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Improving stock assessments through data prioritization

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Keywords: stock assessment, sampling strategy evaluation, data prioritization, simulation study

Abstract: The need for “better data” is a common response of stakeholders and managers when confronted with the uncertainty of advice resulting from quantitative stock assessments. Most contemporary stock assessments are based on an integrated analysis of multiple data types each with their associated cost to collect. Data collection resources are inevitably limited, therefore it is important to quantify the relative value of increased sampling for alternative data types in terms of improving stock assessments. We approached this universal problem using a simulation study of a hypothetical, amalgam species developed from eight separate stock assessments conducted in the southeastern U.S. Atlantic waters. We simulated a population and a stock assessment from the amalgam species, and then individually improved alternative data types (indices, age compositions, landings and discards), by either increasing precision or sample size. We also simulated the effects of increased sampling for alternative groupings of data that might be collected in concert (e.g., commercial, all recreational, or survey). Our results show that, for the snapper-grouper complex we modeled, age composition data have the largest effect on the accuracy of assessments, with commercial age compositions being the most influential. This is due in part to the relative paucity of age composition data for many southeast U.S. marine stocks, so that modest increases in collection efforts have relatively high benefits for age-based assessment models currently in use for the region. Though this study used data from a particular region of the U.S., our investigative framework is broadly applicable for quantitatively evaluating the benefits of improved data collection in terms of the precision of stock assessments in any region.

41 Introduction

42 Fisheries management often depends on stock assessments to inform decisions about potential
43 catch limits relative to the dynamics of the stock. Uncertainty, or a lack of data, may necessitate
44 a more precautionary approach to management, which often leads to lower available yields.
45 Thus, more certainty about the data included in a stock assessment is highly desirable. When the
46 data are available, stock assessments are an integrated analysis of those multiple data sources,
47 including landings and discards, life history information, size and age compositions, and indices
48 of abundance, each of which has an associated level of uncertainty (Maunder and Punt 2013).
49 For example, fishery catches and discards may be imprecise due to low observer coverage or
50 sporadic port sampling. Life history data used to inform natural mortality, growth, and
51 reproductive output may be sparse or borrowed from other species (Punt et al. 2011). Age
52 composition data require considerable post-collection processing that varies greatly across
53 laboratories. Fishery-independent indices require extensive field survey efforts and consistent
54 funding to maintain the integrity of the relative abundance time series. Research
55 recommendations compiled during assessments inevitably contain requests for more of each of
56 these data types, yet few efforts have focused on how best to prioritize data collection efforts.
57 Even in the face of an increasing demand for assessments, only minimal improvements to data
58 collection may be economically feasible. Thus, there is a pressing need to develop approaches
59 for prioritizing data in terms of its utility for stock assessments (Magnusson and Hilborn 2007).

60 When faced with the question of which data type to collect more of, no clear priority
61 exists. Scientists want the assessment to reflect the population and characterize uncertainty as
62 well as possible, but there have only been a few studies that address the effects of various data

sources on assessment results (Powers and Restrepo 1993; Yin and Sampson 2004; Szuwalski and Punt 2012).

Data collection efforts, as well as the perceived needs for additional data types, vary considerably across geographic regions. In regions where catches are hardly characterized (e.g. the Caribbean), data collection priorities are clearer. However, regions that have conducted multiple age-structured stock assessments have various data deficits that need to be filled. As an example, fishery scientists working on species in the Atlantic waters of the southeastern U.S. repeatedly encounter a lack of fishery-independent survey data, discards are difficult to characterize, and annual age composition data are insufficient. In addition, a high proportion of the landings and discards are taken by the recreational fleet, which is inherently difficult to monitor. Nevertheless, age-structured assessments are regularly used to inform fishery management decisions. The goal of this work is to develop a framework for providing objective guidance about prioritizing data sources for fish stock assessments. Using simulation, we evaluate which data types are most effective at improving assessment accuracy by modeling the effect of improving each data source. Although our study design is applied to data from a single region, the approach is general and could be applied in other regions.

Methods

We simulated a hypothetical population (i.e., an amalgam species) based on information available for actual stocks from the snapper-grouper complex that have been individually assessed in the Atlantic waters off the southeastern U.S. We reviewed the assessed stocks in the region and averaged the results of eight stocks: Vermilion Snapper (*Rhomboplites aurorubens*), Red Porgy (*Pagrus pagrus*), Black Sea Bass (*Centropristis striata*), Red Snapper (*Lutjanus*

campechanus), Greater Amberjack (*Seriola dumerili*), Red Grouper (*Epinephelus morio*), Snowy Grouper (*Hyporthodus niveatus*), and Gag (*Mycteroperca microlepis*) (SEDAR 2008, 2009, 2010, 2012a, b, 2013a, b, 2014). The combined results from the eight assessments provide an amalgam stock that represents the snapper/grouper complex from 1963 to 2012 (Table 1).

We modeled ages 1 to 16 years using annual time steps, with an average maximum age of 16. We used an averaged von Bertalanffy (von Bertalanffy 1938) growth curve ($L_{\infty} = 792$ mm, $k = 0.18$, $t_0 = -1.36$) (Figure 1), and an average age of 50% maturity of 2.25 years. For the growth curve, we excluded Greater Amberjack, as its growth pattern seemed to diverge from the other species. However, its other life history parameters were similar to the other species in the complex. We modeled two fleets (recreational and commercial) and two relative abundance indices (one fishery-dependent and one fishery-independent) each based on the averaged trends of the eight stocks.

According to the amalgam species data, the recreational index data were typically available beginning in 1981 and ran continuously through the terminal year. The fishery-independent index began in 1996 and also ran through the terminal year of the model (Figure 2). The average commercial fishery landings were assumed to be known very well, with a coefficient of variation (CV) of 0.05. The CV for the recreational fishery was related to the percent standard error (PSE) provided by a Marine Recreational Information Program (MRIP) catch data query (Personal communication from the National Marine Fisheries Service, Fisheries Statistics Division. [Queried November 2014]). Discards for each fishery were available annually since 1992. Age composition data were compiled from the survey (9 years), commercial fleet (12 years), and the recreational fleet (12 years). We did not simulate length

composition data as it has been shown to provide relatively little information to estimate population dynamics for snapper-grouper species in the region (SEDAR 2012b).

We use a catch-age model called the Beaufort Assessment Model (BAM) that is commonly used for assessments in the southeastern U.S. as the operating model for the simulations (Williams and Shertzer 2015). Briefly, BAM is a statistical catch-age model implemented with the AD Model Builder software (Fournier et al. 2012), and offers the flexibility of a customizable source code while providing the basic constructs and functions of most other age-based assessment models (e.g., Beverton-Holt stock recruitment relationship, a variety of age-based selectivity options, weighting options for the likelihood components, penalties to constrain parameter spaces, etc.). We only altered the operating model between runs to change either the precision or the sample size of each data type (Table 2).

We used the average of the parameters from each of the stock assessments (see Table 2) to create a set of input parameters to simulate a “true” population with the operating model. Each true population data set was then fit with the same operating model using optimization.

Our algorithm for the simulation was as follows:

Step 1: Configure the operating model with fixed parameters to create a simulated data set using BAM by imputing the mean of each of the following parameters from our amalgam stock: start year, maximum age, years of recruitment deviations, catch per unit effort time series (CPUEs), landings time series, von Bertalanffy growth parameters, steepness, selectivities, catchabilities, weight at age, maturity at age, and fishing mortality trends (Figures 3-4, see the Supplementary Material for the data input file). We used

2012 as the terminal year, which was the last assessment year in our amalgam stock. The mean selectivity for each sector was used for the amalgam species: commercial, recreational, survey, and discards (Figure 5). We generated age compositions with a multinomial distribution using the mean sample size and the number of years that composition data were available for our amalgam species. We then allow for random recruitment assuming lognormal deviations (Fogarty et al. 1991).

Step 2: Add observation error to mimic actual assessments. Observation error was added to the recreational CPUE and survey indices based on the average CV of these two data types across the eight prior assessments. Error was also added to the composition data by increasing or decreasing the sample sizes used in the multinomial distribution.

Step 3: Create the operating data set using all stochastic components from step 2 and then use BAM to estimate model parameters of the stochastic, simulated data set.

Step 4: Collect the results from the estimation in step 3, and repeat for the desired number ($N=2000$) of bootstrap iterations.

We tracked model estimates of virgin recruitment, steepness, Acceptable Biological Catch (ABC), and status indicators (spawning stock biomass sufficient to produce maximum sustainable yield (MSY , SSB_{MSY}), fishing mortality required to harvest MSY (F_{MSY}), and minimum stock size threshold ($MSST$)). ABC was calculated for a single year following the terminal year of the assessment using terminal biomass and estimates of fishing mortality from

each fishery. MSST is used as an indicator by the South Atlantic Fishery Management Council of an overfished stock and was calculated as $0.5 * SSB_{MSY}$.

We focused on data types considered to be the best candidates for improved collection: landings, discards, age compositions, and fishery independent data (i.e., CPUE and age composition). The relative cost of each type of data is known, and programs are currently in place that could improve their quality. For example, a larger budget for the fishery-independent survey would likely translate into more sea days and more samples taken, which would translate directly into the type of precision and sample size improvements modeled here. After initial simulations improving each individual data type separately (i.e., commercial discards, commercial age compositions, recreational discards, recreational landings, recreational age compositions, recreational CPUE, survey precision, survey age compositions), we conducted additional simulations where data types were grouped as ‘commercial’, ‘recreational’, and ‘survey.’ In each of the groupings, the CVs of landings, discards, and indices were decreased by four-fold and the sample sizes of age compositions were increased by five-fold. The values four-fold and five-fold were somewhat arbitrary but were chosen based on the extremes of what is considered practical for data collection efforts in the southeastern U.S. For example, because the amount of age data available in prior assessments was relatively small, we deemed it feasible to collect five times more otoliths above current efforts. But given current efforts to monitor landings and discards in our region, improving the precision of these data types by more than four-fold was considered impractical. The separate data types were grouped as: recreational landings and all discards, all age compositions, all survey data, all commercial data (except landings), all commercial data, and all indices (see Table 2 for the particulars of each scenario).

For each scenario, we generated $N = 2000$ bootstrap replicates, which was sufficient for the means of all estimated parameters to converge to stable values. However, one parameter, steepness, proved difficult to estimate in $\sim 7\text{--}12\%$ of replicates, and was estimated at its upper bound of 0.99, a situation common in stock assessment (Conn et al. 2010). These runs were culled before summarizing the results, because in practice steepness hitting an upper bound would not be considered a valid run for assessment purposes. However, we report the proportion of runs culled for each scenario (Table 3), as we consider it one indicator regarding the value of improved data.

Steps two through four were repeated as each data type was improved either by decreasing the CV or increasing the age composition sample sizes. Parameter estimates and management quantities of each assessment fitted to improved data were compared to those of the initial base model estimates using the mean relative error across all bootstrap replicates, $RE_i = (\hat{a}_i/a_i) - 1$, where $\hat{a}_i$ is the estimated value of parameter i and a_i is the true value of parameter i .

Results

The base model run (i.e., without data improvements; see row 1 of Table 3) overestimated the biomass benchmark ($RE = 0.38$), and underestimated the fishing status benchmark ($RE = -0.67$). The estimates of the reference points show a positive bias for the base case. The bias is the result of the variation put into the data and the sample sizes used. If the variation is reduced and sample size increased prior to the data improvements, the model fits the inputs exactly. Steepness was well-estimated in the base case as was the ABC ($RE = -0.01$ and

0.05, respectively). Time series of predicted landings and discards by fishery replicated the general patterns observed across the eight assessed species (Fig. 6). Simulations with improvements to the individual data types reduced the *RE* of model estimates by 10 - 49% (Table 3). Improvements (i.e., increased effective sample sizes) in both the recreational and the commercial age compositions had the greatest effect on model accuracy (23 - 68%). For example, improved commercial age compositions reduced the estimation error of the biomass benchmarks and R_0 by a considerable amount (12.5 - 47%), while improved recreational age compositions had the most effect on the estimates of R_0 , MSY, and ABC (12.5 - 60%).

Overall the grouped components reduced the *RE* of model estimates by 22 - 70%. Specifically, the grouped composition data improvements had the largest effect on model accuracy overall, which is consistent with the results from the improvement of individual components. The effects were approximately double that of the individual component runs. However, the survey components grouping showed an effect that was nearly absent in the runs of their individual components. The improvement of all survey components had a large effect on both the biomass and fishing benchmark estimates (*RE* decreased by 37% and 70% respectively), surpassing the effect of the all-composition data grouping for those two reference points. In general, probability density functions (pdfs) of key management quantities derived from the assessment illustrate how improved data collection can influence fishery management advice (Fig. 7, Supplementary Material). For example, when all age composition data were improved, the relative error in the fishing benchmark (F/F_{msy}) and the biomass benchmark ($\text{SSB}/\text{SSB}_{\text{msy}}$) decreased by 58% and 37%, respectively, while the relative error in the estimated ABC was near zero. For the fishing benchmark in particular, improvements in the age composition data altered

the qualitative determination of stock status from overfishing to not overfishing (Fig. 7). For the amalgam species considered here, the estimated ABC was about 10% larger for models simulating improvements in the age composition data. Further improvements in the age composition data decreased the presence of outliers and resulted in a narrower distribution about the median (i.e. greater precision). The pdfs for all scenarios can be found in the Supplementary Material.

Discussion

Our study provides a framework to generate specific and objective guidance to fishery scientists and managers who must decide how to allocate limited monitoring and research resources towards improving stock assessments. Improving accuracy would provide several benefits, including better characterizing the stock dynamics and reducing the uncertainty in management regulations. In U.S. fisheries management, reduced uncertainty in the assessment generally results in larger catch limits, providing obvious manager and stakeholder benefits.

Our results are interpreted within the framework of the way assessments are conducted and the current data availability in the southeastern U.S. For example, the data could have been improved further (e.g., index CVs down to 5% or samples sizes in the 1000s per year as is the case in other regions), however, it would be an impractical result. It would not be possible to expand the current otolith sampling, survey or observer programs within a reasonable timeframe in order to achieve those improvements. Therefore, we used our judgement, based on the evidence provided in over a decade of snapper/grouper assessments, to improve the data by realistic increments for the region. The feasibility of data improvement will differ across regions depending on the current data collection programs.

