Western and Central Pacific Fisheries Commission

SCIENTIFIC COMMITTEE
THIRD REGULAR SESSION

13-24 August 2007
Honolulu, United States of America

COMPARISON OF SOUTH PACIFIC ALBACORE STOCK ASSESSMENTS USING MULTIFAN-CL AND STOCK SYNTHESIS 2

WCPFC-SC3-ME SWG/WP-6

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Executive Summary

We present a comparison of the MULTIFAN-CL (MFCL) stock assessment of South Pacific albacore with a new assessment using the same data, but carried out using Stock Synthesis 2 (SS2). We describe differences between the two software applications and discuss their relative merits for carrying out stock assessments in the WCP-CA. The comparison did not involve improving the existing MFCL assessment, but areas for potential improvement were explored. Results confirm that there is a strong need to re-analyse the data used in the South Pacific albacore assessment and to reconfigure the model, to resolve a number of problems with the assessment (Langley and Hampton 2005, 2006).

In general very similar dynamics could be obtained from both MFCL and SS2, but subtle differences in some of the parameterizations and defaults also had significant effects. Small changes in assumptions about selectivity parameterization, both within and between models, substantially changed results. This was largely because of data problems and mis-specification of both models. Care is required in assessing what parameterization to use, and the sensitivity to assumptions.

Stock assessment software requires continual validation. This could be done by regularly running parallel assessments in MFCL and another analysis package such as SS2. SS2 needs more features, including the ability to fit to tagging data and weight frequency data, to be usable for the full yellowfin and bigeye assessments. Some of these features are planned, and a cut-down version of the data would be usable with the current version of SS2.

Introduction

This paper presents a comparison of the MULTIFAN-CL (MFCL) stock assessment of South Pacific albacore with a new assessment using the same data, but carried out using Stock Synthesis 2 (SS2) (Methot 2005; Methot 2007). WCPFC Scientific Committee 2 called for a comparison of an MFCL stock assessment with an assessment carried out using a different platform. MFCL has been used since 1998 and is the principal software used in the assessment of tuna stocks in the WCP-CA (Fournier *et al.* 1998), (Hampton and Fournier 2001).

Several alternative models use similar data and methodology to MFCL. These include SS2, A-SCALA (Maunder and Watters 2003) and CASAL (Bull *et al.* 2003) (see Appendix A). These age-based statistical population dynamics models estimate model

parameters using likelihood-based methods to measure goodness of fit, and maximize an objective function that includes both data and prior information components. SS2 was selected for the comparison with MFCL because it is able to handle the large volume of data used in WCP-CA assessments, it is under continuing active development, and because it is the most widely used of the four models identified above. It is programmed using AD Model Builder, which like MFCL uses the AUTODIFF library . Its general approach allows it to be used for a variety of stocks and species, and it is actively being developed further. It is increasingly being applied to highly migratory species: for example, it was used for the 2007 IATTC assessment of bigeye tuna in the eastern Pacific (Aires-da-Silva and Maunder 2007), and has been applied to North Pacific albacore (Crone *et al.* 2005), southeastern Pacific swordfish (Hinton and Maunder 2006) and northern bluefin tuna (Piner *et al.* 2006).

SS2 was originally developed for analysis of groundfish populations, which like tuna are harvested by multiple distinct fleets with varying selectivities. There are commonly also fishery-independent surveys, which SS2 fits to as a time series of relative abundance. Tagging data are not generally available for these groundfish stocks, so SS2 does not fit to tagging data. Ageing data are available but there is generally considerable ageing error, so SS2 fits to age frequency and length at age data, and models ageing error. Length frequency data are often collected and SS2 fits to these, but not to weight frequency or multiple resolutions of length frequency data. Groundfish growth variability is considerable, and SS2 models 'growth rate cohorts' as described below.

South Pacific albacore was selected as the stock to assess using SS2 because it is less reliant on tagging data than the other WCP-CA assessments and involves no weight frequency data; features not currently available in SS2. It is also modelled as a single region which simplifies the comparison, since tagging data can be particularly informative about movement rates among regions. The latest version of SS2 (version 2) includes both regions and movement between regions. The most recent full south Pacific albacore stock assessment was carried out in 2005 (Langley and Hampton 2005), with a data update and sensitivity analysis in 2006 (Langley and Hampton 2006). The present assessment was carried out using the same data as in (Langley and Hampton 2006).

In the 2005 albacore assessment, Langley and Hampton (2005) concluded that there was a conflict between the observed trends in catch rate from the Taiwanese longline fisheries, and the length frequency data from the longline fisheries. They stated "Future improvements to the assessment should concentrate on a detailed reanalysis of the two main data sets."

This paper focuses on comparing the modelling platforms rather than on re-analyzing datasets, and so cannot draw new conclusions about stock status. The contrast between the two modelling platforms has been used to examine the strengths and weakness of MFCL, and the prospects for using SS2 more generally for comparative assessments of WCP-CA stocks. We have also identified additional areas in which the albacore stock assessment could be improved. The results of the SS2 assessment are different from those of the MFCL assessment for reasons explained below, but no more reliable.

Background

We use the following criteria to compare MFCL and SS2.
1) Ease of implementation and use, speed, and adaptability;
2) Features relevant to the tuna species / fisheries, such as tags and regional structure; and
3) Technical issues and differences in estimated dynamics.

1. Key differences between MFCL and SS2

The main differences between MFCL and SS2 and the other modelling applications A-SCALA and CASAL are summarized in Appendix A (with tables updated from (Maunder 2005). The main differences include fitting to tagging data in MFCL but not in SS2, different methods for modelling selectivity, and different approaches to modelling catch and fishing mortality.

1) MFCL fits to tagging data, but SS2 does not. Tagging data can be informative about harvest rate, movement, and growth. Tagging data are used in many WCP-CA assessments, including the south Pacific albacore assessment.

2) MFCL selectivity is age-based only, whereas SS2 has both age-based and length-based selectivity. These approaches are described below in more detail.

3) New options for modelling catch and fishing mortality (F) have recently been added in both MFCL (Hampton *et al.* 2007) and SS2, but in this application the standard approaches were used. The standard SS2 approach is to assume that the reported catch is known exactly. Fish are removed all at once, usually in the middle of the time step though timing can be adjusted by fishery, using Pope's approximation which enables straightforward calculation of fishing mortality. The new SS2 option uses continuous F rather than Pope's approximation, but still assumes exact catch. A new option in MFCL also uses exact catch, and either Pope's approximation or continuous F.

The standard MFCL approach, used in this application, is to estimate catch rather than using exact catch. This is done by assuming that fishing mortality is proportional to catchability x effort, and estimating a parameter known as an effort deviate for each time period and fishery. Penalties for deviation from observed catch are high, so there is little difference between observed and estimated catches.

4) SS2 does not have effort deviates, but the purpose of constraining the relationship between CPUE and abundance is served by entering CPUE data as 'surveys'. Using this approach, CPUE need only be entered if it will be used / fitted to. Each CPUE entry has its own standard deviation, as estimated during CPUE standardization for example, allowing adjustment of the weight given to each data point. Catchability can be allowed to have a random walk, or a relationship with abundance or an environmental factor.

In MFCL the penalties (equivalent to standard deviations) applied to the effort deviates apply to the whole fishery, with an option to vary by time step in inverse proportion to the square root of effort. The relationship between CPUE and relative abundance can be decoupled by replacing an effort time step entry with -1; by applying a very small penalty (large standard deviation) to the whole fishery; or by allowing catchability to have a random walk.

2. Overall model run sequence and structuring

MFCL runs in Linux or in MS Windows, using an appropriately compiled version of the executable. In MFCL, the entire assessment is controlled by the doitall file, a Linux batch script that runs the assessment (and must be run under Cygwin in Windows). The doitall file takes the .ini file (which has the initial values and model structure information) and the .frq file (which holds all the data and more model structure information) and invokes the MFCL executable to create the first .par file, 00.par. The .par file contains both flags and current parameter values. The doitall then calls the MFCL executable repeatedly, through a series of 'phases' in which it adjusts program options, and switches parameters switched on and off by changing flags in the .par file. At each phase a new .par file is created. After the last phase .rep and .fit files are produced, which summarize the results and diagnostics.

SS2 runs in windows only, the executable is called directly. Model structure is defined in the .ctl and .dat files. Initial values are given in the .ctl file. SS2 also estimates parameters in a series of phases, and the estimation phase for each parameter is defined in the ctl file. Parameter values after each phase are saved in the .p01, .p02 etc files. After the model has run successfully it saves optimized parameter values in a .par file, and saves a summary of results and diagnostics in the .rep file. A new version of the control file is saved as SS2-nucontrol.ctl, with optimized parameter values as the initial values. There are some additional files: starter.ss2, which does some basic model control such as naming the .dat and .ctl files; forecast.ss2, which controls forecasting; and profilevalues.ss2, which defines how the model produces likelihood profiles.

3. Defining model structure

The structure of the SS2 South Pacific albacore model was kept similar to the MFCL model, with 20 annual age classes, one region, recruitment in the third quarter, and the same maturity at age schedule. The same 23 fisheries were defined (Table 1).

Initial values were set the same for natural mortality, von Bertalanffy growth parameters, length-weight relationship, and variation of length at age. Growth cohorts were not used; nor were time series changes in selectivity or biological parameters.

Natural mortality (M) in the albacore model is fixed as a constant value across all ages, which can easily be modelled in both MFCL and SS2. However, natural mortality varies by age in the bigeye and yellowfin MFCL assessments, to accommodate a trend from high juvenile mortality to moderate adult mortality, followed by a 'hump' in age-specific M representing increasing female mortality (Harley and Maunder 2003). SS2 would require a change to model both features, since natural mortality is restricted to two constant values with the change points connected by a linear trend.

Variation of length at age is modelled slightly differently in MFCL and SS2. In MFCL the relationship between length and SD of length at age is exponential. In SS2 there are 4 options: either age or length is linearly related to either SD or CV of length at age. The option of relating length to SD of length at age was used.

The starting year of the model was set as 1952 and defined as unexploited conditions in both MFCL and SS2. Initial conditions in MFCL and SS2 have a similar range of

options available. In MFCL the initial population size was set by recruitment at the average estimated recruitment for first 9 years, and the age structure defined by natural mortality only. In SS2 the initial equilibrium population was defined by recruitment at the expected value given maximum population size, and age structure based on natural mortality only.

SS2 and MFCL use slightly different approaches to recruitment timing and age increments, which affects age-based selectivity. In MFCL recruitment can occur in all four quarters or in one quarter. When recruitment occurs in the third quarter (as in this case), the age increment occurs at the start of the third quarter. This is arranged internally by effectively time-shifting the model to start at the recruitment quarter, and then re-mapping the results back to the initial time frame.

In SS2 selectivity can occur in any combination of quarters, and the age increment always occurs at the start of the first quarter. Since selectivity applies across the whole age class over four quarters of growth, the MFCL and SS2 selectivity estimates are not equivalent. To make the results easier to compare, this difference was resolved (when using age-based selectivity) by time-shifting the SS2 data file by two quarters, and applying recruitment in the first quarter. N.B. In this document the terms 'season' and 'quarter' are roughly equivalent, though quarter is used more for timing, while season is used more where the effects vary between quarters.

Recruitment in SS2 also occurs at age 0, whereas in the MFCL base case the first age class is defined as age 1. When comparing recruitment estimates between the models, the SS2 estimate was offset a further year and multiplied by exp(-M).

Catchability

As described above, catchability must be determined for each fishery in MFCL since catch is estimated. In SS2, catch is assumed to be exact, so catchability need only be calculated when fitting to the observed abundance indices. Two additional issues influence the CPUE data: seasonality in catchability, and changes in catchability through time.

Albacore catch rates are quite strongly seasonal in all fisheries, which is modelled in MFCL by estimating quarterly catchability offsets for each fishery. In SS2 this was modelled in an equivalent way by splitting the index by quarter, each index with its own catchability, and associating the selectivity of the fishery with each of its indices.

The various albacore fisheries have very different long term trends in CPUE, which is not consistent with all fisheries having constant catchability. These variations are thought to mostly relate to changes in targeting, gear configuration, and fisher experience, which affect catchability. For example, large decreases in Japanese longline albacore catch rates are associated with known shifts in targeting towards yellowfin and bigeye tuna.

In MFCL the catchability of the Taiwanese fisheries is held constant, but for other fisheries a random walk in catchability is estimated. Steps in this walk are estimated every 2 years, and have penalty of 50, equivalent to standard deviation of 0.1 on a log scale. The flexibility of the trend in catchability is affected by the frequency of the steps and the penalty applied. Decreasing the flexibility of the random walk will influence vulnerable abundance to follow the observed CPUE trend more closely.

MFCL estimates very large changes in catchability through time for those fisheries with a random walk in catchability.

Version 2 of SS2 is able to model a random walk in catchability, but it does not appear to be possible yet to share the random walk in q across the 4 quarters of a fishery with seasonal q, as it is in MFCL. Random walk in catchability was not used. Instead, the CPUE data were omitted for fisheries given a random walk in MFCL. The effect of omitting these data was modelled as a sensitivity analysis in MFCL by reducing the penalty on the random walk, and estimating a deviate each quarter rather than every two years.

Selectivity

MFCL has a number of options for modelling selectivity, all of which are age-based in that they produce expected catch-at-length based on the product of length-at-age and expected catch-at-age matrices. Options include a logistic curve, a double normal curve, a cubic spline curve, and an approach using penalised second and third differences. The current standard MFCL approach uses a user-specified number of parameters to define a cubic spline, though logistic functions may also be used for longline fisheries. The cubic spline approach seems stable with four parameters per fishery for the albacore tuna fishery data. The MFCL base case used cubic spline selectivity for all fisheries. A sensitivity run used the logistic model for the longline fisheries to enable more direct comparisons with the SS2 results.

SS2 has options for various functional forms and non-parametric approaches, for both age-based and length-based selectivity. Like MFCL these include logistic selectivity and double normal (in a number of different versions), and with some additional survey-related options such as pre- and post-density dependence recruitment, and spawning biomass. A cubic spline option has not been implemented.

Length-based selectivity in SS2 still applies age-based fishing mortality, but calculates the expected catch at length – C(length) – by transforming N(age) to N(length), then multiplying N(length) by S(length), rather than by multiplying N(age) by S(age) and transforming C(age) to C (length). It is also possible to use length-based fishing mortality in SS2, but we did not in this case.

Several options were tested in SS2, for both the longline fisheries and the small-fish (troll and driftnet) fisheries. Longline fisheries were initially modelled using age-based selectivity with a logistic model, and small fish fisheries were modelled using a combination of normal distributions with smoothed junctions. Subsequently the longline fisheries were modelled using length-based selectivity using the same approach – a combination of normal distributions with smoothed junctions. Two versions of fully length-based models were also examined: one with asymptotic selectivity on longline fisheries, and one with declining selectivity for some longline fisheries. In addition, the model was run with age-based selectivities fixed at the values estimated in MFCL.

Priors and likelihood weights

Both MFCL and SS2 allow the user to assign prior distributions to parameters. The two programs differ in the way they are applied, and in the parameters which can have them.

MFCL applies prior distributions via penalties, which are defined using flags. The process is complicated and not intuitive, since priors are available for some parameters but not all; the flags to use for each parameter are not systematic; some flag values are used directly and some are divided by 10; flags must be entered as integers; and (for normal distributions) the standard deviation implied by the penalty is equal to 1/sqrt(penalty). Flags are applied by commands in the doitall file, which has the advantages of flexibility and repeatability, and the disadvantages of being non-intuitive and, for the inexperienced user, prone to errors.

For example, standard deviation of 0.6 is commonly assumed for tuna recruitment variation on a lognormal scale. In MFCL when there is no SRR imposed, parest_flag(149) is used to penalize lognormal deviation from mean recruitment, but when a SRR is assumed, parest_flag(149) is turned off and age_flags(145) is used to penalize deviation from the SRR. In the first case, penalty weight of 14 gives standard deviation of 0.6. When there is an SRR, integer flags mean that 0.6 is not available, and penalty weight of 2 is used to give standard deviation of 0.5.

The SS2 approach is much more intuitive and flexible. Priors and bounds can be applied to any parameter. All values relating to a parameter are entered on the same line, including initial value, upper and lower bounds, prior distribution type, prior parameters (e.g. mean and sd for normal distribution) as real numbers, estimation phase, and links to environmental variables.

According to likelihood theory, the relationships between expected values and data are assigned a likelihood value and used to identify the parameter values that fit the data best. Likelihoods from different fits to data can be combined, because the likelihood translates the fits of the model components into a common currency. This common currency is the basis of parameter sharing, likelihood profiling, and hypothesis testing. Likelihoods usually require the user to specify the standard deviation σ of the parameter of interest. For example, the lognormal recruitment deviate likelihood might be specified as $L_R = \dfrac{1}{2\sigma_R^2}\sum_t R_t^2 + n_R \ln(\sigma_R)$. For likelihood estimation in general, the standard deviations are difficult to estimate within the model so must almost always be added and then validated later. The standard deviation (or variance) serves (at least) three purposes: to weight the likelihood appropriately against other likelihoods, to allocate appropriate levels of uncertainty to deviates with little data, and to restrain parameter estimates to within a reasonable range.

A useful feature in SS2 is that the relative weighting of variance factors in the likelihoods can be adjusted using variance adjustment factors, and likelihood components can be given greater or lesser weight by multiplying them by 'emphasis factors' (lambdas). Both types of factor are entered in the .ctl file, and are available by fishery and survey for each likelihood component.

The variance adjustment factors are added to survey CV's or multiplied by effective sample size. The output of SS2 includes estimates of effective variance, which can then be applied when re-running the model using iterative reweighting. This is more convenient than adjusting individual data components in the .dat or .frq file, such as changing effective sample sizes of length frequency data, or the standard deviations of CPUE estimates.

The lambdas are multiplied by their relevant likelihood components and can be changed from phase to phase, in order to make the process of fitting to the data run smoothly. The equivalent approach in MFCL for progressively emphasizing different parts of the likelihood during the fitting process is to use commands in the doitall file to change penalties, although this is equivalent to adjusting CV or effective sample size.

4. Formulation of datasets

The data for SS2 were taken from the MFCL input data set.

Catch data

Most catch data could be transferred directly from the MFCL to SS2 data files after changing it to the appropriate data format. Both models accept catch in either weight or numbers, but SS2 counts numbers in thousands whereas MFCL uses actual values. Both models take weight in metric tonnes, lengths in cm, and parameterize the length-weight relationship in cm and kg.

MFCL permits entries of -1 where catch estimates are missing, but SS2 requires catch estimates for every time step and fishery. Catch data and effort for 2005 were missing for fisheries 1, 2, 7, 8, 9, 11, 13, 14, 17, and 18, so these catch data were replicated by season from 2004 catch data. Catch data for fishery 14 were also missing for 2003, so both 2004 and 2005 catches were replaced with 2003 catches.

This replacement process has a slightly different effect from the approach used in this MFCL albacore assessment, which was to copy effort data from the previous year or years. This approach results in estimated catch that follows the assumed relationship between effort and fishing mortality, so catch will not be the same given the effects of effort deviates and changes in abundance. The reliability of any estimates for the last year is low, given that the catch (or effort) invented for SS2 (or MFCL) represents about half the total catch (or effort) and harvest rate, but effort may be more consistent than catch when biomass is changing. In both cases the data are invented, but either catch or effort can be invented in MFCL. Replicating effort data may also give more realistic estimates of uncertainty in harvest rate and biomass, because of the uncertainty in the effort deviates.

CPUE data

As outlined above, CPUE data need only be entered in SS2 for those fisheries for which CPUE is thought to be informative about abundance. In the MFCL albacore analysis the penalty is multiplied by sqrt(effort) and normalised to average effort. The standard deviation at average effort is, given effort penalty of 10, equal to 1/sqrt(20) or 0.2236, and varies in inverse proportion to the fourth root of effort. Survey values were entered into SS2 as year, quarter, index ID, observation, standard deviation. Standard deviation was calculated by multiplying the CV at average effort by the fourth root of (average effort divided by effort).

Length frequency data

The length frequency data in MFCL are entered as frequencies by individual length bin. Adjustment to sample sizes (n) occurs during processing using fish flag 49, with min(1000, n)/flag giving effective sample size. The default value of 10 for the flag was used for the albacore analysis, with maximum effective sample size of 100 in this case.

In SS2, length frequency data are entered with sample size given first, followed by the proportion in each length bin. The bin width may vary. Sample sizes may be adjusted at data entry to effective sample size, or can be adjusted later using lambdas (emphasis factors) which exist for each fishery and survey, and are multiplied by the variance.

In the SS2 albacore analysis, the same effective sample sizes of nominal/10 with a maximum of 100 were used as in the MFCL analysis. Length bins were 2 cm wide instead of 1 cm in order to speed up the analysis, and sensitivity was checked by running the final version with 1 cm bins.

Tag data

The current version of SS2 does not fit to tagging data. To facilitate comparisons and see where differences in results might originate, we also ran MFCL without tagging data.

Other data types

Unlike the south Pacific albacore analysis, the WCP-CA yellowfin and bigeye stock assessments use weight frequency data as well as length frequency data. SS2 does not fit to this data type. Weight frequency could be converted into length frequency according to the length-weight relationship, but this would introduce problems with lack of smoothness in the bins and with appropriate sample sizes. Rick Methot (personal communication) has plans to add this data type to SS2.

Summary of methods

MFCL was set up as described by Langley and Hampton (2006) for the 'base case', except that natural mortality was fixed at 0.35 in order to increase model stability. In order to focus on model structure and comparisons between approaches, the 2006 data were not updated. The model includes 23 fisheries (Table 1).

SS2 was set up as described above. The SS2 control file for the base case run and parts of the data file are included in Appendix B. The various runs are described below, with the names of the runs in brackets at the start of each paragraph. Options are summarized in Table 3.

1. Initial comparison run (SS2 with MFCL selectivities, MFCL base case)

To assess the similarity of outcomes under similar conditions at several levels, an initial run was carried out with parameters constrained to be the same in SS2 as they are in MFCL. Constrained parameters were: selectivity at age by fishery, the

biological parameters including growth, natural mortality rates, and variance of length at age. Only the mean recruitment and temporal recruitment deviates were estimated.

