2838000	3489000	2388000	2845000	3439000	2455000	2934000	3554000	2486000	2939000	3667000	2560000	3069000	3733000
M	0.203	0.227	0.254	0.203	0.227	0.257	0.205	0.228	0.253	0.206	0.231	0.257	0.211	0.234	0.262	0.219	0.242	0.270
qCR	0.047	0.075	0.130	0.049	0.078	0.138	0.048	0.079	0.139	0.049	0.079	0.140	0.050	0.083	0.170	0.051	0.087	0.158
qFSU	0.001	0.002	0.002	0.001	0.002	0.002	0.001	0.002	0.002	0.001	0.002	0.002	0.001	0.002	0.003	0.001	0.002	0.003
qCELR	0.001	0.002	0.003	0.001	0.002	0.003	0.001	0.002	0.003	0.001	0.002	0.003	0.001	0.002	0.004	0.002	0.002	0.003
mat50	38.02	41.70	43.64	37.74	41.59	43.79	37.85	41.62	43.55	38.59	41.64	43.61	37.96	41.54	43.63	37.56	41.62	43.71
qdrift	-0.005	0.003	0.011	-0.005	0.004	0.012	-0.005	0.004	0.012	-0.003	0.005	0.013	-0.009	0.000	0.009	-0.022	-0.008	0.005
Galpha males	2.582	2.680	2.771	2.576	2.671	2.776	2.579	2.678	2.771	2.574	2.669	2.760	2.577	2.677	2.778	2.569	2.676	2.779
Gbeta males	2.089	2.306	2.521	2.093	2.312	2.514	2.097	2.309	2.542	2.178	2.381	2.580	2.121	2.331	2.535	2.111	2.330	2.545
GCV males	0.683	0.718	0.752	0.682	0.719	0.752	0.684	0.717	0.754	0.684	0.718	0.755	0.683	0.717	0.754	0.685	0.717	0.753
Galpha females	1.877	2.035	2.208	1.884	2.041	2.212	1.884	2.042	2.207	1.862	2.023	2.176	1.901	2.045	2.212	1.928	2.087	2.248
Gbeta females	1.107	1.236	1.368	1.107	1.230	1.360	1.108	1.239	1.377	1.132	1.248	1.392	1.127	1.251	1.381	1.134	1.259	1.388
GCV females	1.161	1.276	1.400	1.161	1.276	1.405	1.162	1.275	1.399	1.170	1.283	1.419	1.169	1.277	1.401	1.144	1.256	1.380
Stdobs	0.445	0.492	0.544	0.450	0.495	0.548	0.447	0.494	0.543	0.445	0.492	0.543	0.444	0.493	0.547	0.445	0.492	0.544
vuln1	0.529	0.806	0.983	0.493	0.798	0.982	0.514	0.787	0.981	0.504	0.797	0.979	0.441	0.795	0.980	0.551	0.814	0.980
vuln2	0.438	0.665	0.817	0.402	0.653	0.810	0.424	0.646	0.805	0.412	0.639	0.792	0.360	0.638	0.781	0.431	0.641	0.774
vuln3	0.404	0.597	0.786	0.377	0.579	0.776	0.391	0.573	0.767	0.392	0.574	0.778	0.345	0.581	0.762	0.404	0.584	0.759
vuln4	0.248	0.370	0.494	0.236	0.360	0.479	0.239	0.352	0.477	0.245	0.366	0.489	0.218	0.372	0.486	0.264	0.378	0.505