Assessments conducted in the southeastern U.S. are dominated by fishery-dependent data. Commercial landings data are treated as known with high precision because there are often both trip ticket and logbook programs in place. There is also a need to anchor the model at the reported landings values, though the historical reconstruction of landings time series are inherently less certain. Commercial discards are much less certain and often estimated using logbook or observer data where available. General recreational landings are assumed less precise, and are estimated using an angler intercept survey. The angler intercepts are variable and bring significant uncertainty to the model. Recreational effort is estimated using a phone survey (Andrews et al. 2014), which has historically suffered from a low response rate. This has motivated the Marine Recreational Information Program (MRIP) to switch to a mail survey to decrease uncertainty around the landings and effort estimates. However, our study showed that the most influential portion of recreational data for assessment purposes in the region is the composition data. The improvement of the recreational discards also had an effect on the fishing benchmark estimate. Both recreational and commercial discards are estimated with very large CVs and are rarely verified with observer data. For our simulation, we used the same selectivity for the recreational and commercial fisheries discards because of a lack of information to differentiate the two. Due to the fact that much of the recreational fishing for most of these species is done using similar gear and in similar depths, there are few possibilities for recreational fisherman to discard different age classes. However, we did not model only undersized fish as being discarded. The dome-shaped selectivity we used takes into account both the closures and undersized fish. The difficulty specifying discard selectivity may have a very small impact on the assessment, as our study suggests that improving the commercial discard data had almost no effect on the model accuracy.

Fish stocks in the Atlantic waters of the southeastern US have not been adequately sampled by a fishery independent survey in the past (e.g. Rindone et al. 2015). When such data are used in assessments, corresponding age compositions are typically available but noisy. In practice, we use length compositions only when age compositions are absent because they are often too noisy to provide informative demographic information to the model. Therefore we did not attempt to model length compositions in this study. None of the survey components has a noticeable effect individually, but the survey grouping was the second most influential data source in our study. While the composition grouping improved the biomass benchmarks, virgin recruitment, and MSY estimates, the survey grouping improved the fishing benchmark. It should be noted that the component grouping also had an effect on the fishing benchmark, but the relative error improvement was slightly less (58% vs. 70%).

A few other studies have investigated the prioritization of data collection or improvements in different ways. Powers and Restrepo (1993) investigated how increasing precision in some of the data inputs changed the outcome of the assessment model used for King Mackerel (*Scomberomorus cavalla*) management in the Gulf of Mexico. Their study did not contain a simulation component, so it cannot be known whether the changes in the outcomes were any closer to the truth. If the true population dynamics are not known, results cannot be measured in terms of accuracy, but rather the desirability of the assessment outcome. Szuwalski and Punt (2012) used a simulation framework to determine research priorities in light of multiple model uncertainties. Using Eastern Bering Sea Snow Crab (*Chionoecetes opilio*), they increased the precision on the survey CPUE and the number of samples to develop the growth curve. This improved the estimability of some parameters; however their results are much more applicable to a length-structured model. The current study is most similar to Yin and Sampson's (2004), with

a few key differences. Their study used a fractional factorial design to evaluate how input data errors and the characteristics of the stock (with a focus on Pacific coast groundfish using the Stock Synthesis program (Methot 2000)) affected the bias and precision of the model outcomes. We used the BAM model, and formed an amalgam species data set to represent species in the Atlantic waters of the southeastern U.S. We used sample sizes and CVs that are reasonable for our region, which are lower than Yin and Sampson's (2004) composition sample size and a larger range of CVs than theirs for the survey CPUE. Nonetheless, we have one key result the same: age composition sample size is very influential on the accuracy of assessment outcomes.

For our region, we demonstrated that the individual components as well as the landings and discards grouping had very little impact on model accuracy. The composition grouping had the biggest effect on the accuracy of the assessment, followed by all survey components. Of the individual component runs, the commercial composition data was most influential followed by the recreational compositions. Interpreting the results in light of the cost of improving the data is encouraging. Composition data are relatively inexpensive when an aging lab is already established and operational. All otoliths have a similar cost to process but not necessarily to collect. A recreational otolith may be more expensive to collect because the process by which a port sampler gathers otoliths is typically opportunistic. Consequently, rather than additions to the daily sampling, data improvement may require additional days of sampling. Commercial composition data are easier to gather through standard sampling procedures at the dealers or fish houses. Compared to the cost of increasing a recreational effort sampling program, increasing fishery observer coverage, or increasing sampling days of a fishery-independent survey, composition data require the smallest investment with the biggest return.

Our results come with a variety of caveats. Most importantly, the results are dependent on the combination of data sources used for the simulation. In other words, the history of removals, the biology of the stock and the availability of the different data sources through time will be unique by region and stock and will likely result in different data prioritization results. As an example, our amalgam stock had a very small proportion of the biomass removed through discarding. Other stocks' main source of removals may be discards, and improvements in the accuracy of discard reporting would likely factor in more heavily than the precision of catches or composition sample sizes. Stocks in regions where fishery-independent surveys have covered the stock well may not show a large effect if the survey CVs were reduced. Also, we examined how improvements in the existing data would affect accuracy of the assessment. We did not look at the effect of adding a new data source, such as a survey, or expanding the spatial coverage of the fleets or surveys, though that is a future research goal.

Our input data were compiled using a number of reconstructed data sets (e.g. recreational landings before 1981), but we did not look into whether those methods of reconstruction had an effect on our results. We did this for two reasons: we were interested in the effect of improving data collection now, and the methods for historical reconstruction were too varied (ranging from linear interpolation between no catches and the first year of reported data to applying a catch rate to effort estimates back in time). Changing the uncertainty of those catches back in time would not address our main objective of informing current data collection efforts.

Steepness is difficult to estimate and is often fixed in practice. However, the contrast in our data likely allowed for the parameter to be estimated in a large proportion of our model runs (Conn et al. 2010). In the model runs that remained after we culled the bounded runs (as

described in the Methods section) the estimates of steepness were consistently accurate. If our amalgam species demonstrated a different exploitation pattern, steepness may not have been estimable.

We did not attempt to address bias in any of the data sets. We have little information about which direction bias might occur in the actual data. For example, we only have speculative information about whether landings may be over or underreported, or whether discards are over or underestimated. It is known that an increase in sample size cannot overcome a known bias (Coggins and Quinn II 1998). However, without better evidence of the direction of a potential bias, we decided to focus our study on precision.

Finally, we did not initially incorporate aging error in our simulation. The assessments conducted in our region rarely show an effect when the aging error matrix is used for a sensitivity analysis. However, our results beg the question of whether substantial aging error would dampen our results, and change the data prioritization advice. Again we considered precision rather than bias, and ran alternative scenarios with an aging error matrix that was larger than any ever used for our region (i.e. the readers agreed only half the time) before we saw a change in the results. The amount of aging error normally reported for stocks in our region did not cause a change in the data prioritization advice. In the extreme scenario we had to use in order to perturb our initial results, one might argue that an age-structured model should be avoided if the aging is so uncertain.

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410

Figure Legends

Fig. 1. The von Bertalanffy growth curve for the amalgam species plotted with the curves for each of the species included in the amalgam.

Fig. 2. Recreational CPUE and survey index used in the base model run. The points represent the model inputs and the grey error bars are the 5th and 95th quantiles of the model fits to the data.

Fig. 3. Proportion of total fishing mortality attributed to commercial landings, recreational landings, commercial discards, and recreational discards used in the base model. Each of the eight stocks is plotted in grey with the averaged trend over all the stocks in black.

Fig. 4. Total fishing mortality applied to the stock in the base model (shown in black). Each of the eight stocks used to inform the average trend are shown in grey for reference.

Fig. 5. Proportional selectivity by age for each fleet and survey. The commercial, recreational, and survey selectivities are each means of the various assessment model fits from the eight species. The discard selectivity is for both the commercial and recreational fleet.

Fig. 6. Model fits to the recreational (column one) and commercial (column two) landings (row one) and discards (row two). The points represent the model inputs and the grey error bars are the 5th and 95th quantiles of the model fits to the data.

Fig. 7. Estimates of F/F_{MSY} , SSB/SSB_{MSY} , and ABC (klb) plotted alongside the relative error of the base data (solid line) and the improved data (dashed line) assessments. The vertical lines are medians of the bootstrap replicates.

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Table 1. The compiled parameters for the amalgam species. These parameters represent species in the Atlantic waters of the southeast U.S.: Vermilion Snapper (VS), Red Porgy (RP), Black Sea Bass (BSB), Red Snapper (RS), Greater Amberjack (GAJ), Red Grouper (RG), Snowy Grouper (SG), and Gag (GAG). AVG represents the value used in the simulated population. In most cases, we used an arithmetic mean. However, we excluded GAJ growth parameters, as they seemed to deviate from the snapper/grouper complex. MSST is the minimum stock size threshold, which is used to determine whether a stock is considered overfished.

	VS	RP	BSB	GAJ	RS	RG	GAG	SG	AVG
Start year	1946	1972	1978	1946	1955	1976	1962	1974	1963
L_{∞}	506	528	496	1194	902	848	1091	1065	792
k	0.12	0.20	0.18	0.34	0.24	0.21	0.17	0.09	0.18
t_0	-3.50	-1.53	-0.92	-0.45	-0.03	-0.67	-1.31	-2.88	-1.36
Steepness	0.71	0.41	0.48	0.74	0.85	0.92	0.95	0.84	0.74
M_{MSST}	0.22	0.225	0.38	0.23	0.08	0.14	0.115	0.12	0.19
A_{mat}	1	1	1	1	2	3	3	6	2.25
Max age	12	14	11	10	20	16	20	25	16
Years of Commercial comps	19	13	12	7	8	5	15	14	12
Years of Recreational comps	27	8	11	1	20	11	12	3	12
Years of Survey comps	10	22	23	0	0	11	0	5	9

Table 2. Scenarios considered for each of the data improvements. The rows are each model run, either the base model or a run named after the data source that was improved. The columns are either CVs (in the case of indices, landings, or discards) or sample size (in the case of composition data). The base case contains no data improvements and each data improvement across columns is in bold and denoted with an asterisk.

	Survey CPUE CV	Survey comps sample size	Recreational landings CV	Recreational discards CV	Recreational CPUE CV	Recreational comps sample size	Commercial landings CV	Commercial discards CV	Commercial comps sample size
Base	0.75	25	0.75	1	0.5	10	0.05	1	30
Commercial comps sample size	0.75	25	0.75	1	0.5	10	0.05	1	150*
Commercial discards CV	0.75	25	0.75	1	0.5	10	0.05	0.25*	30
Recreational comps sample size	0.75	25	0.75	1	0.5	50*	0.05	1	30
Recreational CPUE CV	0.75	25	0.75	1	0.125*	10	0.05	1	30
Recreational discards CV	0.75	25	0.75	0.25*	0.5	10	0.05	1	30
Recreational landings CV	0.75	25	0.1875*	1	0.5	10	0.05	1	30
Survey CPUE CV	0.1875*	25	0.75	1	0.5	10	0.05	1	30
Survey comps sample size	0.75	125*	0.75	1	0.5	10	0.05	1	30
Survey CPUE CV + comps sample size	0.1875*	125*	0.75	1	0.5	10	0.05	1	30
Commercial discards CV + comps sample size	0.75	25	0.75	1	0.5	10	0.05	0.25*	150*
All recreational components	0.75	25	0.1875*	0.25*	0.125*	50*	0.05	1	30
All comps sample sizes	0.75	125*	0.75	1	0.5	50*	0.05	1	150*
All indices CVs	0.1875*	25	0.1875*	1	0.125*	10	0.05	1	30
Rec landings CV + all discards CVs	0.75	25	0.1875*	0.25*	0.5	10	0.05	0.25*	30

Table 3. The mean relative errors of the base assessment and each assessment of an improved data set. The values and category names in bold are the components or categories that contributed most to the accuracy of the assessment. The top section is the grouped data improvements, and the bottom contains the individual data component improvements. Culled is the proportion of runs culled due to steepness hitting the upper bound.

