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DEALING WITH TIME-VARYING COMPOSITION DATA IN FISHERIES STOCK ASSESSMENT THROUGH SELECTIVITY: ADDING PROCESS OR SIMPLIFYING?

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ABSTRACT

Selectivity is one of the main processes modeled in contemporary statistical stock assessments, but its influence on management advice has been under-appreciated. Recent research has shown that selectivity curves can take on much less regular shapes than those commonly used in statistical catch-at-age models, and are likely to change over time due to spatial variation in the age structure of the population or in the fishery. Therefore, it is important to model selectivity correctly (*e.g.* model time-varying selectivity if highly variable composition data are present).

A good case study to investigate the time-varying nature of composition data and the impact of different selectivity assumptions on stock assessment results is the assessment of yellowfin tuna (YFT, *Thunnus albacares*) in the eastern Pacific Ocean (EPO). For simplicity, the selectivity curves for all fisheries in the yellowfin assessment are assumed to be constant over time; but this is an oversimplification of reality.

This investigation focuses on the yellowfin assessment to illustrate and compare several approaches to modeling selectivity to mitigate potential biases associated with highly variable composition data. The Stock Synthesis (SS) statistical age-structured model is used for this investigation. The methods explored range from a full time-varying selectivity process through allowing for quarterly changes in selectivity (the "process" approach) to the "simplified" approach currently in use, which assumes constant selectivity (ignoring time-varying selectivity). The "truth" (true population dynamics model) is not known in this analysis. It is assumed that using the "process approach" by improving the model fit to the highly variable composition data though time-varying selectivity provides the best "unbiased" description of the population dynamics. The results suggest that assessments of yellowfin tuna and other tuna stocks in the EPO should use time-varying selectivity for some fisheries, particularly the purse-seine fisheries on floating objects, in order to avoid possible biases. It is also shown that a "hybrid" approach, which models only the terminal period of the assessment (6 years, at least) with time-varying selectivity and ignores (is not fitted to) earlier composition data, can replicate modeling temporal variation in selectivity for the whole time period. This hybrid approach offers a compromise between modelling time-varying selectivity and computational demands. The performance of this and other selectivity approaches explored in this document to deal with highly variable composition data should be simulation tested.

1. INTRODUCTION

Selectivity is one of the main processes modeled in contemporary statistical stock assessments, but its influence on management advice has been under-appreciated. Selectivity, as used in stock assessment models, is the relative vulnerability of fish to the gear by size or age, and is a combination of both availability (*i.e.* being in the area where the gear is deployed) and contact selectivity (*i.e.* being retained if contacted by the gear). Surprisingly, assumptions about selectivity have changed from one extreme to another as stock assessments have moved from virtual population analysis (VPA; Gulland 1965) to statistical catch-at-age analysis (SCAA; Fournier and Archibald 1982). VPAs make few assumptions about the form of the fishery selectivity and how it changes over time, while SCAAs often use the separability assumption that separates fishing mortality into an age component (which is constant over time) and a time component, and assumes that the age component follows a functional form. SCAAs usually break the catch data into multiple fisheries, in an attempt to make the constant selectivity assumption more reasonable, but recent research suggests that this is probably inadequate (Sampson and Scott 2011; Waterhouse *et al.* 2014).

In general, VPAs were historically used for high-value stocks for which long time series of catch-at-age data were available, while SCAAs were developed to address the lack of complete time series of catch-at-age for less valuable or newly-developed fisheries. However, this is a somewhat misleading generalization, since many VPAs (*e.g.* for tropical tunas) were based on crude methods for converting catch length compositions into catch-at-age data, and SCAAs have been applied to stocks with long time series of catch-at-age data. Nevertheless, in most, if not all, cases, the catch-at-age data are not perfect, and there has been a lack of recognition that there may be significant biases in the application of both VPAs and SCAAs. In particular, there has been a history of over-weighting composition data (both catch-at-age and catch-at-length), and misspecification of selectivity can substantially bias results (Lee *et al.* 2014). In particular, assuming that the selectivity of a fishery is asymptotic when it is in fact dome-shaped can highly bias estimates of absolute abundance (*e.g.* Wang *et al.* 2009). Recent research has shown that selectivity curves can take on much less regular shapes than those commonly assumed by the functional forms used in SCAAs, and are likely to change over time due to spatial variation in the age structure of the population or in the fishery (Sampson 2014; Waterhouse *et al.* 2014). Therefore, it is important to model selectivity correctly (*e.g.* model time-varying selectivity if it is present and use flexible selectivity curves) and weight composition data appropriately in SCAAs.

One way of thinking about the difference between VPAs and SCAAs is that VPAs essentially assume that there is no error in the catch-at-age data, even if missing data are substituted, and that variation in the catch-at-age data is due to population (*e.g.* recruitment and natural mortality) or fishing processes (*e.g.* timevarying selectivity), while SCAA assumes that a substantial amount of the variation in the catch-at-age data is due to sampling error. In fact, many SCAA applications attempt to estimate the amount of sampling (observation error), which essentially weights the influence of the catch-at-age data (*e.g.* McAllister and Ianelli 1997; Maunder 2011; Francis 2011). These methods cause the model to interpret process error (*e.g.* unmodelled temporal variation in selectivity) as observation error. Recently, methods have been developed that take an intermediate approach and allow for both sampling error and temporal variation in selectivity (Nielsen and Bergh 2014). Unfortunately, these approaches are computationally intensive because they involve high dimensional integrals, which are not possible in most stock assessment packages, although some less computationally-intensive approximations using these packages have been developed (Thorson *et al.* 2015; Thompson and Lauth 2012).

A good case study for investigating the time-varying nature of composition data and the impact of different selectivity assumptions on stock assessment results is the assessment of yellowfin tuna (YFT, *Thunnus albacares*) in the eastern Pacific Ocean (EPO) (Aires-da-Silva and Maunder 2012). For simplicity, the selectivity curves for all fisheries in the yellowfin assessment are assumed to be constant over time. While this stationary assumption may be reasonable for some fisheries in the model, it may be inappropriate for others. This is the case for the purse-seine fisheries on floating objects (OBJ), for which the length-composition data are highly variable over time (Figure 1). The appearance, disappearance, and subsequent reappearance of strong cohorts in the length-frequency data is a common phenomenon for yellowfin in the EPO. It may indicate spatial movement of cohorts or fishing effort, spatial variation in recruitment, limitations in the length-frequency sampling, or fluctuations in the catchability and/or selectivity of the fisheries. Bayliff (1971) observed that groups of tagged fish have also disappeared and then reappeared in this fishery, which he attributed to fluctuations in catchability and/or selectivity.

This investigation focuses on the assessment of yellowfin tuna in the eastern Pacific Ocean, in order to illustrate and compare several approaches to modeling selectivity to mitigate potential biases associated with highly-variable composition data for the floating-object fisheries.

The first approach is the most complex, since it estimates time-varying selectivity for the floating-object fishery, which is a combination of the four original floating object fisheries, in each time step of the model. This is done by using the approximation to a random effects approach described by Thompson and Lauth (2012). The second, which is currently used for assessing the EPO yellowfin stock, is a "simplified" approach, which considers selectivity to be time-invariant. A constant selectivity is estimated for the floating-object fisheries while fitting to the highly variable composition data. The third approach is a variant of the second approach, which is not fitted to the length-composition data for the floating-object fishery. In addition, it fixes (rather than estimates) a constant selectivity for theses fisheries (*i.e.* it assumes that selectivity is time-invariant). This is not a reasonable approach, but it is included to illustrate the biases that might occur if it is used naively; it presupposes that it is only important to remove the fish at about the right age, and avoids the problems of bias caused by a misspecified model when fitting to composition data. However, it loses information from the floating-object fishery composition data on, for example, recent recruitment. Results are also compared with those from the current assessment approach, which attempts to deal with some aspects of the time-varying selectivity by dividing the floating-object fishery into four spatially-defined fisheries.

The fourth method, the "hybrid" approach, combines methods one and two by estimating time-varying selectivity for the later years, but assumes constant selectivity for the earlier years and does not fit to the composition data for the early years. The idea behind this method is that the information provided by the composition data about recent recruitment and fishing mortality rates is more important than the information given by the composition data from the early historic period. The question about how many years the time-varying selectivity needs to be estimated for is investigated. For evaluation purposes, it is assumed that method 1, which estimates time-varying selectivity for all years, is the most reliable approach, and we compare the results *(e.g.* estimates of management quantities, biomass and recruitment time series) of each method to that approach.

2. METHODS

2.1. A simplified yellowfin stock assessment model – pooling of floating-object fisheries

The Stock Synthesis (SS) software (Methot and Wetzel 2013) is used to assess the status of yellowfin tuna in the EPO. SS is an integrated (fitted to multiple types of data) statistical age-structured stock assessment model (Maunder and Punt 2013). The yellowfin base case assessment model assumes one single stock of yellowfin in the EPO, with negligible or no mixing with the stock(s) of the western and central Pacific Ocean (Aires-da-Silva and Maunder 2012). Although this model is not spatially structured, an attempt is made to account for spatial structure by considering sixteen fisheries which are spatially defined and based on gear type, purse-seine set type, and length-frequency statistical sampling area[1]. Since these fisheries catch different sizes of yellowfin, the model allows for different selectivity curves acting on the yellowfin stock. More specifically, the selectivity curves of eleven of the sixteen fisheries are estimated while fitting to their historic series of length-composition data (one of the others mirrors another fishery rather than being estimated, while the other four are discard fisheries with assumed selectivities)[2].

Variability in the yellowfin length-composition data over time is particularly strong for all four purse-

[1] see Table 2.1. in Aires-da-Silva and Maunder (2012) for more information on fishery definitions in the yellowfin assessment.