2. Base case runs (SS2 base case, MFCL base case)

The base-case version of the SS2 model was run with age-based selectivity on longline fisheries and length-based selectivity on the troll and driftnet fisheries that target small fish. Age-based selectivity on longline fisheries was estimated using a logistic function with two parameters: age at inflexion point, and width of the 95% selection. Age-based selectivity on small fish fisheries (troll and driftnet) using a functional form-based parameterization in SS2 was difficult to stabilize, because the narrow length range observed in the length frequency data did not sit easily within one or more age classes, given the growth curve and the distribution of lengths at age. Length-based selectivity was stable and parameterized as a 6 parameter double normal distribution, estimating peak, plateau width, ascending width, descending width, initial selectivity and final selectivity. In the MFCL base case there were no tagging data, and natural mortality was fixed at 0.35.

3. Longline selectivity functional form

A version of the MFCL model was run with longline selectivities defined using the logistic function. This was done for comparison with SS2 age-based longline selectivities, which were also parameterized using the logistic function.

4. CPUE time series (MFCL flexible q, MFCL penalized effort)

The MFCL analysis was run with a more flexible random walk in catchability deviates for the non-Taiwanese fisheries, and with a minimal penalty on the effort deviates of those fisheries ("MFCL flexible q"). This was to identify the source of differences with SS2, because CPUE series other than those from the Taiwanese fisheries were not used in the SS2 analysis. Another version was run with the additional change of higher weights on effort deviates in the Taiwanese fisheries ("MFCL penalised effort").

5. Tagging data (MFCL tagging data)

Tagging data are used in MFCL to estimate harvest rate, and to constrain movement in multiple-region models. SS2 does not currently fit to tagging data. The importance of the tagging data for the assessment was investigated by estimating likelihood profiles for the population scaling parameter in MFCL with and without the tagging data (using "MFCL base case"). A likelihood profile was also estimated for the SS2 base case.

6. Length-based selectivity (SS2 length-based selectivity)

A version of the SS2 model was run using length-based selectivity on all fisheries, including the longline fisheries. Length-based selectivity for longline fisheries was

parameterized as for small-fish fisheries, except that final selectivity was fixed at full selectivity. Due to problems with stability and with estimating growth rate, this model was run with growth rate and variation of length at age fixed at the MFCL posterior estimate.

Results

The SS2 run with MFCL selectivity gave similar initial spawning biomass and subsequent trend early in the time series to the MFCL model (Figure 1). However, the two time series diverged due to different recruitments in recent years (Figure 2) and the 2006 spawning biomass was estimated to be much lower. Recruitments were mostly similar, though SS2 was more variable and with lower recruitments at the end of the time series.

Patterns in the length frequency and residuals reflect conflicts between the various data sources, inadequacies in the overall model structure, and problems with the data, as identified in previous MFCL assessments. Similar results were obtained using the model with age-based selectivity, and more detail is given in that section.

Age based selectivity

The MFCL base case consistently estimating full selectivity to occur much older than the SS2 base case (Figure 3). The MFCL logistic selectivity run estimated selectivities for the major fisheries (1, 2, 7, and 8) and some other fisheries that were much closer to the SS2 base case, but in some cases quite different, particularly for fishery 11 which selected only fish aged 20. Overall biomass in the MFCL logistic selectivity model increased to the upper bound of the scaling parameter, indicating that the solution found by MFCL with cubic spline selectivity is not stable with this form of selectivity. A similar problem occurs with length-based selectivity in SS2 – see below. The form of the selectivity function appears influential, particularly in a case like this one in which selectivity appears to vary through the time series (see below).

Length frequency residuals are similar from the MFCL base case and the SS2 base case (Figure 5, Figure 6, Figure 7, and Figure 8).

Both analyses show remarkably poor fit to some strong cohorts in recent years. For example, a strong cohort, substantially under-predicted by the model, can be seen entering the longline fishery in the late 1990's, particularly in data from the New Caledonian longline fishery (fishery 4) in area 1. The cohort is also apparent in data from the Tonga and French Polynesia longline fisheries (fisheries 10 and 11) in area 2 and the New Zealand longline fishery in area 3 (fishery 16).

The residuals suggest changes in selectivity through time in the Taiwanese fisheries, since in all four fisheries (2, 8, 14, and 18) positive residuals are more common among small fish early in the time series and among large fish late in the time series, though the fisheries all have different selectivities. Length frequency residuals for the Japanese longline fishery in area 3 (fishery 13) show influential residuals from more small fish than expected early in the time series, and more large fish than expected later in the time series. Some of this is probably due to seasonal selectivity, and some due to changes in fishing practises, such as targeting different species.

The SS2 and MFCL base case recruitment time series have similar patterns of peaks and troughs, but the SS2 time series is consistently higher early, and finishes at a lower level (Figure 9). Similarly, the spawning biomass (Figure 10) and total biomass (Figure 11) time series start higher and finish lower than the MFCL base case time series.

Effort deviates were only estimated in the SS2 analyses for the Taiwanese longline fisheries. In these fisheries, estimates are very similar to the MFCL base case estimates (Figure 12, Figure 13, Figure 14,). Results from both models indicate that, from the early 1960's until the mid 1970's, the increasing estimated vulnerable biomass time series does not fit the decreasing Taiwanese longline CPUE trends in areas 1 (fishery 2), 2 (fishery 8), and 4 (fishery 18). These effort deviate series are reasonably consistent across all areas and seasons (Figure 16 and Figure 17), although in area 3 the data are too sparse to observe a pattern.

Growth rates and variation of length at age estimated from the two models are also similar, although the SS2 base case analysis results in slightly higher length at maximum age and narrower distribution of length at age (Figure 18).

Catch rates of non-Taiwanese fisheries

The MFCL flexible q model was run with reduced penalties on the q deviates and the effort deviate for the non-Taiwanese fisheries, to effectively remove the influence of this catch rate information as an index of abundance. From 1968 until 1982 there was a slight increase in the relative spawning biomass of the version without q deviates, followed by, after 1997, a sharp reduction in the spawning biomass (Figure 19). The recent decline is more consistent with the results from the SS2 base case model (Figure 1).

Weight on effort deviates

The MFCL penalized effort was run with more penalty weight on effort deviations in the Taiwanese longline fisheries, given the poor fit to these data early in the time series. Relative to the standard model, the reduced penalty model finishes with spawning biomass much lower than initial biomass (43% versus 65%) (Figure 20). Most of the relative differences occur between 1964 and 1981. Data from the Taiwanese longline fisheries is introduced in 1964, and the other data during this period come from the Japanese and Korean longline fleets.

The effort deviates of the Taiwanese fisheries show poor fit to the CPUE time series in both the standard version of the model and the version with down-weighted CPUE time series.

Tagging data

Likelihood profiles for MFCL with and without the tagging data were similar (Figure 21). The maximum likelihood value for the population scaling parameter was smaller with the tagging data than without the tagging data, but the difference was not statistically significant. The width of the distribution on a log scale was similar with and without the tagging data. The difference between the two profiles may be due to the very low prior applied to the tag recovery rate (mean = 0.1).

SS2 with length-based selectivity

SS2 was run with longline fishery selectivity length-based rather than age-based. Likelihoods (Table 2) for the length-based model were generally worse, indicated by a negative value in the 'Difference' column. Age-based selectivities fitted the data better in all but one of the longline fisheries in areas 1 and 2. Length-based selectivities fitted better in four of the six longline fisheries with data in areas 3 and 4. Both models used length-based selectivities for the small-fish fisheries, and the worse fit to these by the fully length-based model reflects the way the model is trying to fit to another component of the likelihood. The recruitment likelihood is also larger in the length-based model, reflecting both higher variability and a long term trend that takes recruitment further from the average.

Selectivities are shown in Figure 22. Recruitment is much higher in the length-based selectivity model than in the age-based (Figure 23), as are spawning biomass (Figure 24) and total biomass (Figure 25), but the overall relative trends in the three time series are similar.

Length frequency residuals (Figure 26, Figure 27, and Figure 28) appear very similar to those estimated using age-based selectivity in SS2. However, differences appear when the expected length frequencies for age-based and length-based selectivity are compared (Figure 29). Both seasonality and long term temporal differences between length frequencies before and after 1975 are apparent (Figure 30), indicating that including them would improve the model. They appear in the plots of observed versus expected length frequencies for a number of the fisheries – the Taiwanese longline fishery in area 2 (fishery 8) is one example.

Discussion

Very similar dynamics can be obtained from both MFCL and SS2, but subtle differences in some of the parameterizations and defaults can also have significant effects. This may be particularly the case when data are limiting or confounded. In this example small changes in assumptions about selectivity parameterization have substantially changed results, because of data problems and mis-specification of both models. Care is required in assessing what parameterization to use, and the sensitivity to assumptions.

Comparing the applications of MFCL and SS2 to the south Pacific albacore assessment has indicated a number of areas in which the albacore assessment, MFCL, and SS2 could be improved. In the following section the relative merits and abilities of the two programs are discussed in reference to both to this assessment, and more generally to tuna assessments in the WCP-CA.

1. Features relevant to tuna species

MFCL was developed for tunas, and more specifically for assessing stocks of tunas in the WCPO, using the available data. SS2 on the other hand was developed for groundfish species in the Pacific northwest of the US. This difference is reflected in some of their features.

For example, MFCL's more flexible parameterization of natural mortality is used in bigeye and yellowfin models to model high juvenile mortality and to accommodate

the decline in proportion of females with age in a single sex model. High juvenile mortality can be modelled in SS2, and the sex ratio change could be modelled in the current version SS2 using a two-sex model. However, it would not be possible to model both high juvenile mortality and the sex ratio change with SS2's relatively inflexible natural mortality schedule.

The WCP-CA yellowfin and bigeye assessments include a lot of tagging data, and more is being collected, so fitting to this data type is essential for these assessments, although with appropriate constraints the models will fit without tagging data. There are plans to begin work on adding tagging data to SS2 (Richard Methot personal communication).

Similarly, the WCP-CA yellowfin and bigeye assessments include weight frequency data as well as length frequency data, and the weight frequency data are an important input. Although SS2 does not currently fit to weight frequency data, there are plans to add the ability to fit to size data at more than one resolution (Richard Methot personal communication), which would permit the use of weight frequency data. Assessments using MFCL would also benefit from changing the model to accommodate weight frequency data at more than one resolution. For example, many recent striped marlin data are reported at 1 kg resolution, but some historic data are available at 5 kg or 10 kg resolution.

MFCL will model trends in catchability, as will SS2, but because MFCL estimates seasonal catchability, it is able to share the catchability trend (which is presumably driven by changes in targeting and technology) among all the seasons in the fishery. In SS2 on the other hand, seasonal catchability is modelled by splitting the overall CPUE index among 4 indices, and we could not work out a way to share the catchability trend parameters among all the indices in a fishery. There may be a way to trick SS2 into accommodating this feature, or it may require a change to the code.

Length-based selectivity is a realistic SS2 feature that appears appropriate for modelling tuna fisheries. The analysis using length-based selectivity on all fisheries did not work well in this application, giving inflated estimates of biomass in a similar way to the MFCL logistic selectivity model. Given the known major inconsistencies in the length frequency data, this was probably not a fair comparison. Length-based selectivity did work well for the small fish fisheries, giving more reasonable selectivity estimates than the age-based estimates.

2. Ease of implementation, speed, and adaptability

Fisheries modelling software tends to have a steep learning curve, because using them appropriately requires a great deal of background knowledge about population dynamics, mathematical statistics, fish biology, fishery data, and the fisheries themselves. However, MFCL is more difficult to learn to use than most. SS2 has similar functionality, but is more straightforward to learn and to work with.

The way flags are used in MFCL is one of the main differences in user-friendliness with SS2. Flags control most of the program options, but it is difficult to remember which flag relates to which option, and easy to mistakenly set the wrong flags. There are plans to develop a user interface to record the flags and relate them to their function.

One of the things that has stopped MFCL from being used more widely is a perceived lack of transparency. The updated manual (Kleiber et al. 2006) from April 2006 has improved this situation and provides good information about the internal structure of the model and the equations used. However, it does not cover all the features, and information about some flags is missing.

It is difficult to debug MFCL and decipher the code, because it is constantly under development, there is redundancy in the code, variable names may be somewhat cryptic, and the code is very sparsely documented. Changes between versions can only be determined by running a 'differences' analysis on the source code. The code distribution contains multiple versions of a number of files, some of which are not included in the executable and some of which are, so that it is hard to tell which sections of code are being used. The only reliable way to understand what MFCL may be doing is to run it through a debugger. This is not a trivial exercise and may be beyond many practitioners.

SS2 is more transparent. The technical manual (Methot 2005) is informative about the model structure and underlying equations. The user manual (Methot 2007) provides step by step instructions on how to implement a model. The technical manual is somewhat out of date (version 1.17, March 2005), but the user manual (version 2.00c, March 2007) is only slightly behind the code (version 2.00g, June 2007). Debugging SS2 is easier than debugging MFCL because it has many more internal comments, variable names are not quite as cryptic as those in MFCL, there is only one file in the code distribution, and changes between versions are listed in the user manual.

3. Technical issues and differences in estimated dynamics

A few technical issues lead to differences in the dynamics between the two models. One of these is the different methods for parameterizing selectivity. To remove this effect the initial run fixed the SS2 selectivities and other parameters at the MFCL selectivity estimates, but differences in dynamics were still apparent (Figure 1 and Figure 2). Part of this was due to another technical difference – the fact that SS2 updates ages on January 1, but MFCL updates ages before the quarter of recruitment (quarter 3). Time-shifting SS2 in order to make selectivities-at-age comparable with MFCL was probably responsible for the timing offset apparent in the early period. The offset after 1970 and the steeper decline of the SS2 analysis at the end were probably caused by stiffness in the catchability deviates in MFCL for the non-Taiwanese longline fisheries. Despite different methods for parameterizing initial conditions, the models' behaviour is similar at the start of the time series.

The SS2 base case model using age-based selectivity estimated dynamics quite similar to those estimated using MFCL. Differences are likely to mainly relate to two features: the form of the selectivities, including the use of length-based selectivity for small-fish fisheries, and the logistic function for age-based selectivities; and including CPUE trends of all the fisheries in the MFCL model. The similarity is expected given that the data and approaches were basically the same.

The probably unrepresentative decline in the Taiwanese CPUE at the end of the time series is followed more closely by biomass in the SS2 assessment than in MFCL. This sharp decline coincides with a change in Taiwanese longline fishing practices towards targeting bigeye and is unlikely to reflect an actual change in abundance. The difference between the models is because in the MFCL assessment the decline is

restricted by increasing CPUE in other fisheries and by stiffness in the catchability deviates of those fisheries. This fairly arbitrary level of stiffness is influential, as demonstrated by the results when the catchability deviates are loosened. A much better approach would to find an explanation for the observed decline in Taiwanese CPUE and, by standardization or otherwise, account for it appropriately.

Age-based selectivity on small-fish fisheries using a functional form-based parameterization in SS2 was unstable, and was not used. The length range observed did not fit the model, given the growth curve and the distribution of lengths at age. MFCL was able to estimate parameters using the cubic spline approach, and estimates that these fisheries are primarily based on a single age class (Figure 3). The residual pattern suggests that the length-based selectivity fits the data better for these fisheries (Figure 8). Selectivity is by nature a length-based process, and modelling it as age-based is usually an approximation. There is an interaction between estimating selectivity and estimating growth rates, and using length-based selectivity is likely to give better estimates of growth rates. In an age-class for which only the larger half of the fish are selected, the expected mean observed length at age will be the true mean length at age for age-based selectivity but larger than the mean length at age for length-based selectivity.

The cubic spline and logistic selectivity functions for longline selectivities in MFCL also resulted in different selectivity estimates, demonstrating how influential the functional form can be. The cubic spline is more flexible and seems more stable, so may be a better approach for both age-based and length-based selectivities.

The assessment using length-based selectivity estimated a similar biomass trajectory to the other assessments, but considerably scaled up. The SS2 and MFCL base case model estimates were more consistent with the tagging data, but may also be scaled up overall. Biomass scaling from tagging data is limited at the upper end by the maximum bound of tag return rate for a few fisheries, and also influenced by the prior mean on the tag reporting rate. Even with the low prior mean tag return rate of 0.1, the model predicts more tag returns from most fisheries than are observed, so lower biomass estimates would also be consistent with the tagging data.

More investigation is needed as to why biomass is so large in the length-selectivity model, but the length-frequencies have the most effect on the overall likelihood, and larger biomass may have helped the model reduce the length frequency likelihood. A similar effect occurred with logistic longline selectivities in MFCL. The effective seasonality of age-based selectivities (given that fish grow all year but stay the same age all year), combined with the flexible cubic spline, may have matched observed patterns in some of the more influential fisheries, and explain why the age-based selectivity model has a better likelihood.

4. The albacore assessment

As pointed out previously (Langley and Hampton 2005; Langley 2006), a number of improvements could be made to the south Pacific albacore assessment. In the SS2 assessment, there were strong patterns in the CPUE (Figure 17) and length frequency residuals, which indicated the same problems with the data found in previous MFCL assessments. There is a lack of fit at the start of the time series, due to conflicting information in the Taiwanese longline CPUE data and the longline length frequency data.

Conflicting data sources

One of the main problems is unresolved conflicting data sources in the model. There is a strong trend in the effort deviates of the Taiwanese fishery CPUE time series from 1964 until 1981 (Figure 16). There is a conflict between information in the length frequency data, which the model interprets as due to increasing stock size, and in the Taiwanese CPUE time series, which imply a decline over this period. Given the relative sample sizes, the length frequency data are more influential in the model and they prevail.

However, when conflicting information comes from two data sources, it is not appropriate to include both without resolving the discrepancy (Schnute and Hilborn 1993;Patterson *et al.* 2001). Explanations for the conflict should be investigated. If there is doubt about the correct solution, the uncertainty can be included in the stock assessment by running alternative models under different assumptions.

Catchability deviates and CPUE time series

The stiffness of the non-Taiwanese CPUE time series is influential, given that removing it strongly affects the end of time series. One problem with using catchability deviates is that the somewhat arbitrary selection of deviate weight and frequency can affect the assessment results. Estimating catchability deviates should remove the contribution of the time series to estimating overall abundance, though this depends on the flexibility in catchability granted by the deviates. Without an *a priori* method for estimating an appropriate level of stiffness for the deviates, there may be little benefit in retaining these CPUE series in the model, particularly for longline fisheries. CPUE series for fisheries targeting small fish may be informative about pulses of recruitment, but CPUE of these fisheries, on aggregated schools of fish, is generally an imprecise indicator of abundance and may be hyperstable. Major changes in catchability are likely to reflect changes in fishing practises, which may also affect selectivities.

The effect of the catchability deviates has been to mitigate the effect of the recent steep decline in Taiwanese longline CPUE, which is itself more likely to reflect a change in fishing practices than a change in abundance. This steep decline in CPUE has a significant effect on estimates of stock status. It will be important to determine the reasons for this decline, perhaps through standardizing the time series by introducing targeting information. Alternatively, the time series may need to be truncated.

Length frequency data

Length frequency data are very influential in the south Pacific albacore model. SS2 provides a number of diagnostic tools for length frequency data which are good for looking for lack of fit in the data. Several issues were apparent in the length frequency data. First, selectivity of many fisheries is seasonal (e.g. Figure 30). This no doubt occurs because the fisheries are subtropical and defined spatially, so that temperatures and thermocline depths change with the seasons, affecting the way longline gear fishes, and fish of different sizes move around during the year.

Given the effects of seasonality on the size of fish caught, the assumption of asymptotic selectivity for longline fisheries will need to be relaxed for a number of fisheries when seasonal selectivity is introduced.

Selectivity of several fisheries appears to change considerably through time, and there also are occasional short term changes. The spatial distribution of the length frequency samples needs to be representative and consistent; the samples need to be investigated and unrepresentative samples omitted. Changes in fishing practices can change selectivity, in which case fisheries should be modelled in two or more parts.

Very strong cohorts are apparent in some of the length frequency residuals, but are not being picked up by the assessment. Estimates of recruitment in the model seem to be driven by overall biomass trend indicators, such as the recent decline in the Taiwanese CPUE, and the changes in average length through time discussed above, rather than picking up cohorts in the length frequency data. These cohorts appear to be important in driving abundances, and the ability of future assessments to pick these up will be an important diagnostic of their reliability and usefulness.

Tagging data

The MFCL likelihood profiles indicate that the information in the tagging data is compatible with the conclusions reached without these data. The results are not significantly different, though the population scaling parameter is slightly lower when tagging data are included.

Some problems might be expected modelling the tagging data with a single region model, given that the tagging model assumes complete mixing throughout each region. However, in general the data fit the model reasonably well, although tag returns in area 1 are generally lower than expected. The tag return rate for the New Zealand longline fishery in area 3 has hit the upper bound of 0.9, which is likely to be limiting the population scaling factor at the upper end. A larger population would imply lower F and hence fewer expected tag returns.

5. Future WCP-CA assessments

The software used for WCP-CA stock assessments is an integral part of the science, and to be reliable it needs to be carefully examined. All software contains errors. Software engineers have used mark-recapture techniques to estimate the number of errors in computer systems, and the rule of thumb is generally that the more bugs you find in a given amount of searching, the more remain that you have missed. For example, this year at least 2 bugs have been found and fixed in MFCL that changed the biomass trajectory early in the time series, and a bug in the implementation of seasonal recruitment was found in SS2 during this model comparison.

MFCL is seen as reliable because it has been used for a number of years, and has given results that have been accepted. Similarly, software packages such as Matlab or R are trusted because they have been very widely used and the results tested, and errors are now rarely found in most routines. However, MFCL is under constant development which can introduce new errors; and the user base is very small, so errors can remain a long time without being picked up.

Much science is done using open source software such as R. The code used in open-source software is available for anyone to check, but this potential advantage of open source is most effective if there is a large knowledgeable user base who can follow the code. MFCL is open source and the code is available on request. However, the user base is very small and the code is not written to be easy to follow.

A more effective way to continually validate the MFCL assessments would be to regularly run parallel assessments in another analysis package such as SS2. As described above, SS2 needs more features to be usable for the full yellowfin and bigeye assessments, but some of these features are planned, and a cut-down version of the data would be usable with the current version of SS2. The ability to run parallel assessments, both for WCP-CA tuna and for other fisheries, is a good reason to stay with and further improve MFCL, rather than switching to SS2 if it were to be developed into a more tuna-friendly package.