	Base_2018			cpue-1y_2017			cpue-2y_2016			cpue-3y_2015			cpue-5y_2013			cpue-10y_2008		
	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%
SelL males < 1993	4.808	5.782	6.993	4.774	5.738	7.048	4.768	5.722	6.864	4.678	5.661	6.689	4.854	5.729	6.848	4.846	5.777	7.016
SelM males < 1993	6.771	8.733	11.460	6.775	8.727	11.190	6.717	8.874	11.530	6.990	8.869	11.410	7.096	9.345	12.040	7.895	10.320	13.010
SelL females < 1993	3.796	4.023	4.269	3.812	4.033	4.277	3.830	4.044	4.299	3.814	4.027	4.255	3.817	4.043	4.279	3.810	4.025	4.261
SelM females < 1993	5.938	6.352	6.806	5.975	6.358	6.794	5.975	6.374	6.773	6.008	6.377	6.798	5.961	6.391	6.817	5.977	6.390	6.829
SelL males >= 1993	52.65	54.24	56.12	52.58	54.19	55.95	52.62	54.14	55.90	52.65	54.10	55.85	52.71	54.23	56.04	52.85	54.45	56.41
SelM males >= 1993	58.89	62.58	67.49	58.93	62.49	67.10	58.71	62.70	67.58	59.52	63.06	67.56	59.78	64.00	69.08	60.90	65.91	71.12
SelL females >= 1993	55.21	55.60	56.03	55.23	55.61	56.04	55.22	55.62	56.04	55.25	55.63	56.02	55.25	55.64	56.05	55.22	55.63	56.07
SelM females >= 1993	64.08	64.92	65.89	64.07	64.95	65.87	64.13	64.97	65.86	64.25	65.07	65.98	64.22	65.05	66.02	64.20	65.07	66.03

Table 10: CRA 4 base case (base_2018) and model runs when removing years of CPUE data. MCMC outputs, reporting the 5th, 50th (median; highlighted in yellow), and 95th quantiles of the posterior distributions. Growth increment values in mm TW, biomass values in tonnes and R_0 in numbers. Handling mortality (H) in tonnes and CPUE in kg/potlift (continued next page).

	Base_2018			cpue-1y_2017			cpue-2y_2016			cpue-3y_2015			cpue-5y_2013			cpue-10y_2008		
	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%
Derived parameters: AW adjusted vulnerable biomass																		
B_0	2209	3406	4413	2066	3311	4320	2098	3233	4309	2103	3260	4233	1833	3195	4173	2083	3133	4022
B_{0now}	1555	2425	3200	1429	2288	3037	1357	2104	2827	1373	2135	2878	1205	2094	2822	1313	1976	2629
B_{min}	211	326	410	196	313	405	186	283	379	182	296	387	164	292	392	194	291	385
B_{2019}	288	454	611	231	395	568	182	299	464	185	321	492	167	310	501	179	303	478
B_{2023}	196	609	1372	137	507	1205	52	327	970	60	354	981	62	352	1004	62	313	940
B_{2019} / B_0	0.10	0.13	0.17	0.09	0.12	0.16	0.07	0.09	0.14	0.07	0.10	0.15	0.07	0.10	0.15	0.07	0.10	0.14
B_{2023} / B_0	0.06	0.19	0.39	0.05	0.16	0.36	0.02	0.10	0.30	0.02	0.11	0.28	0.02	0.12	0.31	0.02	0.10	0.28
B_{2019} / B_{0now}	0.15	0.19	0.23	0.14	0.17	0.22	0.11	0.15	0.19	0.11	0.15	0.20	0.11	0.15	0.21	0.11	0.16	0.21
B_{2023} / B_{0now}	0.09	0.26	0.51	0.07	0.23	0.48	0.03	0.16	0.43	0.03	0.17	0.40	0.04	0.18	0.42	0.03	0.16	0.42
B_{2023} / B_{2019}	0.51	1.39	2.85	0.43	1.29	2.75	0.22	1.09	2.89	0.25	1.13	2.55	0.27	1.16	2.56	0.25	1.05	2.49
Derived parameters: spawning biomass (females only)																		
SSB_0	2993	3336	3705	2991	3306	3680	2949	3271	3676	2983	3308	3661	2939	3264	3653	2889	3238	3616
SSB_{0now}	2067	2307	2619	1973	2225	2510	1799	2067	2381	1843	2110	2437	1814	2071	2414	1724	1980	2285
SSB_{2019}	1437	1724	2168	1347	1635	2035	1141	1449	1871	1200	1497	1900	1170	1480	1928	1123	1438	1823
SSB_{2023}	1143	1868	2962	1094	1734	2769	786	1482	2551	866	1533	2478	885	1535	2514	822	1451	2380
SSB_{2019} / SSB_0	0.43	0.52	0.64	0.41	0.49	0.61	0.36	0.44	0.56	0.36	0.45	0.57	0.36	0.45	0.58	0.36	0.44	0.56
SSB_{2023} / SSB_0	0.35	0.56	0.86	0.33	0.53	0.84	0.25	0.45	0.77	0.27	0.47	0.74	0.28	0.47	0.76	0.26	0.45	0.72
SSB_{2019} / SSB_{0now}	0.67	0.75	0.85	0.65	0.74	0.84	0.61	0.70	0.81	0.62	0.71	0.81	0.61	0.71	0.82	0.63	0.73	0.83
SSB_{2023} / SSB_{0now}	0.54	0.81	1.18	0.52	0.79	1.15	0.41	0.72	1.14	0.45	0.74	1.08	0.47	0.74	1.11	0.46	0.73	1.11
SSB_{2023} / SSB_{2019}	0.77	1.08	1.44	0.77	1.06	1.42	0.66	1.02	1.42	0.70	1.03	1.38	0.72	1.04	1.36	0.70	1.02	1.37