[2] See page 10 on Section 4 in Aires-da-Silva and Maunder (2012) for details.

seine floating-object fisheries (OBJ) defined in the base case assessment model (Figure 1). Allowing for time-varying selectivity in OBJ fisheries is not an issue in the yellowfin assessment since the model is not fitted to OBJ indices of abundance (catch-per-unit-effort, CPUE). Otherwise, the time-varying selectivity approach would not be desirable, since there could be a trade-off between the model fits to the composition and the CPUE data. This would defeat the purpose of obtaining the best fit to the length-composition data through the time-varying approach and/or compromise Francis (2011) best practice of not letting other data (composition in particular) to stop the model from fitting well to the abundance data.

Unfortunately, allowing for time-varying selectivity for all four OBJ fisheries in the yellowfin base case assessment is not trivial. The model has a quarterly (152 quarters) rather than an yearly time-step, and a time-varying selectivity process would imply one selectivity curve for each quarter per fishery, each dome-shaped curve defined by four parameters (152 x 4 x 4 = 2,432 parameters). This would greatly increase computational time and likely result in estimation issues (*e.g.* unstable selectivity estimation, inability to obtain a positive hessian matrix in AD Model Builder, and others).

In an attempt to strike a balance between getting the right selectivity process and model parsimony (number of parameters), a reduced yellowfin Stock Synthesis model was developed. Since the main goal of the time-varying selectivity application for yellowfin is to remove OBJ catch out of the right age-classes, the original four OBJ fisheries were pooled into a single fishery in the reduced model. To obtain the yellowfin length-composition data for this new pooled fishery, the average length compositions across the original four OBJ fisheries, weighted by the total catch of each fishery, were taken (Figure 2). The definitions of the other fisheries in the reduced model, as well as the model assumptions, are the same as in the yellowfin base case assessment model (Aires-da-Silva and Maunder 2012) .

2.2. Approaches to dealing with highly variable length-composition data

2.2.1. The "process" approach - full time-varying selectivity

On the high side of model complexity lies the assumption of a full time-varying selectivity process, hereafter referred to as the "process approach" (TvarSelex_full). This assumption implies that selectivity parameters are changing at each time step of the model, which in the yellowfin model is a quarter. To implement this approach in SS, the estimated four parameters which define the assumed dome-shaped OBJ selectivity curve were allowed to have quarterly deviates. Only parameters 1, 3 and 4 were estimated in this time-varying fashion; parameter 2, which defines the width of the top of the double normal selectivity curve, was fixed at a low value to avoid numerical estimation issues.

In SS, time-varying parameter estimation can be implemented using a penalized likelihood approach (Maunder and Deriso 2003). The variability allowed for each parameter is constrained by the standard deviation of the deviates (σ) specified in the penalty added to the negative log-likelihood function based on the normal distribution assumption:

$$\sum\left(\ln(\sigma)+\frac{\varepsilon_t^2}{2\sigma^2}\right) \qquad (1)$$

Defining the variability of the time-varying parameters can be somewhat arbitrary. Thompson and Lauth (2012) proposed the following approximation to the random effects approach to obtain estimates of the standard deviation used in the penalty for time-varying parameters. Consider:

$$s_{a,t}=f\left(a,\theta_t\right) \qquad (2)$$

$$\theta_t=\theta+\varepsilon_t \qquad (3)$$

$$\varepsilon_t\sim N\left(0,\sigma^2\right) \qquad (4)$$

where

$s_{a,t}$ is the selectivity at age a in time t,

$f(\ )$ is the selectivity functional form with parameters θ_t at time t,

θ is the mean parameter value,

ε_t is the deviation from the mean,

σ is the standard deviation of the random effect

The variance parameter for the penalty is calculated using the following three steps

1. Estimate the parameter deviates with as little penalty as possible and calculate the standard deviation (σ_1):
    a) Set the standard deviation of the distributional penalty to a large number and estimate deviates
    b) Remove outliers
    c) Estimate the standard deviation of the deviates.
2. Iteratively estimate the standard deviation σ_2:
    a) Set the standard deviation at a reasonable value (*e.g.* the value estimated in (1))
    b) Estimate the deviates
    c) Estimate the standard deviation of the deviates
    d) Repeat b and c by using the new standard deviation from c until the standard deviation converges.
3. Calculate the standard deviation as:

$$\sigma = \sqrt{\sigma_1^2 - \sigma_2(\sigma_1 - \sigma_2)}$$

The Thompson and Lauth (2012) method has three steps. Each step provides an estimate of the standard deviation of the penalty for the selectivity parameter deviates. The second step has a series of estimates, the last of which is used in the formula in step 3 to get the final estimate. Figure 3 provides the estimates from each step for the three selectivity parameters. Two of the parameters iterated to a value of zero by the end of step 2. However, when inserted into the equation in step 3, the resulting standard deviation is similar to that estimated in step 1. In general, the final estimate from step 3 is similar to the value from step 1.

2.2.2. The "simplified" approach: constant selectivity

On the low side of model complexity and choice on how to deal with time-varying composition data is the option to simply ignore the time-varying process and assume that selectivity is constant (stationary) over time. This approach can be taken in two ways. The first is to estimate the constant selectivity while fitting to the length-composition data, hereafter referred to as the "simplified – fit to comps (Simple-FitComps)" approach. Most modern tuna assessments relying on integrated statistical age-structured models are taking this approach. One example is yellowfin tuna in the EPO (Aires-da-Silva and Maunder 2012).

However, estimating a stationary selectivity curve while fitting to highly variable composition data can be problematic. Model misspecification (*e.g.* unmodeled temporal variation in selectivity) can cause substantial bias in stock assessment results when fitting to composition data, particularly when the composition is given too much weight in the analysis (Francis 2011), which is often the case. For these reasons, the stock assessment scientist may simply wish to assume (fix) a reasonable stationary selectivity in the model that, on average, will remove catch out of the right age-classes. In this version of the simplified approach, the model is not fitted to the length-composition data. This will be hereafter referred to as the "simplified – not fit to comps (Simple-NotFitComps)" approach.

We also compare the results with the current assessment approach, which attempts to deal with some aspects of the time-varying selectivity by dividing the floating-object fishery into four spatially-defined fisheries. The current approach, which fits to the composition data, is termed the "base case".

2.2.3. The hybrid approach – terminal time-varying selectivity

Modelling time-varying selectivity for the whole time period, perhaps for multiple fisheries, may be too computationally intensive, depending on what the stock assessment model is being used for (*e.g.* management strategy evaluation), or cause convergence problems (*e.g.* parameters on bounds). Therefore, a hybrid approach that models time-varying selectivity for the recent period, which is the most important, and a constant selectivity without fitting to the composition data for the early period, might be practical and produce reasonable results. It is unclear how many years would need to be included to produce reasonable results, so several alternatives are explored, and the results compared. Hereafter this is referred to as the "hybrid" approach.

3. RESULTS

3.1. Selectivity estimates

There is great variability in the yellowfin length-composition data for the floating-object fishery (Figure 2). The "process" approach explored in this research to deal with this issue lies on the complex side of model development, since it allows selectivity to be time-varying on a quarterly basis. Given this flexibility, it is not surprising that the estimated shape of the OBJ selectivity varies greatly among quarters (Figures 4a and 5a).

On the simpler side of process complexity is the "simplified" approach, in which selectivity is assumed to be constant over time. The constant selectivity curve estimated in the stock assessment model while fitting to the OBJ length-composition data is quite different from the "base" selectivity which is estimated from the full time-varying run in the "process" approach (Figures 4b and 5b,c).

Finally, the "hybrid" approach lies in the middle of model complexity, by allowing time-varying selectivity to take place in the terminal period only. This dynamic selectivity period follows an early historical period in which selectivity is assumed to be constant (Figure 4c and 5d). A decision needs to be made in defining the number of years to include in the time-varying terminal period. In the case of yellowfin, a 6-year period was chosen since this seems to be a reasonable amount of terminal years necessary to stabilize important management quantities (Figure 8).

3.2. Model fit to composition data

As expected, the "process" approach through time-varying selectivity gave more flexibility to the model and resulted in a better fit to the highly-variable OBJ length-composition data. Not only are residuals smaller than those obtained for the other approaches, but they are also more evenly distributed across time (quarters) and length classes (Figure 6). The "simplified" approach produced the worst fit (largest residuals), with no fit to the lengthcomposition data (Figure 6c). This result is not surprising, since the model is not fitting to the length-composition data at all, and an "average" constant selectivity is fixed in the model.

3.3. Recruitment and biomasses

The effect on the estimates of absolute recruitment throughout the historical period varies depending on which selectivity approach is chosen to deal with the highly variable length compositions (Figure 9a). These differences should receive particular attention in the terminal period of the assessments (Figure 9b). It is important to obtain reliable estimates of recruitment in this late period so that biases are not propagated into the estimation of management quantities and future projections (forecast) of the population.

For comparative purposes, it is assumed that the "process" approach (TvarSelex_full) produces the most reliable estimates, since the full time-varying flexibility allowed the model to better fit the length-composition data for small yellowfin caught by the floating-object fishery. The simplified approach, the hybrid approach, and the base case, produced recruitment estimates similar to those from the process approach (Figure 9b), except recruitment estimates were generally higher, and were much higher during the last two years of the historic period (2010 and 2011). This is a concern, since this simplified approach is used in the base case model for yellowfin in the EPO and in most statistical integrated tuna stock assessments worldwide. The constant selectivity method, while not fitting to the composition data (ConstSelex_NoFitComps), produced the greatest differences in most years compared to the TvarSelex_full method. However, surprisingly, this version of the simplified approach provided very similar recruitment estimates to the TvarSelex_full method in 2010 and 2011. At this stage of the research, it is not clear whether this is a robust property of this simplified approach, or simply that the terminal OBJ length composition for yellowfin coincidentally corresponded "very well" with the "average" constant selectivity fixed in the model. Not surprisingly, the hybrid approach produced the estimates most similar to the "process approach" in recent years, since it also allowed for a time-varying selectivity process in the terminal years.