The MFCL work program includes a re-write as a multi-species multi-stock model. This will be a significant task, but also an opportunity. Writing the new software using modern versioning and documentation protocols in an open-source programming framework would allow the code to be understood, maintained, and improved by competent scientific programmers other than the primary developer. Maintaining and updating poorly documented software is generally a lot more time consuming than writing a new or enhanced version of the same software. The user interface could also be changed to generalize the use of priors, bounds and initial values, and improve usability. Improving the documentation, transparency and usability of MFCL will help to increase the user base. More scrutiny of the code and results will help to further improve the reliability of MFCL.

Acknowledgements

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Tables

Table 1: Fisheries defined in the model

Fishery	Gear	Nation	Area
1	Longline	Japan, Japan deep water longline, Korea	1
2	Longline	Taiwan deep water	1
3	Longline	Australia	1
4	Longline	New Caledonia	1
5	Longline	Fiji	1
6	Longline	Other	1
7	Longline	Japan, Japan deep water longline, Korea	2
8	Longline	Taiwan deep water	2
9	Longline	Western Samoa	2
10	Longline	Tonga	2
11	Longline	French Polynesia	2
12	Longline	Other	2
13	Longline	Japan, Japan deep water longline, Korea	3
14	Longline	Taiwan deep water	3
15	Longline	Australia	3
16	Longline	New Zealand	3
17	Longline	Japan, Japan deep water longline, Korea	4
18	Longline	Taiwan deep water	4
19	Longline	Other	4
20	Troll	All troll	3
21	Troll	All troll	4
22	Driftnet	All driftnet	3
23	Driftnet	All driftnet	4

Table 2: Likelihood components for the age-based and length-based SS2 models.

Likelihood component		Age-based	Length-based	Difference	MFCL
Total		12792.8	13649.2	-856.4	-304070.7
Indices		153.7	184.2	-30.4	3071.6
Length composition		12625.4	13397.4	-772.0	-307657.1
Recruitment		14.7	62.0	-47.2	
Priors		0.1	5.7	-5.7	
Len comp by fleet					
	1	1653.7	1841.3	-187.6	-39867.1
	2	740.5	756.5	-16.0	-25674.8
	3				
	4	528.0	595.7	-67.7	-16625.5
	5	198.3	235.2	-36.9	-8401.8
	6	514.4	563.0	-48.6	-9785.1
	7	2665.3	2890.5	-225.2	-49708.0
	8	1206.8	1324.2	-117.4	-34617.6
	9	194.9	241.3	-46.5	-7420.4
	10	334.8	377.0	-42.2	-12355.2
	11	492.9	406.6	86.3	-9366.1
	12	233.9	260.3	-26.3	-7124.8
	13	1218.7	1217.8	0.9	-25131.8
	14	24.5	24.7	-0.2	-2201.0
	15				
	16	349.8	339.1	10.7	-4861.1
	17	612.5	620.8	-8.3	-19828.2
	18	373.5	343.6	29.9	-14513.1
	19	1.6	1.2	0.4	-193.4
	20	668.7	733.6	-64.9	-8455.1
	21	573.2	587.7	-14.4	-9471.0
	22	20.8	22.5	-1.7	-1368.3
	23	18.7	15.1	3.6	-688.1
Indices by fleet					
	2	41.8	53.3	-11.5	
	8	146.9	165.9	-18.9	
	14	-6.0	-2.7	-3.3	
	18	-29.0	-32.3	3.3	

Table 3: Model runs in both MFCL and SS2, and their characteristics.

Run name	MFCL					SS2		
	Base case	logistic selectivity	flexible q	pen. effort	tagging data	Base case	MFCL sel.	length-based sel.
Longline selectivity	age-based cubic spline	age-based logistic	age-based cubic spline	age-based cubic spline	age-based cubic spline	age-based logistic	age-based	length-based asympt. half-norm
Troll & driftnet selectivity	age-based	age-based	age-based	age-based	age-based	length-based	age-based	length-based
Tagging data	No	No	No	No	Yes	No	No	No
Offset timing	No	No	No	No	No	Yes	Yes	No
Mean LL effort dev penalties	0.22	0.22	0.22 TW LL, 0.7 other	0.1 TW LL, 0.22 other	0.22	0.22 TW LL	0.22 TW LL	0.22 TW LL
q dev penalties (non-TW LL)	sd=0.1, freq = 2 years	sd=0.1, freq = 2 years	sd=0.7, freq = 6 months	sd=0.1, freq = 2 years	sd=0.1, freq = 2 years	n/a	n/a	n/a
Estimated parameters								
Selectivity	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
Growth pars (L∞, K)	Yes	Yes	Yes	Yes	Yes	Yes	No	No
sd L at age	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes

Figures
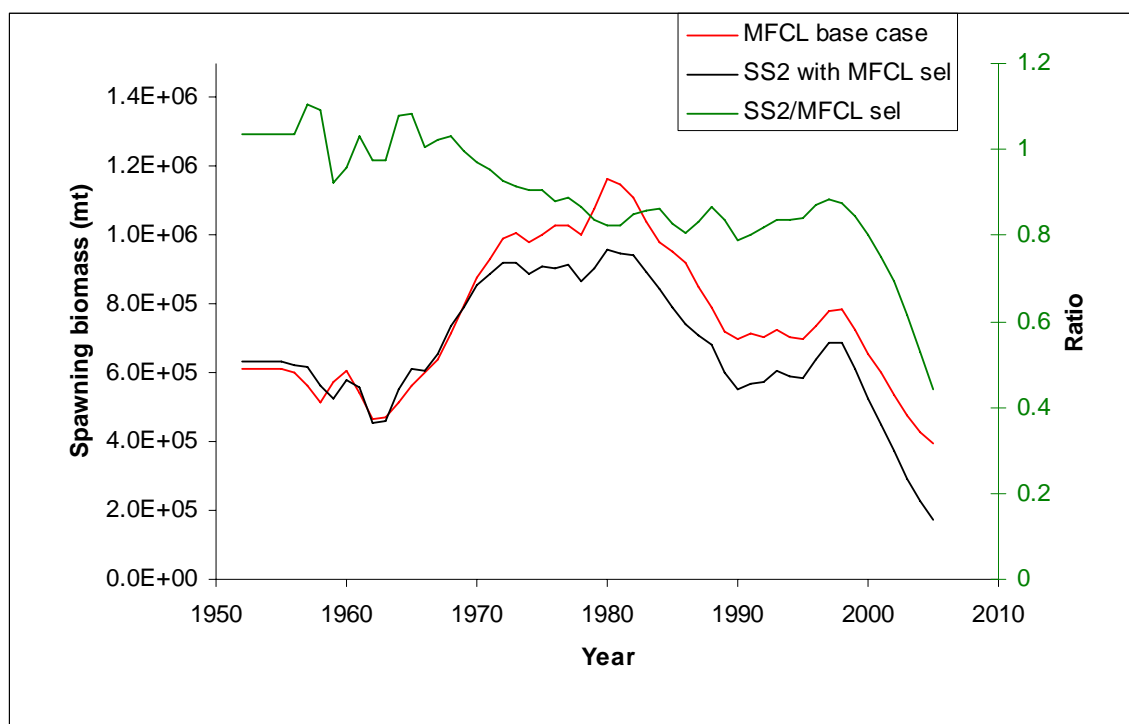
Figure 1: Spawning biomass estimated using the MFCL base case and SS2 with MFCL selectivities, and the ratio of the two spawning biomass estimates.
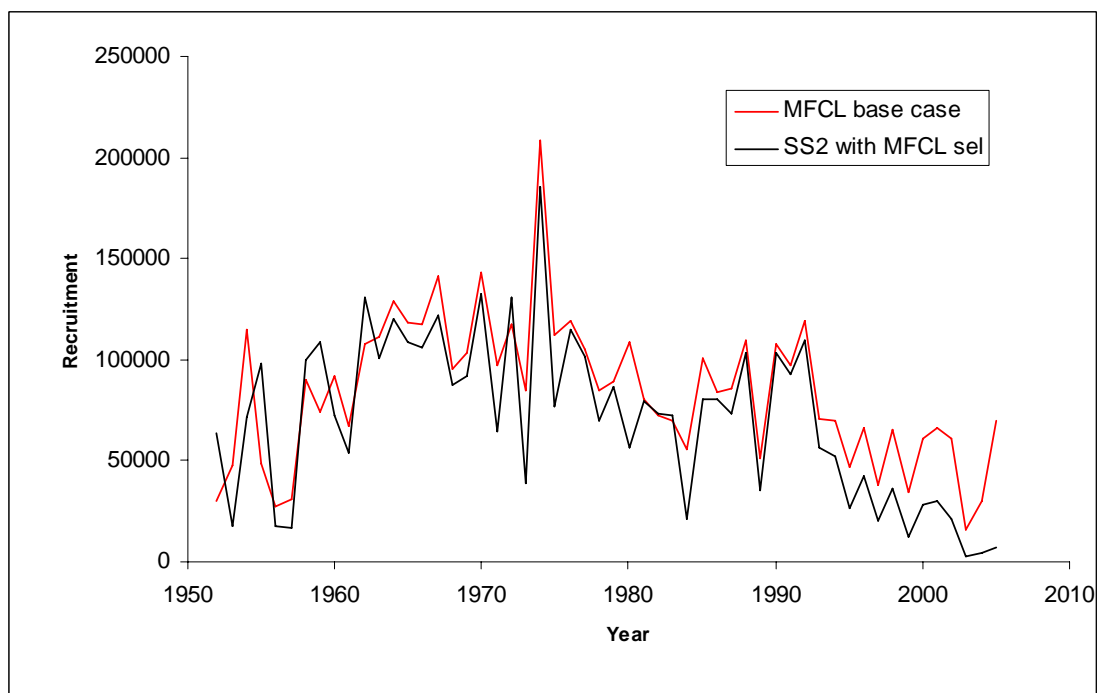
Figure 2: Annual recruitment time series for the MFCL base case and SS2 with MFCL selectivities.
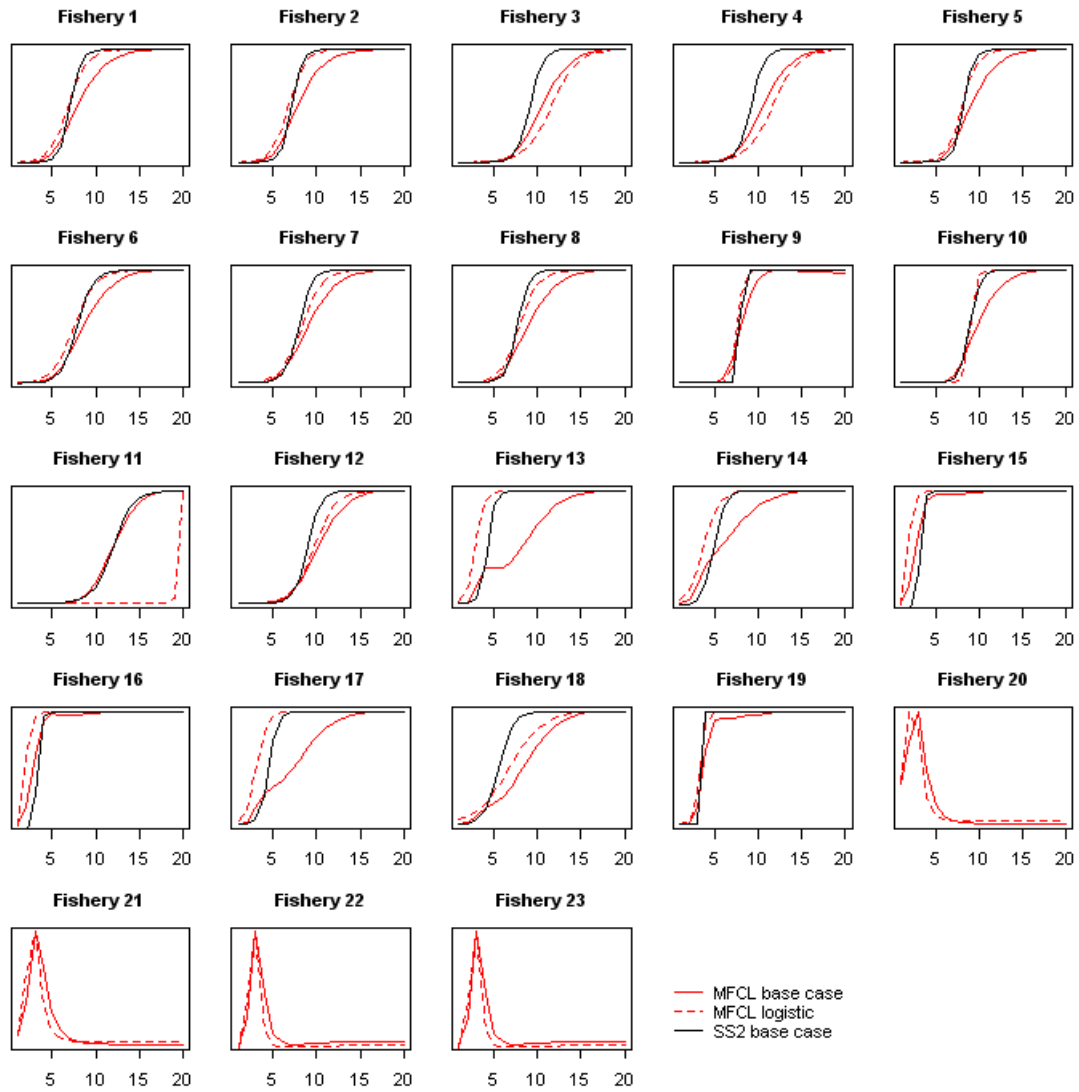
Figure 3: Selectivity at age estimated using the MFCL base case, the MFCL logistic selectivity model, and the SS2 base case. Selectivities for fisheries 20 to 23 were length-based in SS2.
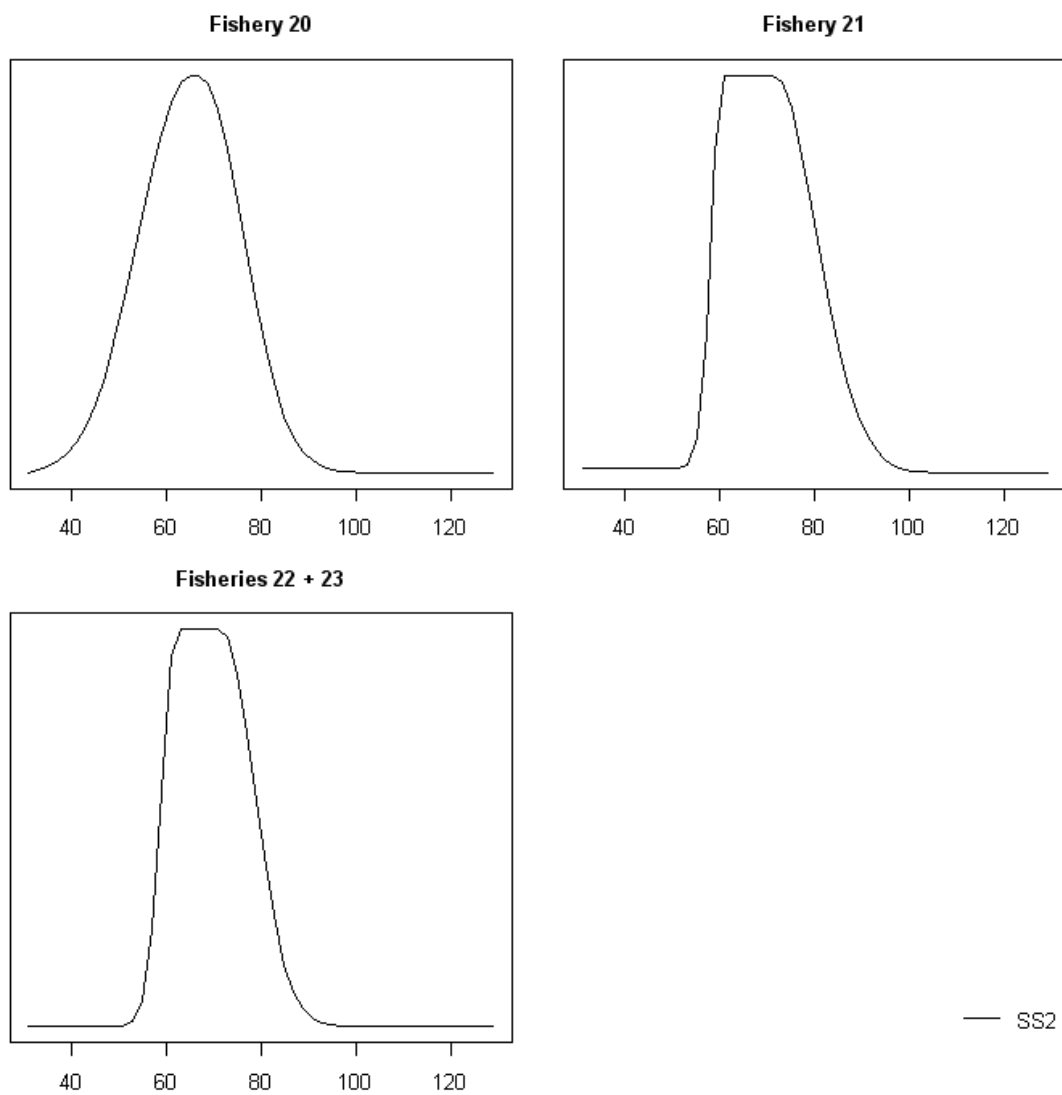
Figure 4: Length selectivities for small fish fisheries estimated in the SS2 base case.
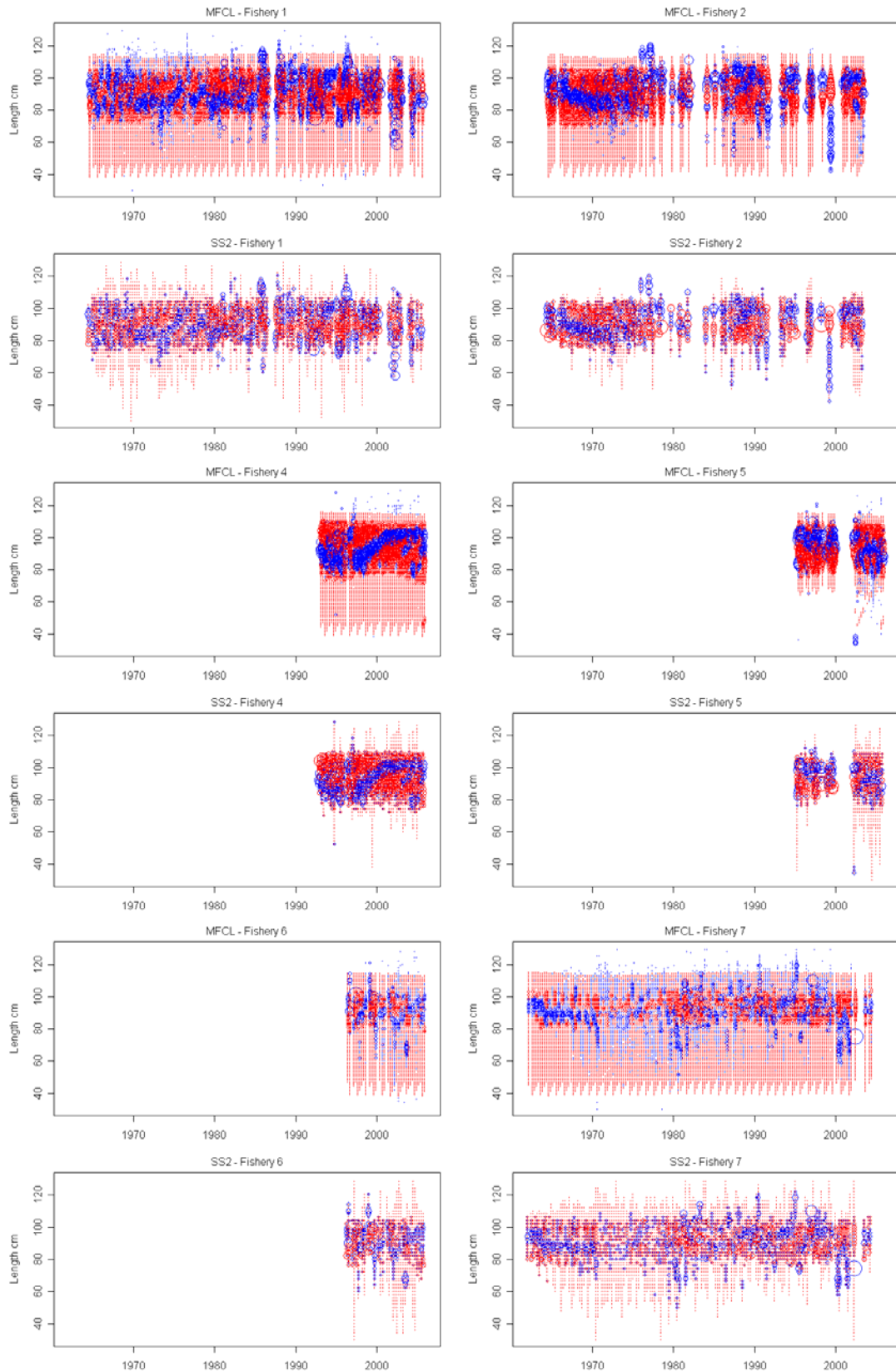
Figure 5: Length frequency residuals for fisheries 1 to 7, from the MFCL base case and the SS2 base case. Positive residuals (observed – predicted > 0) are in blue and negative in red. Note that MFCL bins are at 1cm and SS2 at 2cm. Circle areas are proportional to residual size.
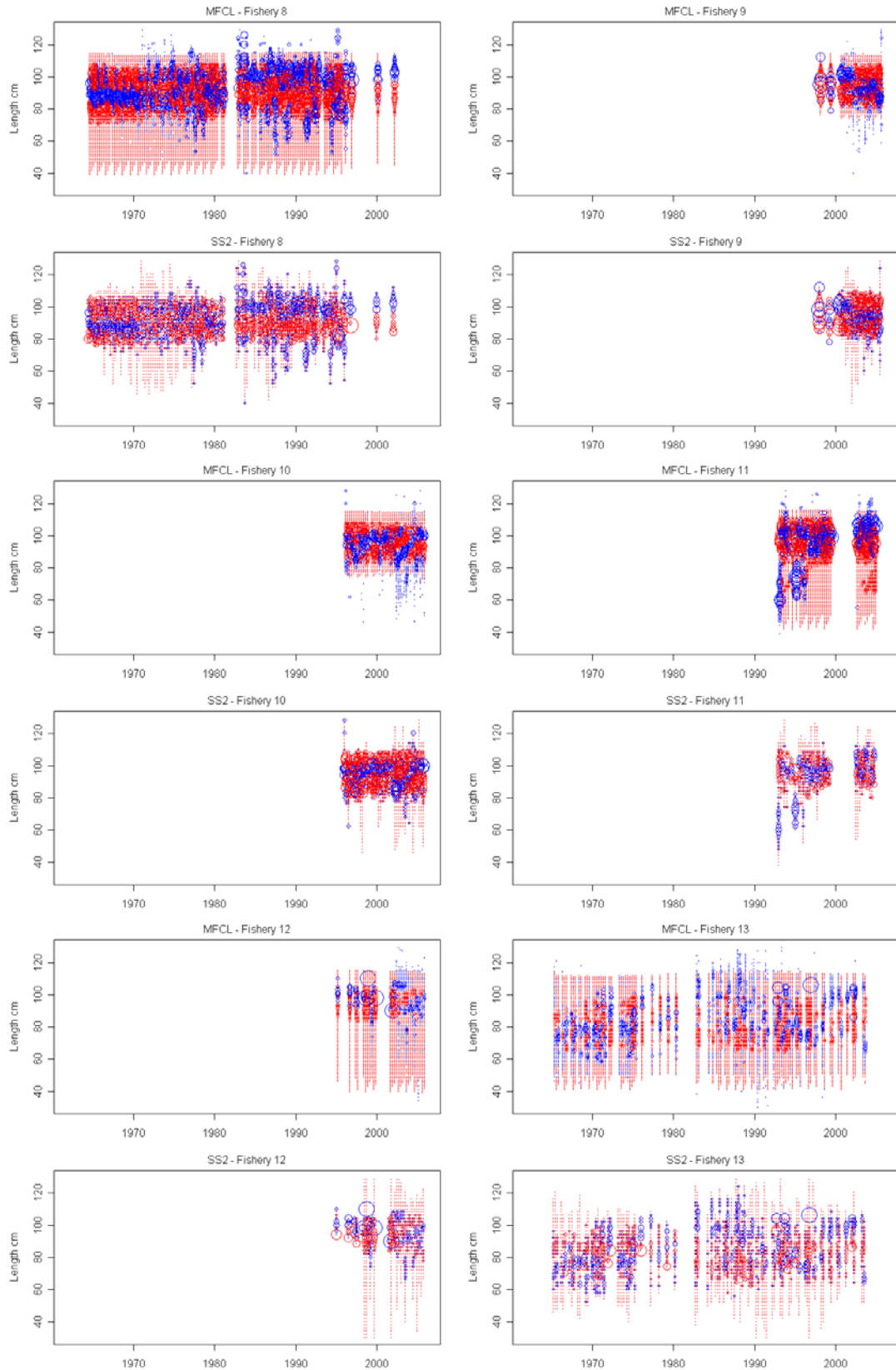
Figure 6: Length frequency residuals for fisheries 8 to 12, from the MFCL base case and the SS2 base case. Positive residuals (observed – predicted > 0) are in blue and negative in red. Note that MFCL bins are at 1cm and SS2 at 2cm. Circle areas are proportional to residual size.
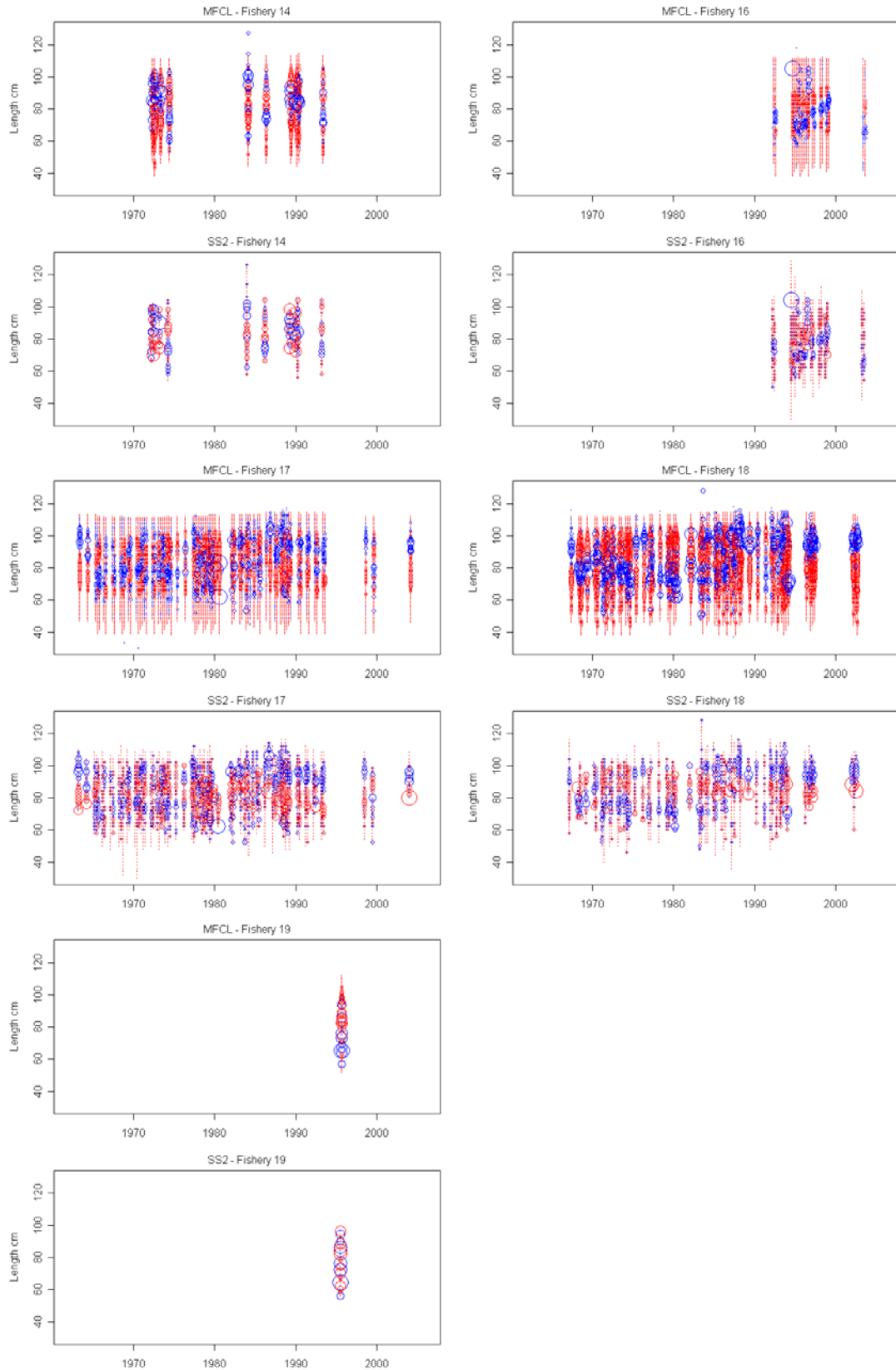
Figure 7: Length frequency residuals for fisheries 14 to 19, from the MFCL base case and the SS2 base case. Positive residuals (observed – predicted > 0) are in blue and negative in red. Note that MFCL bins are at 1cm and SS2 at 2cm. Circle areas are proportional to residual size.
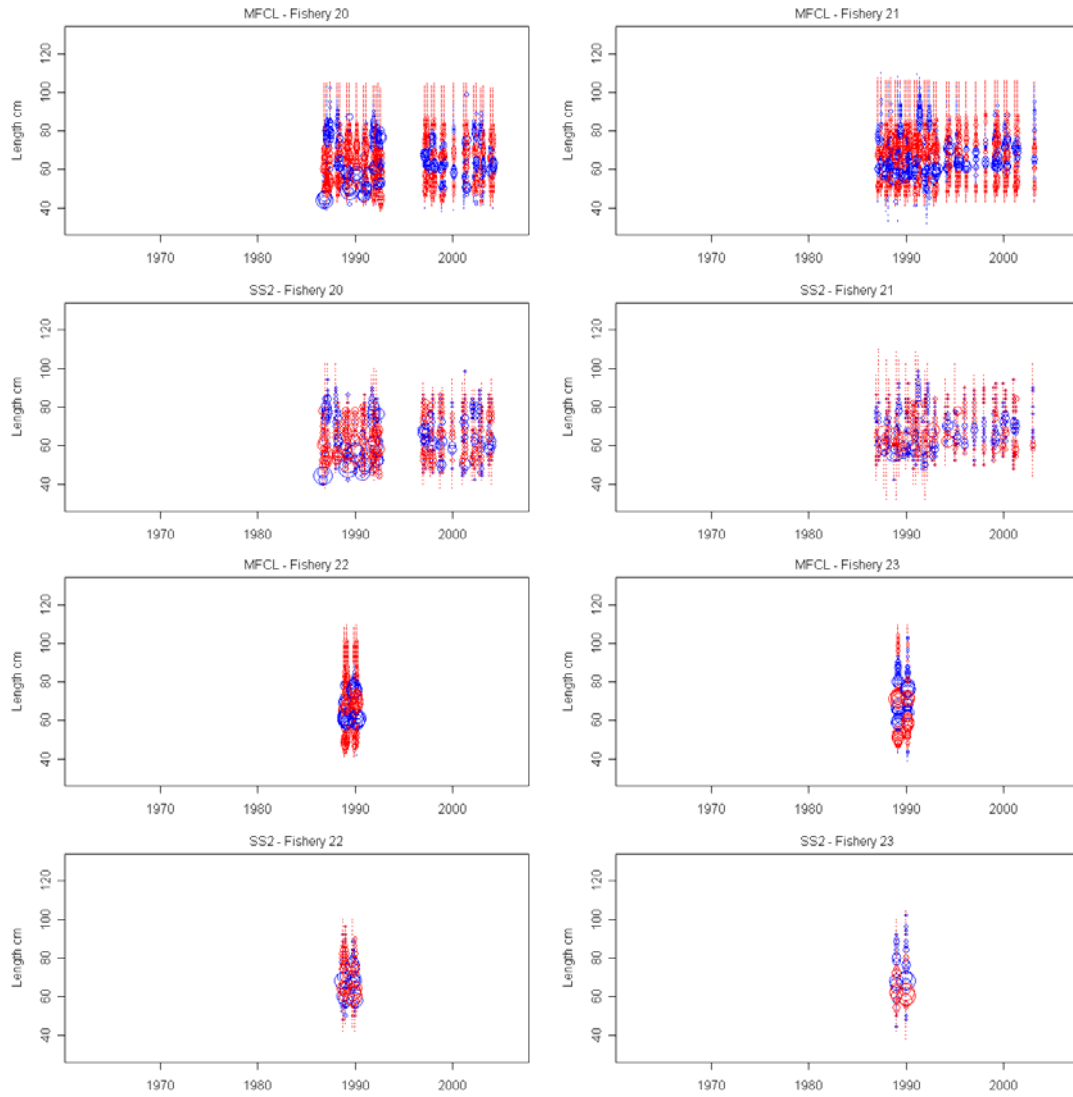
Figure 8: Length frequency residuals for small-fish fisheries 20 to 23, from the MFCL base case and the SS2 base case. Positive residuals (observed – predicted > 0) are in blue and negative in red. Note that MFCL bins are at 1cm and SS2 at 2cm. Circle areas are proportional to residual size.
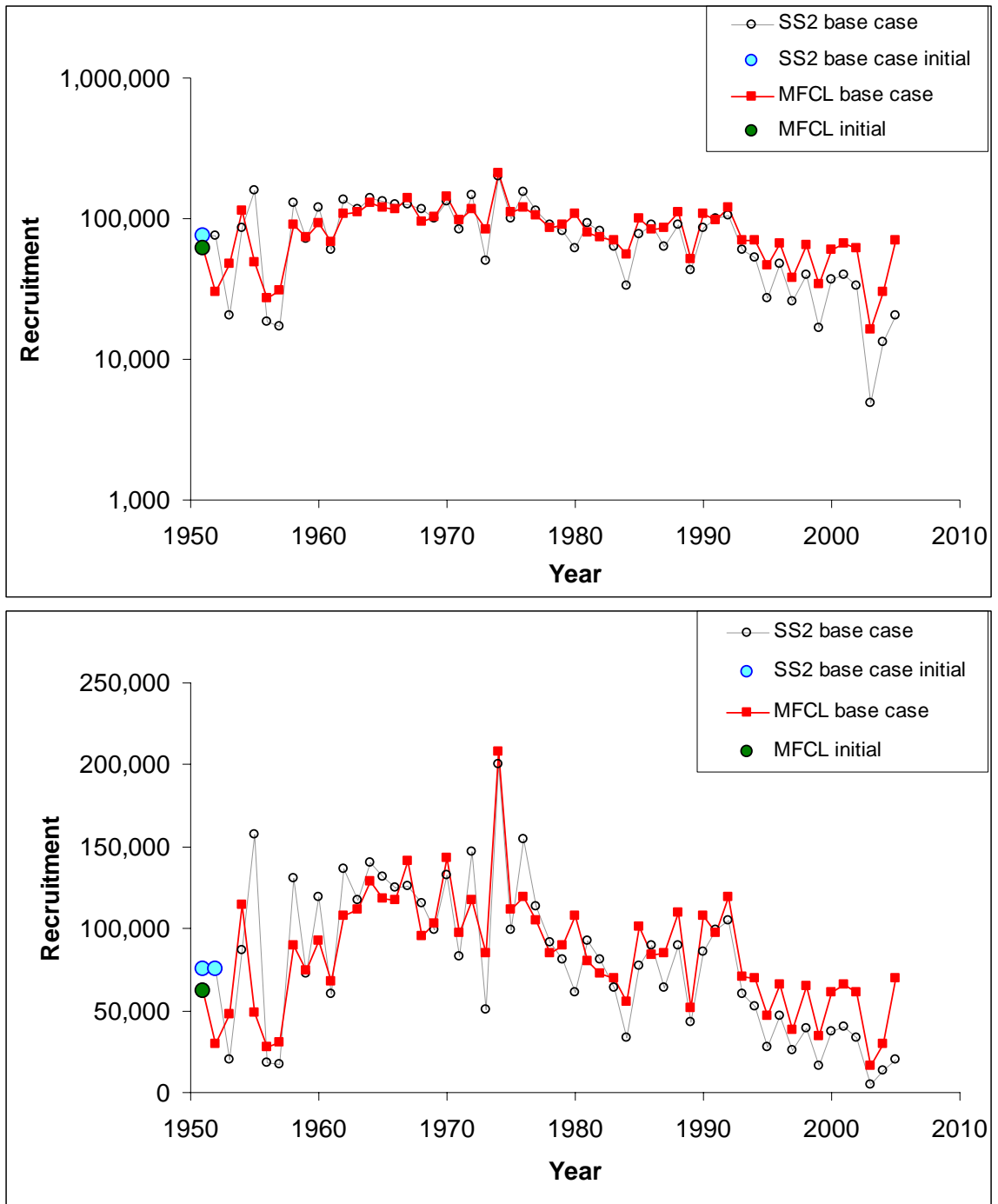
Figure 9: Recruitment time series in thousands of individuals from the MFCL base case and the SS2 base case, on both log (above) and nominal (below) scales.
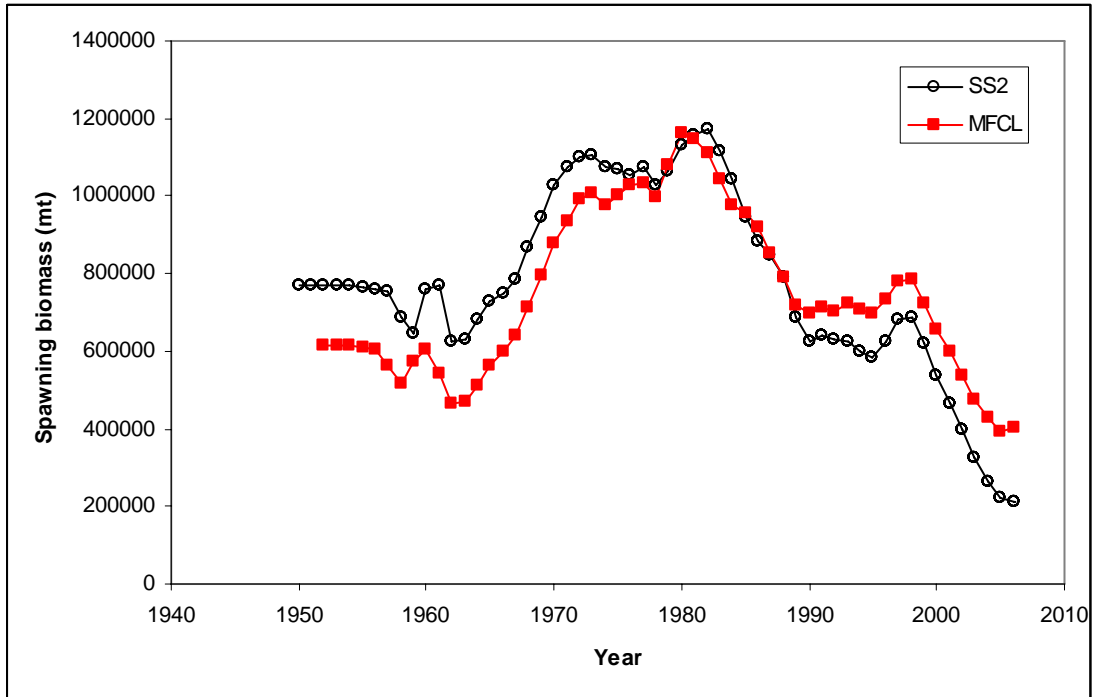
Figure 10: Spawning biomass time series for the MFCL base case and the SS2 base case.
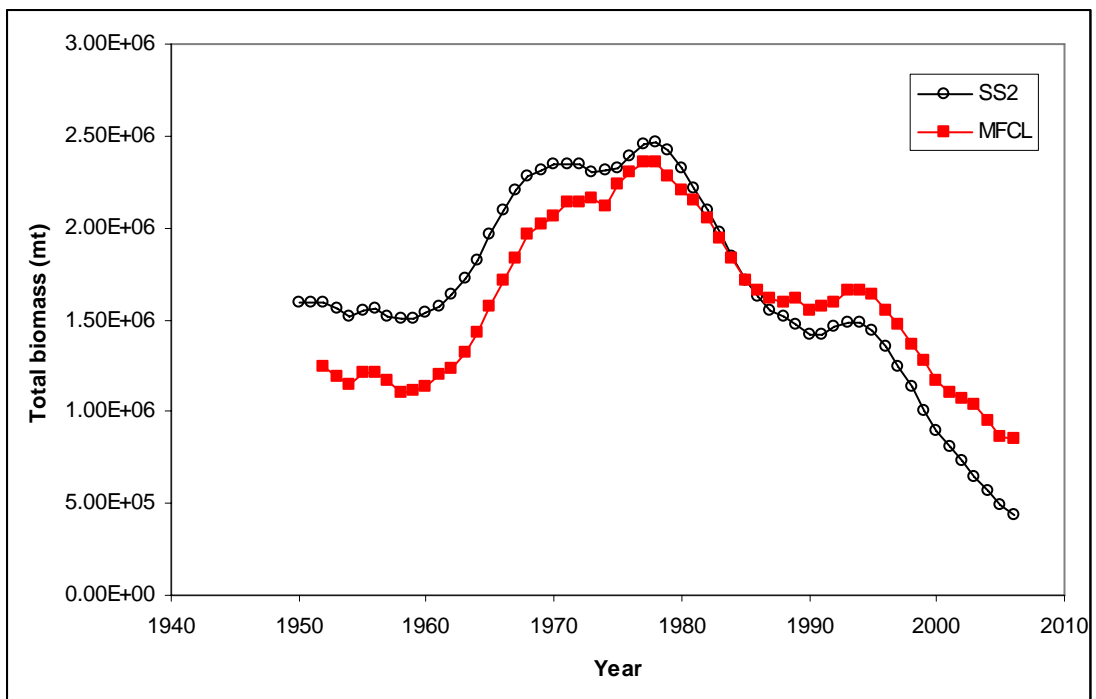
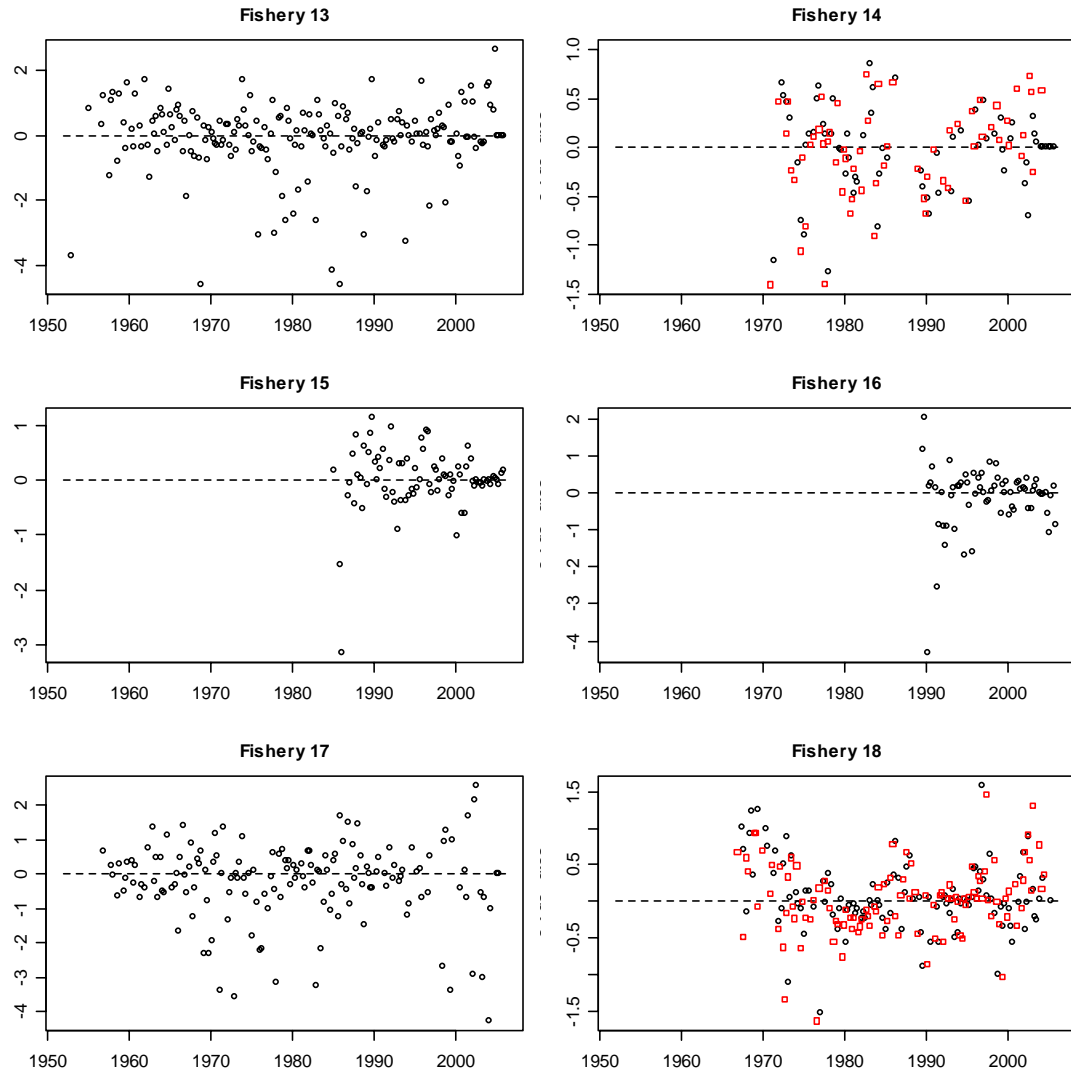**Figure 11: Total biomass time series from the MFCL base case and the SS2 base case.**
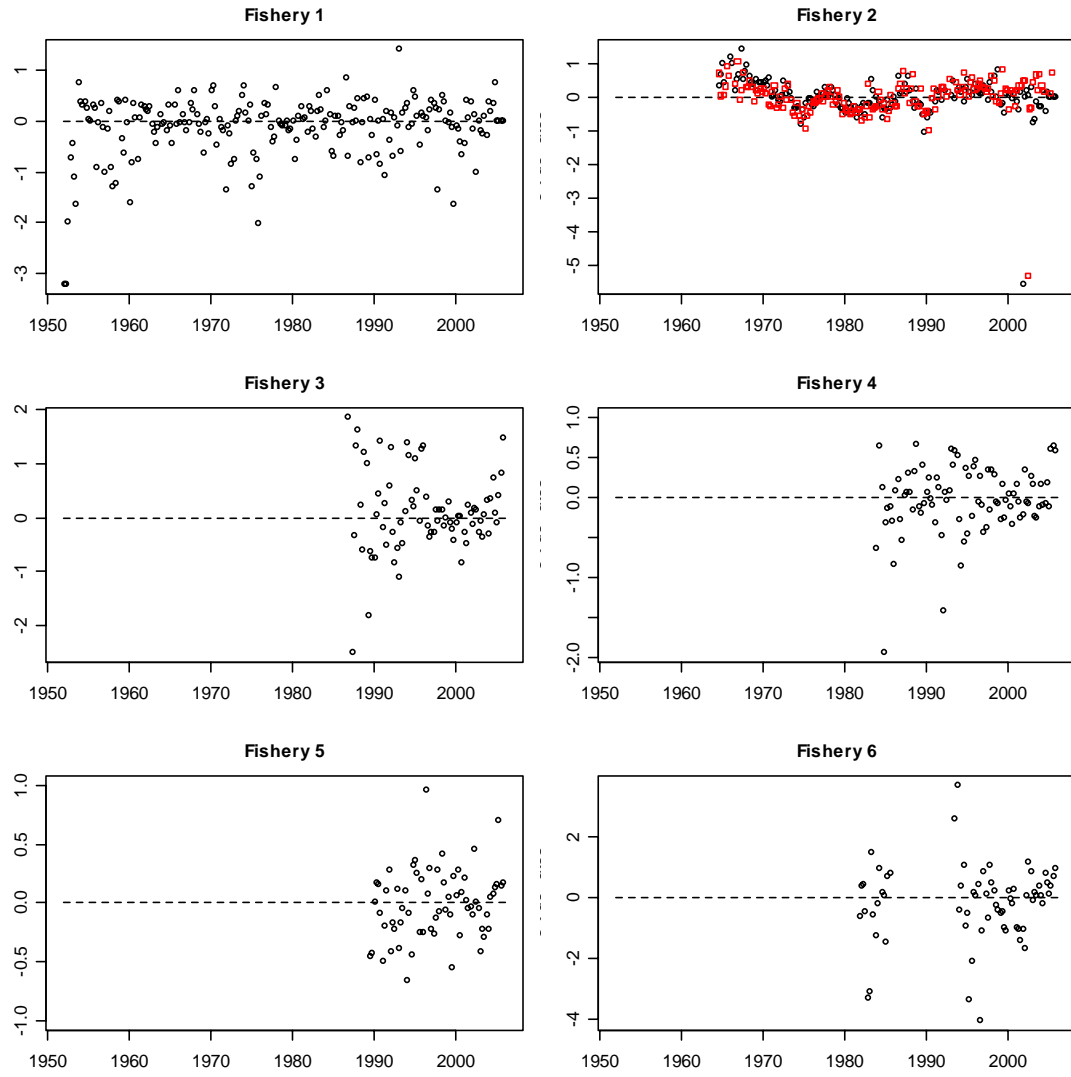
Figure 12: Effort deviates from MFCL base case (black) and SS2 base case (red) for fisheries 1 to 6.
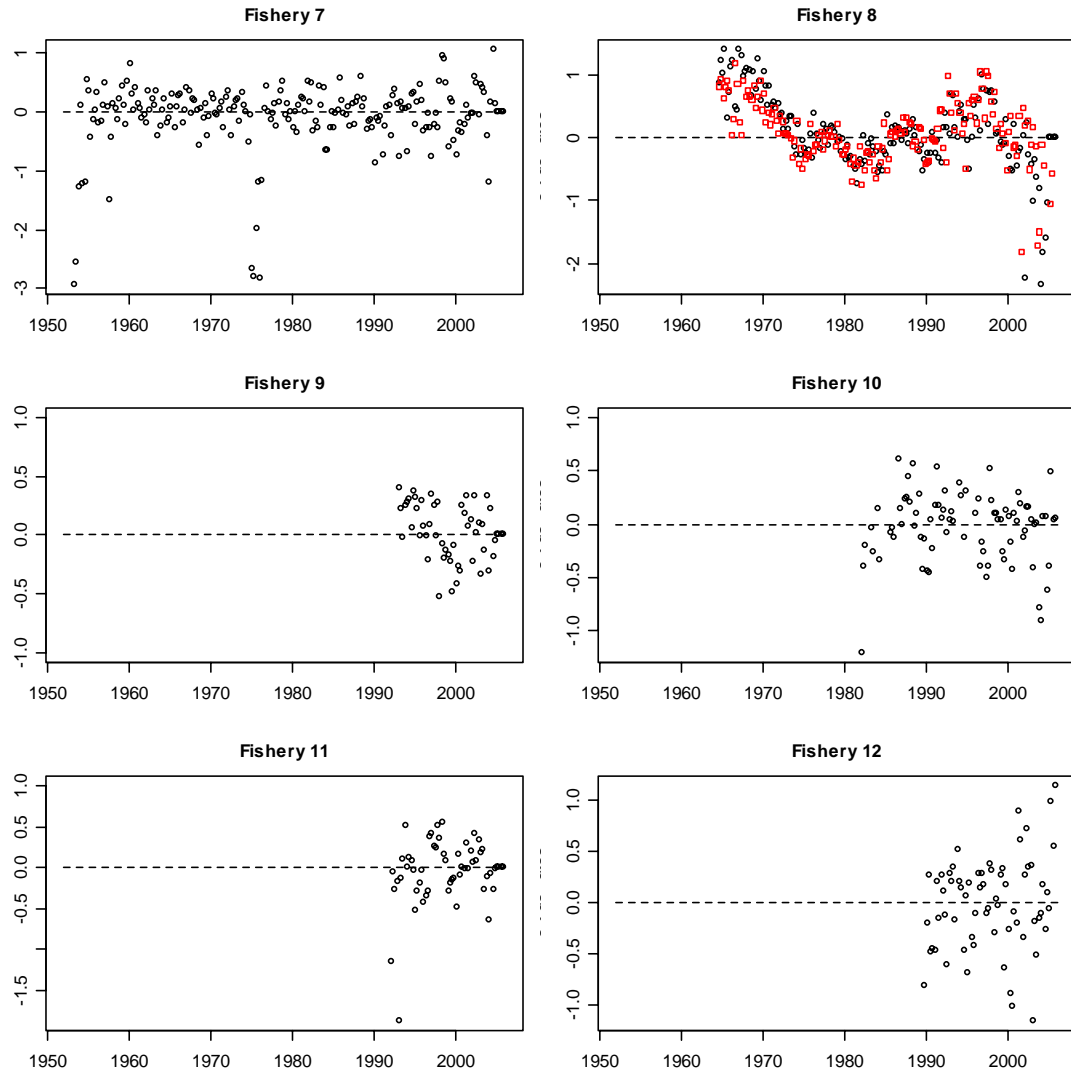
Figure 13: Effort deviates from the MFCL base case (black) and the SS2 base case (red) for fisheries 7 to 12.