	Steepness	Culled	R_0	ABC	MSY	F_{msy}	F/F_{msy}	SSB_{msy}	SSB/SSB_{msy}
Base	-0.01	0.116	-0.32	0.05	-0.22	-0.15	-0.67	-0.35	0.38
All commercial	-0.01	0.095	-0.28	-0.01	-0.21	-0.11	-0.37	-0.31	0.29
All recreational	-0.01	0.102	-0.29	0.01	-0.22	-0.11	-0.48	-0.32	0.35
Landings and discards	0	0.113	-0.32	0.05	-0.23	-0.12	-0.72	-0.36	0.39
All survey components	-0.01	0.075	-0.28	-0.06	-0.22	-0.09	-0.2	-0.31	0.24
All indices	-0.02	0.114	-0.26	0.05	-0.19	-0.17	-0.58	-0.27	0.36
All comps	-0.01	0.088	-0.22	-0.03	-0.17	-0.1	-0.28	-0.23	0.24
Recreational age comps	0	0.111	-0.28	0.02	-0.2	-0.13	-0.53	-0.32	0.35
Survey age comps	-0.01	0.107	-0.31	-0.02	-0.23	-0.11	-0.41	-0.34	0.33
Commercial age comps	-0.01	0.100	-0.28	-0.02	-0.21	-0.12	-0.36	-0.30	0.29
Recreational index	-0.02	0.125	-0.29	0.05	-0.21	-0.16	-0.58	-0.31	0.38
Survey index	0	0.110	-0.31	0.06	-0.22	-0.14	-0.65	-0.35	0.4
Recreational landings	-0.01	0.120	-0.3	0.06	-0.2	-0.15	-0.69	-0.34	0.39
Commercial discards	-0.01	0.123	-0.31	0.05	-0.22	-0.14	-0.65	-0.35	0.38
Recreational discards	-0.01	0.114	-0.3	0.05	-0.22	-0.13	-0.34	-0.69	0.38

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Draft

Supplementary Material

Figure S1. Commercial age compositions (increased sample size)

Supplementary Material

Figure S2. Commercial age compositions (increased sample size)

Supplementary Material

Figure S3. Commercial age compositions (increased sample size)

Supplementary Material

Figure S4. Commercial discards

Supplementary Material

Figure S5. Commercial discards

Supplementary Material

Figure S6. Commercial discards

Supplementary Material

Figure S7. Recreational age compositions (increased sample size)

Supplementary Material

Figure S8. Recreational age compositions (increased sample size)

Supplementary Material

Figure S9. Recreational age compositions (increased sample size)

Supplementary Material

Figure S10. Recreational CPUE

Supplementary Material

Figure S11. Recreational CPUE

Supplementary Material

Figure S12. Recreational CPUE

Supplementary Material

Figure S13. Recreational discards

Supplementary Material

Figure S14. Recreational discards

Supplementary Material

Figure S15. Recreational discards

Supplementary Material

Figure S16. Recreational landings

Supplementary Material

Figure S17. Recreational landings

Supplementary Material

Figure S18. Recreational landings

Supplementary Material

Figure S19. Survey age compositions (increased sample size)

Supplementary Material

Figure S20. Survey age compositions (increased sample size)

Supplementary Material

Figure S21. Survey age compositions (increased sample size)

Supplementary Material

Figure S22. Survey index

Supplementary Material

Figure S23. Survey index

Supplementary Material

Figure S24. Survey index

Supplementary Material

Figure S25. All commercial components (increased age comp N, decrease discard CV)

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Figure S26. All commercial components (increased age comp N, decrease discard CV)

Supplementary Material

Figure S27. All commercial components (increased age comp N, decrease discard CV)

Supplementary Material

Figure S28. All recreational components (Increased rec agec sample size, increased discard estimate precision, increased landings precision, decreased CPUE CV)

Supplementary Material

Figure S29 All recreational components (Increased rec agec sample size, increased discard estimate precision, increased landings precision, decreased CPUE CV)

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Figure S30. All recreational components (Increased rec agec sample size, increased discard estimate precision, increased landings precision, decreased CPUE CV)

Supplementary Material

Figure S31. All recreational components (Increased rec agec sample size, increased discard estimate precision, increased landings precision, decreased CPUE CV)

Supplementary Material

Figure S32. All indices

Supplementary Material

Figure S33. All indices

Supplementary Material

Figure S34. All indices

Supplementary Material

Figure S35. All survey components (increased sample size)

Supplementary Material

Figure S36. All survey components (increased sample size)

Supplementary Material

Figure S37. All survey components (increased sample size)

Supplementary Material

Figure S38. All compositions (increased sample size)

Supplementary Material

Figure S39. All compositions (increased sample size)

Supplementary Material

Figure S40. Landings and discards

Supplementary Material

Figure S41. Landings and discards

Supplementary Material

Figure S42. Landings and discards

[illegible]

[illegible]

Supplementary Material

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//Tune Fapex (tuning removed in final year of optimization)
init_number set_Ftune;
init_int set_Ftune_yr;

//threshold sample sizes for age comps
init_number minSS_survey1_agec;
init_number minSS_fleet1_agec;
init_number minSS_fleet2_agec;

//ageing error matrix (columns are true ages, rows are ages as read for age comps: columns should sum to one)
init_matrix age_error(1,nages,1,nages);

// #####Indexing integers for year(iyear), age(iage),length(ilen) #####
int iyear;
int iage;
int ilen;
int ff;

number sqrt2pi;
number g2mt;           //conversion of grams to metric tons
number g2kg;           //conversion of grams to kg
number g2klb;          //conversion of grams to 1000 lb
number mt2klb;         //conversion of metric tons to 1000 lb
number mt2lb;          //conversion of metric tons to lb
number dzero;          //small additive constant to prevent division by zero
number huge_number;    //huge number, to avoid irregular parameter space

init_number end_of_data_file;

//this section MUST BE INDENTED!!!
LOCAL_CALCS
if(end_of_data_file!=999)
{
    cout << "**** WARNING: Data File NOT READ CORRECTLY ****" << endl;
    exit(0);
}
else
{cout << "Data File read correctly" << endl;}
END_CALCS

PARAMETER_SECTION

LOCAL_CALCS
const double dummy_optimize_PH=set_dummy_optimize;

const double Linf_LO=set_Linf(2); const double Linf_HI=set_Linf(3); const double Linf_PH=set_Linf(4);
const double K_LO=set_K(2); const double K_HI=set_K(3); const double K_PH=set_K(4);
const double t0_LO=set_t0(2); const double t0_HI=set_t0(3); const double t0_PH=set_t0(4);
const double steep_LO=set_steep(2); const double steep_HI=set_steep(3); const double steep_PH=set_steep(4);
const double log_R0_LO=set_log_R0(2); const double log_R0_HI=set_log_R0(3); const double log_R0_PH=set_log_R0(4);
const double R_autocorr_LO=set_R_autocorr(2); const double R_autocorr_HI=set_R_autocorr(3); const double
R_autocorr_PH=set_R_autocorr(4);
const double rec_sigma_LO=set_rec_sigma(2); const double rec_sigma_HI=set_rec_sigma(3); const double rec_sigma_PH=set_rec_sigma(4);
const double selpar_L50_survey1_LO=set_selpar_L50_survey1(2); const double selpar_L50_survey1_HI=set_selpar_L50_survey1(3); const
double selpar_L50_survey1_PH=set_selpar_L50_survey1(4);
const double selpar_slope_survey1_LO=set_selpar_slope_survey1(2); const double selpar_slope_survey1_HI=set_selpar_slope_survey1(3);
const double selpar_slope_survey1_PH=set_selpar_slope_survey1(4);
const double selpar_L50_fleet1_LO=set_selpar_L50_fleet1(2); const double selpar_L50_fleet1_HI=set_selpar_L50_fleet1(3); const double
selpar_L50_fleet1_PH=set_selpar_L50_fleet1(4);
const double selpar_slope_fleet1_LO=set_selpar_slope_fleet1(2); const double selpar_slope_fleet1_HI=set_selpar_slope_fleet1(3); const
double selpar_slope_fleet1_PH=set_selpar_slope_fleet1(4);
//const double selpar_L50_fleet1_D_LO=set_selpar_L50_fleet1_D(2); const double selpar_L50_fleet1_D_HI=set_selpar_L50_fleet1_D(3);
const double selpar_L50_fleet1_D_PH=set_selpar_L50_fleet1_D(4);

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//const double selpar_slope_fleet1_D_LO=set_selpar_slope_fleet1_D(2); const double
selpar_slope_fleet1_D_HI=set_selpar_slope_fleet1_D(3); const double selpar_slope_fleet1_D_PH=set_selpar_slope_fleet1_D(4);
//const double selpar_L502_fleet1_D_LO=set_selpar_L502_fleet1_D(2); const double selpar_L502_fleet1_D_HI=set_selpar_L502_fleet1_D(3);
const double selpar_L502_fleet1_D_PH=set_selpar_L502_fleet1_D(4);
//const double selpar_slope2_fleet1_D_LO=set_selpar_slope2_fleet1_D(2); const double
selpar_slope2_fleet1_D_HI=set_selpar_slope2_fleet1_D(3); const double selpar_slope2_fleet1_D_PH=set_selpar_slope2_fleet1_D(4);
const double selpar_peak_fleet1_D_LO=set_selpar_peak_fleet1_D(2); const double selpar_peak_fleet1_D_HI=set_selpar_peak_fleet1_D(3);
const double selpar_peak_fleet1_D_PH=set_selpar_peak_fleet1_D(4);
const double selpar_top_fleet1_D_LO=set_selpar_top_fleet1_D(2); const double selpar_top_fleet1_D_HI=set_selpar_top_fleet1_D(3); const
double selpar_top_fleet1_D_PH=set_selpar_top_fleet1_D(4);
const double selpar_ascwid_fleet1_D_LO=set_selpar_ascwid_fleet1_D(2); const double
selpar_ascwid_fleet1_D_HI=set_selpar_ascwid_fleet1_D(3); const double selpar_ascwid_fleet1_D_PH=set_selpar_ascwid_fleet1_D(4);
const double selpar_deswid_fleet1_D_LO=set_selpar_deswid_fleet1_D(2); const double
selpar_deswid_fleet1_D_HI=set_selpar_deswid_fleet1_D(3); const double selpar_deswid_fleet1_D_PH=set_selpar_deswid_fleet1_D(4);
const double selpar_init_fleet1_D_LO=set_selpar_init_fleet1_D(2); const double selpar_init_fleet1_D_HI=set_selpar_init_fleet1_D(3); const
double selpar_init_fleet1_D_PH=set_selpar_init_fleet1_D(4);
const double selpar_final_fleet1_D_LO=set_selpar_final_fleet1_D(2); const double selpar_final_fleet1_D_HI=set_selpar_final_fleet1_D(3);
const double selpar_final_fleet1_D_PH=set_selpar_final_fleet1_D(4);
const double selpar_L50_fleet2_LO=set_selpar_L50_fleet2(2); const double selpar_L50_fleet2_HI=set_selpar_L50_fleet2(3); const double
selpar_L50_fleet2_PH=set_selpar_L50_fleet2(4);
const double selpar_slope_fleet2_LO=set_selpar_slope_fleet2(2); const double selpar_slope_fleet2_HI=set_selpar_slope_fleet2(3); const
double selpar_slope_fleet2_PH=set_selpar_slope_fleet2(4);
//const double selpar_L50_fleet2_D_LO=set_selpar_L50_fleet2_D(2); const double selpar_L50_fleet2_D_HI=set_selpar_L50_fleet2_D(3);
const double selpar_L50_fleet2_D_PH=set_selpar_L50_fleet2_D(4);
//const double selpar_slope_fleet2_D_LO=set_selpar_slope_fleet2_D(2); const double
selpar_slope_fleet2_D_HI=set_selpar_slope_fleet2_D(3); const double selpar_slope_fleet2_D_PH=set_selpar_slope_fleet2_D(4);
//const double selpar_L502_fleet2_D_LO=set_selpar_L502_fleet2_D(2); const double selpar_L502_fleet2_D_HI=set_selpar_L502_fleet2_D(3);
const double selpar_L502_fleet2_D_PH=set_selpar_L502_fleet2_D(4);
//const double selpar_slope2_fleet2_D_LO=set_selpar_slope2_fleet2_D(2); const double
selpar_slope2_fleet2_D_HI=set_selpar_slope2_fleet2_D(3); const double selpar_slope2_fleet2_D_PH=set_selpar_slope2_fleet2_D(4);
const double selpar_peak_fleet2_D_LO=set_selpar_peak_fleet2_D(2); const double selpar_peak_fleet2_D_HI=set_selpar_peak_fleet2_D(3);
const double selpar_peak_fleet2_D_PH=set_selpar_peak_fleet2_D(4);
const double selpar_top_fleet2_D_LO=set_selpar_top_fleet2_D(2); const double selpar_top_fleet2_D_HI=set_selpar_top_fleet2_D(3); const
double selpar_top_fleet2_D_PH=set_selpar_top_fleet2_D(4);
const double selpar_ascwid_fleet2_D_LO=set_selpar_ascwid_fleet2_D(2); const double
selpar_ascwid_fleet2_D_HI=set_selpar_ascwid_fleet2_D(3); const double selpar_ascwid_fleet2_D_PH=set_selpar_ascwid_fleet2_D(4);
const double selpar_deswid_fleet2_D_LO=set_selpar_deswid_fleet2_D(2); const double
selpar_deswid_fleet2_D_HI=set_selpar_deswid_fleet2_D(3); const double selpar_deswid_fleet2_D_PH=set_selpar_deswid_fleet2_D(4);
const double selpar_init_fleet2_D_LO=set_selpar_init_fleet2_D(2); const double selpar_init_fleet2_D_HI=set_selpar_init_fleet2_D(3); const
double selpar_init_fleet2_D_PH=set_selpar_init_fleet2_D(4);
const double selpar_final_fleet2_D_LO=set_selpar_final_fleet2_D(2); const double selpar_final_fleet2_D_HI=set_selpar_final_fleet2_D(3);
const double selpar_final_fleet2_D_PH=set_selpar_final_fleet2_D(4);
const double log_q_survey1_LO=set_log_q_survey1(2); const double log_q_survey1_HI=set_log_q_survey1(3); const double
log_q_survey1_PH=set_log_q_survey1(4);
const double log_q_fleet1_LO=set_log_q_fleet1(2); const double log_q_fleet1_HI=set_log_q_fleet1(3); const double
log_q_fleet1_PH=set_log_q_fleet1(4);
const double F_init_LO=set_F_init(2); const double F_init_HI=set_F_init(3); const double F_init_PH=set_F_init(4);
const double log_avg_F_fleet1_LO=set_log_avg_F_fleet1(2); const double log_avg_F_fleet1_HI=set_log_avg_F_fleet1(3); const double
log_avg_F_fleet1_PH=set_log_avg_F_fleet1(4);
const double log_avg_F_fleet1_D_LO=set_log_avg_F_fleet1_D(2); const double log_avg_F_fleet1_D_HI=set_log_avg_F_fleet1_D(3); const
double log_avg_F_fleet1_D_PH=set_log_avg_F_fleet1_D(4);
const double log_avg_F_fleet2_LO=set_log_avg_F_fleet2(2); const double log_avg_F_fleet2_HI=set_log_avg_F_fleet2(3); const double
log_avg_F_fleet2_PH=set_log_avg_F_fleet2(4);
const double log_avg_F_fleet2_D_LO=set_log_avg_F_fleet2_D(2); const double log_avg_F_fleet2_D_HI=set_log_avg_F_fleet2_D(3); const
double log_avg_F_fleet2_D_PH=set_log_avg_F_fleet2_D(4);