	Base_2018			cpue-1y_2017			cpue-2y_2016			cpue-3y_2015			cpue-5y_2013			cpue-10y_2008		
	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%
Derived parameters: total biomass																		
B_{0tot}	9569	10610	11680	9538	10510	11580	9434	10420	11510	9590	10550	11510	9446	10390	11440	9199	10200	11360
$B_{0totnow}$	6857	7585	8528	6485	7289	8150	5941	6769	7691	6124	6923	7999	5965	6832	7937	5667	6465	7482
$B_{2019tot}$	3621	4698	6330	3350	4402	6034	2712	3856	5530	2949	4001	5543	2893	3999	5638	2797	3880	5438
$B_{2029tot}$	2800	5036	8628	2690	4697	7949	1932	3947	7360	2215	4154	6997	2231	4164	7275	2115	3954	6939
$B_{2019tot} / B_{0tot}$	0.34	0.44	0.59	0.31	0.42	0.57	0.27	0.37	0.52	0.28	0.38	0.53	0.28	0.38	0.54	0.28	0.38	0.52
$B_{2023tot} / B_{0tot}$	0.27	0.47	0.80	0.26	0.45	0.75	0.19	0.38	0.70	0.21	0.40	0.67	0.22	0.40	0.70	0.21	0.39	0.67
$B_{2019tot} / B_{0totnow}$	0.50	0.62	0.79	0.48	0.61	0.78	0.44	0.57	0.75	0.46	0.58	0.74	0.46	0.59	0.75	0.47	0.60	0.76
$B_{2023tot} / B_{0totnow}$	0.39	0.66	1.05	0.39	0.65	1.02	0.30	0.58	1.01	0.34	0.60	0.95	0.35	0.61	0.97	0.36	0.61	0.98
$B_{2023tot} / B_{2019tot}$	0.78	1.07	1.37	0.78	1.06	1.35	0.69	1.03	1.36	0.72	1.04	1.32	0.75	1.04	1.31	0.73	1.02	1.31
Other derived parameters																		
$CPUE_{2018}$	0.64	0.70	0.77	0.55	0.65	0.76	0.42	0.52	0.64	0.44	0.57	0.76	0.37	0.51	0.72	0.29	0.43	0.63
$CPUE_{2023}$	0.41	1.07	2.10	0.30	0.89	1.90	0.02	0.55	1.57	0.03	0.65	1.55	0.03	0.59	1.52	0.02	0.43	1.22
H_{2018}	15.97	17.61	19.65	16.07	17.99	20.19	17.34	19.64	22.80	16.21	18.96	22.11	16.52	19.40	23.01	16.92	19.95	23.58
H_{2023}	10.34	12.88	20.61	10.82	14.53	25.90	12.22	19.47	91.48	11.78	18.07	90.10	11.80	18.18	93.38	12.44	20.76	98.28

Table 11: CRA 4 probabilities for the base case (base_2018) and model runs when removing years of CPUE data.

	base_2018	cpue-1y_2017	cpue-2y_2016	cpue-3y_2015	cpue-5y_2013	cpue-10y_2008
P(B2019 > Bmin)	0.999	0.972	0.700	0.729	0.695	0.611
P(SSB2019 < 20%SSB0)	0.000	0.000	0.000	0.000	0.000	0.000
P(SSB2019 < 10%SSB0)	0.000	0.000	0.000	0.000	0.000	0.000
P(SSB2019 < 20%SSB0now)	0.000	0.000	0.000	0.000	0.000	0.000
P(SSB2019 < 10%SSB0now)	0.000	0.000	0.000	0.000	0.000	0.000
P(SSB2023 < 20%SSB0)	0.000	0.002	0.012	0.006	0.005	0.011
P(SSB2023 < 10%SSB0)	0.000	0.000	0.000	0.000	0.000	0.000
P(SSB2023 < 20%SSB0now)	0.000	0.000	0.000	0.000	0.000	0.000
P(SSB2023 < 10%SSB0now)	0.000	0.000	0.000	0.000	0.000	0.000
P(B2023 > B2019)	0.731	0.679	0.534	0.567	0.575	0.518
P(SSB2023 > SSB2019)	0.652	0.626	0.537	0.556	0.569	0.531
P(B2023tot > B2019tot)	0.651	0.636	0.558	0.581	0.583	0.546