Figure 14: Effort deviates from the MFCL base case (black) and the SS2 base case (red) for fisheries 13 to 18.
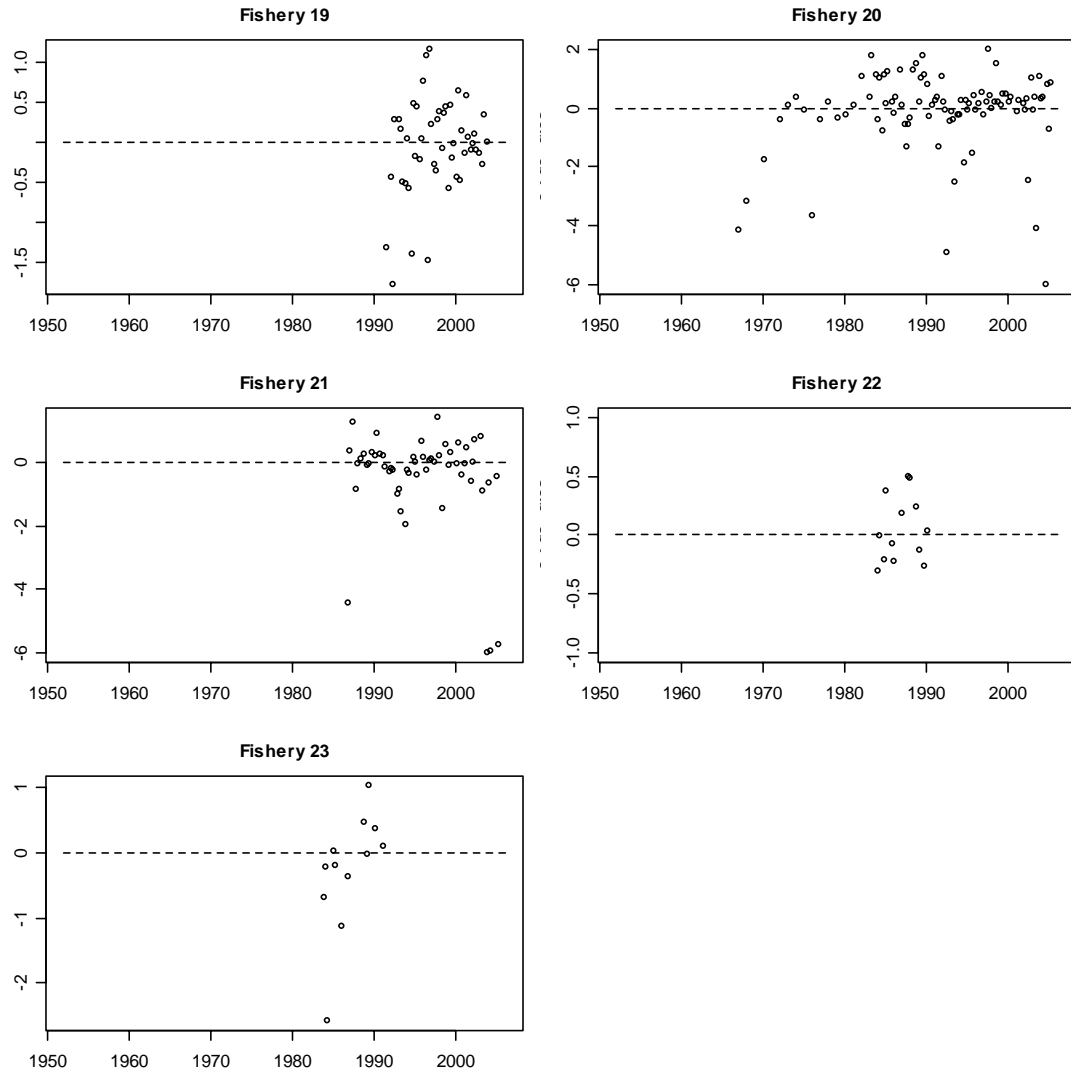
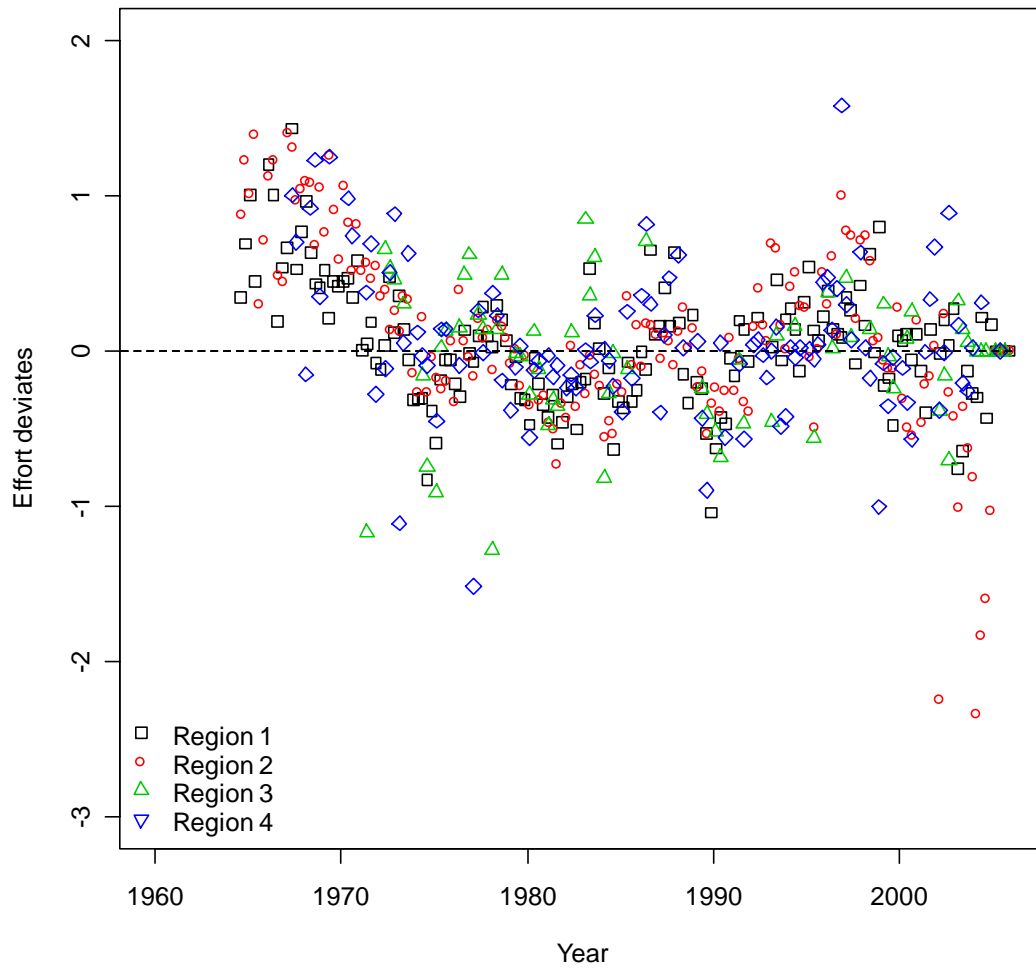**Figure 15: Effort deviates from the MFCL base case (black) for fisheries 19 to 23.**

Figure 16: Effort deviates from the SS2 base case for Taiwanese longline fisheries in areas 1 to 4
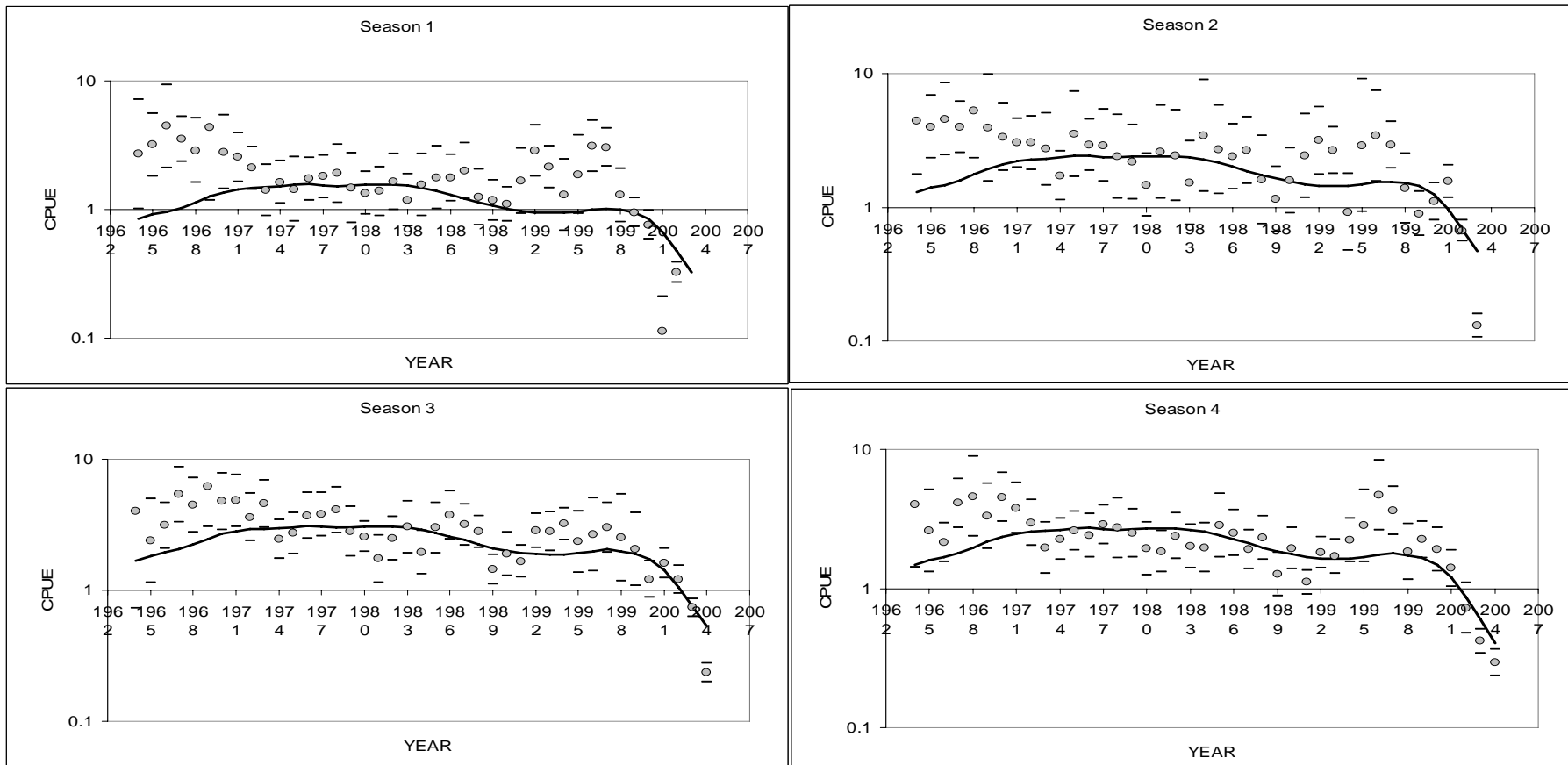
Figure 17: CPUE time series from the SS2 base case for Taiwanese longline fisheries in area 2 (fishery 8), showing lack of fit to data both at the start and at the end of the time series. The line represents the estimated relative abundance trend. Points are CPUE estimates with dashes ± 2SE.
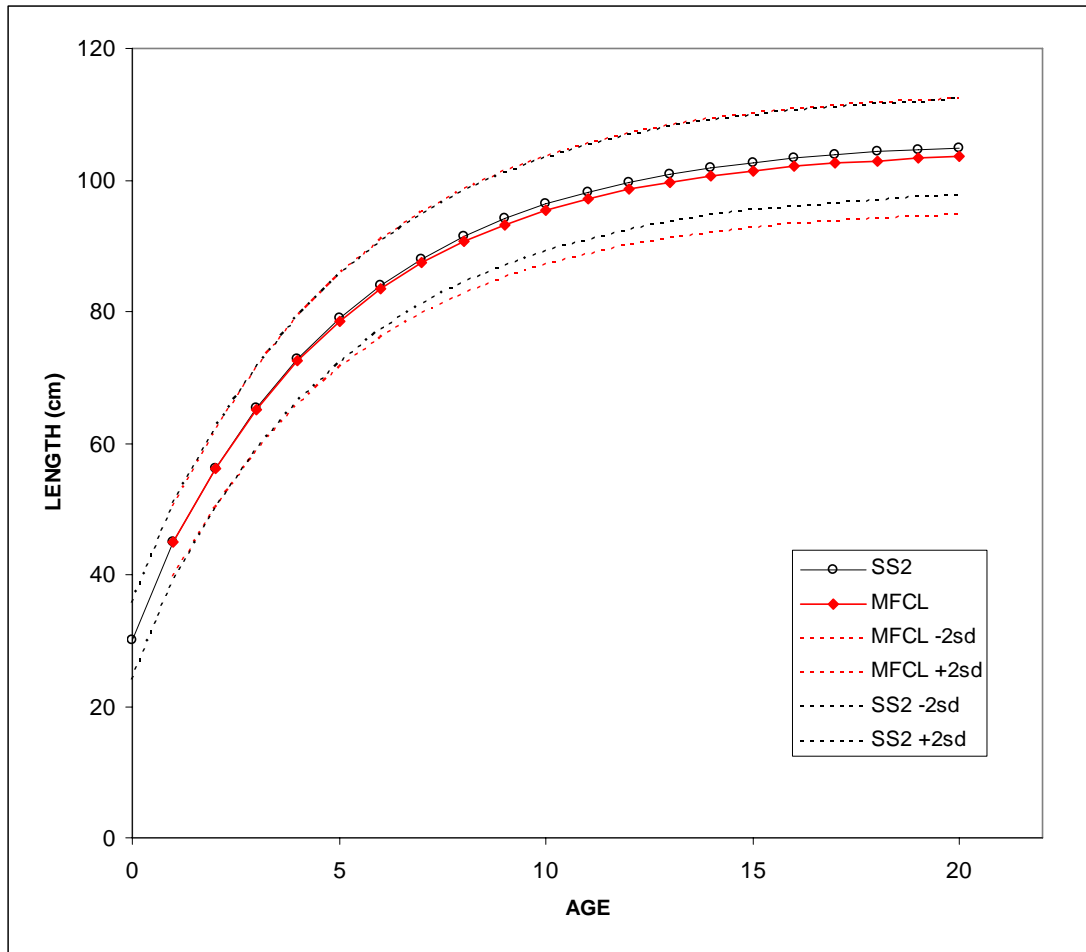
Figure 18: Growth curves from the MFCL base case and the SS2 base case, with ± 2 standard deviations of length at age.
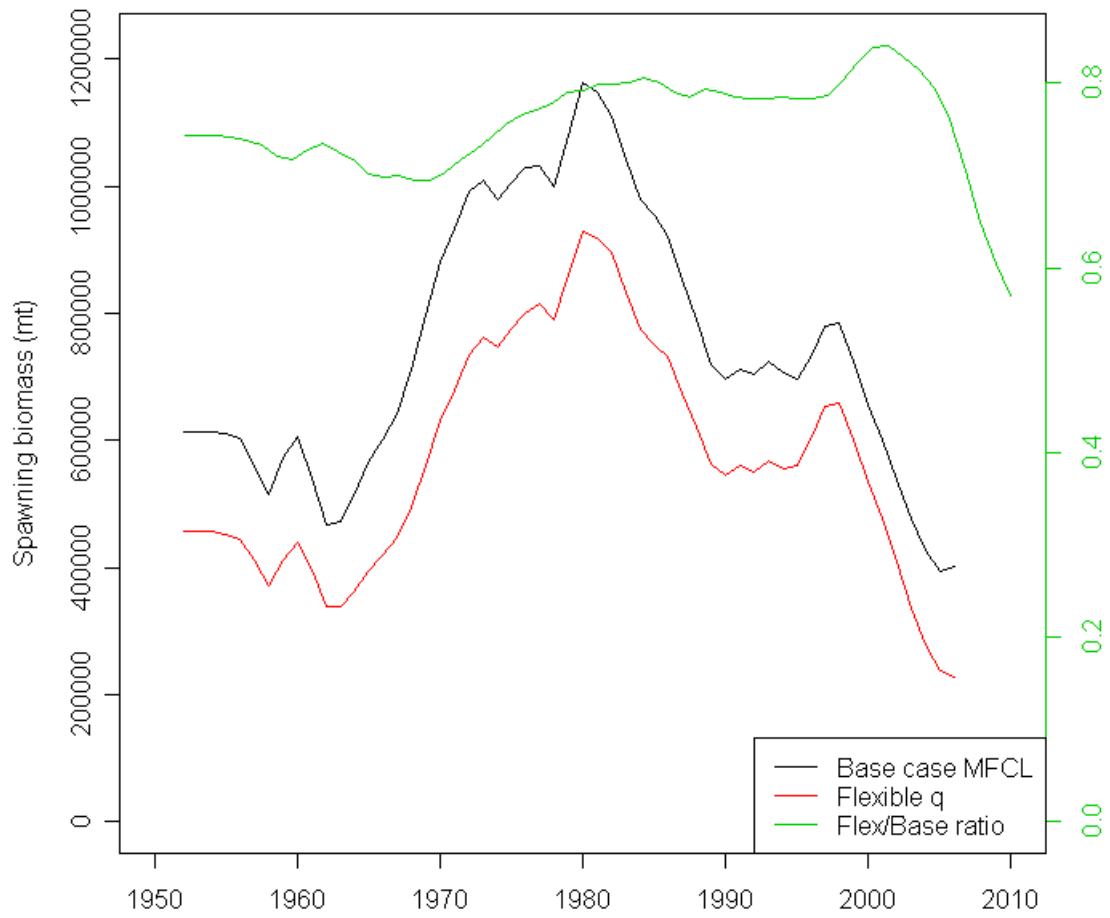
Figure 19: Comparison of estimated spawning biomass from the MFCL base case with the MFCL flexible q model, in which the impact of the non-Taiwanese longline fishery CPUE's are reduced by lowering effort deviate and q deviate penalties and increasing the frequency of effort deviates. The green line indicates the ratio of the two spawning biomasses.