//dev vectors-----
const double log_F_dev_fleet1_LO=set_log_F_dev_fleet1(1); const double log_F_dev_fleet1_HI=set_log_F_dev_fleet1(2); const double
log_F_dev_fleet1_PH=set_log_F_dev_fleet1(3);
const double log_F_dev_fleet1_D_LO=set_log_F_dev_fleet1_D(1); const double log_F_dev_fleet1_D_HI=set_log_F_dev_fleet1_D(2); const
double log_F_dev_fleet1_D_PH=set_log_F_dev_fleet1_D(3);
const double log_F_dev_fleet2_LO=set_log_F_dev_fleet2(1); const double log_F_dev_fleet2_HI=set_log_F_dev_fleet2(2); const double
log_F_dev_fleet2_PH=set_log_F_dev_fleet2(3);

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const double log_F_dev_fleet2_D_LO=set_log_F_dev_fleet2_D(1); const double log_F_dev_fleet2_D_HI=set_log_F_dev_fleet2_D(2); const
double log_F_dev_fleet2_D_PH=set_log_F_dev_fleet2_D(3);
const double log_rec_dev_LO=set_log_rec_dev(1); const double log_rec_dev_HI=set_log_rec_dev(2); const double
log_rec_dev_PH=set_log_rec_dev(3);
const double log_Nage_dev_LO=set_log_Nage_dev(1); const double log_Nage_dev_HI=set_log_Nage_dev(2); const double
log_Nage_dev_PH=set_log_Nage_dev(3);

END_CALCS

//----dummy optimization parameter-----
init_number dummy_optimize(dummy_optimize_PH);

////-----Growth-----
init_bounded_number Linf(Linf_LO,Linf_HI,Linf_PH);
init_bounded_number K(K_LO,K_HI,K_PH);
init_bounded_number t0(t0_LO,t0_HI,t0_PH);
vector Linf_out(1,8);
vector K_out(1,8);
vector t0_out(1,8);

vector meanlen_TL(1,nages); //mean total length (mm) at age all fish
vector wgt_g(1,nages); //whole wgt in g
vector wgt_kg(1,nages); //whole wgt in kg
vector wgt_mt(1,nages); //whole wgt in mt
vector wgt_klb(1,nages); //whole wgt in 1000 lb
vector wgt_lb(1,nages); //whole wgt in lb

matrix wholewgt_fleet1_klb(styr,endyr,1,nages); //whole wgt of fleet1 landings in 1000 lb
matrix wholewgt_fleet2_klb(styr,endyr,1,nages); //whole wgt of fleet2 landings in 1000 lb
matrix wholewgt_fleet1_D_klb(styr,endyr,1,nages); //whole wgt of fleet1 landings in 1000 lb
matrix wholewgt_fleet2_D_klb(styr,endyr,1,nages); //whole wgt of fleet2 landings in 1000 lb

//----Predicted age compositions
matrix pred_survey1_aged(1,nyr_survey1_aged,1,nages);
matrix pred_survey1_aged_allages(1,nyr_survey1_aged,1,nages);
matrix ErrorFree_survey1_aged(1,nyr_survey1_aged,1,nages);
matrix pred_fleet1_aged(1,nyr_fleet1_aged,1,nages);
matrix pred_fleet1_aged_allages(1,nyr_fleet1_aged,1,nages);
matrix ErrorFree_fleet1_aged(1,nyr_fleet1_aged,1,nages);
matrix pred_fleet2_aged(1,nyr_fleet2_aged,1,nages);
matrix pred_fleet2_aged_allages(1,nyr_fleet2_aged,1,nages);
matrix ErrorFree_fleet2_aged(1,nyr_fleet2_aged,1,nages);

//effective sample size applied in multinomial distributions
vector nsamp_survey1_aged_allyr(styr,endyr);
vector nsamp_fleet1_aged_allyr(styr,endyr);
vector nsamp_fleet2_aged_allyr(styr,endyr);

//Nfish used in MCB analysis (not used in fitting)
vector nfish_survey1_aged_allyr(styr,endyr);
vector nfish_fleet1_aged_allyr(styr,endyr);
vector nfish_fleet2_aged_allyr(styr,endyr);

//Computed effective sample size for output (not used in fitting)
vector neff_survey1_aged_allyr_out(styr,endyr);
vector neff_fleet1_aged_allyr_out(styr,endyr);
vector neff_fleet2_aged_allyr_out(styr,endyr);

//-----Population-----
matrix N(styr,endyr+1,1,nages); //Population numbers by year and age at start of yr
matrix N_mdpr(styr,endyr,1,nages); //Population numbers by year and age at mdpt of yr: used for comps and cpue
matrix N_spawn(styr,endyr,1,nages); //Population numbers by year and age at peaking spawning: used for SSB
vector N_proj(1,nages);

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init_bounded_vector log_Nage_dev(2,nages,log_Nage_dev_LO,log_Nage_dev_HI,log_Nage_dev_PH);
vector log_Nage_dev_output(1,nages); //used in output. equals zero for first age
matrix B(styr,endyr+1,1,nages); //Population biomass by year and age at start of yr
vector totB(styr,endyr+1); //Total biomass by year
vector totN(styr,endyr+1); //Total abundance by year
vector SSB(styr,endyr); //Total spawning biomass by year (female + male mature biomass)
vector MatFemB(styr,endyr); //Total spawning biomass by year (mature female biomass)
vector rec(styr,endyr+1); //Recruits by year
vector prop_f(1,nages); //Proportion female by age, all males assumed mature
vector maturity_f(1,nages); //Proportion of female mature at age
vector reprod(1,nages); //vector used to compute spawning biomass (total mature biomass - males + females)

//---Stock-Recruit Function (Beverton-Holt, steepness parameterization)-----
init_bounded_number log_R0(log_R0_LO,log_R0_HI,log_R0_PH); //log(virgin Recruitment)
vector log_R0_out(1,8);
number R0; //virgin recruitment
init_bounded_number steep(steep_LO,steep_HI,steep_PH); //steepness
vector steep_out(1,8);
init_bounded_number rec_sigma(rec_sigma_LO,rec_sigma_HI,rec_sigma_PH); //sd recruitment residuals //KC comment out; this should fix it
at the initial value
vector rec_sigma_out(1,8);
init_bounded_number R_autocorr(R_autocorr_LO,R_autocorr_HI,R_autocorr_PH); //autocorrelation in SR KC commented out since not
estimated
vector R_autocorr_out(1,8);

number rec_sigma_sq; //square of rec_sigma
number rec_logL_add; //additive term in -logL term

//vector log_rec_dev(styr_rec_dev,endyr_rec_dev);
init_bounded_dev_vector log_rec_dev(styr_rec_dev,endyr_rec_dev,log_rec_dev_LO,log_rec_dev_HI,log_rec_dev_PH);
vector log_rec_dev_output(styr,endyr+1); //used in t.series output. equals zero except for yrs in log_rec_dev
vector log_rec_dev_out(styr_rec_dev,endyr_rec_dev); //used in output for bound fleet1ecking

number var_rec_dev; //variance of log recruitment deviations, from yrs with unconstrained S-R(XXXX-XXXX)
number sigma_rec_dev; //sample SD of log residuals (may not equal rec_sigma

number BiasCor; //Bias correction in equilibrium recruits

number S0; //equal to spr_F0*R0 = virgin SSB
number B0; //equal to bpr_F0*R0 = virgin B
number R1; //Recruits in styr
number R_virgin; //unfished recruitment with bias correction
vector SdS0(styr,endyr); //SSB / virgin SSB

//-----
////---Selectivity-----

//survey1-----
matrix sel_survey1(styr,endyr,1,nages);
init_bounded_number selpar_L50_survey1(selpar_L50_survey1_LO,selpar_L50_survey1_HI,selpar_L50_survey1_PH);
init_bounded_number selpar_slope_survey1(selpar_slope_survey1_LO,selpar_slope_survey1_HI,selpar_slope_survey1_PH);
vector selpar_L50_survey1_out(1,8);
vector selpar_slope_survey1_out(1,8);
//fleet1 landings-----
matrix sel_fleet1(styr,endyr,1,nages);
init_bounded_number selpar_L50_fleet1(selpar_L50_fleet1_LO,selpar_L50_fleet1_HI,selpar_L50_fleet1_PH);
init_bounded_number selpar_slope_fleet1(selpar_slope_fleet1_LO,selpar_slope_fleet1_HI,selpar_slope_fleet1_PH);
vector selpar_L50_fleet1_out(1,8);
vector selpar_slope_fleet1_out(1,8);
//fleet1 discards-----
matrix sel_fleet1_D(styr,endyr,1,nages);
//init_bounded_number selpar_L50_fleet1_D(selpar_L50_fleet1_D_LO,selpar_L50_fleet1_D_HI,selpar_L50_fleet1_D_PH);
//init_bounded_number selpar_slope_fleet1_D(selpar_slope_fleet1_D_LO,selpar_slope_fleet1_D_HI,selpar_slope_fleet1_D_PH);
//init_bounded_number selpar_L502_fleet1_D(selpar_L502_fleet1_D_LO,selpar_L502_fleet1_D_HI,selpar_L502_fleet1_D_PH);

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//init_bounded_number selpar_slope2_fleet1_D(selpar_slope2_fleet1_D_LO,selpar_slope2_fleet1_D_HI,selpar_slope2_fleet1_D_PH);
//vector selpar_L50_fleet1_D_out(1,8);
//vector selpar_slope_fleet1_D_out(1,8);
//vector selpar_L502_fleet1_D_out(1,8);
//vector selpar_slope2_fleet1_D_out(1,8);
init_bounded_number selpar_peak_fleet1_D(selpar_peak_fleet1_D_LO,selpar_peak_fleet1_D_HI,selpar_peak_fleet1_D_PH);
init_bounded_number selpar_top_fleet1_D(selpar_top_fleet1_D_LO,selpar_top_fleet1_D_HI,selpar_top_fleet1_D_PH);
init_bounded_number selpar_ascwid_fleet1_D(selpar_ascwid_fleet1_D_LO,selpar_ascwid_fleet1_D_HI,selpar_ascwid_fleet1_D_PH);
init_bounded_number selpar_deswid_fleet1_D(selpar_deswid_fleet1_D_LO,selpar_deswid_fleet1_D_HI,selpar_deswid_fleet1_D_PH);
init_bounded_number selpar_init_fleet1_D(selpar_init_fleet1_D_LO,selpar_init_fleet1_D_HI,selpar_init_fleet1_D_PH);
init_bounded_number selpar_final_fleet1_D(selpar_final_fleet1_D_LO,selpar_final_fleet1_D_HI,selpar_final_fleet1_D_PH);
vector selpar_peak_fleet1_D_out(1,8);
vector selpar_top_fleet1_D_out(1,8);
vector selpar_ascwid_fleet1_D_out(1,8);
vector selpar_deswid_fleet1_D_out(1,8);
vector selpar_init_fleet1_D_out(1,8);
vector selpar_final_fleet1_D_out(1,8);
//fleet2 landings-----
matrix sel_fleet2(styr,endyr,1,nages);
init_bounded_number selpar_L50_fleet2(selpar_L50_fleet2_LO,selpar_L50_fleet2_HI,selpar_L50_fleet2_PH);
init_bounded_number selpar_slope_fleet2(selpar_slope_fleet2_LO,selpar_slope_fleet2_HI,selpar_slope_fleet2_PH);
vector selpar_L50_fleet2_out(1,8);
vector selpar_slope_fleet2_out(1,8);
//fleet2 discards-----
matrix sel_fleet2_D(styr,endyr,1,nages);
//init_bounded_number selpar_L50_fleet2_D(selpar_L50_fleet2_D_LO,selpar_L50_fleet2_D_HI,selpar_L50_fleet2_D_PH);
//init_bounded_number selpar_slope_fleet2_D(selpar_slope_fleet2_D_LO,selpar_slope_fleet2_D_HI,selpar_slope_fleet2_D_PH);
//init_bounded_number selpar_L502_fleet2_D(selpar_L502_fleet2_D_LO,selpar_L502_fleet2_D_HI,selpar_L502_fleet2_D_PH);
//init_bounded_number selpar_slope2_fleet2_D(selpar_slope2_fleet2_D_LO,selpar_slope2_fleet2_D_HI,selpar_slope2_fleet2_D_PH);
//vector selpar_L50_fleet2_D_out(1,8);
//vector selpar_slope_fleet2_D_out(1,8);
//vector selpar_L502_fleet2_D_out(1,8);
//vector selpar_slope2_fleet2_D_out(1,8);
init_bounded_number selpar_peak_fleet2_D(selpar_peak_fleet2_D_LO,selpar_peak_fleet2_D_HI,selpar_peak_fleet2_D_PH);
init_bounded_number selpar_top_fleet2_D(selpar_top_fleet2_D_LO,selpar_top_fleet2_D_HI,selpar_top_fleet2_D_PH);
init_bounded_number selpar_ascwid_fleet2_D(selpar_ascwid_fleet2_D_LO,selpar_ascwid_fleet2_D_HI,selpar_ascwid_fleet2_D_PH);
init_bounded_number selpar_deswid_fleet2_D(selpar_deswid_fleet2_D_LO,selpar_deswid_fleet2_D_HI,selpar_deswid_fleet2_D_PH);
init_bounded_number selpar_init_fleet2_D(selpar_init_fleet2_D_LO,selpar_init_fleet2_D_HI,selpar_init_fleet2_D_PH);
init_bounded_number selpar_final_fleet2_D(selpar_final_fleet2_D_LO,selpar_final_fleet2_D_HI,selpar_final_fleet2_D_PH);
vector selpar_peak_fleet2_D_out(1,8);
vector selpar_top_fleet2_D_out(1,8);
vector selpar_ascwid_fleet2_D_out(1,8);
vector selpar_deswid_fleet2_D_out(1,8);
vector selpar_init_fleet2_D_out(1,8);
vector selpar_final_fleet2_D_out(1,8);

//Weighted total selectivity-----
//effort-weighted, recent selectivities
vector sel_wgtd_L(1,nages); //toward landings
vector sel_wgtd_D(1,nages); //toward discards
vector sel_wgtd_tot(1,nages); //toward Z, landings plus dead discards