With respect to estimated biomasses, the differences follow patterns similar to those for recruitment. In particular, the hybrid approach (HybridSelex_6years) and simplified approach with no fit to the composition data (ConstSelex-NoFitComps) resulted in summary biomasses (Figure 10) and spawning biomass ratio levels (SBR, Figure 11) that are closer to those derived from the process approach (TvarSelex_full). These similarities are particularly strong for the hybrid approach during the terminal years and the first few years of the forecast period (Figures 10b and 11b), both periods of critical importance for management quantities. The simplified approach that fits to the composition data and the base case overestimated summary and SBR levels in the terminal and forecast years.

3.4. Projected catches

The results for the projected catches are similar to those for the projected biomass, as might be expected, with the hybrid method being closest to the process approach. The greatest difference for the purse-seine catch occurs in the first few years of the projection period, when the estimates of recent recruitments have most impact on the catch. The longline catch continues to be different for the whole projection period, which is related to the differences in absolute biomass estimated by the different models. However, the results of the time invariant-selectivity model that does not fit to the composition data produces larger longline catch later in the projection period despite having lower biomass, and this is probably due to differences in the assumed selectivity compared to the other models and the yield tradeoff among fisheries.

3.5. Management quantities

Estimates of MSY, the depletion level relative to that corresponding to MSY, and the amount by which effort would have to be changed to achieve MSY, also follow the results for recruitment and biomass, with the hybrid method being closest to the process approach (Table 1). The difference in MSY is small, but the difference in the other quantities can be important in terms of management measures.

3.6. Retrospective bias

None of the selectivity approaches explored in this paper to deal with highly variable composition data removed the retrospective pattern. The model with full-time varying selectivity still has moderate retrospective bias (Figures 13-15). The retrospective bias is similar for all methods except for the one that has constant selectivity and fits to the composition data (the base case is assumed to have the same retrospective pattern as this run, but the results were not calculated), which has larger retrospective "error" for recruitment and summary biomass, but with a less consistent pattern. It is possible that the retrospective pattern is caused by other factors (*e.g.* time-varying natural mortality) in addition to the highly variable composition data. Also, the yellowfin model contains other fisheries with highly variable composition data in addition to the floating-object fishery, for instance the purse-seine fisheries on unassociated tunas. Therefore, it is possible that these fisheries also need to be dealt with a time-varying approach to minimize persisting retrospective biases in the yellowfin assesssment.

3.7. The hybrid method's number of years

The performance of the hybrid approach was evaluated for the number of years that need to be included in the terminal time-varying period while fitting to the composition data. The stability in the estimates of MSY, the current spawning biomass (S) relative to that corresponding to MSY ($S_{\text{recent}}/S_{\text{MSY}}$) and the amount by which current fishing mortality would have to change to equal that corresponding to MSY (F multiplier) were investigated. It was found that after about 5 years (20 quarters of selectivity parameters) of estimated selectivities, these quantities leveled off (Figure 8). Therefore, a 6-year period was used in the comparisons presented above.

4. DISCUSSION

Correct specification of selectivity is critical in fisheries stock assessment models that fit to composition data. Temporal variation in selectivity is expected for many fisheries (Watterhouse *et al.* 2015; Martell and Stewart 2015) and should be included in the stock assessment. This research shows that unmodelled temporal variation in selectivity can cause bias in the estimates of absolute biomass in general, current status, and short-term projections. These are all critical quantities for management advice. It is also shown with the yellowfin example that modelling only the temporal variation in selectivity for the recent period and ignoring earlier composition data can replicate modelling temporal variation in selectivity for the whole time period.

The "truth" is not known in this analysis, so the performance of the model cannot be determined, only the performance relative to modelling time-varying selectivity for the whole time period. Therefore, the performance of the Thompson and Lauth (2012) approximation to random effects cannot be evaluated. However, it was found that the final estimates of the standard deviation used in the analysis were similar to the estimates from the first step in the procedure, indicating that the iterations of step 2 may not be required. Simulation testing of the approach is needed and some work on this subject has been initiated (H. H. Lee and K. Piner, SWFSC NOAA-NMFS).

The results suggest that assessments of yellowfin tuna and other tunas in the EPO should use time-varying selectivity for some fisheries, particularly the purse-seine fisheries on floating objects, to avoid possible biases. The hybrid approach seems to offer a compromise between modelling time-varying selectivity and computational demands, particularly if management strategy evaluation (MSE) is to be conducted.

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TABLE 1. Management quantities estimated from different approaches to deal with highly variable length-composition data: a) process approach (TvarSelex_full; full time-varying selectivity), b) simplified approach (constant selectivity while fitting (ConstSelex_FitComps} or not (ConstSelex_NoFitComps) to the length-composition data), and c) hybrid approach (Hybrid Selex_6years ; full time-varying selectivity in 6-year terminal period, constant selectivity in early period).

Quantities	Base case	TvarSelex_ full	ConstSelex_ FitComps	ConstSelex_ NoFitComps	Hybrid Selex_6years
MSY	262,642	255,654	262,852	257,868	255,383
B_{MSY}	356,682	352,561	348,836	351,797	348,430
S_{MSY}	3,334	3,292	3,208	3,283	3,239
B_{MSY}/B_0	0.31	0.31	0.31	0.31	0.31
S_{MSY}/S_0	0.26	0.25	0.25	0.26	0.25
C_{recent}/MSY	0.79	0.81	0.78	0.80	0.81
$B_{\mathrm{recent}}/B_{\mathrm{MSY}}$	1.00	0.87	1.04	0.81	0.86
$S_{\mathrm{recent}}/S_{\mathrm{MSY}}$	1.00	0.91	1.07	0.84	0.89
F multiplier	1.15	1.02	1.20	1.04	0.99

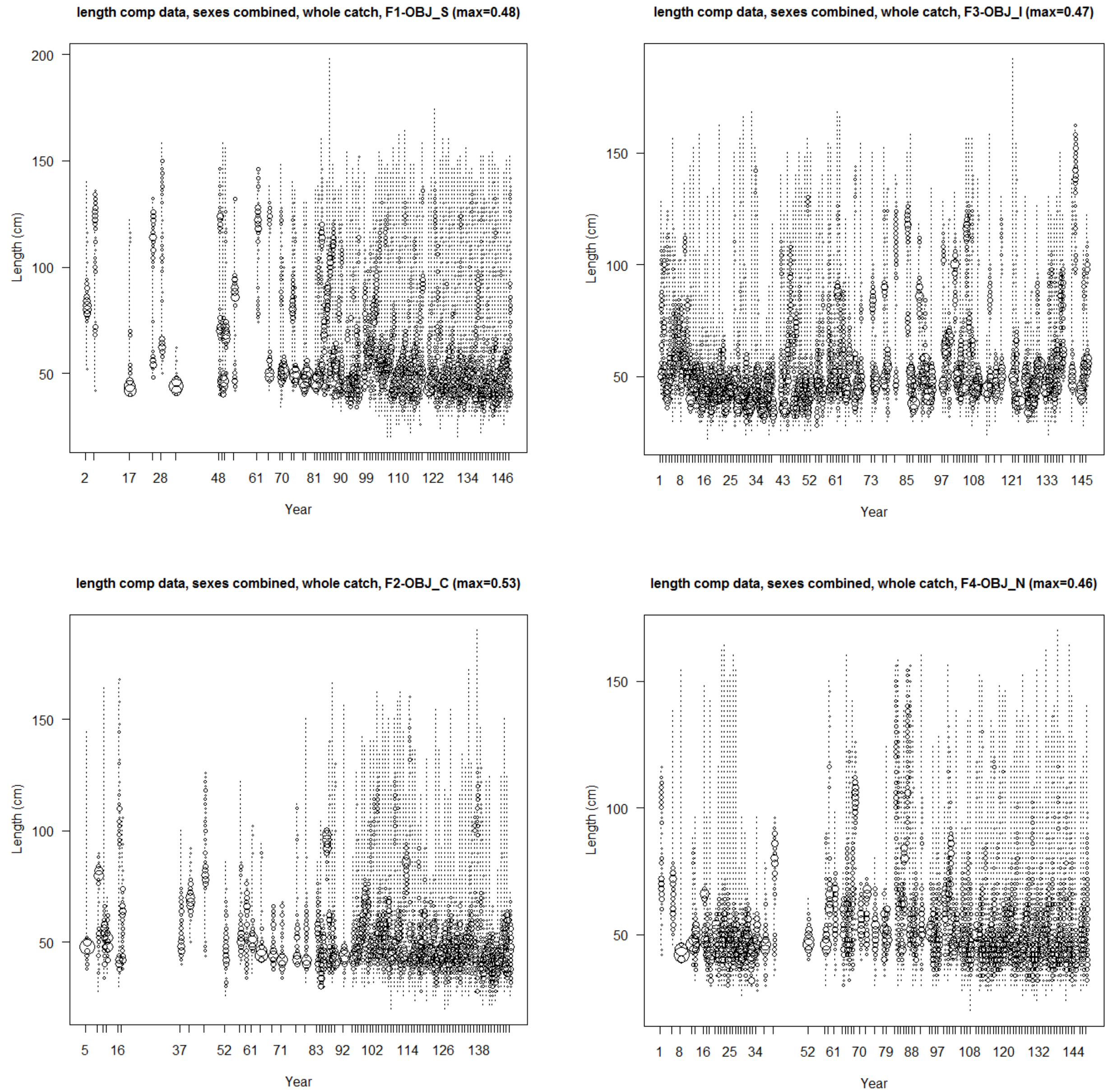

FIGURE 1. Observed length compositions of the quarterly catches of yellowfin tuna taken by the floating-object fisheries (OBJ). Four OBJ fisheries are defined in the yellowfin base case model (Aires-da-Silva and Maunder 2012). The size of the circles is proportional to the catches.