Figure 20: Comparison of estimated spawning biomass from the MFCL base case with the MFCL penalized effort model, in which penalties on the Taiwanese longline fishery effort deviates are increased. The green line indicates the ratio of the two spawning biomasses.
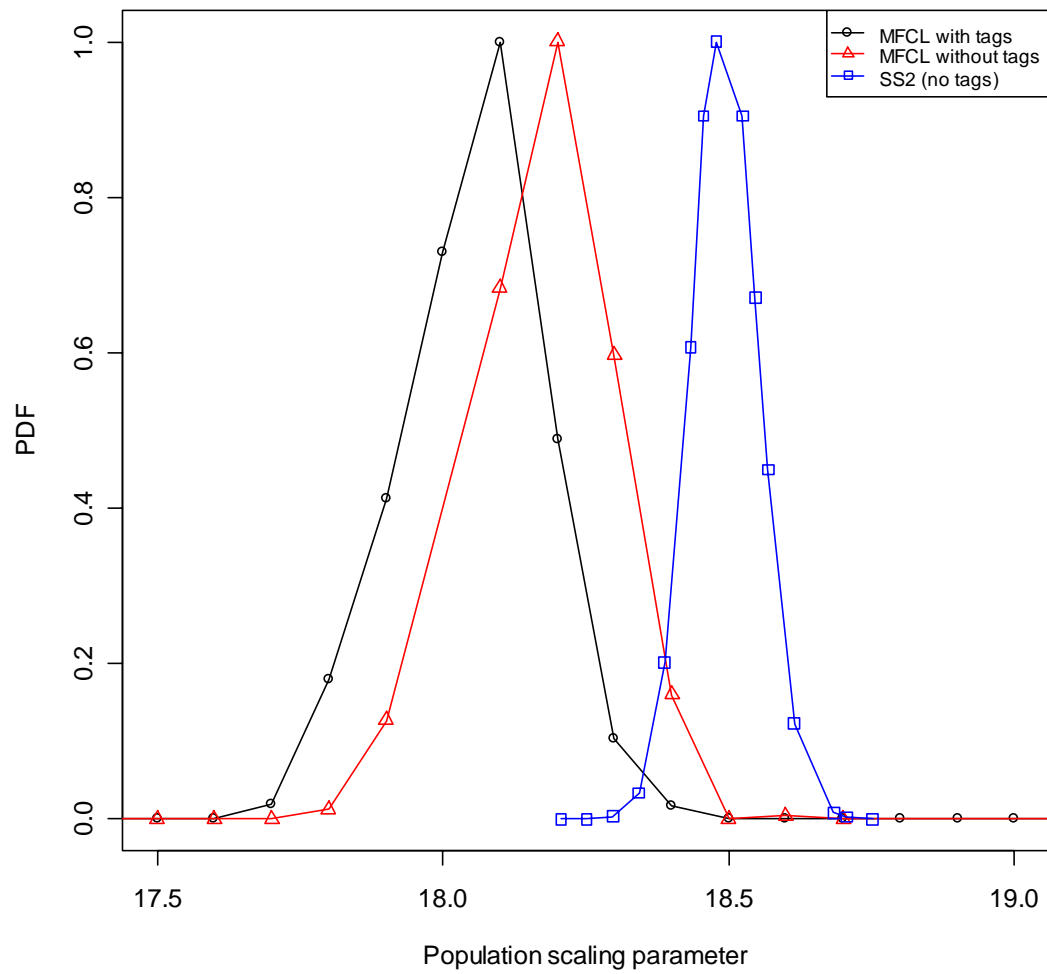
Figure 21: Likelihood profile for population scaling parameter estimated in the MFCL base case and the MFCL tagging data model. Maximum likelihood value for the MFCL base case was 18.12 which is equivalent to mean recruitment of 7.4 x 10[7] individuals. For the MFCL tagging data model the MLE was 18.05, and for the SS2 base case, the MLE was 18.48.
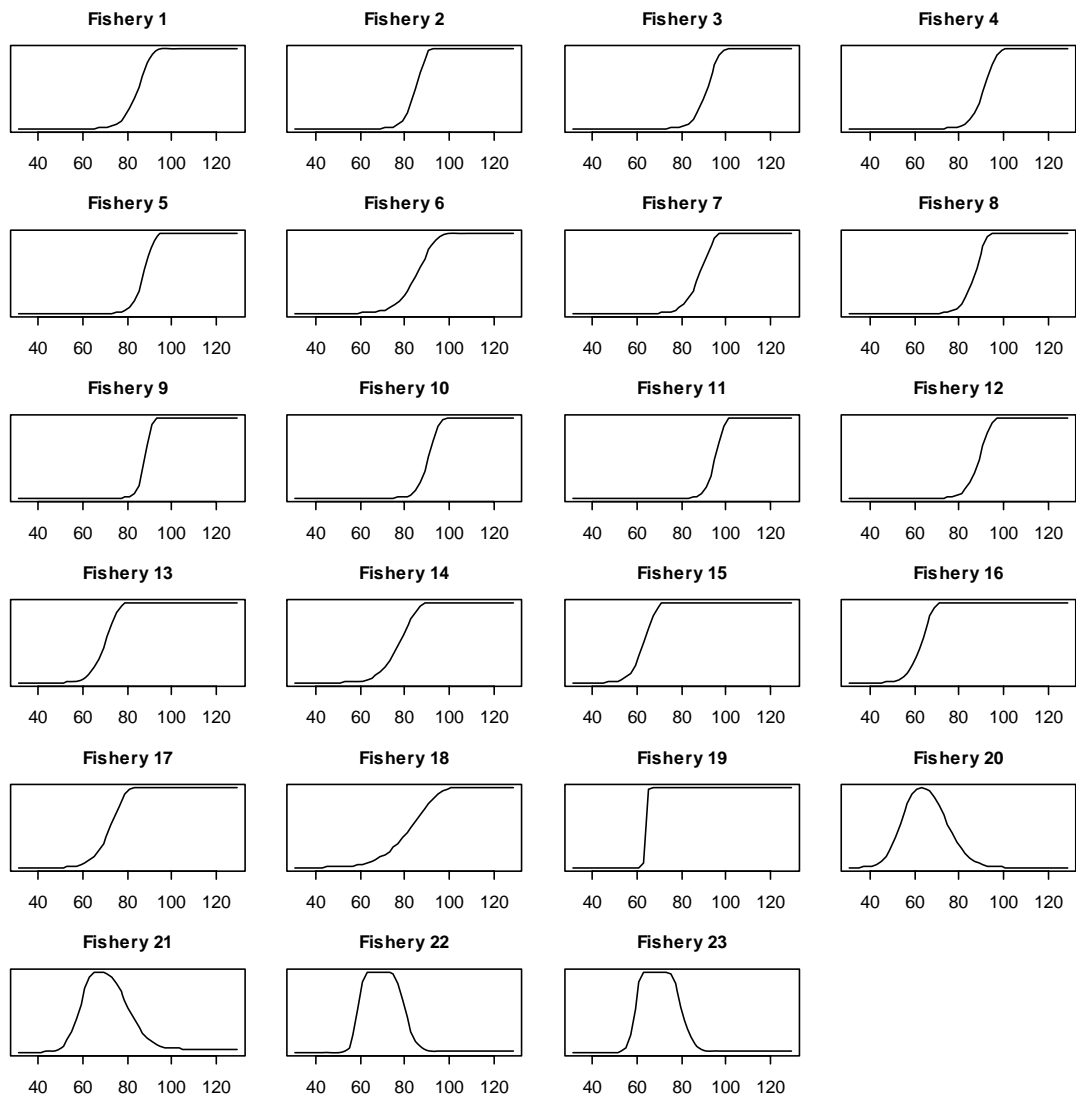
Figure 22: Estimates of length-based selectivity for the SS2 length-based selectivity model.
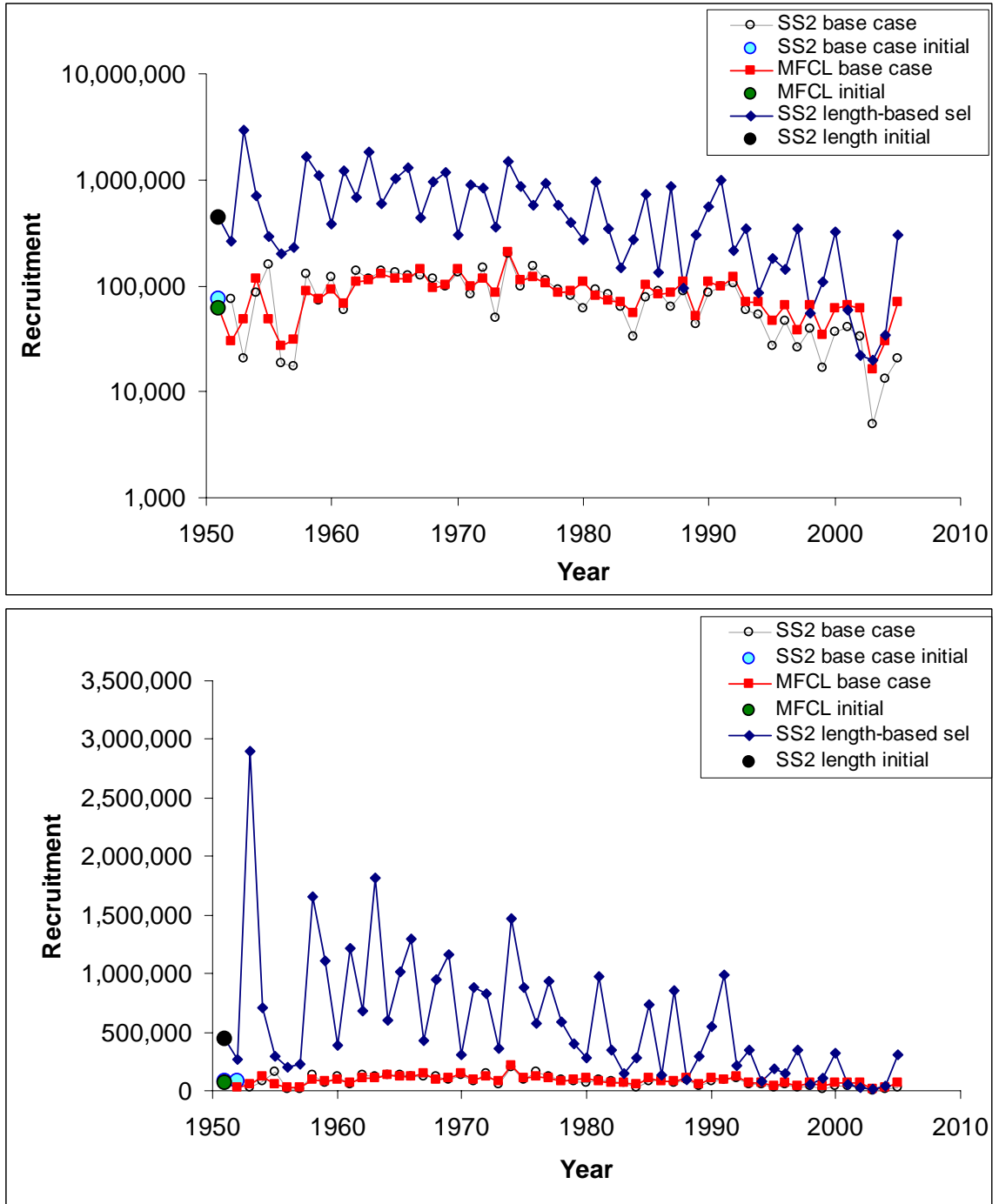
Figure 23: Recruitment (in thousands of fish) on log and nominal scales for the MFCL base case, the SS2 base case, and the SS2 length-based selectivity model.
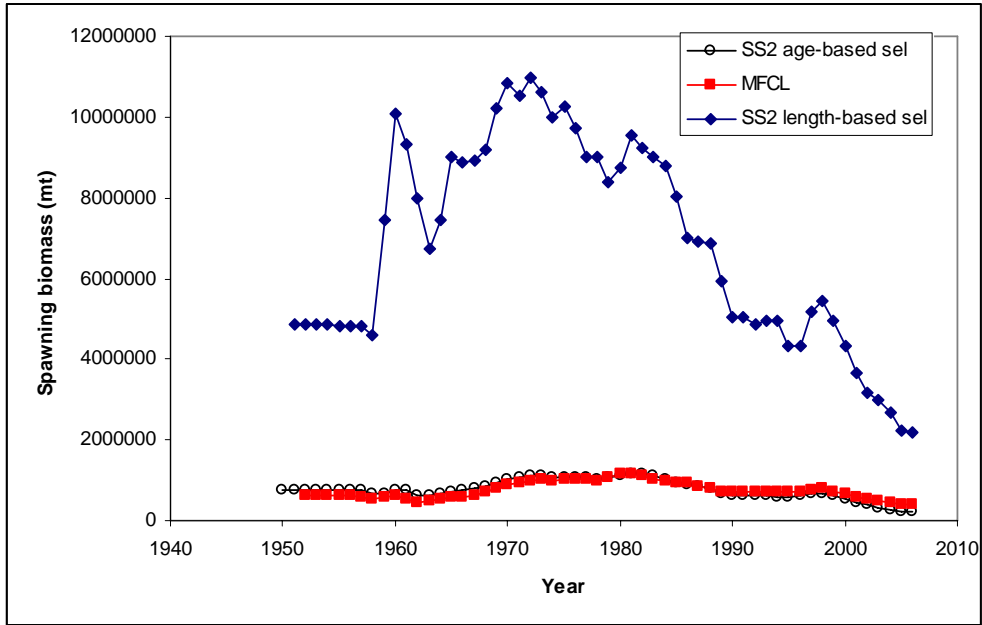
Figure 24: Spawning biomass time series for the MFCL base case, the SS2 base case, and the SS2 length-based selectivity model.
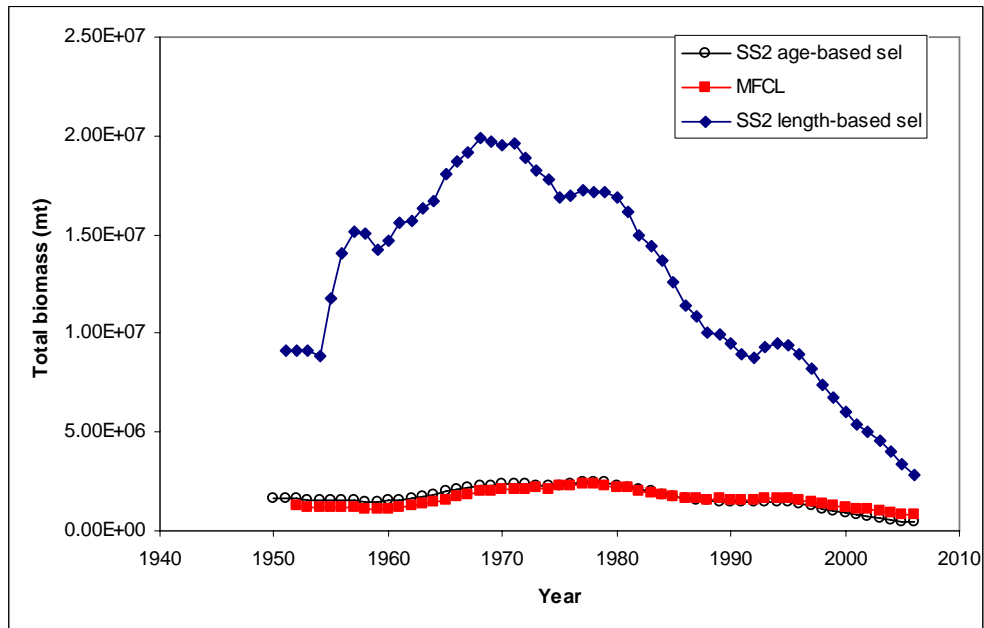
Figure 25: Total biomass time series for the MFCL base case, the SS2 base case, and the SS2 length-based selectivity model.
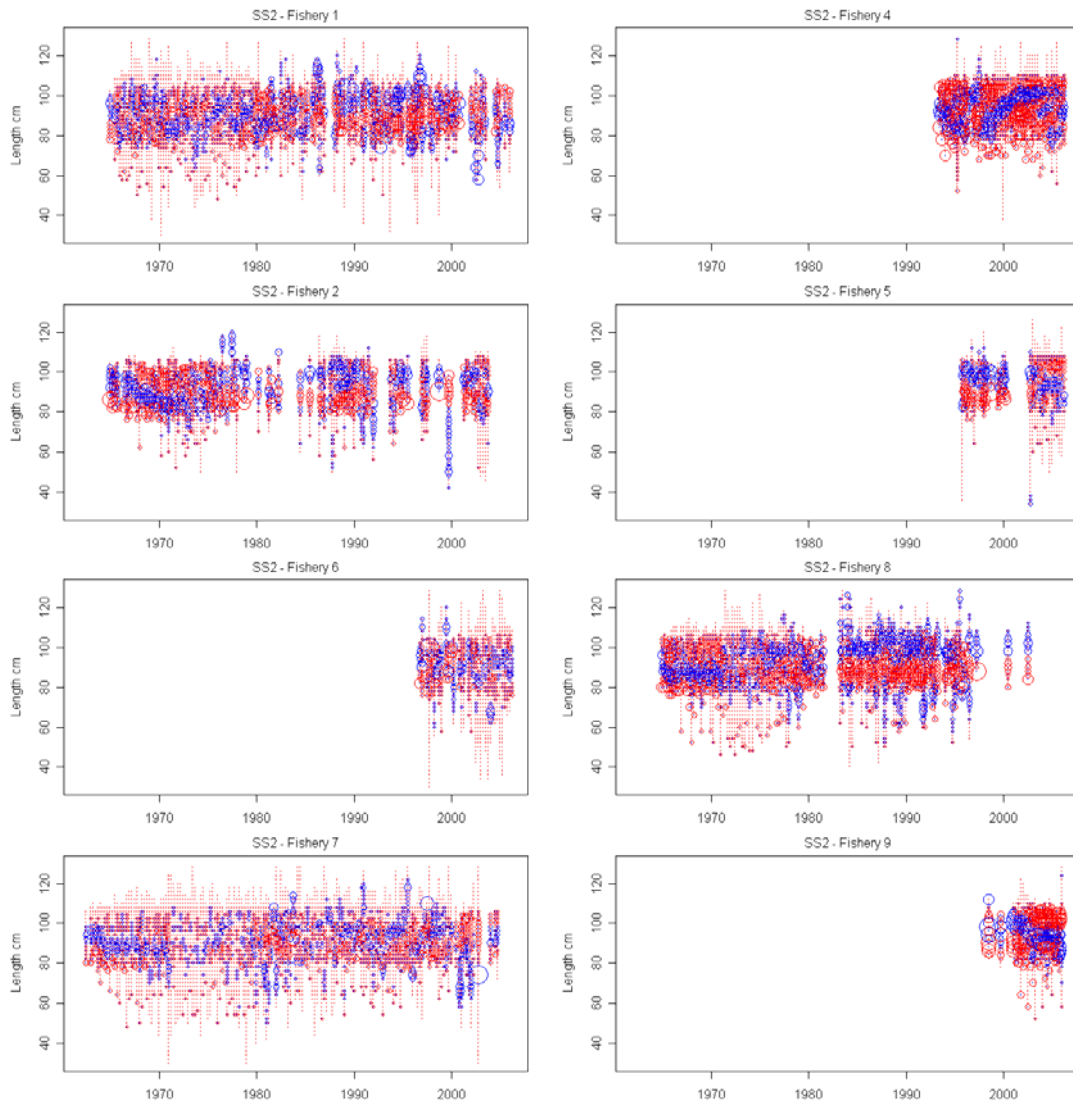
Figure 26: Length selectivity residuals for the SS2 length-based selectivity model, fisheries 1 to 9, with positive residuals (observed – predicted > 0) in blue and negative in red. Circle areas are proportional to residual size.
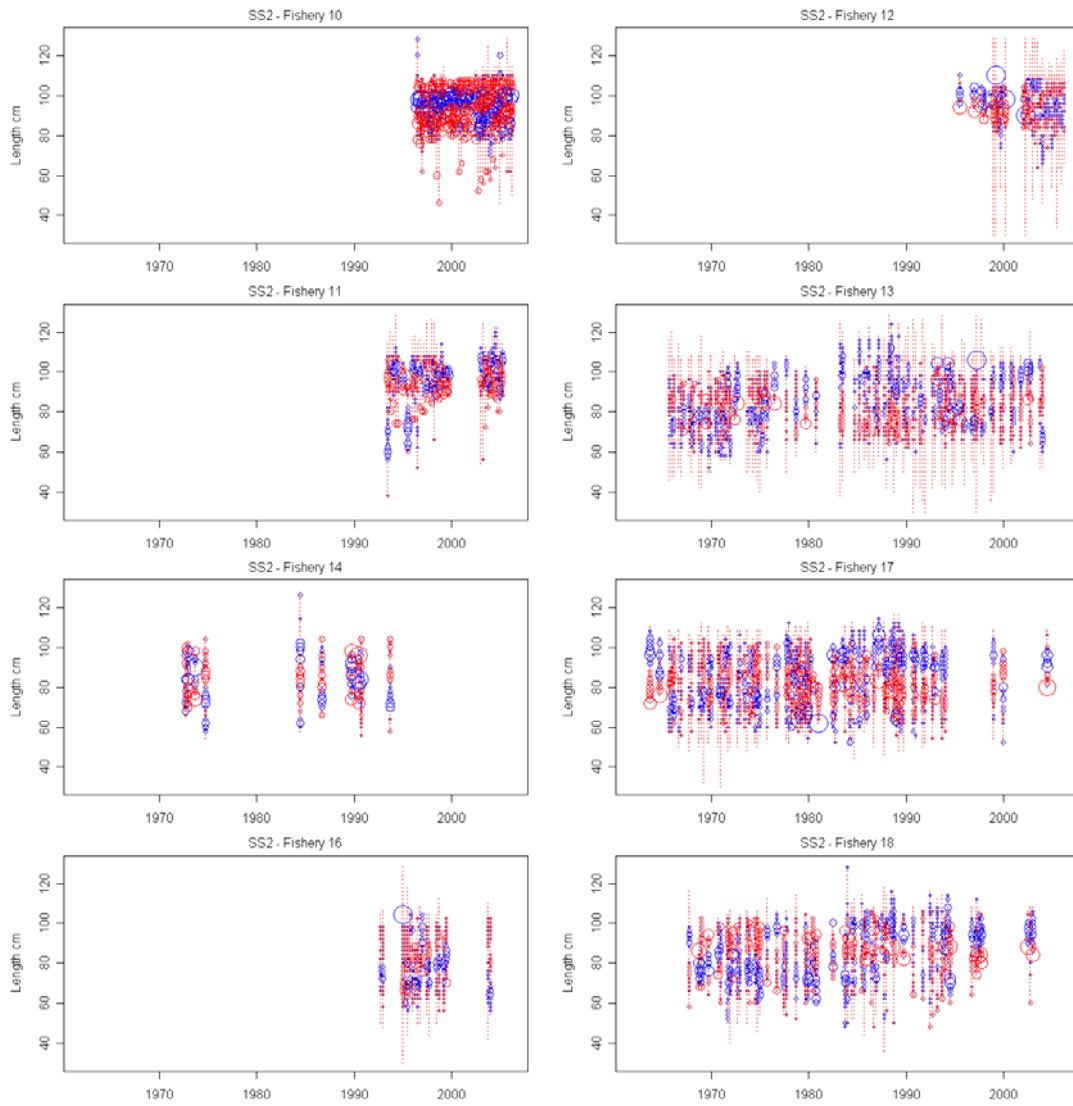
Figure 27: Length selectivity residuals for the SS2 length-based selectivity model, fisheries 10 to 18, with positive residuals (observed – predicted > 0) in blue and negative in red. Circle areas are proportional to residual size.
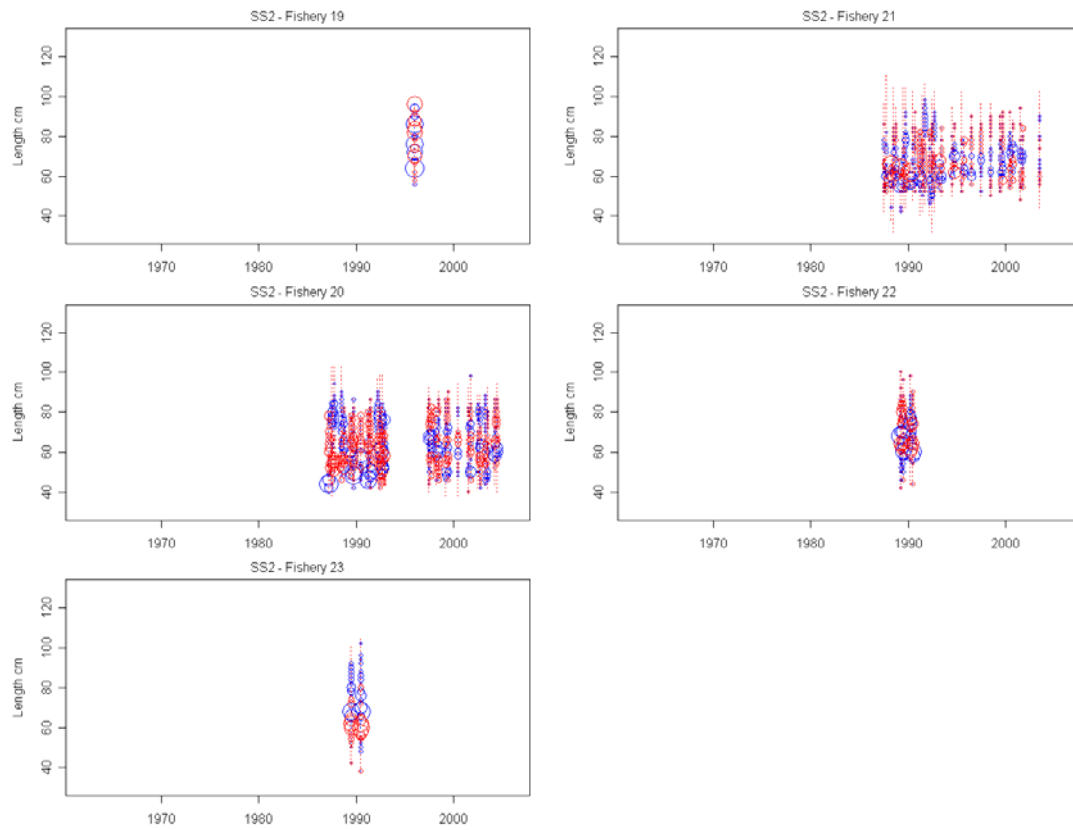
Figure 28: Length selectivity residuals for the SS2 length-based selectivity model, fisheries 19 to 23, with positive residuals (observed – predicted > 0) in blue and negative in red. Circle areas are proportional to residual size.
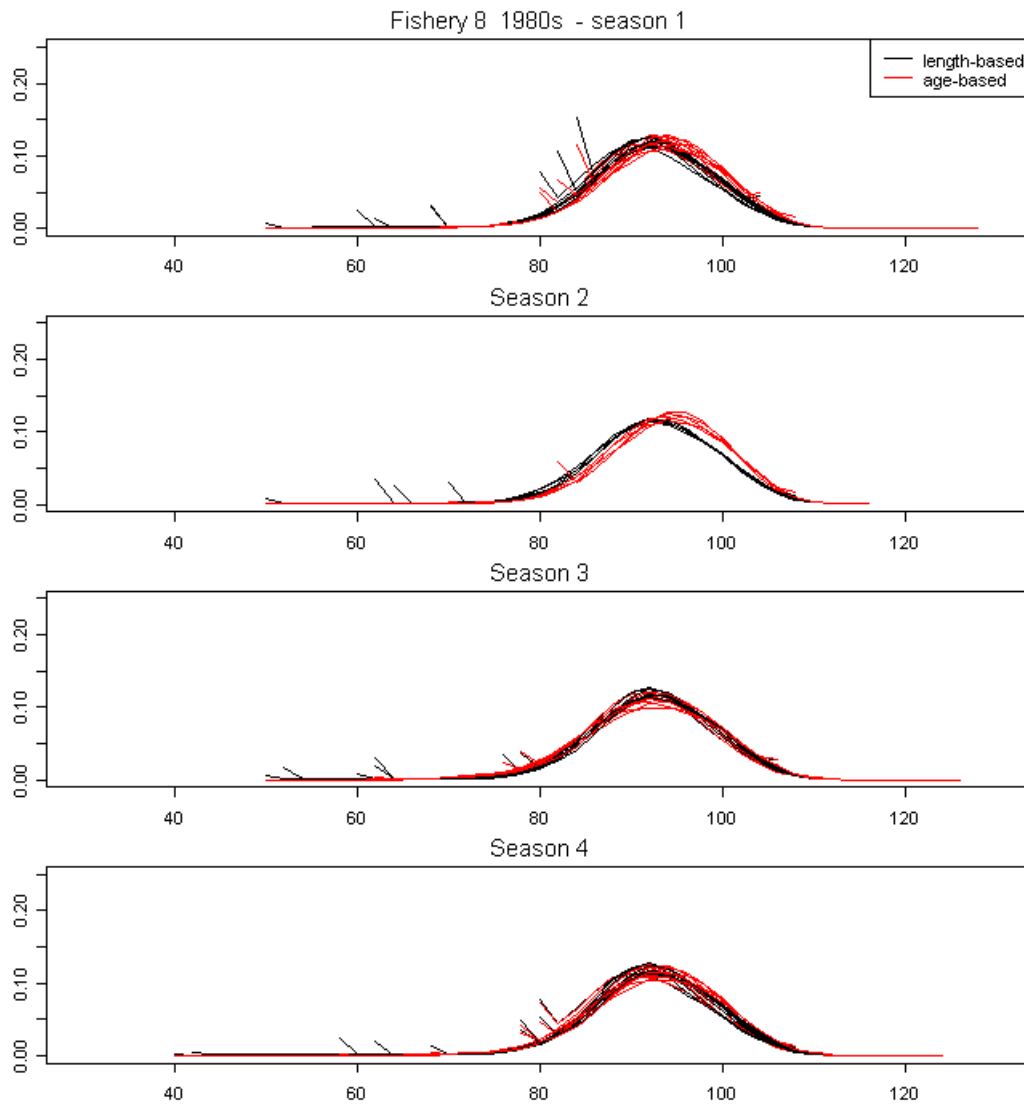
Figure 29: Comparison of expected length frequencies (length versus proportion at length) from the SS2 base case and the SS2 length-based selectivity model, for the Taiwanese longline fishery in area 2 (fishery 8) in the 1980's. Note that the first season is season 3.
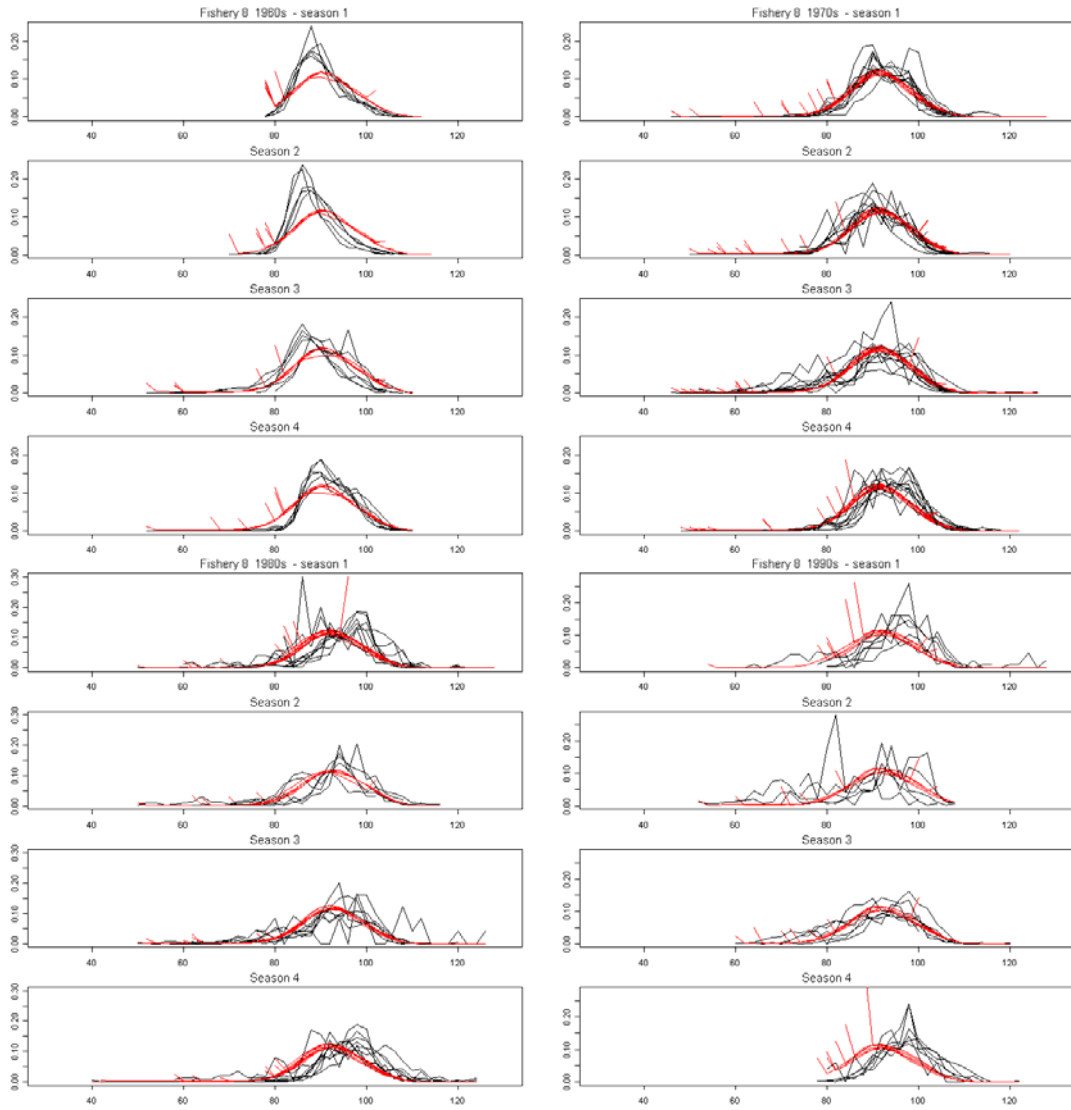
Figure 30: Seasonal length frequency plots by decade from the SS2 length-based selectivity model for the Taiwanese longline fishery in area 2 (fishery 8). Observed LF are in black and expected in red.