//-----
//-----CPUE Predictions-----
vector pred_survey1_cpue(styr_survey1_cpue,endyr_survey1_cpue); //predicted survey1 index (number fish per effort)
matrix N_survey1(styr_survey1_cpue,endyr_survey1_cpue,1,nages); //used to compute survey1 index
vector pred_fleet1_cpue(styr_fleet1_cpue,endyr_fleet1_cpue); //predicted fleet1 index (weight fish per effort)
matrix N_fleet1(styr_fleet1_cpue,endyr_fleet1_cpue,1,nages); //used to compute fleet1 index

//---Catchability (CPUE q's)-----
init_bounded_number log_q_survey1(log_q_survey1_LO,log_q_survey1_HI,log_q_survey1_PH);
init_bounded_number log_q_fleet1(log_q_fleet1_LO,log_q_fleet1_HI,log_q_fleet1_PH);
vector log_q_survey1_out(1,8);
vector log_q_fleet1_out(1,8);

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// init_bounded_number q_rate(0.001,0.1,set_q_rate_phase); //KC not estimated so commented out, defleet2ared as number
//number q_rate;
//vector q_rate_fcn_rec(styr_rec_cpue,endyr_rec_cpue); //increase due to tefleet1nology creep (saturates in 2003) //KWS
//vector q_rate_fcn_fleet1(styr_fleet1_cpue,endyr_fleet1_cpue); //increase due to tefleet1nology creep (saturates in 2003) //KWS

// init_bounded_number q_DD_beta(0.1,0.9,set_q_DD_phase); //KC not estimated so commented out and defleet2ared as number (below)
//number q_DD_beta;
//vector q_DD_fcn(styr,endyr); //density dependent function as a multiple of q (scaled a la Katsukawa and Matsuda. 2003)
//number B0_q_DD; //B0 of ages q_DD_age plus
//vector B_q_DD(styr,endyr); //annual biomass of ages q_DD_age plus

//Fishery dependent random walk catfleet1ability
// init_bounded_vector q_RW_log_dev_rec(styr_rec_cpue,endyr_rec_cpue-1,-3.0,3.0,set_q_RW_phase); //NOT estimated in this model
//vector q_RW_log_dev_rec(styr_rec_cpue,endyr_rec_cpue-1);
//vector q_RW_log_dev_fleet1(styr_fleet1_cpue,endyr_fleet1_cpue-1);

//Fishery dependent catfleet1ability over time, may be constant
vector q_fleet1(styr_fleet1_cpue,endyr_fleet1_cpue);

//-----
//---Landings in numbers (total or 1000 fish) and in wgt (klb)-----
matrix L_fleet1_num(styr,endyr,1,nages); //landings (numbers) at age
matrix L_fleet1_klb(styr,endyr,1,nages); //landings (1000 lb whole weight) at age
vector pred_fleet1_L_knum(styr,endyr); //yearly landings in 1000 fish summed over ages
vector pred_fleet1_L_klb(styr,endyr); //yearly landings in 1000 lb summed over ages

matrix D_fleet1_num(styr,endyr,1,nages); //discards (numbers) at age
matrix D_fleet1_klb(styr,endyr,1,nages); //discards (1000 lb whole weight) at age
vector pred_fleet1_D_knum(styr,endyr); //yearly discards in 1000 fish summed over ages
vector pred_fleet1_D_klb(styr,endyr); //yearly discards in 1000 lb summed over ages

matrix L_fleet2_num(styr,endyr,1,nages); //landings (numbers) at age
matrix L_fleet2_klb(styr,endyr,1,nages); //landings (1000 lb whole weight) at age
vector pred_fleet2_L_knum(styr,endyr); //yearly landings in 1000 fish summed over ages
vector pred_fleet2_L_klb(styr,endyr); //yearly landings in 1000 lb summed over ages

matrix D_fleet2_num(styr,endyr,1,nages); //discards (numbers) at age
matrix D_fleet2_klb(styr,endyr,1,nages); //discards (1000 lb whole weight) at age
vector pred_fleet2_D_knum(styr,endyr); //yearly discards in 1000 fish summed over ages
vector pred_fleet2_D_klb(styr,endyr); //yearly discards in 1000 lb summed over ages

matrix L_total_num(styr,endyr,1,nages); //total landings in number at age
matrix L_total_klb(styr,endyr,1,nages); //landings in klb at age
vector L_total_knum_yr(styr,endyr); //total landings in 1000 fish by yr summed over ages
vector L_total_klb_yr(styr,endyr); //total landings (klb) by yr summed over ages

matrix D_total_num(styr,endyr,1,nages); //total landings in number at age
matrix D_total_klb(styr,endyr,1,nages); //landings in klb at age
vector D_total_knum_yr(styr,endyr); //total landings in 1000 fish by yr summed over ages
vector D_total_klb_yr(styr,endyr); //total landings (klb) by yr summed over ages

vector L_proj(1,nages); //total landings at-age for one year projection to get ABC
number L_proj_klb; //total landings in klb for one year projection
number L_proj_knum; //total landings in 1000 fish for one year projection

vector D_proj(1,nages); //total landings at-age for one year projection to get ABC
number D_proj_klb; //total landings in klb for one year projection
number D_proj_knum; //total landings in 1000 fish for one year projection

///---MSY calcs-----
number F_fleet1_prop; //proportion of F_sum attributable to fleet1, last X yr
number F_fleet1_D_prop; //proportion of F_sum attributable to fleet1, last X yr
number F_fleet2_prop; //proportion of F_sum attributable to fleet2, last X yr

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number F_fleet2_D_prop; //proportion of F_sum attributable to fleet2, last X yr
number F_init_fleet1_prop; //proportion of F_init attributable to fleet1, first X yrs
number F_init_fleet1_D_prop; //proportion of F_init attributable to fleet1, first X yrs
number F_init_fleet2_prop; //proportion of F_init attributable to fleet2, first X yrs
number F_init_fleet2_D_prop; //proportion of F_init attributable to fleet2, first X yrs

number F_temp_sum; //sum of geom mean Fsum's in last X yrs, used to compute F_fishery_prop

vector F_end(1,nages);
vector F_end_L(1,nages);
number F_end_apex;

number SSB_msy_out; //SSB (total mature biomass) at msy
number F_msy_out; //F at msy
number msy_klb_out; //max sustainable yield (1000 lb)
number msy_knum_out; //max sustainable yield (1000 fish)
number B_msy_out; //total biomass at MSY
number R_msy_out; //equilibrium recruitment at F=Fmsy
number spr_msy_out; //spr at F=Fmsy

vector N_age_msy(1,nages); //numbers at age for MSY calculations: beginning of yr
vector N_age_msy_spawn(1,nages); //numbers at age for MSY calculations: time of peak spawning
vector L_age_msy(1,nages); //landings at age for MSY calculations
vector D_age_msy(1,nages); //discards at age for MSY calculations
vector Z_age_msy(1,nages); //total mortality at age for MSY calculations
vector F_L_age_msy(1,nages); //fishing mortality landings (not discards) at age for MSY calculations
vector F_D_age_msy(1,nages); //fishing mortality discards at age for MSY calculations
vector F_msy(1,n_iter_msy); //values of full F to be used in equilibrium calculations
vector spr_msy(1,n_iter_msy); //reproductive capacity-per-recruit values corresponding to F values in F_msy
vector R_eq(1,n_iter_msy); //equilibrium recruitment values corresponding to F values in F_msy
vector L_eq_klb(1,n_iter_msy); //equilibrium landings(klb) values corresponding to F values in F_msy
vector L_eq_knum(1,n_iter_msy); //equilibrium landings(1000 fish) values corresponding to F values in F_msy
vector D_eq_klb(1,n_iter_msy); //equilibrium discards(klb) values corresponding to F values in F_msy
vector D_eq_knum(1,n_iter_msy); //equilibrium discards(1000 fish) values corresponding to F values in F_msy
vector SSB_eq(1,n_iter_msy); //equilibrium reproductive capacity values corresponding to F values in F_msy
vector B_eq(1,n_iter_msy); //equilibrium biomass values corresponding to F values in F_msy

vector FdF_msy(styr,endyr);
vector SdSSB_msy(styr,endyr);
number SdSSB_msy_end;
number FdF_msy_end;
number FdF_msy_end_mean; //geometric mean of last X yrs

vector wgt_wgted_L_klb(1,nages); //fishery-weighted average weight at age of landings
number wgt_wgted_L_denom; //used in intermediate calculations
vector wgt_wgted_D_klb(1,nages); //fishery-weighted average weight at age of discards
number wgt_wgted_D_denom; //used in intermediate calculations

number iter_inc_msy; //increments used to compute msy, equals 1/(n_iter_msy-1)

////-----Mortality-----

// Stuff immediately below used only if M is estimated
// //init_bounded_number M_constant(0.1,0.2,1); //age-independent: used only for MSST
// vector Mscale_ages(1,max_obs_age);
// vector Mscale_len(1,max_obs_age);
// vector Mscale_wgt_g(1,max_obs_age);
// vector M_lorenzen(1,max_obs_age);
// number cum_surv_1plus;

vector M(1,nages); //age-dependent natural mortality
//init_bounded_number M_constant(M_constant_LO,M_constant_HI,M_constant_PH); //age-independent: used only for MSST
//vector M_constant_out(1,8);

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matrix F(styr,endyr,1,nages);
vector F_proj(1,nages);
vector F_D_proj(1,nages);
vector Fsum(styr,endyr);           //Full fishing mortality rate by year
vector Fapex(styr,endyr);         //Max across ages, fishing mortality rate by year (may differ from Fsum bc of dome-shaped sel
matrix Z(styr,endyr,1,nages);
vector Z_proj(1,nages);

init_bounded_number log_avg_F_fleet1(log_avg_F_fleet1_LO,log_avg_F_fleet1_HI,log_avg_F_fleet1_PH);
vector log_avg_F_fleet1_out(1,8);
init_bounded_dev_vector log_F_dev_fleet1(styr_fleet1_L,endyr_fleet1_L,log_F_dev_fleet1_LO,log_F_dev_fleet1_HI,log_F_dev_fleet1_PH);
vector log_F_dev_fleet1_out(styr_fleet1_L,endyr_fleet1_L);
matrix F_fleet1(styr,endyr,1,nages);
vector F_fleet1_out(styr,endyr);    //used for intermediate calculations in fcn get_mortality
number log_F_dev_init_fleet1;
number log_F_dev_end_fleet1;

init_bounded_number log_avg_F_fleet1_D(log_avg_F_fleet1_D_LO,log_avg_F_fleet1_D_HI,log_avg_F_fleet1_D_PH);
vector log_avg_F_fleet1_D_out(1,8);
init_bounded_dev_vector
log_F_dev_fleet1_D(styr_fleet1_D,endyr_fleet1_D,log_F_dev_fleet1_D_LO,log_F_dev_fleet1_D_HI,log_F_dev_fleet1_D_PH);
vector log_F_dev_fleet1_D_out(styr_fleet1_D,endyr_fleet1_D);
matrix F_fleet1_D(styr,endyr,1,nages);
vector F_fleet1_D_out(styr,endyr);    //used for intermediate calculations in fcn get_mortality
number log_F_dev_init_fleet1_D;
number log_F_dev_end_fleet1_D;

init_bounded_number log_avg_F_fleet2(log_avg_F_fleet2_LO,log_avg_F_fleet2_HI,log_avg_F_fleet2_PH);
vector log_avg_F_fleet2_out(1,8);
init_bounded_dev_vector log_F_dev_fleet2(styr_fleet2_L,endyr_fleet2_L,log_F_dev_fleet2_LO,log_F_dev_fleet2_HI,log_F_dev_fleet2_PH);
vector log_F_dev_fleet2_out(styr_fleet2_L,endyr_fleet2_L);
matrix F_fleet2(styr,endyr,1,nages);
vector F_fleet2_out(styr,endyr);    //used for intermediate calculations in fcn get_mortality
number log_F_dev_init_fleet2;
number log_F_dev_end_fleet2;

init_bounded_number log_avg_F_fleet2_D(log_avg_F_fleet2_D_LO,log_avg_F_fleet2_D_HI,log_avg_F_fleet2_D_PH);
vector log_avg_F_fleet2_D_out(1,8);
init_bounded_dev_vector
log_F_dev_fleet2_D(styr_fleet2_D,endyr_fleet2_D,log_F_dev_fleet2_D_LO,log_F_dev_fleet2_D_HI,log_F_dev_fleet2_D_PH);
vector log_F_dev_fleet2_D_out(styr_fleet2_D,endyr_fleet2_D);
matrix F_fleet2_D(styr,endyr,1,nages);
vector F_fleet2_D_out(styr,endyr);    //used for intermediate calculations in fcn get_mortality
number log_F_dev_init_fleet2_D;
number log_F_dev_end_fleet2_D;

// init_bounded_number F_init(F_init_LO,F_init_HI,F_init_PH);
// vector F_init_out(1,8);
// //number F_init
init_bounded_number F_init(F_init_LO,F_init_HI,F_init_PH); //scales early F for initialization
vector F_init_out(1,8);
// vector sel_initial(1,nages);    //initial selectivity (a combination of for-hire and commercial selectivities)
//
//---Per-recruit stuff-----
vector N_age_spr(1,nages);    //numbers at age for SPR calculations: beginning of year
vector N_age_spr_spawn(1,nages); //numbers at age for SPR calculations: time of peak spawning
vector L_age_spr(1,nages);    //catfleet1 at age for SPR calculations
vector D_age_spr(1,nages);    //catfleet1 at age for SPR calculations
vector Z_age_spr(1,nages);    //total mortality at age for SPR calculations
vector spr_static(styr,endyr); //vector of static SPR values by year
vector F_L_age_spr(1,nages);   //fishing mortality of landings (not discards) at age for SPR calculations
vector F_D_age_spr(1,nages);   //fishing mortality of discards at age for SPR calculations
vector F_spr(1,n_iter_spr);    //values of full F to be used in per-recruit calculations
vector spr_spr(1,n_iter_spr);  //reproductive capacity-per-recruit values corresponding to F values in F_spr