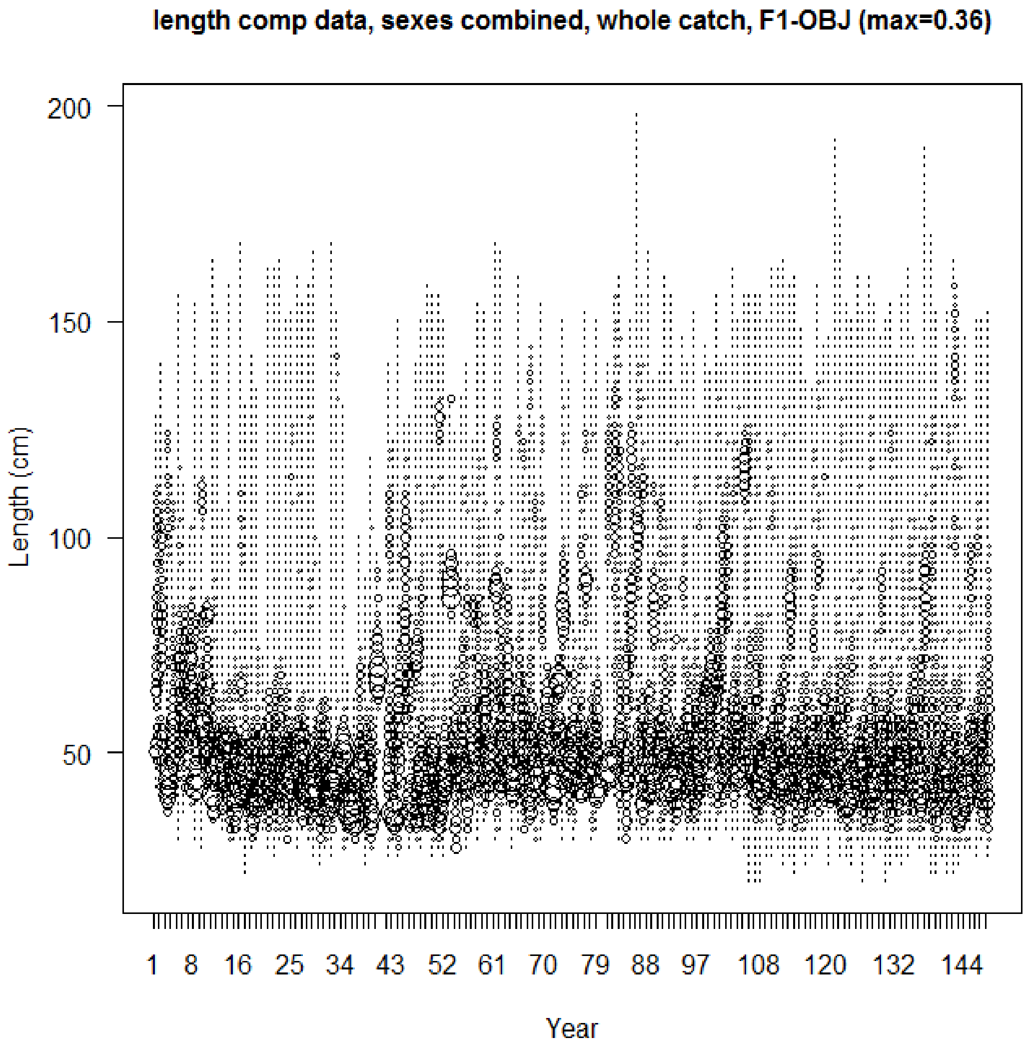

FIGURE 2. Observed length compositions of the quarterly catches of yellowfin taken by the pooled floating-object (OBJ) fisheries in the simplified yellowfin model constructed for this investigation. The size of the circles is proportional to the catches.

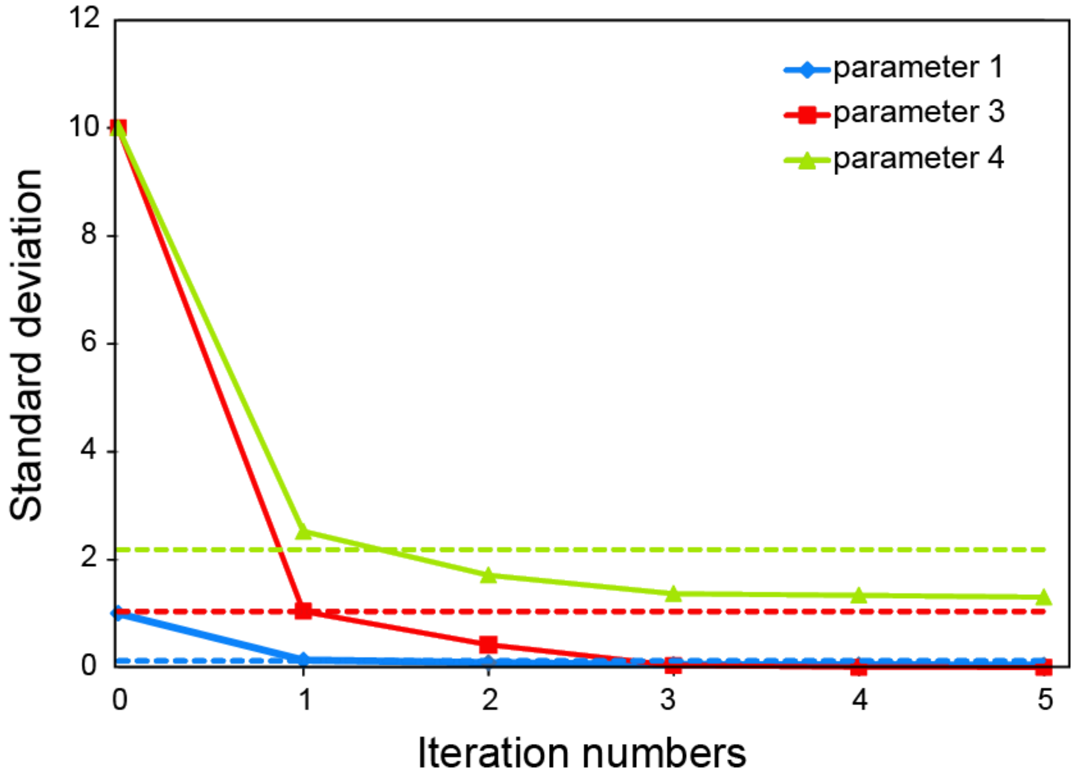

FIGURE 3. Standard deviation (SD) estimates of the time-varying dome-shaped selectivity parameters 1, 3 and 4. SD estimates are shown over the solid lines for five iterations of the Grant-Thomson method. To begin the iterative procedure, initial values of 1, 10, and 10 were used as SD starting values (iteration 0) for parameters 1, 3, and 4, respectively. The dashed lines show the final SD estimates used for the process approach..

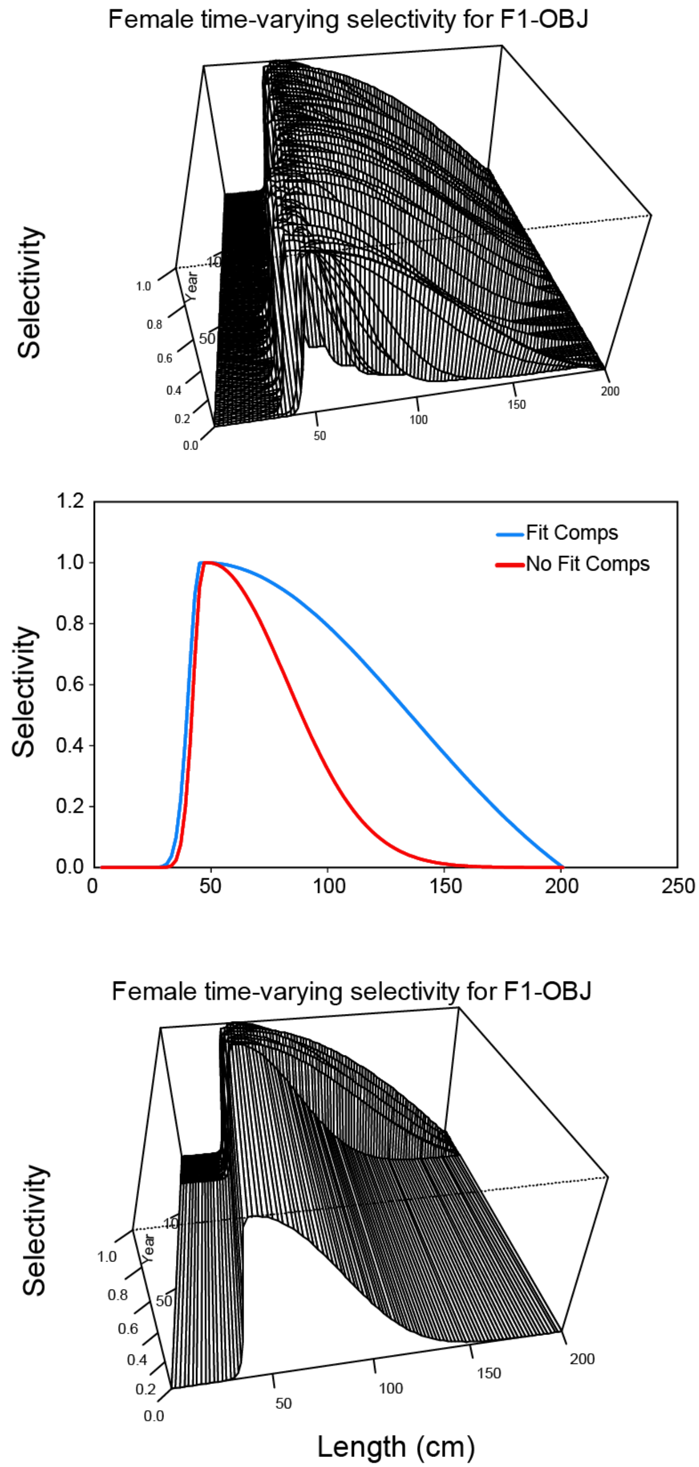

FIGURE 4. Selectivity curves for the floating-object (OBJ) fishery estimated with different approaches to deal with highly variable length-composition data: a) process approach (full time-varying selectivity), b) simplified approach (constant selectivity while fitting or not to the length-composition data), and c) hybrid approach (full time-varying selectivity in 6-year terminal period, constant selectivity in early period).