Table 12: CRA 2 stock assessment parameter estimates: MCMC runs for base case and retrospective runs. Growth increment values in mm TW and R_0 in numbers (continued next page).

	Base_2016			full-1y_2015			full-2y_2014			full-3y_2013			full-5y_2011			full-10y_2006		
	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%
R_0	540400	611800	695400	535100	605600	688100	536500	611000	694600	540600	616700	712000	530600	615000	702700	515800	601800	701800
M	0.1482	0.1626	0.1795	0.1429	0.1585	0.1739	0.142	0.1569	0.1728	0.1423	0.1578	0.1741	0.1404	0.157	0.1733	0.135	0.1542	0.1755
qFSU	0.00052	0.00061	0.00071	0.00053	0.00062	0.00073	0.00053	0.00062	0.00073	0.00053	0.00062	0.00073	0.00051	0.0006	0.00071	0.00049	0.00058	0.00069
qCELR	0.00132	0.00142	0.00151	0.00133	0.00143	0.00153	0.00135	0.00146	0.00156	0.00134	0.00144	0.00155	0.00132	0.00143	0.00155	0.00123	0.00136	0.00151
qPuerulus	48.91	49.9	50.76	48.95	49.88	50.79	48.82	49.89	50.78	48.78	49.83	50.69	48.07	49.37	50.51	46.83	48.69	50.22
mat50	8.346	10.47	13.43	8.332	10.41	13.12	8.086	10.43	13.24	8.141	10.43	13.4	7.831	10.23	13.65	7.468	10.56	14.78
Mat95add	0.1028	0.1442	0.1947	0.1089	0.1518	0.201	0.117	0.1588	0.2113	0.1179	0.1634	0.2122	0.1143	0.1554	0.2145	0.1139	0.1605	0.22
Galpha males	6.642	6.819	6.99	6.656	6.836	7.016	6.658	6.854	7.042	6.732	6.921	7.123	6.739	6.935	7.143	6.933	7.149	7.357
Gbeta males	2.591	2.86	3.16	2.573	2.838	3.12	2.565	2.816	3.138	2.512	2.775	3.047	2.45	2.687	2.994	2.253	2.491	2.745
Gshape males	2.016	2.607	3.235	1.967	2.599	3.281	2.005	2.636	3.302	2.15	2.719	3.387	2.097	2.679	3.327	2.539	3.16	3.817
GCV males	0.4164	0.4383	0.4619	0.411	0.4337	0.4579	0.4126	0.4363	0.4601	0.4027	0.4278	0.4543	0.4008	0.4264	0.4537	0.3864	0.4124	0.4408
Galpha females	4.554	4.729	4.905	4.495	4.666	4.851	4.499	4.659	4.827	4.547	4.713	4.881	4.555	4.733	4.918	4.729	4.916	5.132
Gbeta females	1.112	1.189	1.27	1.11	1.188	1.269	1.107	1.184	1.271	1.104	1.177	1.264	1.094	1.171	1.258	1.084	1.163	1.247
Gshape females	4.121	4.432	4.723	4.162	4.447	4.756	4.146	4.458	4.783	4.162	4.488	4.817	4.216	4.535	4.854	4.381	4.743	5.136
GCV females	0.731	0.7752	0.8185	0.7351	0.7819	0.828	0.7376	0.7845	0.8319	0.7299	0.7733	0.8242	0.7256	0.7743	0.8236	0.6977	0.7481	0.8022
Stdobs	0.9046	1.007	1.109	0.9451	1.044	1.15	0.9436	1.05	1.151	1.109	1.219	1.326	1.105	1.223	1.328	1.165	1.276	1.39
vuln1	0.6328	0.6671	0.7005	0.6291	0.661	0.6978	0.6184	0.6544	0.6917	0.6177	0.6536	0.6917	0.6114	0.6511	0.6922	0.597	0.6401	0.6838
vuln2	0.5059	0.6022	0.718	0.5043	0.5987	0.7091	0.4833	0.5909	0.7153	0.4992	0.6071	0.7322	0.5143	0.6452	0.8009	0.5052	0.6621	0.8587
vuln3	0.5218	0.5735	0.6276	0.5204	0.5731	0.6303	0.5144	0.569	0.6286	0.5203	0.5771	0.6363	0.531	0.5985	0.6664	0.5474	0.6298	0.7235
vuln4	0.4701	0.5161	0.5677	0.473	0.5208	0.5719	0.4719	0.5192	0.5729	0.4732	0.5269	0.5823	0.4854	0.536	0.6019	0.5029	0.5732	0.6541