Appendix A: Overview of differences among stock assessment software

Comparison of four stock assessment programs potentially applicable to WCP-CA assessments. These 3 tables are updated from Maunder (2005), Report on IATTC Workshop on Stock Assessment Methods.

1) General

|	MULTIFAN-CL	Stock Synthesis II	A-SCALA	CASAL
Approach	AUTODIFF	ADMB	ADMB	BETADIFF
Normal approximation	Yes	Yes	Yes	Yes
Automatic profile likelihood	No	Yes[1]	Yes	Yes
Bayesian	No	MCMC	MCMC	MCMC
Model uncertainty in MCMC	No	No	No	No
Bootstrapping	No	Automatic	No	Automatic
Review	Publication review, comparison with A-SCALA (no spatial or tagging)	Modelling workshop with independent review, STAR panel intensive reviews of applications, comparisons with other models at UW and elsewhere, simulation tests.	Dual programming, comparisons with MFCL, publication review	Comparisons with Coleraine; with existing Hoki and Paua models; with other models at UW. Applications reviewed by independent experts
Assessments	WCPO YFT BET, ALB, SKJ, BUM, SWO, MLS, Blue shark, Lobster, Atlantic BET ALB MLS	15 west coast and Alaska groundfish assessments, SEPO swordfish, EPO BET	IATTC Assessments (YFT, BET, SKJ) and comparisons with WCP-CA	From 10 to 20 stocks in NZ and CCAMLR, fin fish and Shellfish
Approximate parameters estimated in an application	3000[2]	200	2000	200
Approximate time required for the EPO YFT model	4 hrs	40 min[3]	4 hrs	Not evaluated

---

[1] Added since IATTC workshop
[2] Many of these parameters are realizations of random effects, some of which may now be removed from the parameterization (Hampton *et al.* 2007)
[3] With restructured length bins

2) Model structure

Structure	MULTIFAN-CL	Stock Synthesis II	A-SCALA	CASAL
Spatial population dynamics	Yes	Yes	No	Yes
Fishing mortality	Continuous F or Pope's[1]	Pope's or continuous F[1]	Continuous F	Pope's, or continuous F (1 fishery)
	Effort deviates or exact catch[1]	Exact catch	Effort deviates	Exact catch
Seasons	General	General	Restricted	General
Model discards specifically	No	Yes	No	No
Sex structured	To be developed	Optional	No	Optional
Growth morphs	No	Yes	No	Yes
multi-species (no pred/prey)	To be developed	No	No	Yes
Selectivity	Functional forms, non-parametric with smoothness penalties, and cubic splines	Functional forms and non-parametric	Smoothness penalties	Functional forms and non-parametric with smoothness penalties
Selectivity basis	Age, length penalty	Age, length, and sex	Age, length penalty	Age, length, and partition
Time varying parameters	Catchability	All estimated parameters	Catchability	Limited
Environment	R	All estimated parameters	R and q	R (untested)
Stock-recruitment relationship	B-H	B-H, Ricker	B-H	B-H, Ricker
M	Full age-structure with smoothness	2 breakpoints	Full age-structure	Full age-structure with smoothness
Movement	Transfer rates with implicit time steps	Transfer rates	NA	Transfer rates, density dependent
Aging error	No	Yes	No	Yes
Variable length bin size	No	Yes	No	Yes

---

[1] Added since IATTC workshop

3) Data types used in model

Data	MULTIFAN-CL	Stock Synth. II	A-SCALA	CASAL
Catch-effort	Effort deviates	Index	Effort deviates	Index
Catch-at-age	√	√		√
Catch-at-length	√	√	√	√
Abundance index		√	√	√
Tagging	√			√
Catch-at-weight	√			
Age-length		√	√	√
Average weight		√		
Discard (fit)		√		
Proportions mature				√
Proportions migrating				√
Age at maturity				√

Appendix B: SS2 input file formats

South Pacific Albacore Population Analysis (1962-02)
Stock Synthesis 2 Program (SS2)
Simon Hoyle
June 2007
Definition of sub-areas - THIS IS A SINGLE REGION MODEL
TWDW data incomplete for 2005, used 2004 effort, also 2002 only includes WCPO
not further east
Data from other fisheries is reasonable OK to the end of 2005, except JP/KR - also
use 2004 effort. AND A.SAMOA for 2005
#
Area 1: 0-30S, 140E-180
Area 2: 0-30S, 180-90W
Area 3: 30S-50S, 140E-180
Area 4: 30S-50S, 180-90W
#
Definition of fisheries
#
Fishery Gear Nation   Area
1   L   JP,JPDW,KR   1
2   L   TWDW   1
3   L   AU   1
4   L   NC   1
5   L   FJ   1
6   L   OT   1
7   L   JP,JPDW,KR   2
8   L   TWDW   2
9   L   AS,WS   2
10   L   TO   2
11   L   PF   2
12   L   OT   2
13   L   JP,JPDW,KR   3
14   L   TWDW   3
15   L   AU   3
16   L   NZ   3
17   L   JP,JPDW,KR   4
18   L   TWDW   4
19   L   OT   4
20   T   ALL   3
21   T   ALL   4
22   D   ALL   3
23   D   ALL   4
albss.ctl
datafile: albss.dat
1   #_N_growthmorphs
1 # sub-morphs
1   #_N_Areas_(populations)
#_each_fleet/survey_operates_in_just_one_area

#_but_different_fleets/surveys_can be assigned_to_share_same_selex
1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 #area_for_each_fleet/survey
1 1 1 1 1 1 1 1 1 1
1 1

1 0 0 0 # Recruitment distribution (G_Pattern_x_birthseas_x_area)