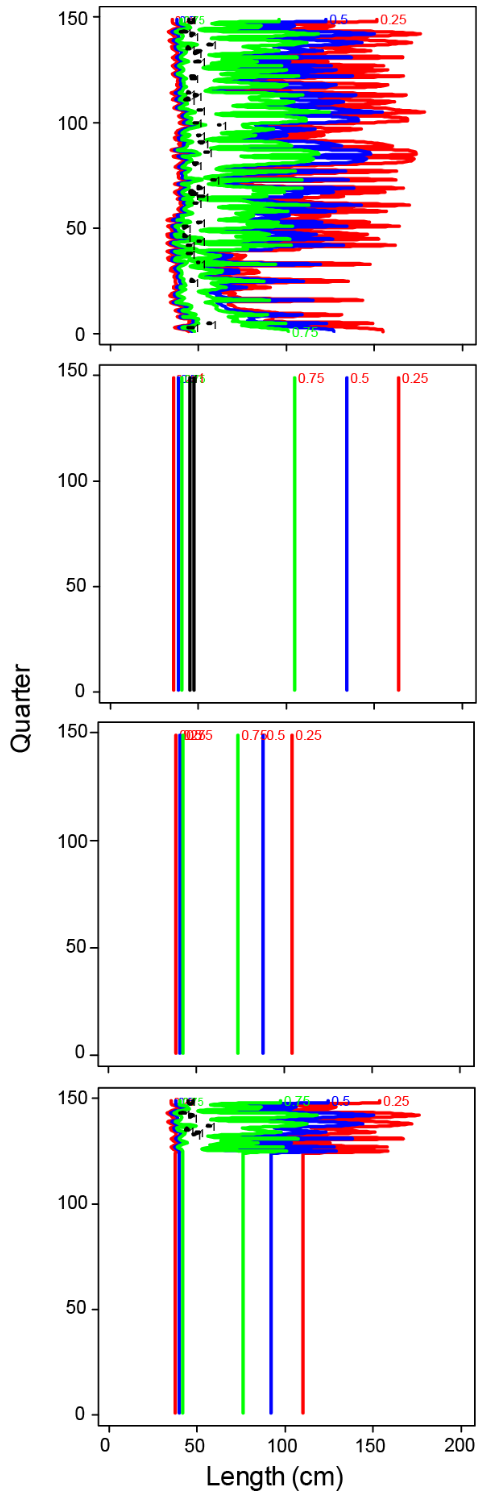

FIGURE 5. Selectivity isoclines (levels of 0.25, 0.50, 0.75, 1) for the floating-object (OBJ) fishery estimated from different approaches to deal with highly variable length-composition data: a) process approach (full time-varying selectivity), b) simplified approach (constant selectivity while fitting or not to the length-composition data), and c) hybrid approach (full time-varying selectivity in 6-year terminal period, constant selectivity in early period).

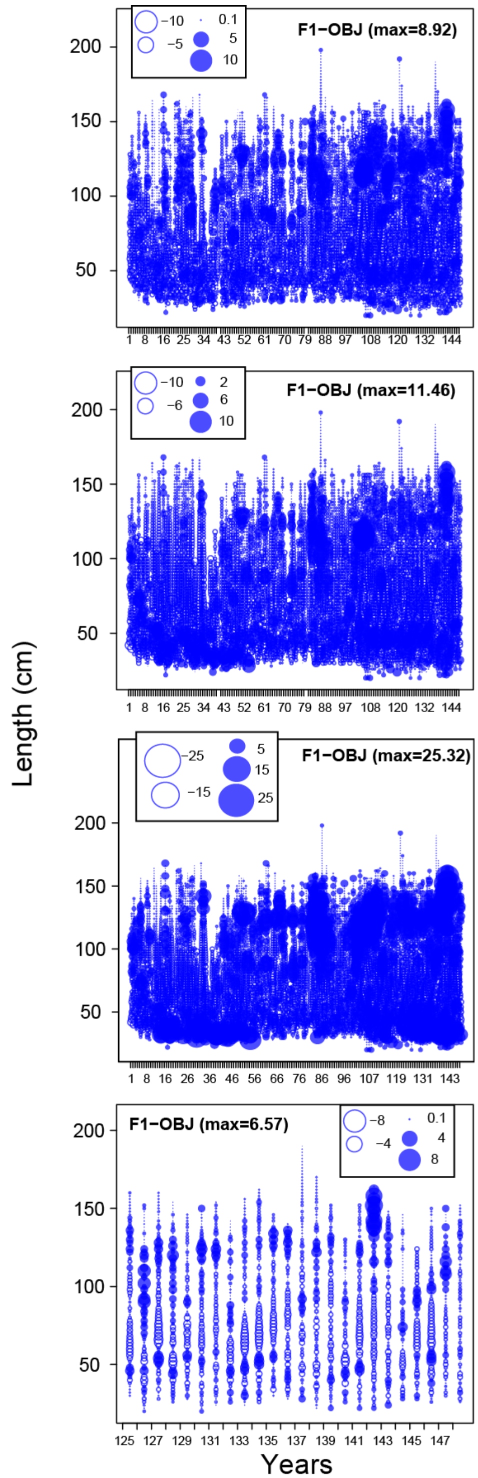

FIGURE 6. Pearson residual (bubble) plots for the model fits to the length-composition data for the floating-object (OBJ) fishery. The filled and open circles represent observations that are higher and lower, respectively, than the model predictions. The following approaches to deal with highly variable length-composition data were applied: a) process approach (full time-varying selectivity), b) simplified approach (constant selectivity while fitting or not to the length-composition data), and c) hybrid approach (full time-varying selectivity in 6-year terminal period, constant selectivity in early period).

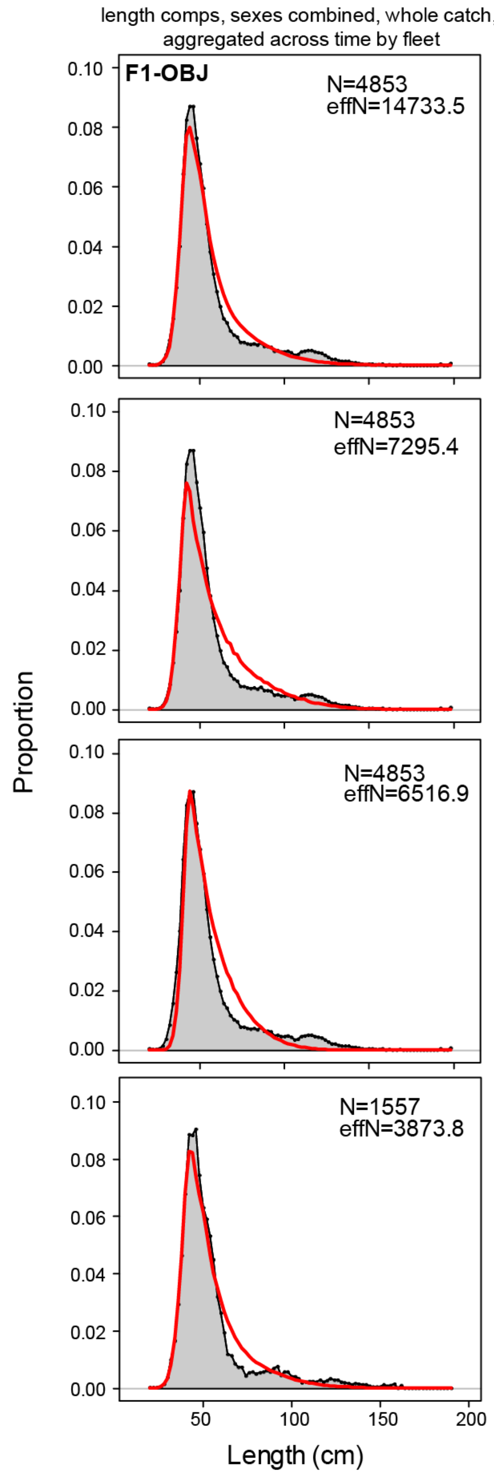

FIGURE 7. Average observed (shaded area) and predicted (red lines) length-composition distributions of the yellowfin catches taken by the floating-object fishery. The following approaches to deal with highly variable length-composition data were applied: a) process approach (full time-varying selectivity), b) simplified approach (constant selectivity while fitting or not to the length-composition data), and c) hybrid approach (full time-varying selectivity in 6-year terminal period, constant selectivity in early period).