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vector L_spr(1,n_iter_spr); //landings(lb)-per-recruit (ypr) values corresponding to F values in F_spr
vector D_spr(1,n_iter_spr); //discards(lb)-per-recruit (ypr) values corresponding to F values in F_spr

vector N_spr_F0(1,nages); //Used to compute spr at F=0: at time of peak spawning
vector N_bpr_F0(1,nages); //Used to compute bpr at F=0: at start of year
vector N_spr_initial(1,nages); //Initial spawners per recruit at age given initial F
vector N_initial_eq(1,nages); //Initial equilibrium abundance at age
vector F_initial(1,nages); //initial F at age
vector Z_initial(1,nages); //initial Z at age
number spr_initial; //initial spawners per recruit
number spr_F0; //Spawning biomass per recruit at F=0
number bpr_F0; //Biomass per recruit at F=0

number iter_inc_spr; //increments used to compute msy, equals max_F_spr_msy/(n_iter_spr-1)

///-----SDNR output-----

number sdnr_ac_survey1;
number sdnr_ac_fleet1;
number sdnr_ac_fleet2;

number sdnr_I_survey1;
number sdnr_I_fleet1;

///-----Objective function components-----

number w_L_fleet1;
number w_L_fleet2;

number w_D_fleet1;
number w_D_fleet2;

number w_I_survey1;
number w_I_fleet1;

number w_ac_survey1;
number w_ac_fleet1;
number w_ac_fleet2;

number w_Nage_init;
number w_rec;
number w_rec_early;
number w_rec_end;
number w_Ftune;

number f_fleet1_L;
number f_fleet2_L;

number f_fleet1_D;
number f_fleet2_D;

number f_survey1_cpue;
number f_fleet1_cpue;

number f_survey1_agec;
number f_fleet1_agec;
number f_fleet2_agec;

//Penalties and constraints. Not all are used.
number f_Nage_init; //weight on log devs to estimate initial abundance (ex fleet2uding first age)
number f_rec_dev; //weight on recruitment deviations to fit S-R curve
number f_rec_dev_early; //extra weight on deviations in first recruitment stanza
number f_rec_dev_end; //extra weight on deviations in ending recruitment stanza
number f_Ftune; //penalty for tuning F in Ftune yr. Not applied in final optimization phase.
//number f_rec_RW_cpue; //random walk component of index

```

[illegible]

Supplementary Material

```
// }
//} //end q_rate conditional

w_L_fleet1=set_w_L_fleet1;
w_L_fleet2=set_w_L_fleet2;

w_D_fleet1=set_w_D_fleet1;
w_D_fleet2=set_w_D_fleet2;

w_I_survey1=set_w_I_survey1;
w_I_fleet1=set_w_I_fleet1;

w_ac_survey1=set_w_ac_survey1;
w_ac_fleet1=set_w_ac_fleet1;
w_ac_fleet2=set_w_ac_fleet2;

w_Nage_init=set_w_Nage_init;
w_rec=set_w_rec;
w_rec_early=set_w_rec_early;
w_rec_end=set_w_rec_end;
w_Ftune=set_w_Ftune;

F_init=set_F_init(1);
log_avg_F_fleet1=set_log_avg_F_fleet1(1);
log_avg_F_fleet2=set_log_avg_F_fleet2(1);
log_avg_F_fleet1_D=set_log_avg_F_fleet1_D(1);
log_avg_F_fleet2_D=set_log_avg_F_fleet2_D(1);

log_F_dev_fleet1=set_log_F_dev_fleet1_vals;
log_F_dev_fleet2=set_log_F_dev_fleet2_vals;
log_F_dev_fleet1_D=set_log_F_dev_fleet1_D_vals;
log_F_dev_fleet2_D=set_log_F_dev_fleet2_D_vals;

selpar_L50_survey1=set_selpar_L50_survey1(1);
selpar_slope_survey1=set_selpar_slope_survey1(1);

selpar_L50_fleet1=set_selpar_L50_fleet1(1);
selpar_slope_fleet1=set_selpar_slope_fleet1(1);

selpar_peak_fleet1_D=set_selpar_peak_fleet1_D(1);
selpar_top_fleet1_D=set_selpar_top_fleet1_D(1);
selpar_ascwid_fleet1_D=set_selpar_ascwid_fleet1_D(1);
selpar_deswid_fleet1_D=set_selpar_deswid_fleet1_D(1);
selpar_init_fleet1_D=set_selpar_init_fleet1_D(1);
selpar_final_fleet1_D=set_selpar_final_fleet1_D(1);

selpar_L50_fleet2=set_selpar_L50_fleet2(1);
selpar_slope_fleet2=set_selpar_slope_fleet2(1);

selpar_peak_fleet2_D=set_selpar_peak_fleet2_D(1);
selpar_top_fleet2_D=set_selpar_top_fleet2_D(1);
selpar_ascwid_fleet2_D=set_selpar_ascwid_fleet2_D(1);
selpar_deswid_fleet2_D=set_selpar_deswid_fleet2_D(1);
selpar_init_fleet2_D=set_selpar_init_fleet2_D(1);
selpar_final_fleet2_D=set_selpar_final_fleet2_D(1);