	Base_2016			full-1y_2015			full-2y_2014			full-3y_2013			full-5y_2011			full-10y_2006		
	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%
SelL males < 1993	2.669	18.03	45.01	2.871	18.95	44.65	2.488	18.79	45.16	2.899	19.06	45.28	2.834	18.46	44.66	3.354	20.43	45.36
SelM males < 1993	2.847	10.74	29.91	3.236	11.28	30.73	3.155	11.42	30.79	3.091	11.94	28.38	2.831	12.56	32.5	3.207	14.12	36.01
SelL females < 1993	4.397	4.665	4.945	4.38	4.681	4.964	4.446	4.726	5.017	4.458	4.763	5.067	4.445	4.759	5.097	4.486	4.909	5.39
SelM females < 1993	6.891	7.252	7.654	6.972	7.356	7.77	7.005	7.402	7.829	7.042	7.476	7.969	7.102	7.557	8.052	7.291	7.883	8.59
SelL males >= 1993	32.21	45.73	66.3	32.11	46.41	65.11	32.38	45.66	63.98	31.9	44.98	62.52	31.95	46.35	64.21	32.2	44.82	61.89
SelM males >= 1993	47.65	60.56	75.93	47.56	61.64	79.04	48.53	61.65	77.42	48.12	62.51	77.01	47.65	62.55	80.6	46.4	63.04	81.8
SelL females >= 1993	55.37	55.84	56.32	55.3	55.81	56.31	55.37	55.86	56.36	55.37	55.87	56.38	55.22	55.74	56.29	54.83	55.55	56.36
SelM females >= 1993	62.51	63.12	63.77	62.62	63.26	63.95	62.61	63.3	64	62.66	63.37	64.12	62.61	63.39	64.15	62.25	63.24	64.35

Table 13: CRA 2 stock assessment parameter estimates: MCMC runs for base case and model runs when removing years of CPUE data. Growth increment values in mm TW and R_0 in numbers (continued next page).