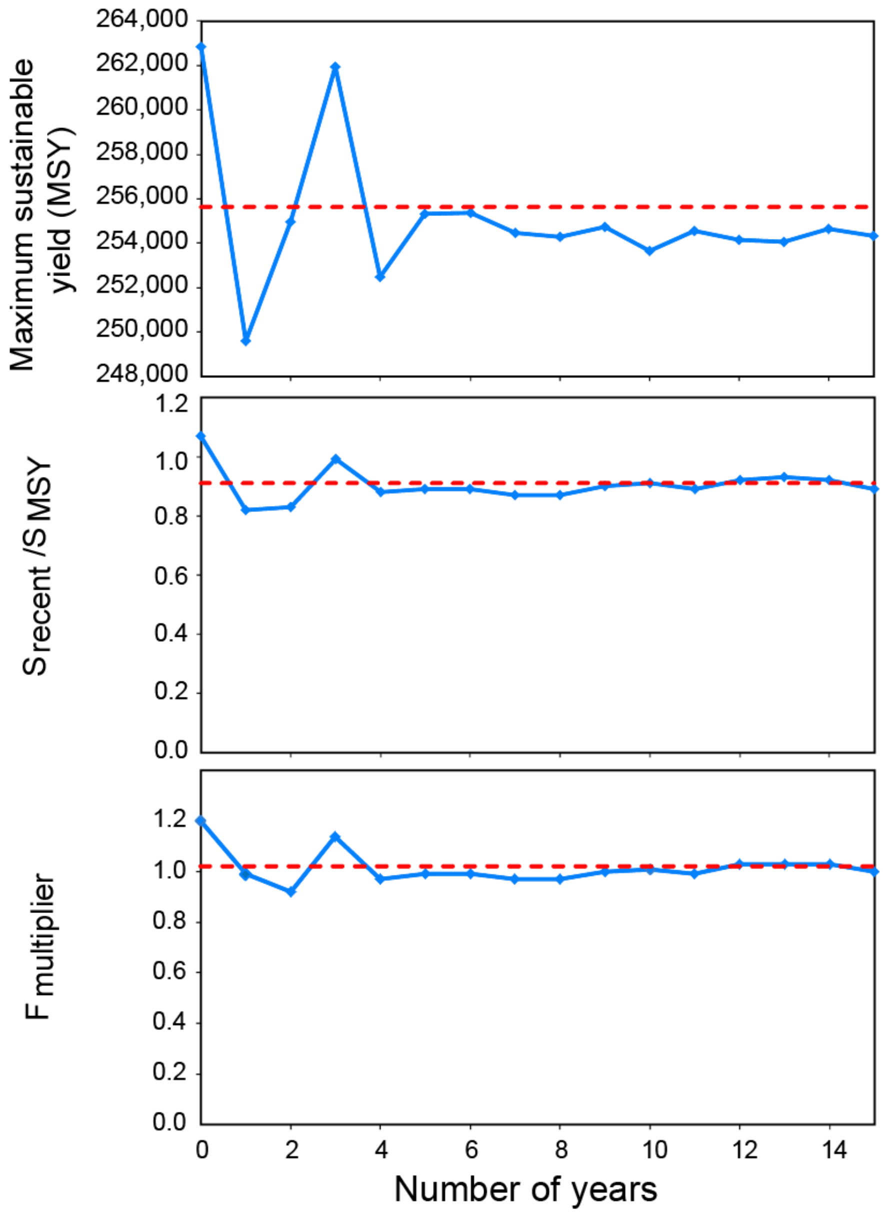

FIGURE 8. Impact on management quantities of including N terminal years in the late time-varying selectivity period used in the hybrid approach. The impact on the following management quantities is shown: a) maximum sustainable yield (MSY), b) recent spawning biomass (S) relative to that corresponding to MSY ($S_{\mathrm{recent}}/S_{\mathrm{MSY}}$); and c) the F multiplier, the factor that the current fishing mortality (F) needs to be multiplied by in order to attain F_{MSY}.

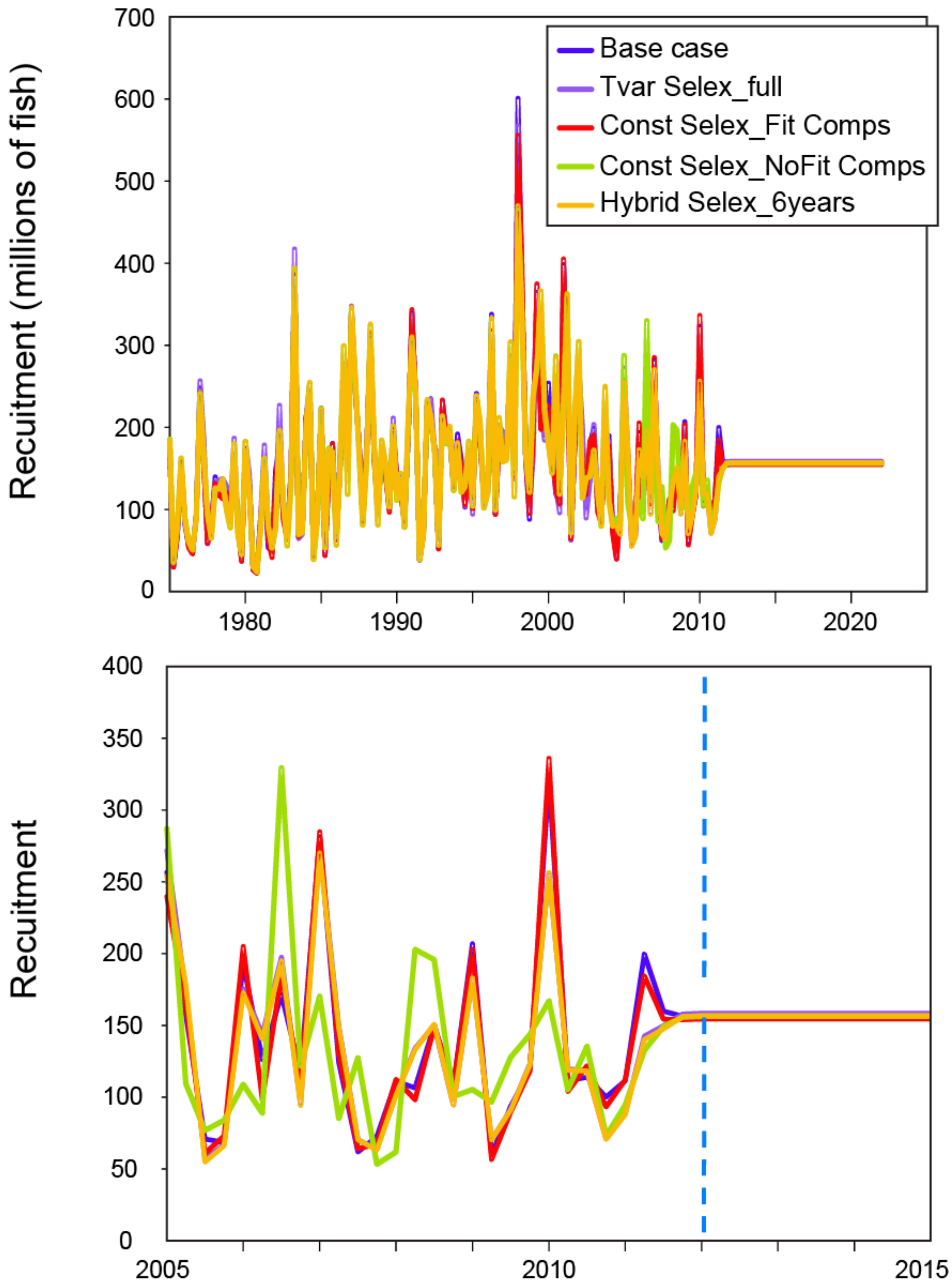

FIGURE 9. Time series of recruitments estimated with the different selectivity approaches to deal with highly variable length-composition data: a) historic (1975-2011) and forecast (2012-2022) periods, b) detail of terminal historic period (2005-2011) and forecast.

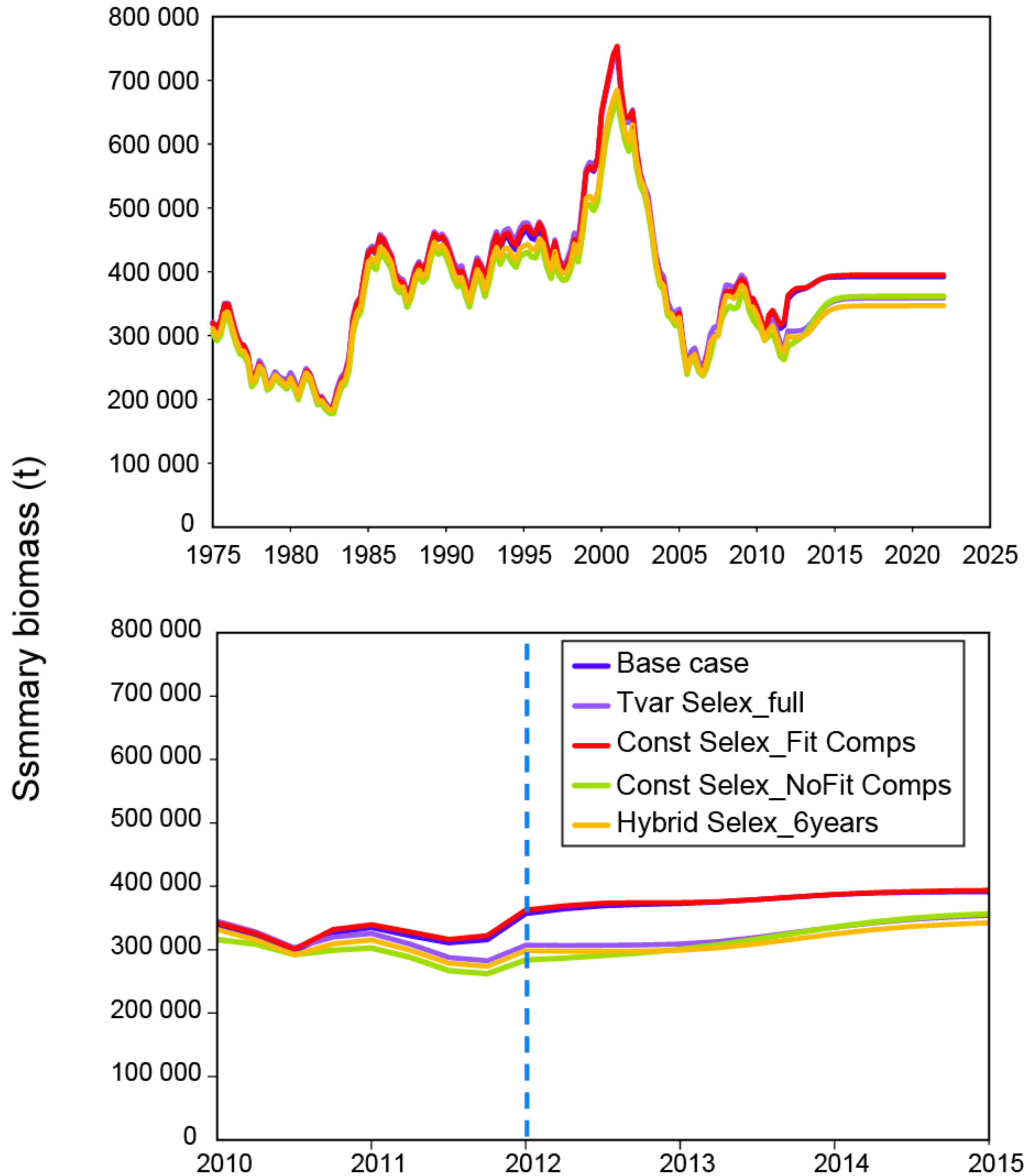

FIGURE 10. Time series of the summary biomass (3+ quarter and older fish) estimated from the different selectivity approaches to deal with highly variable length-composition data: a) historic (1975-2011) and forecast (2012-2022) periods, b) detail of terminal historic period (2010-2011) and forecast.