sqrt2pi=sqrt(2.*3.14159265);
g2mt=0.000001; //conversion of grams to metric tons
g2kg=0.001; //conversion of grams to kg
mt2klb=2.20462; //conversion of metric tons to 1000 lb
mt2lb=mt2klb*1000.0; //conversion of metric tons to lb
g2klb=g2mt*mt2klb; //conversion of grams to 1000 lb
dzero=0.00001;
huge_number=1.0e+10;
```

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SSB_msy_out=0.0;

iter_inc_msy=max_F_spr_msy/(n_iter_msy-1);
iter_inc_spr=max_F_spr_msy/(n_iter_spr-1);

maturity_f=maturity_f_obs;
prop_f=prop_f_obs;

//Fill in sample sizes of comps, possibly sampled in nonconsec yrs
//Used primarily for output in R object

nsamp_survey1_agec_allyr=missing;
nsamp_fleet1_agec_allyr=missing;
nsamp_fleet2_agec_allyr=missing;

nsamp_survey1_agec_allyr=missing;
nsamp_fleet1_agec_allyr=missing;
nsamp_fleet2_agec_allyr=missing;

for (iyear=1; iyear<=nyr_survey1_agec; iyear++)
{if (nsamp_survey1_agec(iyear)>=minSS_survey1_agec)
{nsamp_survey1_agec_allyr(yrs_survey1_agec(iyear))=nsamp_survey1_agec(iyear);
nfish_survey1_agec_allyr(yrs_survey1_agec(iyear))=nfish_survey1_agec(iyear);}}

for (iyear=1; iyear<=nyr_fleet1_agec; iyear++)
{if (nsamp_fleet1_agec(iyear)>=minSS_fleet1_agec)
{nsamp_fleet1_agec_allyr(yrs_fleet1_agec(iyear))=nsamp_fleet1_agec(iyear);
nfish_fleet1_agec_allyr(yrs_fleet1_agec(iyear))=nfish_fleet1_agec(iyear);}}

for (iyear=1; iyear<=nyr_fleet2_agec; iyear++)
{if (nsamp_fleet2_agec(iyear)>=minSS_fleet2_agec)
{nsamp_fleet2_agec_allyr(yrs_fleet2_agec(iyear))=nsamp_fleet2_agec(iyear);
nfish_fleet2_agec_allyr(yrs_fleet2_agec(iyear))=nfish_fleet2_agec(iyear);}}

//fill in Fs for msy and per-recruit analyses
F_msy(1)=0.0;
for (ff=2;ff<=n_iter_msy;ff++) {F_msy(ff)=F_msy(ff-1)+iter_inc_msy;}
F_spr(1)=0.0;
for (ff=2;ff<=n_iter_spr;ff++) {F_spr(ff)=F_spr(ff-1)+iter_inc_spr;}

//fill in F's, Catch matrices, and log rec dev with zero's
F_fleet1.initialize();
L_fleet1_num.initialize();
F_fleet2.initialize();
L_fleet2_num.initialize();

F_fleet1_D.initialize();
D_fleet1_num.initialize();
F_fleet2_D.initialize();
D_fleet2_num.initialize();

F_fleet1_out.initialize();
F_fleet2_out.initialize();
F_fleet1_D_out.initialize();
F_fleet2_D_out.initialize();

sel_survey1.initialize();
sel_fleet1.initialize();
sel_fleet2.initialize();
sel_fleet1_D.initialize();
sel_fleet2_D.initialize();

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for (iyear=styr; iyear<=endyr; iyear++)
{
  wholewgt_fleet1_klb(iyear)=wgt_klb;
  wholewgt_fleet2_klb(iyear)=wgt_klb;
  wholewgt_fleet1_D_klb(iyear)=wgt_klb;
  wholewgt_fleet2_D_klb(iyear)=wgt_klb;
}

FUNCTION get_spr_F0
//at mdyr, apply half this yr's mortality, half next yr's
N_spr_F0(1)=1.0*mfexp(-1.0*M(1)*spawn_time_frac); //at peak spawning time
N_bpr_F0(1)=1.0; //at start of year
for (iage=2; iage<=nages; iage++)
{
  //N_spr_F0(iage)=N_spr_F0(iage-1)*mfexp(-1.0*(M(iage-1)));
  N_spr_F0(iage)=N_spr_F0(iage-1)*mfexp(-1.0*(M(iage-1)*(1.0-spawn_time_frac) + M(iage)*spawn_time_frac));
  N_bpr_F0(iage)=N_bpr_F0(iage-1)*mfexp(-1.0*(M(iage-1)));
}
N_spr_F0(nages)=N_spr_F0(nages)/(1.0-mfexp(-1.0*M(nages))); //plus group (sum of geometric series)
N_bpr_F0(nages)=N_bpr_F0(nages)/(1.0-mfexp(-1.0*M(nages)));

spr_F0=sum(elem_prod(N_spr_F0,reprod));
bpr_F0=sum(elem_prod(N_bpr_F0,wgt_mt));

FUNCTION get_selectivity

for (iyear=styr; iyear<=endyr; iyear++)
{
  sel_survey1(iyear)=logistic(agebins, selpar_L50_survey1, selpar_slope_survey1);

  sel_fleet1(iyear)=logistic(agebins, selpar_L50_fleet1, selpar_slope_fleet1);
  sel_fleet2(iyear)=logistic(agebins, selpar_L50_fleet2, selpar_slope_fleet2);

  //sel_fleet1_D(iyear)=logistic_double(agebins, selpar_L50_fleet1_D, selpar_slope_fleet1_D, selpar_L502_fleet1_D, selpar_slope2_fleet1_D);
  //sel_fleet2_D(iyear)=logistic_double(agebins, selpar_L50_fleet2_D, selpar_slope_fleet2_D, selpar_L502_fleet2_D, selpar_slope2_fleet2_D);

  sel_fleet1_D(iyear)=gaussian_double(agebins, selpar_peak_fleet1_D, selpar_top_fleet1_D, selpar_ascwid_fleet1_D,
selpar_deswid_fleet1_D, selpar_init_fleet1_D, selpar_final_fleet1_D);
  sel_fleet2_D(iyear)=gaussian_double(agebins, selpar_peak_fleet2_D, selpar_top_fleet2_D, selpar_ascwid_fleet2_D,
selpar_deswid_fleet2_D, selpar_init_fleet2_D, selpar_final_fleet2_D);
}

FUNCTION get_mortality
Fsum.initialize();
Fapex.initialize();
F.initialize();
//initialization F is avg from first 3 yrs of observed landings
log_F_dev_init_fleet1=sum(log_F_dev_fleet1(styr_fleet1_L,(styr_fleet1_L+2)))/3.0;
log_F_dev_init_fleet2=sum(log_F_dev_fleet2(styr_fleet2_L,(styr_fleet2_L+2)))/3.0;
log_F_dev_init_fleet1_D=sum(log_F_dev_fleet1_D(styr_fleet1_D,(styr_fleet1_D+2)))/3.0;
log_F_dev_init_fleet2_D=sum(log_F_dev_fleet2_D(styr_fleet2_D,(styr_fleet2_D+2)))/3.0;

F_init_fleet1_prop=mfexp(log_avg_F_fleet1+log_F_dev_init_fleet1)/(mfexp(log_avg_F_fleet1+log_F_dev_init_fleet1)+mfexp(log_avg_F_fleet2+
log_F_dev_init_fleet2));

F_init_fleet2_prop=mfexp(log_avg_F_fleet2+log_F_dev_init_fleet2)/(mfexp(log_avg_F_fleet1+log_F_dev_init_fleet1)+mfexp(log_avg_F_fleet2+
log_F_dev_init_fleet2));

F_init_fleet1_D_prop=mfexp(log_avg_F_fleet1_D+log_F_dev_init_fleet1_D)/(mfexp(log_avg_F_fleet1_D+log_F_dev_init_fleet1_D)+mfexp(log_
avg_F_fleet2_D+log_F_dev_init_fleet2_D));

F_init_fleet2_D_prop=mfexp(log_avg_F_fleet2_D+log_F_dev_init_fleet2_D)/(mfexp(log_avg_F_fleet1_D+log_F_dev_init_fleet1_D)+mfexp(log_
avg_F_fleet2_D+log_F_dev_init_fleet2_D));

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for (iyear=styr; iyear<=endyr; iyear++)
{
  if(iyear>=styr_fleet1_L & iyear<=endyr_fleet1_L)
  { F_fleet1_out(iyear)=mfexp(log_avg_F_fleet1+log_F_dev_fleet1(iyear));
    F_fleet1(iyear)=sel_fleet1(iyear)*F_fleet1_out(iyear);
    Fsum(iyear)+=F_fleet1_out(iyear);
  }

  if(iyear>=styr_fleet1_D & iyear<=endyr_fleet1_D)
  { F_fleet1_D_out(iyear)=mfexp(log_avg_F_fleet1_D+log_F_dev_fleet1_D(iyear));
    F_fleet1_D(iyear)=sel_fleet1_D(iyear)*F_fleet1_D_out(iyear);
    Fsum(iyear)+=F_fleet1_D_out(iyear);
  }

  if(iyear>=styr_fleet2_L & iyear<=endyr_fleet2_L)
  { F_fleet2_out(iyear)=mfexp(log_avg_F_fleet2+log_F_dev_fleet2(iyear));
    F_fleet2(iyear)=sel_fleet2(iyear)*F_fleet2_out(iyear);
    Fsum(iyear)+=F_fleet2_out(iyear);
  }

  if(iyear>=styr_fleet2_D & iyear<=endyr_fleet2_D)
  { F_fleet2_D_out(iyear)=mfexp(log_avg_F_fleet2_D+log_F_dev_fleet2_D(iyear));
    F_fleet2_D(iyear)=sel_fleet2_D(iyear)*F_fleet2_D_out(iyear);
    Fsum(iyear)+=F_fleet2_D_out(iyear);
  }

  //Total F at age
  F(iyear)=F_fleet1(iyear);
  F(iyear)+=F_fleet1_D(iyear);
  F(iyear)+=F_fleet2(iyear);
  F(iyear)+=F_fleet2_D(iyear);

  Fapex(iyear)=max(F(iyear));
  Z(iyear)=M+F(iyear);
} //end iyear

FUNCTION get_bias_corr
var_rec_dev=norm2(log_rec_dev(styr_rec_dev,endyr_rec_dev)-
  sum(log_rec_dev(styr_rec_dev,endyr_rec_dev))/nyrs_rec)
  /(nyrs_rec-1.0);
//if (set_BiasCor <= 0.0) {BiasCor=mfexp(var_rec_dev/2.0);} //bias correction based on empirical residuals
rec_sigma_sq=square(rec_sigma);
if (set_BiasCor <= 0.0) {BiasCor=mfexp(rec_sigma_sq/2.0);} //bias correction based on Rsigma
else {BiasCor=set_BiasCor;}

FUNCTION get_numbers_at_age
//Initialization
R0=mfexp(log_R0);
S0=spr_F0*R0;
//R_virgin=(R0/((5.0*steep-1.0)*spr_F0))*
//  (BiasCor*4.0*steep*spr_F0-spr_F0*(1.0-steep));
//R_virgin=R0/(spr_F0/spr_F0)*BiasCor*(1.0+log(spr_F0/spr_F0)/steep); //Ricker

R_virgin=SR_eq_func(R0, steep, spr_F0, spr_F0, BiasCor, SR_switch);

B0=bpr_F0*R_virgin;
//B0_q_DD=R_virgin*sum(elem_prod(N_bpr_F0(set_q_DD_stage,nages),wgt_mt(set_q_DD_stage,nages)));

//F_initial=sel_fleet1(styr)*mfexp(log_avg_F_fleet1+log_F_dev_init_fleet1)+sel_fleet2(styr)*mfexp(log_avg_F_fleet2+log_F_dev_init_fleet2);
F_initial=sel_fleet1(styr)*F_init*F_init_fleet1_prop
  +sel_fleet1_D(styr)*F_init*F_init_fleet1_D_prop
  +sel_fleet2(styr)*F_init*F_init_fleet2_prop

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+sel_fleet2_D(styr)*F_init*F_init_fleet2_D_prop;

Z_initial=M+F_initial;

//Initial equilibrium age structure
N_spr_initial(1)=1.0*mfexp(-1.0*Z_initial(1)*spawn_time_frac); //at peak spawning time;
for (iage=2; iage<=nages; iage++)
{
    N_spr_initial(iage)=N_spr_initial(iage-1)*
        mfexp(-1.0*(Z_initial(iage-1)*(1.0-spawn_time_frac) + Z_initial(iage)*spawn_time_frac));
}
N_spr_initial(nages)=N_spr_initial(nages)/(1.0-mfexp(-1.0*Z_initial(nages))); //plus group
spr_initial=sum(elem_prod(N_spr_initial,reprod));

//if (styr==styr_rec_dev) {R1=(R0/((5.0*steep-1.0)*spr_initial))*
//    (4.0*steep*spr_initial-spr_F0*(1.0-steep));} //without bias correction (deviation added later)
//else {R1=(R0/((5.0*steep-1.0)*spr_initial))*
//    (BiasCor*4.0*steep*spr_initial-spr_F0*(1.0-steep));} //with bias correction

if (styr==styr_rec_dev) {R1=SR_eq_func(R0, steep, spr_F0, spr_initial, 1.0, SR_switch);} //without bias correction (deviation added later)
else {R1=SR_eq_func(R0, steep, spr_F0, spr_initial, BiasCor, SR_switch);} //with bias correction
if(R1<10.0) {R1=10.0;} //Avoid unrealistically low popn sizes during searfleet1 algorithm

//Compute equilibrium age structure for first year
N_initial_eq(1)=R1;
for (iage=2; iage<=nages; iage++)
{
    N_initial_eq(iage)=N_initial_eq(iage-1)*
        mfexp(-1.0*(Z_initial(iage-1)));
}
//plus group calculation
N_initial_eq(nages)=N_initial_eq(nages)/(1.0-mfexp(-1.0*Z_initial(nages))); //plus group

//Add deviations to initial equilibrium N
N(styr)(2,nages)=elem_prod(N_initial_eq(2,nages),mfexp(log_Nage_dev));

if (styr==styr_rec_dev) {N(styr,1)=N_initial_eq(1)*mfexp(log_rec_dev(styr_rec_dev));}
else {N(styr,1)=N_initial_eq(1);}

N_mdyr(styr)(1,nages)=elem_prod(N(styr)(1,nages),(mfexp(-1.*(Z_initial(1,nages))*0.5))); //mid year
N_spawn(styr)(1,nages)=elem_prod(N(styr)(1,nages),(mfexp(-1.*(Z_initial(1,nages))*spawn_time_frac))); //peak spawning time

SSB(styr)=sum(elem_prod(N_spawn(styr),reprod));
//B_q_DD(styr)=sum(elem_prod(N(styr)(set_q_DD_stage,nages),wgt_mt(set_q_DD_stage,nages)));

//Rest of years
for (iyear=styr; iyear<endyr; iyear++)
{
    if(iyear<(styr_rec_dev-1) || iyear>(endyr_rec_dev-1)) //recruitment follows S-R curve (with bias correction) exactly
    {
        N(iyear+1,1)=BiasCor*SR_func(R0, steep, spr_F0, SSB(iyear),SR_switch);
        N(iyear+1)(2,nages)=++elem_prod(N(iyear)(1,nages-1),(mfexp(-1.*(Z(iyear)(1,nages-1)))));
        N(iyear+1,nages)+=N(iyear,nages)*mfexp(-1.*(Z(iyear,nages))); //plus group
        N_mdyr(iyear+1)(1,nages)=elem_prod(N(iyear+1)(1,nages),(mfexp(-1.*(Z(iyear+1)(1,nages))*0.5))); //mid year
        N_spawn(iyear+1)(1,nages)=elem_prod(N(iyear+1)(1,nages),(mfexp(-1.*(Z(iyear+1)(1,nages))*spawn_time_frac))); //peak spawning time
        SSB(iyear+1)=sum(elem_prod(N_spawn(iyear+1),reprod));
        //B_q_DD(iyear+1)=sum(elem_prod(N(iyear+1)(set_q_DD_stage,nages),wgt_mt(set_q_DD_stage,nages)));
    }
    else //recruitment follows S-R curve with lognormal deviation
    {
        N(iyear+1,1)=SR_func(R0, steep, spr_F0, SSB(iyear),SR_switch)*mfexp(log_rec_dev(iyear+1));
        N(iyear+1)(2,nages)=++elem_prod(N(iyear)(1,nages-1),(mfexp(-1.*(Z(iyear)(1,nages-1)))));
        N(iyear+1,nages)+=N(iyear,nages)*mfexp(-1.*(Z(iyear,nages))); //plus group
        N_mdyr(iyear+1)(1,nages)=elem_prod(N(iyear+1)(1,nages),(mfexp(-1.*(Z(iyear+1)(1,nages))*0.5))); //mid year
    }
}

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N_spawn(iyear+1)(1,nages)=elem_prod(N(iyear+1)(1,nages),(mfexp(-1.*Z(iyear+1)(1,nages))*spawn_time_frac)); //peak spawning time
SSB(iyear+1)=sum(elem_prod(N_spawn(iyear+1),reprod));
//B_q_DD(iyear+1)=sum(elem_prod(N(iyear+1)(set_q_DD_stage,nages),wgt_mt(set_q_DD_stage,nages)));
}
}

//last year (projection) has no recruitment variability
N(endyr+1,1)=BiasCor*SR_func(R0, steep, spr_F0, SSB(endyr),SR_switch);
N(endyr+1)(2,nages)=++elem_prod(N(endyr)(1,nages-1),(mfexp(-1.*Z(endyr)(1,nages-1))));
N(endyr+1,nages)+=N(endyr,nages)*mfexp(-1.*Z(endyr,nages)); //plus group

//Time series of interest
rec=column(N,1);
SdS0=SSB/S0;

FUNCTION get_landings_numbers //Baranov catch eqn
for (iyear=styr; iyear<=endyr; iyear++)
{
  for (iage=1; iage<=nages; iage++)
  {