	Base_2016			cpue-1y_2015			cpue-2y_2014			cpue-3y_2013			cpue-5y_2011			cpue-10y_2006		
	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%
R_0	540400	611800	695400	531400	608400	692500	532700	613200	702900	537900	615700	701500	536000	609500	696600	534400	609500	693100
M	0.15	0.16	0.18	0.15	0.16	0.18	0.14	0.16	0.18	0.14	0.16	0.18	0.14	0.16	0.17	0.14	0.16	0.18
qFSU	0.0005	0.0006	0.0007	0.0005	0.0006	0.0007	0.0005	0.0006	0.0007	0.0005	0.0006	0.0007	0.0005	0.0006	0.0007	0.0005	0.0006	0.0007
qCELR	0.0013	0.0014	0.0015	0.0013	0.0014	0.0015	0.0013	0.0014	0.0015	0.0013	0.0014	0.0015	0.0013	0.0014	0.0016	0.0014	0.0015	0.0016
qPuerulus	48.91	49.90	50.76	48.98	49.91	50.73	48.90	49.90	50.80	48.89	49.89	50.70	48.83	49.87	50.71	48.93	49.90	50.73
mat50	8.35	10.47	13.43	8.51	10.62	13.40	8.31	10.61	13.47	8.33	10.62	13.48	8.43	10.59	13.37	8.42	10.54	13.43
Mat95add	0.10	0.14	0.19	0.10	0.14	0.20	0.11	0.15	0.20	0.12	0.16	0.21	0.11	0.15	0.20	0.11	0.16	0.21
Galpha males	6.64	6.82	6.99	6.64	6.82	6.99	6.63	6.81	6.99	6.63	6.80	6.98	6.63	6.81	6.99	6.62	6.80	6.99
Gbeta males	2.59	2.86	3.16	2.62	2.87	3.17	2.60	2.86	3.15	2.63	2.87	3.19	2.61	2.86	3.17	2.62	2.87	3.17
Gshape males	2.02	2.61	3.24	2.02	2.60	3.25	2.02	2.59	3.21	2.01	2.59	3.29	2.02	2.60	3.30	2.06	2.67	3.31
GCV males	0.42	0.44	0.46	0.42	0.44	0.46	0.42	0.44	0.46	0.42	0.44	0.46	0.42	0.44	0.46	0.42	0.44	0.46
Galpha females	4.55	4.73	4.91	4.56	4.72	4.89	4.55	4.72	4.89	4.56	4.72	4.89	4.55	4.72	4.89	4.57	4.72	4.90
Gbeta females	1.11	1.19	1.27	1.12	1.19	1.27	1.13	1.19	1.27	1.12	1.20	1.27	1.11	1.19	1.27	1.12	1.19	1.27
Gshape females	4.12	4.43	4.72	4.13	4.44	4.71	4.14	4.41	4.70	4.11	4.42	4.70	4.12	4.42	4.71	4.13	4.42	4.73
GCV females	0.73	0.78	0.82	0.73	0.78	0.82	0.74	0.77	0.82	0.73	0.78	0.82	0.73	0.78	0.82	0.73	0.77	0.82
Stdobs	0.90	1.01	1.11	0.90	1.00	1.11	0.91	1.01	1.11	0.91	1.00	1.10	0.90	1.01	1.11	0.91	1.01	1.12
vuln1	0.63	0.67	0.70	0.63	0.66	0.70	0.62	0.66	0.69	0.62	0.65	0.69	0.62	0.65	0.69	0.60	0.64	0.69
vuln2	0.51	0.60	0.72	0.50	0.60	0.72	0.50	0.60	0.73	0.51	0.61	0.72	0.51	0.61	0.72	0.51	0.61	0.73
vuln3	0.52	0.57	0.63	0.52	0.57	0.63	0.51	0.57	0.62	0.51	0.56	0.62	0.51	0.57	0.62	0.51	0.56	0.62
vuln4	0.47	0.52	0.57	0.47	0.51	0.57	0.47	0.52	0.57	0.47	0.52	0.57	0.47	0.52	0.57	0.47	0.52	0.57

	Base_2016			cpue-1y_2015			cpue-2y_2014			cpue-3y_2013			cpue-5y_2011			cpue-10y_2006		
	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%
SelL males < 1993	2.67	18.03	45.01	2.67	17.83	45.53	2.76	16.07	44.75	2.52	18.08	45.86	2.53	16.27	44.29	2.74	18.42	44.10
SelM males < 1993	2.85	10.74	29.91	2.91	10.18	27.98	2.68	10.12	27.94	3.09	10.55	28.45	2.63	10.46	28.94	2.67	10.18	25.68
SelL females < 1993	4.40	4.67	4.95	4.42	4.67	4.96	4.40	4.66	4.93	4.39	4.67	4.96	4.40	4.66	4.91	4.39	4.66	4.94
SelM females < 1993	6.89	7.25	7.65	6.89	7.27	7.68	6.85	7.23	7.65	6.87	7.24	7.65	6.88	7.26	7.61	6.86	7.25	7.63
SelL males >= 1993	32.21	45.73	66.30	32.19	46.78	65.07	31.95	46.64	63.34	31.98	46.27	63.00	32.29	46.28	63.23	32.88	46.59	62.41
SelM males >= 1993	47.65	60.56	75.93	48.31	60.19	74.46	48.69	60.01	75.10	47.38	60.24	76.06	46.99	60.23	75.69	47.41	59.93	74.37
SelL females >= 1993	55.37	55.84	56.32	55.38	55.83	56.32	55.39	55.83	56.30	55.38	55.84	56.36	55.38	55.84	56.26	55.34	55.81	56.27
SelM females >= 1993	62.51	63.12	63.77	62.51	63.15	63.76	62.45	63.12	63.80	62.51	63.12	63.79	62.50	63.14	63.72	62.46	63.12	63.75

Table 14: CRA 2 base case (base_2016) and model runs when removing years of CPUE data. MCMC outputs, reporting the 5th, 50th (median; highlighted in yellow), and 95th quantiles of the posterior distributions. Growth increment values in mm TW, biomass values in tonnes and R_0 in numbers. Handling mortality (H) in tonnes and CPUE in kg/potlift (continued next page).