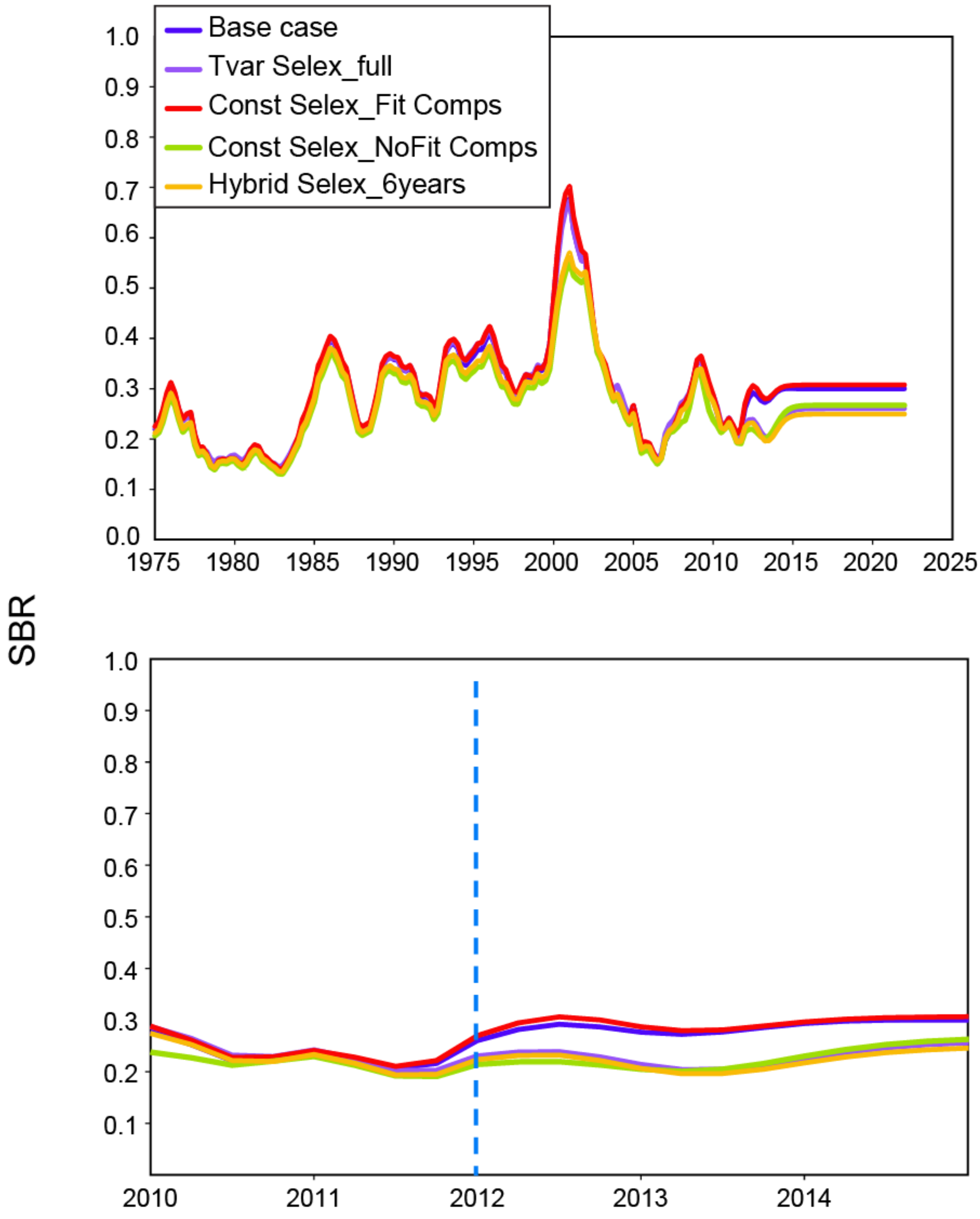

FIGURE 11. Time series of the spawning biomass ratio (SBR) estimated with the different selectivity approaches to deal with highly variable length-composition data: a) historic (1975-2011) and forecast (2012-2022) periods, b) detail of terminal historic period (2010-2011) and forecast.

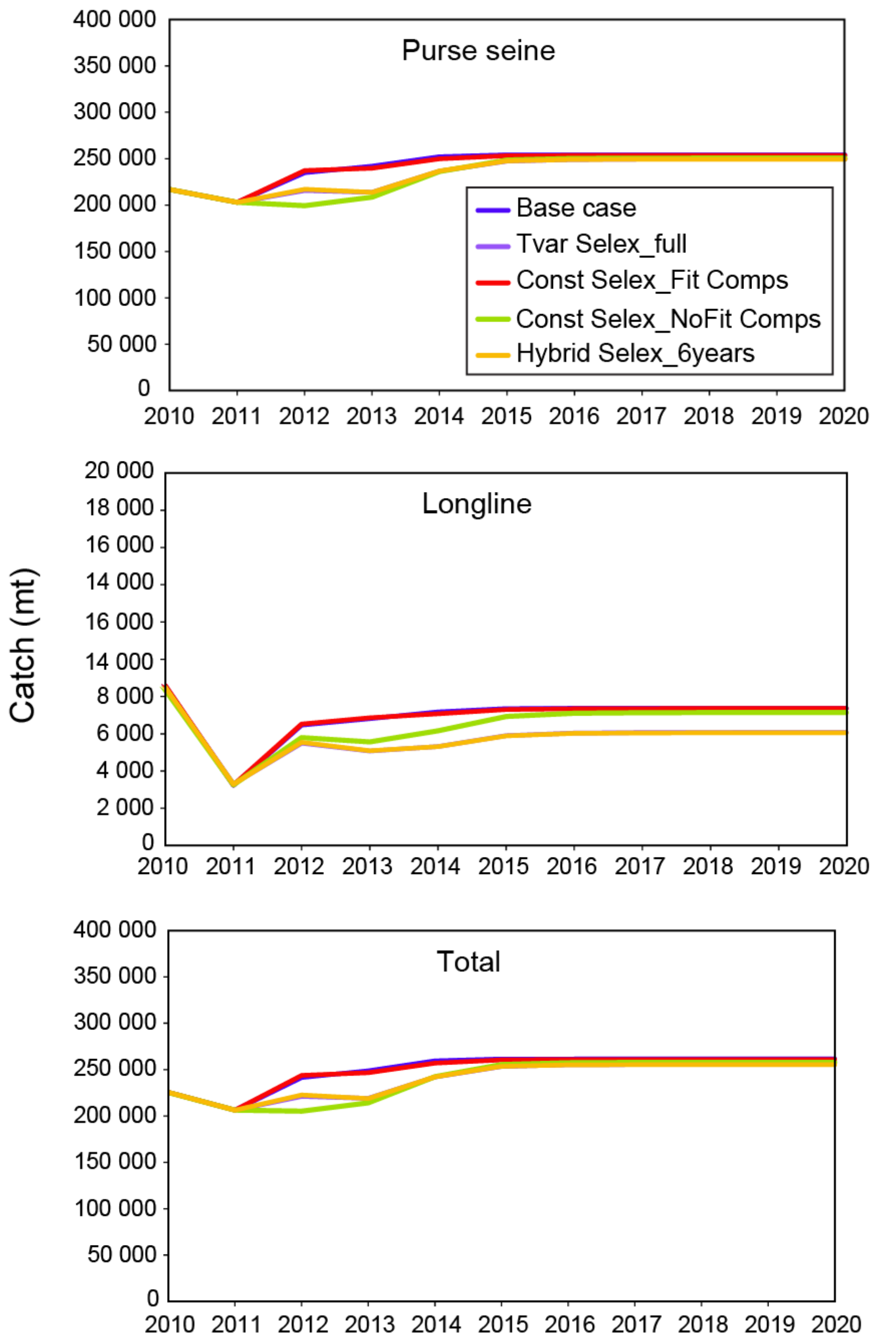

FIGURE 12. Time series of projected catches (2012-2025) estimated with the different selectivity approaches to deal with highly variable length-composition data: a) purse seine, b) longline, c) total.