0 #Recr_distr_interaction (0/1)
0 #do_migration_(0/1)

0 1 1 #Movement pattern
0 1 1
0 1 1
0 1 1

0   #_N_Block_Designs
#0   #_N_Blocks_per_Design(Block_1_always_starts_in_styr)

#_Block_Design_1

0.5 # fracfemale
100 # submorph between within
-1 # vector submorphdist

GROWTH AND NATURAL MORTALITY PARAMETERS --------------------------
----
#
#Natural_mortality_and_growth_parameters_for_each_morph
2   #_Last_age_for_natmort_young
3   #_First_age_for_natmort_old
1   #_age_for_growth_Lmin
20   #_age_for_growth_Lmax
0   # SD add to length at age
2   # CV pattern
3   # maturity option
5   # First mature age
3   # MG Parm as offset
1   #_MGparm_adjust_method
-1   #_MGparm_dev_phase

LO   HI   INIT   PRIOR   PR_type SD PHASE env-variable use_dev dev_minyr
dev_maxyr dev_stddev Use_block Block_type
0.075 1 0.35 0.35 0 1000 -1 0 0 0 0 0 0 0 #M1_natM_young
-3   3   0   0   0 1000 -1 0 0 0 0 0 0 0
#M1_natM_old_as_exponential_offset(rel_young)
30   80   45   45   0 1000 -3 0 0 0 0 0 0 0 #M1_Lmin
90 130 104.877576933 100 0 1000 4 0 0 0 0 0 0 0 #M1_Lmax
0.1 0.5 0.202306754972 .2 0 1000 4 0 0 0 0 0 0 0 #M1_VBK
0.01 10 2.95650839232 0.05 0 1000 7 0 0 0 0 0 0 0 #M1_CV-young

-3   3 0.232993270363   0   0 1000 7 0 0 0 0 0 0 0 #M1_CV-
old_as_exponential_offset(rel_young)

Add 2+2*gender lines to read the wt-Len and mat-Len parameters
1E-6 5E-5 6.9587e-06 6.9587e-06 0 1000 -1 0 0 0 0 0 0 0 #Female wt-len-1
2   4   3.2351   3.2351   0 1000 -1 0 0 0 0 0 0 0 #Female wt-len-2
1   150 -9999   84.74   0 1000 -1 0 0 0 0 0 0 0 #Female mat-len-1 **from
intial growth to give 0, 0.5, 1 maturity at 4, 5, & 6 years old
-8 1 -4.17   -4.17   0 1000 -1 0 0 0 0 0 0 0 #Female mat-len-2   ** as
above
0   2   1   1   0 1000 -1 0 0 0 0 0 0 0 #Female eggs/gm intercept ** fixed at
flat relationship with wt
-1 1 0   0   0 1000 -1 0 0 0 0 0 0 0 #Female eggs/gm slope

RECRUITMENT
===
pop*gmorph lines For the proportion of each morph in each growth pattern, area,
season
LO   HI   INIT   PRIOR PR_type SD PHASE env-variable use_dev dev_minyr
dev_maxyr dev_stddev Use_block Block_type
-4 4 0 1 0 1000 -1 0 0 0 0 0 0 0 ##_recrdistribution_by_growth_pattern   ** only one
area, one growth morph
-4 4 0 1 0 1000 -1 0 0 0 0 0 0 0 ##_recrdistribution_by_area   ** only one
area, one growth morph
-4 4 3 1 0 1000 -1 0 0 0 0 0 0 0 ##_recrdistribution_by_season 1   ** only one
area, one growth morph
-4 4 -3 1 0 1000 -1 0 0 0 0 0 0 0 ##_recrdistribution_by_season 2   ** only one
area, one growth morph
-4 4 -3 0 0 1000 -2 0 0 0 0 0 0 0 ##_recrdistribution_by_season 3   ** only one
area, one growth morph
-4 4 -3 0 0 1000 -2 0 0 0 0 0 0 0 ##_recrdistribution_by_season 4   ** only one
area, one growth morph

#Read one cohort growth deviation parameter; value must be 1 and it must not be
turned on for estimation;
#When cohort growth deviations are desired, then set this parameter to use blocks or
devs which will be estimated
1 1 1 1 -1 99 -3 0 0 0 0 0 0 0 #_cohort_growth_deviation

Custom maturity schedule when set to -9999 above
0 0 0 0 0 .5 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1

#_custom_MG-env_setup
0 #_ 0=read_one_setup_and_apply_to_all_env_fxns;
1=read_a_setup_line_for_each_MGparm_with_Env-var>0

#_custom_MG-block_setup
0 #_ 0=read_one_setup_and_apply_to_all_MG-blocks;
1=read_a_setup_line_for_each_block x MGparm_with_block>0

LO HI INIT PRIOR Pr_type SD PHASE

#_Spawner-Recruitment_parameters
3 # SR_fxn: 1=Beverton-Holt
#LO HI INIT PRIOR Pr_type SD PHASE
0 35 11.5825799456   12   0   1000   1 #Ln(R0). important scaling parameter estimated in first phase
0.2 1 0.870954119479 0.89   0   0.05   6 #steepness of S-R; bound by 0.2 and 1 ** start this at 0.87 - same mean and prior as mfcl.
0 10 0.6   0.6   0   1000 -2 #sigma-r std.dev. of natural log of recruitment deviations. ** Usually 0.6 for tunas
-5 5 0   0   0 1   -3 #Env_link coefficient   ** not using this
-5 5 0   0   0 1   -4 #init_equilibrium recruitment: ** not used initially.
0 0 0   0   0 0   -99 #reserved for future use as auotcorrelation parameter

0   #env-var_for_link
0   #_SR_env_target_1=devs;_2=R0;_3=steepness; this is the model process linke dto the env-Var
1   #do_recr_dev: 0=none; 1=devvector; 2=simple deviations (where a value of 1 is the norma usage)

recruitment_residuals
start_rec_year end_rec_year   Lower_limit   Upper_limit   phase
1952 2005 -15 15 2
1800   #_first_yr_fullbias_adj_in_MPD

#init_F_setupforeachfleet ** Initially set v low and estimated, although equilib catch was defined - should this be eq catch 1952/B1952? Prob doesn't matter.
#_LO HI INIT PRIOR PR_type SD PHASE
LO HI INIT PRIOR PR_type SD PHASE
 0 .1 0 .0 0 1000 -1 #1
 0 .1 .0 .0 0 1000 -1 #2
 0 .1 .0 .0 0 1000 -1 #3
 0 .1 .0 .0 0 1000 -1 #4
 0 .1 .0 .0 0 1000 -1 #5
 0 .2 .0 .0 0 1000 -1 #6
 0 .1 .0 .0 0 1000 -1 #7
 0 .1 .0 .0 0 1000 -1 #8
 0 .3 .0 .0 0 1000 -1 #9
 0 .1 .0 .0 0 1000 -1 #10
 0 .1 .0 .0 0 1000 -1 #11
 0 .1 .0 .0 0 1000 -1 #12
 0 .1 .0 .0 0 1000 -1 #13
 0 .1 .0 .0 0 1000 -1 #14
 0 .1 .0 .0 0 1000 -1 #15
 0 .1 .0 .0 0 1000 -1 #16
 0 .1 .0 .0 0 1000 -1 #17
 0 .1 .0 .0 0 1000 -1 #18
 0 .1 .0 .0 0 1000 -1 #19
 0 .1 .0 .0 0 1000 -1 #20

```
 0 .1 .0   .0   0  1000 -1 #21
 0 .1 .0   .0   0  1000 -1 #22
 0 .1 .0   .0   0  1000 -1 #23
```

#_Qsetup
A=do power, B=env-var, C=extra SD, D=devtype(<0=mirror, 0/1=none,
 #2=cons, 3=rand, 4=randwalk); E=0=num/1=bio, F=err_type
#_A B C D E F

0	0	0	0	0	0	#1
0	0	0	0	0	0	#2
0	0	0	0	0	0	#3
0	0	0	0	0	0	#4
0	0	0	0	0	0	#5
0	0	0	0	0	0	#6
0	0	0	0	0	0	#7
0	0	0	0	0	0	#8
0	0	0	0	0	0	#9
0	0	0	0	0	0	#10
0	0	0	0	0	0	#11
0	0	0	0	0	0	#12
0	0	0	0	0	0	#13
0	0	0	0	0	0	#14
0	0	0	0	0	0	#15
0	0	0	0	0	0	#16
0	0	0	0	0	0	#17
0	0	0	0	0	0	#18
0	0	0	0	0	0	#19
0	0	0	0	0	0	#20
0	0	0	0	0	0	#21
0	0	0	0	1	0	#22
0	0	0	0	1	0	#23
0	0	0	0	0	0	#24
0	0	0	0	0	0	#25
0	0	0	0	0	0	#26
0	0	0	0	0	0	#27
0	0	0	0	0	0	#28
0	0	0	0	0	0	#29
0	0	0	0	0	0	#30
0	0	0	0	0	0	#31
0	0	0	0	0	0	#32
0	0	0	0	0	0	#33
0	0	0	0	0	0	#34
0	0	0	0	0	0	#35

##
SELECTIVITY and RETENTION_PARAMETERS
Size selectivity** Pattern=0 is selectivity=1.0 for all lengths; Pattern=1 is logistic
(asymptotic); Pattern=5 is mimic other Fishery; Pattern=7 is double-logistic (dome-
shaped)
pattern retention(0/1) male(0/1) special
0   0   0   0   #1

0	0	0	0	#2
0	0	0	0	#3
0	0	0	0	#4
0	0	0	0	#5
0	0	0	0	#6
0	0	0	0	#7
0	0	0	0	#8
0	0	0	0	#9
0	0	0	0	#10
0	0	0	0	#11
0	0	0	0	#12
0	0	0	0	#13
0	0	0	0	#14
0	0	0	0	#15
0	0	0	0	#16
0	0	0	0	#17
0	0	0	0	#18
0	0	0	0	#19
24	0	0	0	#20
24	0	0	0	#21
24	0	0	0	#22
5	0	0	22	#23
0	0	0	0	#24
0	0	0	0	#25
0	0	0	0	#26
0	0	0	0	#27
0	0	0	0	#28
0	0	0	0	#29
0	0	0	0	#30
0	0	0	0	#31
0	0	0	0	#32
0	0	0	0	#33
0	0	0	0	#34
0	0	0	0	#35

Age selectivity ** Pattern=10 is age-selectivity = 1.0 one for all ages; Pattern=12 is logistic; Pattern=15 is mimic other Fishery; Pattern=18 is double-logistic
pattern retention(0/1) male(0/1) special

12	0	0	0	#1
12	0	0	0	#2
12	0	0	0	#3
15	0	0	3	#4
12	0	0	0	#5
12	0	0	0	#6
12	0	0	0	#7
12	0	0	0	#8
12	0	0	0	#9
12	0	0	0	#10
12	0	0	0	#11
12	0	0	0	#12

12	0	0	0	#13
12	0	0	0	#14
12	0	0	0	#15
15	0	0	15	#16
12	0	0	0	#17
12	0	0	0	#18
12	0	0	0	#19
10	0	0	0	#20
10	0	0	0	#21
10	0	0	0	#22
10	0	0	0	#23
15	0	0	2	#24
15	0	0	2	#25
15	0	0	2	#26
15	0	0	8	#27
15	0	0	8	#28
15	0	0	8	#29
15	0	0	14	#30
15	0	0	14	#31
15	0	0	14	#32
15	0	0	18	#33
15	0	0	18	#34
15	0	0	18	#35

Size selectivity
#20 3T-ALL
32   127   62   70   0 1000   2 0 0 0 0 0 0 0 #p1 - PEAK
-6   4   -6 0   0 1000   -2 0 0 0 0 0 0 0 #p2 - TOP
-1   9   4.79 0   0 1000   2 0 0 0 0 0 0 0 #p3 - ASC Width
-1   9   5.07 0.3   0 1000   2 0 0 0 0 0 0 0 #p4 - Desc Width
-6   9   -6   -5   0 1000   -2 0 0 0 0 0 0 0 #p5 - INIT
-6   9   -6   0   0 1000   -2 0 0 0 0 0 0 0 #p6 - FINAL
#21 4T-ALL
32   127   65.85 70   0 1000   2 0 0 0 0 0 0 0 #p1 - PEAK
-6   4   -3.16 0   0 1000   2 0 0 0 0 0 0 0 #p2 - TOP
-1   9   4.44 0   0 1000   2 0 0 0 0 0 0 0 #p3 - ASC Width
-1   9   5.20 0.3   0 1000   2 0 0 0 0 0 0 0 #p4 - Desc Width
-6   9   -5.7 -5   0 1000   2 0 0 0 0 0 0 0 #p5 - INIT
-6   9   -3   0   0 1000   2 0 0 0 0 0 0 0 #p6 - FINAL
#22 3D-ALL
32   127   62.4 70   0 1000   2 0 0 0 0 0 0 0 #p1 - PEAK
-6   4   -2.2 0   0 1000   2 0 0 0 0 0 0 0 #p2 - TOP
-1   9   3   0   0 1000   2 0 0 0 0 0 0 0 #p3 - ASC Width
-1   9   4.69 0.3   0 1000   2 0 0 0 0 0 0 0 #p4 - Desc Width
-6   9   -5.05 -5   0 1000   2 0 0 0 0 0 0 0 #p5 - INIT
-6   9   -4.32 0   0 1000   2 0 0 0 0 0 0 0 #p6 - FINAL
#23
-5 5 -1 0 0 1000 -2 0 0 0 0 0 0 0
-5 5 -1 0 0 1000 -2 0 0 0 0 0 0 0

Age selectivity ** The following block (lines 388-462) is for estimating age-based selectivity parameters only, i.e., age-based selectivity is turned ON
lo hi init prior pr_type sd phase env-variable use_dev dev_minyr dev_maxyr dev_stddev block_pattern
#1 1L-JP-JPDW-KR
2 19 5.1   8.09551 0 1000 2 0 0 0 0 0 0 0
0 19 1   0.38936 0 1000 2 0 0 0 0 0 0 0
#2 1L-TWDW
2 19 6.75   8.4359 0 1000 2 0 0 0 0 0 0 0
0 19 1.6   3.01463 0 1000 2 0 0 0 0 0 0 0
#3 1L-AU
2 19 8.3   8.09551 0 1000 2 0 0 0 0 0 0 0
0 19 1.8   3.38936 0 1000 2 0 0 0 0 0 0 0
#4 1L-NC
#2 19 2.6 8.09551 0 1000 2 0 0 0 0 0 0 0
#0 19 0.8 1   0 1000 2 0 0 0 0 0 0 0
#5 1L-FJ
2 19 7.2   8.09551 0 1000 2 0 0 0 0 0 0 0
0 19 1.1   3.38936 0 1000 2 0 0 0 0 0 0 0
#6 1L-OT
2 19 6.9   8.09551 0 1000 2 0 0 0 0 0 0 0
0 19 2.6   3.38936 0 1000 2 0 0 0 0 0 0 0
#7 2L-JP-JPDW-KR
2 19 7.6   8.09551 0 1000 2 0 0 0 0 0 0 0
0 19 2.4   3.38936 0 1000 2 0 0 0 0 0 0 0
#8 2L-TWDW
2 19 7.23   8.09551 0 1000 2 0 0 0 0 0 0 0
0 19 1.75   3.38936 0 1000 2 0 0 0 0 0 0 0
#9 2L-AS,WS
2 19 7.03 8.09551 0 1000 2 0 0 0 0 0 0 0
0 19 0.5   3.38936 0 1000 -2 0 0 0 0 0 0 0
#10 2L-TO
2 19 8.23   8.09551 0 1000 2 0 0 0 0 0 0 0
0 19 1.4   3.38936 0 1000 2 0 0 0 0 0 0 0
#11 2L-PF
2 19 12.0   8.09551 0 1000 2 0 0 0 0 0 0 0
0 19 3.8   3.38936 0 1000 2 0 0 0 0 0 0 0
#12 2L-OT
2 19 8.095   8.09551 0 1000 2 0 0 0 0 0 0 0
0 19 2.2   3.38936 0 1000 2 0 0 0 0 0 0 0
#13 3L-JP-JPDW-KR
2 19 3.86   8.09551 0 1000 2 0 0 0 0 0 0 0
0 19 1.00   3.38936 0 1000 2 0 0 0 0 0 0 0
#14 3L-TWDW

2	19	5.93734	8.09551	0	1000	2	0	0	0
	0	0	0	0					
0	19	2.14129	3.38936	0	1000	2	0	0	0
	0	0	0	0					

#15 3L-AU

2	19	3.00	8.09551	0	1000	-2	0	0	0	0
		0	0	0						
0	19	1	3.38936	0	1000	2	0	0	0	0
		0	0	0						

#16 3L-NZ
#2 19 8.09551 8.09551 0 1000 2 0 0 0 0 0 0 0
#0 19 1 3.38936 0 1000 2 0 0 0 0 0 0 0

#17 4L-JP-JPDW-KR

2	19	3.18433	8.09551	0	1000	2	0	0	0
		0	0	0	0				
0	19	1	3.38936	0	1000	2	0	0	0
		0	0	0					

#18 4L-TWDW

2	19	5.31111	8.09551	0	1000	2	0	0	0
		0	0	0	0				
0	19	2.31932	3.38936	0	1000	2	0	0	0
		0	0	0	0				

#19 4L-OT

2	19	2.20165	8.09551	0	1000	2	0	0	0
		0	0	0	0				
0	19	0.1	3.38936	0	1000	-2	0	0	0	0
		0	0							

#

1 # selparm_adjust_method
#_custom-env_linkage
0 #_ 0=read_one_setup_and_apply_to_all
#_custom-block_setup
0 #_
0=read_one_setup_and_apply_to_all_1=Custom_so_see_detailed_instructions_for_N
_rows_in_Custom_setup
lo hi init prior pr_type sd phase
-10 10 0 0 0 99 4   # ** No time blocks in this analysis
-4 #_phase_for_selex_parm_devs   ** No annual selectivity deviates
#
row 1 value added to survey CV (set to zero for no effect)

0	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	#0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0										

row 2 value added to discard stddev

0	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	#0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0										

row 3 value added to mean body wt stddev

0	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	#0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0										

row 4 multiplier for lencomp effective N (set to 1.0 for no effect)

1	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1
	1	#1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1
	1										

row 5 multiplier for agecomp effective N (set to 1.0 for no effect)

1	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1
	1	#1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1
	1										

row 6 multiplier for size-at-age effective N (set to 1.0 for no effect)

| 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |

1	1	1	1	1	1	1	1	1	1	1
1	#1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1
1										

#
LIKELIHOOD WEIGHTING FACTORS
===
#
#Degrees of Freedom for Discard and Mean Body Weight
30 #Degrees of freedom for Student's T distribution used to scale discard deviations
30 #Degrees of freedom for Student's T distribution used to scale mean body weight deviations.
Lambdas (emphasis factors)
1 #Max_lambda_phase
1 #sd_offset
Fleet and survey CPUE lambdas

1	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1
	1	#1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1
	1										

#_discard_lambdas

0	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	#0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0										

#_meanbodywt
0
#_lenfreq_lambdas

1	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1
	1	1	1	1	1	1	1	1	1	1	1

1	#1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1
1	1	1	1	1	1	1	1	1	1	1
1										

#_age_freq_lambdas

0	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	#0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0										

#_size@age_lambdas

0	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	#0| 0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0										

#_initial_equil_F
1
#_recruitment_lambda
1
#_parm_prior_lambda
1
#_parm_dev_timeseries_lambda
0
crashpen lambda
100
#max F
0.9
2   ** assuming this is continuous F rather than U equivalent
999 #_end-of-file

South Pacific Albacore Population Analysis (1952-02)
Stock Synthesis 2 Program (SS2)
Simon Hoyle
June 2007
#
INPUT DATA FILE
Model Dimensions
1951 #_styr
2005 #_endyr
4 #_nseas
3 3 3 3   # Number of months per quarter
1 # Spawning quarter,' i.e., spawning occurs at the beginning of this quarter
23   # Number of fishing 'fleets' (fisheries)
12   # Number of 'surveys' (CPUE Indices)
#
1L-JP-JPDW-KR%1L-TWDW%1L-AU%1L-NC%1L-FJ%1L-OT%2L-JP-JPDW-
KR%2L-TWDW%2L-AS,WS%2L-TO%2L-PF%2L-OT%3L-JP-JPDW-KR%3L-
TWDW%3L-AU%3L-NZ%4L-JP-JPDW-KR%4L-TWDW%4L-OT%3T-ALL%4T-
ALL%3D-ALL%4D-
ALL%24.2%25.2%26.2%27.8%28.8%29.8%30.14%31.14%32.14%33.18%34.18%3
5.18

 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5
 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5
 0.5 0.5 0.5 #_fishery timing_in_season
 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5
 0.5 0.5

1 #_Ngenders
20 #_Nages
#_init_equil_catch_for_each_fishery
0   0 0   0   0   0   0   0   0   0   0   0   0
         0   0   0   0   0   0   0   0   0   0
#_catch_biomass(mtons):_columns_are_fisheries,_rows_are_year*season
…

489 #_N_cpue_and_surveyabundance_observations
…

2 #_discard_type
0 #_N_discard_obs

0 #_N_meanbodywt_obs

0.00001 #_comp_tail_compression
0.0001 #_add_to_comp
50 #_N_LengthBins
30   32   34   36   38   40   42   44   46   48   50   52
         54   56   58   60   62   64   66   68   70   72   74

76	78	80	82	84	86	88	90	92	94	96
98	100	102	104	106	108	110	112	114	116	118
120	122	124	126	128						

1079 #_N_Length_obs
#Yr Seas Flt/Svy Gender Part Nsamp datavector(female-male)

1964	1	1	0	2	5.5	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0.018181818	0	0	
	0.018181818	0.036363636	0.109090909	0.127272727	0.090909091						
	0.145454545	0.218181818	0.127272727	0.054545455	0.054545455	0					
	0	0	0	0	0	0	0	0	0	0	0
	0										

…

0 #_N_age_bins
0 #_N_ageerror_definitions
0 #_N_Agecomp_obs
#Yr Seas Flt/Svy Gender Part Ageerr Lbin_lo Lbin_hi Nsamp datavector(female-male)

0 #_N_MeanSize-at-Age_obs
#Yr Seas Flt/Svy Gender Part Ageerr Ignore datavector(female-male)
samplesize(female-male)
0 #_N_environ_variables
0 #_N_environ_obs

999