	Base_2016			cpue-1y_2015			cpue-2y_2014			cpue-3y_2013			cpue-5y_2011			cpue-10y_2006		
	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%
Derived parameters: AW adjusted vulnerable biomass																		
B_0	3232	3706	4247	3259	3746	4290	3314	3797	4336	3364	3870	4406	3318	3846	4409	3388	3904	4505
B_{0now}	3038	3358	3702	3055	3399	3758	3112	3441	3890	3126	3488	3900	3126	3487	3933	3148	3532	3918
B_{min}	182	202	223	178	208	236	201	240	270	207	250	282	202	249	283	207	252	286
B_{2017}	162	199	239	159	211	270	194	271	368	198	293	407	197	292	412	203	294	417
B_{2021}	29.90	92.93	353.20	29.72	126.50	460.10	33.75	278.00	712.70	37.67	342.50	847.10	37.99	342.80	869.30	34.82	342.40	853.20
B_{2017} / B_0	0.04	0.05	0.07	0.04	0.06	0.07	0.05	0.07	0.10	0.05	0.08	0.11	0.05	0.08	0.11	0.05	0.07	0.11
B_{2021} / B_0	0.01	0.03	0.10	0.01	0.03	0.12	0.01	0.07	0.19	0.01	0.09	0.22	0.01	0.09	0.21	0.01	0.09	0.22
B_{2017} / B_{0now}	0.05	0.06	0.07	0.05	0.06	0.08	0.06	0.08	0.11	0.06	0.08	0.12	0.06	0.08	0.12	0.06	0.08	0.12
B_{2021} / B_{0now}	0.01	0.03	0.11	0.01	0.04	0.13	0.01	0.08	0.20	0.01	0.10	0.24	0.01	0.10	0.24	0.01	0.10	0.24
B_{2021} / B_{2017}	0.16	0.47	1.54	0.16	0.60	1.74	0.16	1.03	2.13	0.19	1.17	2.31	0.19	1.16	2.28	0.18	1.18	2.26
Derived parameters: spawning biomass (females only)																		
SSB_0	1526	1717	1950	1536	1730	1959	1565	1763	1984	1582	1788	2013	1563	1785	2009	1591	1804	2048
SSB_{0now}	1438	1555	1684	1456	1570	1702	1470	1599	1751	1480	1616	1765	1487	1613	1776	1492	1629	1777
SSB_{2017}	266	305	350	264	317	378	299	372	457	304	390	490	300	392	495	305	389	497
SSB_{2021}	79	204	391	79	234	456	117	346	612	145	391	691	134	388	688	137	388	685
SSB_{2017} / SSB_0	0.15	0.18	0.21	0.15	0.18	0.22	0.17	0.21	0.26	0.17	0.22	0.28	0.17	0.22	0.28	0.17	0.22	0.28
SSB_{2021} / SSB_0	0.05	0.12	0.23	0.05	0.13	0.26	0.06	0.20	0.35	0.08	0.22	0.38	0.08	0.22	0.38	0.08	0.22	0.38
SSB_{2017} / SSB_{0now}	0.17	0.20	0.23	0.17	0.20	0.24	0.19	0.23	0.28	0.19	0.24	0.30	0.19	0.24	0.30	0.19	0.24	0.30
SSB_{2021} / SSB_{0now}	0.05	0.13	0.25	0.05	0.15	0.29	0.07	0.22	0.37	0.09	0.24	0.42	0.09	0.24	0.41	0.08	0.24	0.41
SSB_{2021} / SSB_{2017}	0.28	0.67	1.14	0.28	0.74	1.23	0.38	0.94	1.39	0.47	1.00	1.45	0.43	0.99	1.45	0.41	1.00	1.44