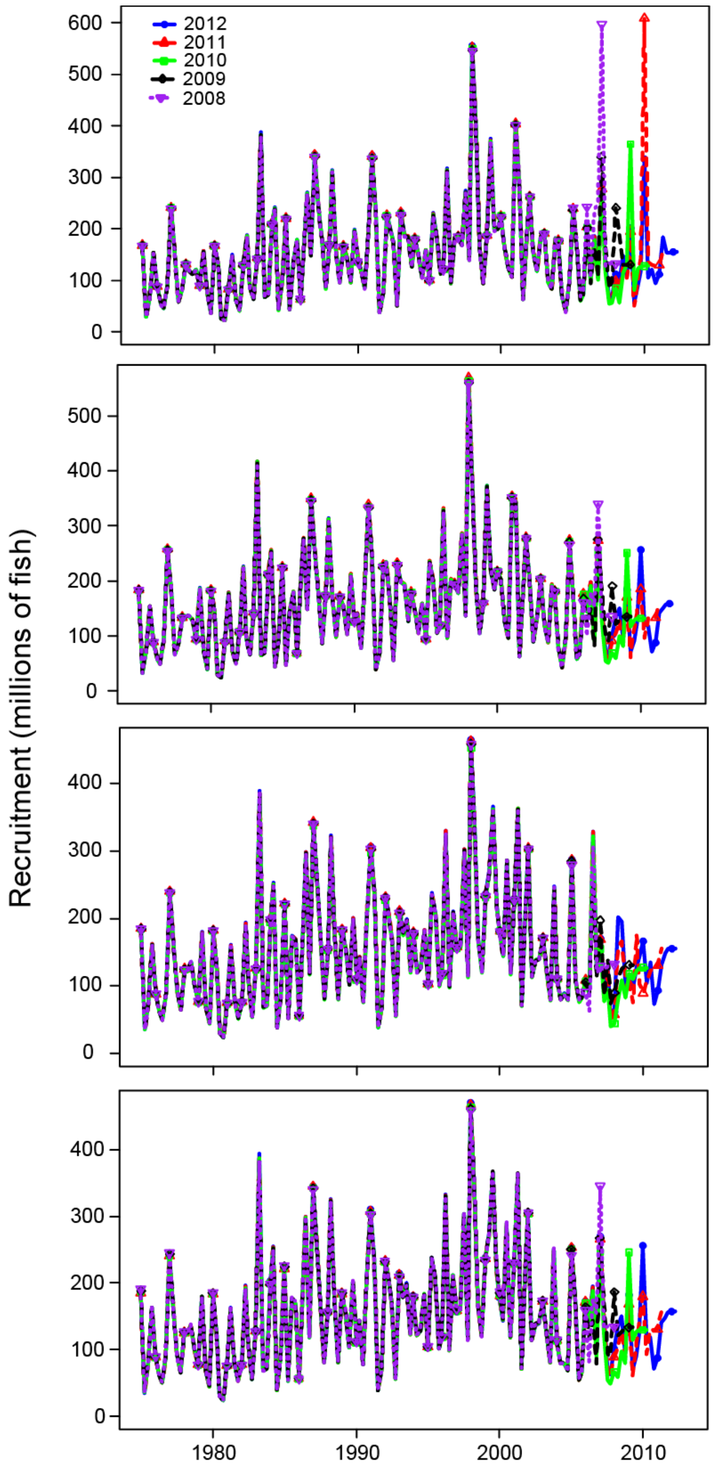

FIGURE 13. Effect of retrospective pattern on recent yellowfin recruitment estimates from removing recent data while applying the following approaches to deal with highly variable length-composition data: a) process approach (full time-varying selectivity), b) simplified approach (constant selectivity while fitting to the length-composition data), c) simplified approach (constant selectivity while not fitting to the length-composition data), and d) hybrid approach (full time-varying selectivity in 6-year terminal period, constant selectivity in early period).

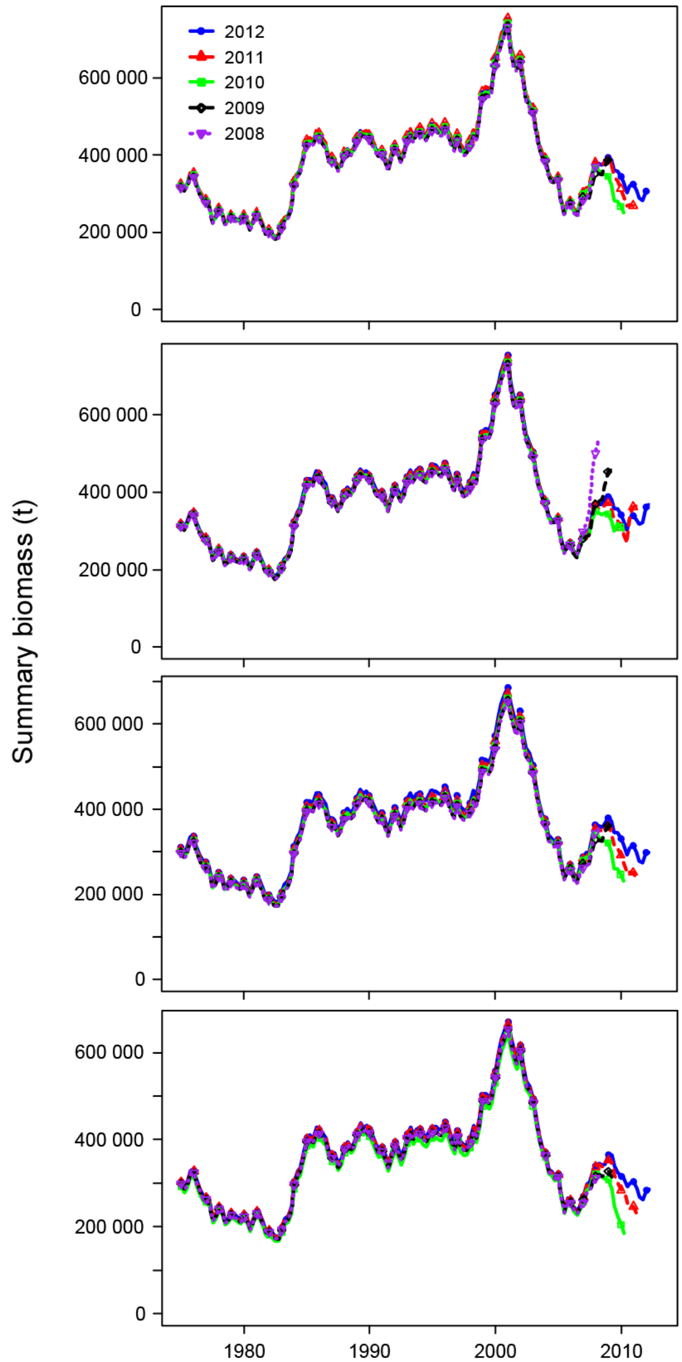

FIGURE 14. Retrospective pattern in yellowfin summary biomass (3+ quarter old fish) estimates from removing recent data while applying the following approaches to deal with highly variable length-composition data: a) process approach (full time-varying selectivity), b) simplified approach (constant selectivity while fitting to the length-composition data), c) simplified approach (constant selectivity while not fitting to the length-composition data), and d) hybrid approach (full time-varying selectivity in 6-year terminal period, constant selectivity in early period).

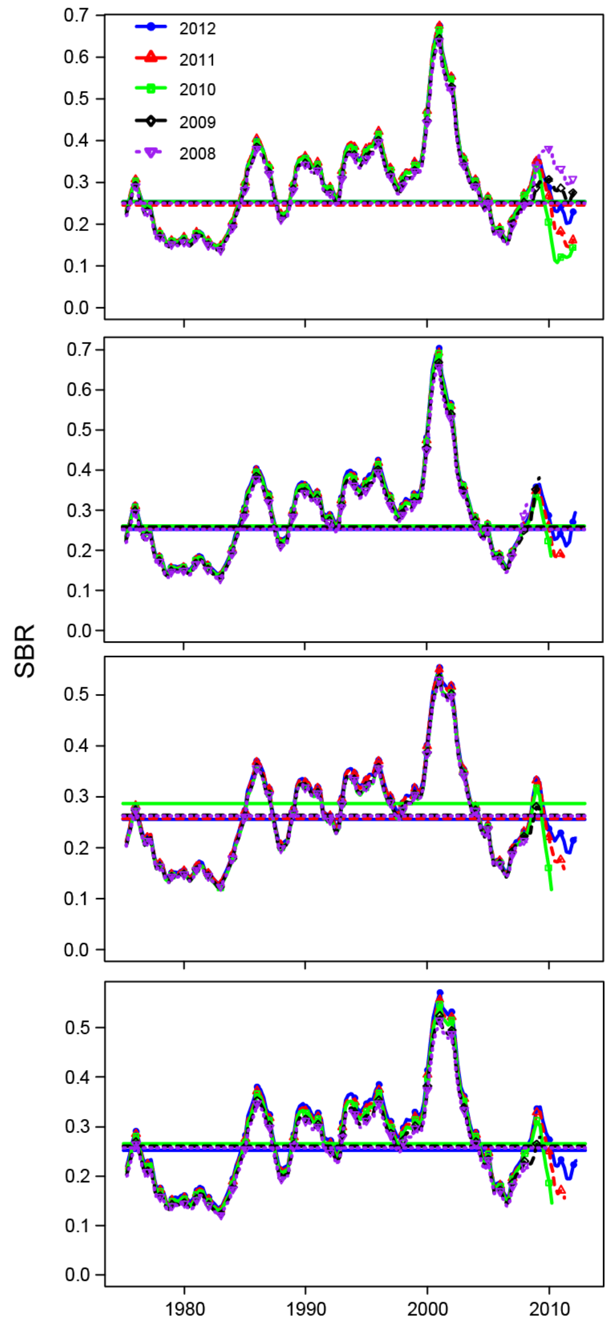

FIGURE 15. Effect of retrospective pattern on recent yellowfin spawning biomass ratio (SBR) estimates from removing recent data while applying the following approaches to deal with highly variable length-composition data: a) process approach (full time-varying selectivity), b) simplified approach (constant selectivity while fitting to the length-composition data), c) simplified approach (constant selectivity while not fitting to the length-composition data), and d) hybrid approach (full time-varying selectivity in 6-year terminal period, constant selectivity in early period).