	Base_2016			cpue-1y_2015			cpue-2y_2014			cpue-3y_2013			cpue-5y_2011			cpue-10y_2006		
	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%	5%	50%	95%
Derived parameters: total biomass																		
B_{0tot}	5333	6027	6839	5371	6056	6821	5461	6167	6922	5539	6254	7041	5459	6222	7075	5559	6312	7177
$B_{0totnow}$	5021	5443	5889	5076	5500	5966	5147	5577	6164	5157	5639	6184	5178	5640	6222	5202	5704	6205
$B_{2017tot}$	626	767	953	627	807	1040	724	967	1292	736	1020	1378	735	1022	1389	752	1022	1415
$B_{2021tot}$	275	580	1107	279	645	1277	358	942	1732	428	1057	1967	402	1052	1994	378	1050	1962
$B_{2017tot} / B_{0tot}$	0.10	0.13	0.16	0.10	0.13	0.17	0.11	0.16	0.21	0.12	0.16	0.22	0.12	0.16	0.22	0.12	0.16	0.22
$B_{2021tot} / B_{0tot}$	0.05	0.10	0.19	0.05	0.11	0.21	0.06	0.15	0.28	0.07	0.17	0.32	0.07	0.17	0.31	0.06	0.17	0.31
$B_{2017tot} / B_{0totnow}$	0.11	0.14	0.18	0.11	0.15	0.19	0.13	0.17	0.23	0.13	0.18	0.24	0.13	0.18	0.25	0.13	0.18	0.24
$B_{2021tot} / B_{0totnow}$	0.05	0.11	0.20	0.05	0.12	0.23	0.06	0.17	0.31	0.08	0.19	0.34	0.07	0.19	0.34	0.07	0.19	0.34
$B_{2021tot} / B_{2017tot}$	0.43	0.75	1.16	0.43	0.81	1.24	0.49	0.98	1.39	0.56	1.04	1.45	0.56	1.04	1.45	0.52	1.04	1.44
Other derived parameters																		
$CPUE_{2016}$	0.21	0.24	0.26	0.21	0.25	0.30	0.24	0.31	0.39	0.25	0.33	0.43	0.24	0.33	0.45	0.25	0.34	0.46
$CPUE_{2021}$	0.01	0.12	0.41	0.01	0.16	0.54	0.01	0.34	0.85	0.05	0.43	1.04	0.05	0.42	1.04	0.04	0.43	1.04
H_{2016}	4.28	4.70	5.17	4.19	4.64	5.13	3.80	4.29	4.82	3.68	4.19	4.76	3.66	4.21	4.83	3.66	4.17	4.79
H_{2021}	3.48	7.53	22.61	3.05	5.90	22.09	2.45	3.66	18.20	2.27	3.25	15.27	2.28	3.26	16.76	2.26	3.23	16.08

Table 15: CRA 2 probabilities for the base case (base_2016) and model runs when removing years of CPUE data.

	base_2016	cpue-1y_2015	cpue-2y_2014	cpue-3y_2013	cpue-5y_2013	cpue-10y_2006
$P(B_{2017} > B_{min})$	0.409	0.546	0.829	0.870	0.867	0.873
$P(SSB_{2017} < 20\%SSB_0)$	0.869	0.768	0.350	0.279	0.260	0.316
$P(SSB_{2017} < 10\%SSB_0)$	0.000	0.000	0.000	0.000	0.000	0.000
$P(SSB_{2017} < 20\%SSB_{0now})$	0.596	0.484	0.139	0.095	0.090	0.096
$P(SSB_{2017} < 10\%SSB_{0now})$	0.000	0.000	0.000	0.000	0.000	0.000
$P(SSB_{2021} < 20\%SSB_0)$	0.886	0.817	0.511	0.424	0.412	0.422
$P(SSB_{2021} < 10\%SSB_0)$	0.384	0.300	0.115	0.081	0.081	0.080
$P(SSB_{2021} < 20\%SSB_{0now})$	0.817	0.742	0.431	0.338	0.340	0.336
$P(SSB_{2021} < 10\%SSB_{0now})$	0.324	0.263	0.098	0.061	0.063	0.066
$P(B_{2021} > B_{2017})$	0.224	0.286	0.519	0.601	0.599	0.602
$P(SSB_{2021} > SSB_{2017})$	0.137	0.206	0.422	0.493	0.495	0.504
$P(B_{2021tot} > B_{2017tot})$	0.185	0.246	0.473	0.557	0.555	0.562