    L_fleet1_num(iyear,iage)=N(iyear,iage)*F_fleet1(iyear,iage)*
      (1.-mfexp(-1.*Z(iyear,iage)))/Z(iyear,iage);
    D_fleet1_num(iyear,iage)=N(iyear,iage)*F_fleet1_D(iyear,iage)*
      (1.-mfexp(-1.*Z(iyear,iage)))/Z(iyear,iage);
    L_fleet2_num(iyear,iage)=N(iyear,iage)*F_fleet2(iyear,iage)*
      (1.-mfexp(-1.*Z(iyear,iage)))/Z(iyear,iage);
    D_fleet2_num(iyear,iage)=N(iyear,iage)*F_fleet2_D(iyear,iage)*
      (1.-mfexp(-1.*Z(iyear,iage)))/Z(iyear,iage);
  }
  pred_fleet1_L_knum(iyear)=sum(L_fleet1_num(iyear))/1000.0;
  pred_fleet1_D_knum(iyear)=sum(D_fleet1_num(iyear))/1000.0;
  pred_fleet2_L_knum(iyear)=sum(L_fleet2_num(iyear))/1000.0;
  pred_fleet2_D_knum(iyear)=sum(D_fleet2_num(iyear))/1000.0;
}

FUNCTION get_landings_wgt
for (iyear=styr; iyear<=endyr; iyear++)
{
  L_fleet1_klb(iyear)=elem_prod(L_fleet1_num(iyear),wholewgt_fleet1_klb(iyear)); //in 1000 lb
  //D_fleet1_klb(iyear)=elem_prod(D_fleet1_num(iyear),wholewgt_fleet1_D_klb(iyear)); //in 1000 lb
  L_fleet2_klb(iyear)=elem_prod(L_fleet2_num(iyear),wholewgt_fleet2_klb(iyear)); //in 1000 lb
  //D_fleet2_klb(iyear)=elem_prod(D_fleet2_num(iyear),wholewgt_fleet2_D_klb(iyear)); //in 1000 lb

  pred_fleet1_L_klb(iyear)=sum(L_fleet1_klb(iyear));
  //pred_fleet1_D_klb(iyear)=sum(D_fleet1_klb(iyear));
  pred_fleet2_L_klb(iyear)=sum(L_fleet2_klb(iyear));
  //pred_fleet2_D_klb(iyear)=sum(D_fleet2_klb(iyear));
}

FUNCTION get_indices
//---Predicted CPUEs-----

//Survey 1: cpue
for (iyear=styr_survey1_cpue; iyear<=endyr_survey1_cpue; iyear++)
{ //index in number units
  N_survey1(iyear)=elem_prod(N_mdryr(iyear),sel_survey1(iyear));
  pred_survey1_cpue(iyear)=mfexp(log_q_survey1)*sum(N_survey1(iyear));
}

//fleet1 cpue
for (iyear=styr_fleet1_cpue; iyear<=endyr_fleet1_cpue; iyear++)
{
  q_fleet1(iyear)=mfexp(log_q_fleet1);
  //index in weight units. original index in lb and re-scaled. predicted in klb, but difference is absorbed by q

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N_fleet1(iyear)=elem_prod(elem_prod(N_mdyr(iyear),sel_fleet1(iyear)),wholewgt_fleet1_klb(iyear));
//N_fleet1(iyear)=elem_prod(N_mdyr(iyear),sel_fleet1(iyear));
pred_fleet1_cpue(iyear)=q_fleet1(iyear)*sum(N_fleet1(iyear));
}

FUNCTION get_age_comps

//survey1
for (iyear=1;iyear<=nyr_survey1_agec;iyear++)
{
  ErrorFree_survey1_agec(iyear)=N_survey1(yrs_survey1_agec(iyear))/sum(N_survey1(yrs_survey1_agec(iyear)));
  pred_survey1_agec_allages(iyear)=age_error*ErrorFree_survey1_agec(iyear);
  for (iage=1; iage<=nages; iage++) {pred_survey1_agec(iyear,iage)=pred_survey1_agec_allages(iyear,iage);}
  for (iage=(nages+1); iage<=nages; iage++) {pred_survey1_agec(iyear,nages)+=pred_survey1_agec_allages(iyear,iage);} //plus group
}

//fleet1
for (iyear=1;iyear<=nyr_fleet1_agec;iyear++)
{
  ErrorFree_fleet1_agec(iyear)=L_fleet1_num(yrs_fleet1_agec(iyear))/sum(L_fleet1_num(yrs_fleet1_agec(iyear)));
  //ErrorFree_fleet1_agec(iyear)=elem_prod(N(yrs_fleet1_agec(iyear)),sel_fleet1(yrs_fleet1_agec(iyear)));
  pred_fleet1_agec_allages(iyear)=age_error*(ErrorFree_fleet1_agec(iyear)/sum(ErrorFree_fleet1_agec(iyear)));
  for (iage=1; iage<=nages; iage++) {pred_fleet1_agec(iyear,iage)=pred_fleet1_agec_allages(iyear,iage);}
  for (iage=(nages+1); iage<=nages; iage++) {pred_fleet1_agec(iyear,nages)+=pred_fleet1_agec_allages(iyear,iage);} //plus group
}

//fleet2
for (iyear=1;iyear<=nyr_fleet2_agec;iyear++)
{
  ErrorFree_fleet2_agec(iyear)=L_fleet2_num(yrs_fleet2_agec(iyear))/sum(L_fleet2_num(yrs_fleet2_agec(iyear)));
  //ErrorFree_fleet2_agec(iyear)=elem_prod(N(yrs_fleet2_agec(iyear)),sel_fleet2(yrs_fleet2_agec(iyear)));
  pred_fleet2_agec_allages(iyear)=age_error*(ErrorFree_fleet2_agec(iyear)/sum(ErrorFree_fleet2_agec(iyear)));
  for (iage=1; iage<=nages; iage++) {pred_fleet2_agec(iyear,iage)=pred_fleet2_agec_allages(iyear,iage);}
  for (iage=(nages+1); iage<=nages; iage++) {pred_fleet2_agec(iyear,nages)+=pred_fleet2_agec_allages(iyear,iage);} //plus group
}

////-----
--
FUNCTION get_weighted_current
F_temp_sum=0.0;
F_temp_sum+=mfexp((selpar_n_yrs_wgtd*log_avg_F_fleet1+
  sum(log_F_dev_fleet1((endyr-selpar_n_yrs_wgtd+1),endyr)))/selpar_n_yrs_wgtd);
F_temp_sum+=mfexp((selpar_n_yrs_wgtd*log_avg_F_fleet1_D+
  sum(log_F_dev_fleet1_D((endyr-selpar_n_yrs_wgtd+1),endyr)))/selpar_n_yrs_wgtd);
F_temp_sum+=mfexp((selpar_n_yrs_wgtd*log_avg_F_fleet2+
  sum(log_F_dev_fleet2((endyr-selpar_n_yrs_wgtd+1),endyr)))/selpar_n_yrs_wgtd);
F_temp_sum+=mfexp((selpar_n_yrs_wgtd*log_avg_F_fleet2_D+
  sum(log_F_dev_fleet2_D((endyr-selpar_n_yrs_wgtd+1),endyr)))/selpar_n_yrs_wgtd);
F_fleet1_prop=mfexp((selpar_n_yrs_wgtd*log_avg_F_fleet1+
  sum(log_F_dev_fleet1((endyr-selpar_n_yrs_wgtd+1),endyr)))/selpar_n_yrs_wgtd)/F_temp_sum;
F_fleet1_D_prop=mfexp((selpar_n_yrs_wgtd*log_avg_F_fleet1_D+
  sum(log_F_dev_fleet1_D((endyr-selpar_n_yrs_wgtd+1),endyr)))/selpar_n_yrs_wgtd)/F_temp_sum;
F_fleet2_prop=mfexp((selpar_n_yrs_wgtd*log_avg_F_fleet2+
  sum(log_F_dev_fleet2((endyr-selpar_n_yrs_wgtd+1),endyr)))/selpar_n_yrs_wgtd)/F_temp_sum;
F_fleet2_D_prop=mfexp((selpar_n_yrs_wgtd*log_avg_F_fleet2_D+
  sum(log_F_dev_fleet2_D((endyr-selpar_n_yrs_wgtd+1),endyr)))/selpar_n_yrs_wgtd)/F_temp_sum;

log_F_dev_end_fleet1=sum(log_F_dev_fleet1((endyr-selpar_n_yrs_wgtd+1),endyr))/selpar_n_yrs_wgtd;
log_F_dev_end_fleet1_D=sum(log_F_dev_fleet1_D((endyr-selpar_n_yrs_wgtd+1),endyr))/selpar_n_yrs_wgtd;
log_F_dev_end_fleet2=sum(log_F_dev_fleet2((endyr-selpar_n_yrs_wgtd+1),endyr))/selpar_n_yrs_wgtd;
log_F_dev_end_fleet2_D=sum(log_F_dev_fleet2_D((endyr-selpar_n_yrs_wgtd+1),endyr))/selpar_n_yrs_wgtd;

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F_end_L=sel_fleet1(endyr)*mfexp(log_avg_F_fleet1+log_F_dev_end_fleet1)+
  sel_fleet1_D(endyr)*mfexp(log_avg_F_fleet1_D+log_F_dev_end_fleet1_D)+
  sel_fleet2(endyr)*mfexp(log_avg_F_fleet2+log_F_dev_end_fleet2)+
  sel_fleet2_D(endyr)*mfexp(log_avg_F_fleet2_D+log_F_dev_end_fleet2_D);

F_end=F_end_L;
F_end_apex=max(F_end);

sel_wgted_tot=F_end/F_end_apex;
sel_wgted_L=elem_prod(sel_wgted_tot, elem_div(F_end_L,F_end));

wgt_wgted_L_denom=F_fleet1_prop+F_fleet2_prop;
wgt_wgted_L_klb=F_fleet1_prop/wgt_wgted_L_denom*wholewgt_fleet1_klb(endyr)+
  F_fleet1_D_prop/wgt_wgted_L_denom*wholewgt_fleet1_D_klb(endyr)+
  F_fleet2_prop/wgt_wgted_L_denom*wholewgt_fleet2_klb(endyr)+
  F_fleet2_D_prop/wgt_wgted_L_denom*wholewgt_fleet2_D_klb(endyr);

FUNCTION get_msy

//compute values as functions of F
for(ff=1; ff<=n_iter_msy; ff++)
{
  //uses fishery-weighted F's
  Z_age_msy=0.0;
  F_L_age_msy=0.0;
  F_D_age_msy=0.0;

  F_L_age_msy=F_msy(ff)*sel_wgted_L;
  F_D_age_msy=F_msy(ff)*sel_wgted_D;
  Z_age_msy=M+F_L_age_msy+F_D_age_msy;

  N_age_msy(1)=1.0;
  for (iage=2; iage<=nages; iage++)
  {N_age_msy(iage)=N_age_msy(iage-1)*mfexp(-1.*Z_age_msy(iage-1));}
  N_age_msy(nages)=N_age_msy(nages)/(1.0-mfexp(-1.*Z_age_msy(nages)));
  N_age_msy_spawn(1,(nages-1))=elem_prod(N_age_msy(1,(nages-1)),
    mfexp((-1.*Z_age_msy(1,(nages-1))))*spawn_time_frac);
  N_age_msy_spawn(nages)=(N_age_msy_spawn(nages-1)*(mfexp(-1.*Z_age_msy(nages-1)*(1.0-spawn_time_frac) +
    Z_age_msy(nages)*spawn_time_frac )))/(1.0-mfexp(-1.*Z_age_msy(nages)));

  spr_msy(ff)=sum(elem_prod(N_age_msy_spawn,reprd));

  R_eq(ff)=SR_eq_func(R0, steep, spr_msy(1), spr_msy(ff), BiasCor, SR_switch);

  if (R_eq(ff)<dzero) {R_eq(ff)=dzero;}
  N_age_msy*=R_eq(ff);
  N_age_msy_spawn*=R_eq(ff);

  for (iage=1; iage<=nages; iage++)
  {
    L_age_msy(iage)=N_age_msy(iage)*(F_L_age_msy(iage)/Z_age_msy(iage))*
      (1.-mfexp(-1.*Z_age_msy(iage)));
    D_age_msy(iage)=N_age_msy(iage)*(F_D_age_msy(iage)/Z_age_msy(iage))*
      (1.-mfexp(-1.*Z_age_msy(iage)));
  }

  SSB_eq(ff)=sum(elem_prod(N_age_msy_spawn,reprd));
  B_eq(ff)=sum(elem_prod(N_age_msy,wgt_mt));
  L_eq_klb(ff)=sum(elem_prod(L_age_msy,wgt_wgted_L_klb));
  D_eq_klb(ff)=sum(elem_prod(D_age_msy,wgt_wgted_D_klb));
  L_eq_knum(ff)=sum(L_age_msy)/1000.0;
  D_eq_knum(ff)=sum(D_age_msy)/1000.0;
}

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msy_klb_out=max(L_eq_klb);

for(ff=1; ff<=n_iter_msy; ff++)
{
  if(L_eq_klb(ff) == msy_klb_out)
  {
    SSB_msy_out=SSB_eq(ff);
    B_msy_out=B_eq(ff);
    R_msy_out=R_eq(ff);
    msy_knum_out=L_eq_knum(ff);
    F_msy_out=F_msy(ff);
    spr_msy_out=spr_msy(ff);
  }
}

//-----
FUNCTION get_miscellaneous_stuff

//switfleet1 here if var_rec_dev <= dzero //KC/KS added
if(var_rec_dev>0.0)
{sigma_rec_dev=sqrt(var_rec_dev);} //pow(var_rec_dev,0.5); //sample SD of predicted residuals (may not equal rec_sigma)
else{sigma_rec_dev=0.0;}

//compute total landings- and discards-at-age in 1000 fish and klb
L_total_num.initialize();
L_total_klb.initialize();
L_total_knum_yr.initialize();
L_total_klb_yr.initialize();
D_total_num.initialize();
//D_total_klb.initialize();
D_total_knum_yr.initialize();
//D_total_klb_yr.initialize();

for(iyear=styr; iyear<=endyr; iyear++)
{
  L_total_klb_yr(iyear)=pred_fleet1_L_klb(iyear)+pred_fleet2_L_klb(iyear);
  //D_total_klb_yr(iyear)=pred_fleet1_D_klb(iyear)+pred_fleet2_D_klb(iyear);
  L_total_knum_yr(iyear)=pred_fleet1_L_knum(iyear)+pred_fleet2_L_knum(iyear);
  D_total_knum_yr(iyear)=pred_fleet1_D_knum(iyear)+pred_fleet2_D_knum(iyear);

  B(iyear)=elem_prod(N(iyear),wgt_mt);
  totN(iyear)=sum(N(iyear));
  totB(iyear)=sum(B(iyear));
}

L_total_num=L_fleet1_num+L_fleet2_num; //landings at age in number fish
L_total_klb=L_fleet1_klb+L_fleet2_klb; //landings at age in klb whole weight
D_total_num=D_fleet1_num+D_fleet2_num; //discards at age in number fish
//D_total_klb=D_fleet1_klb+D_fleet2_klb; //discards at age in klb whole weight

B(endyr+1)=elem_prod(N(endyr+1),wgt_mt);
totN(endyr+1)=sum(N(endyr+1));
totB(endyr+1)=sum(B(endyr+1));

// steep_sd=steep;
// fullF_sd=Fsum;

if(F_msy_out>0)
{
  FdF_msy=Faxpex/F_msy_out;
  FdF_msy_end=FdF_msy(endyr);
  FdF_msy_end_mean=pow((FdF_msy(endyr)*FdF_msy(endyr-1)*FdF_msy(endyr-2)),(1.0/3.0));
}
if(SSB_msy_out>0)

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{
  SdSSB_msy=SSB/SSB_msy_out;
  SdSSB_msy_end=SdSSB_msy(endyr);
}

//fill in log recruitment deviations for yrs they are nonzero
for(iyear=styr_rec_dev; iyear<=endyr_rec_dev; iyear++)
  {log_rec_dev_output(iyear)=log_rec_dev(iyear);}
//fill in log Nage deviations for ages they are nonzero (ages2+)
for(iage=2; iage<=nages; iage++)
  {log_Nage_dev_output(iage)=log_Nage_dev(iage);}

//-----
FUNCTION get_per_recruit_stuff

//static per-recruit stuff

for(iyear=styr; iyear<=endyr; iyear++)
{
  N_age_spr(1)=1.0;
  for(iage=2; iage<=nages; iage++)
    {N_age_spr(iage)=N_age_spr(iage-1)*mfexp(-1.*Z(iyear,iage-1));}
  N_age_spr(nages)=N_age_spr(nages)/(1.0-mfexp(-1.*Z(iyear,nages)));
  N_age_spr_spawn(1,(nages-1))=elem_prod(N_age_spr(1,(nages-1)),
    mfexp(-1.*Z(iyear)(1,(nages-1))*spawn_time_frac));
  N_age_spr_spawn(nages)=(N_age_spr_spawn(nages-1)*
    (mfexp(-1.*Z(iyear)(nages-1)*(1.0-spawn_time_frac) + Z(iyear)(nages)*spawn_time_frac) ))
    /(1.0-mfexp(-1.*Z(iyear)(nages)));
  spr_static(iyear)=sum(elem_prod(N_age_spr_spawn,reprod))/spr_F0;
}

//compute SSB/R and YPR as functions of F
for(ff=1; ff<=n_iter_spr; ff++)
{
  //uses fishery-weighted F's, same as in MSY calculations
  Z_age_spr=0.0;
  F_L_age_spr=0.0;
  F_D_age_spr=0.0;

  F_L_age_spr=F_spr(ff)*sel_wgtd_L;
  F_D_age_spr=F_spr(ff)*sel_wgtd_D;

  Z_age_spr=M+F_L_age_spr+F_D_age_spr;

  N_age_spr(1)=1.0;
  for (iage=2; iage<=nages; iage++)
    {N_age_spr(iage)=N_age_spr(iage-1)*mfexp(-1.*Z_age_spr(iage-1));}
  N_age_spr(nages)=N_age_spr(nages)/(1-mfexp(-1.*Z_age_spr(nages)));
  N_age_spr_spawn(1,(nages-1))=elem_prod(N_age_spr(1,(nages-1)),
    mfexp((-1.*Z_age_spr(1,(nages-1))*spawn_time_frac));
  N_age_spr_spawn(nages)=(N_age_spr_spawn(nages-1)*
    (mfexp(-1.*(Z_age_spr(nages-1)*(1.0-spawn_time_frac) + Z_age_spr(nages)*spawn_time_frac) ))
    /(1.0-mfexp(-1.*Z_age_spr(nages)));

  spr_spr(ff)=sum(elem_prod(N_age_spr_spawn,reprod));
  L_spr(ff)=0.0;
  D_spr(ff)=0.0;
  for (iage=1; iage<=nages; iage++)
  {
    L_age_spr(iage)=N_age_spr(iage)*(F_L_age_spr(iage)/Z_age_spr(iage))*
      (1-mfexp(-1.*Z_age_spr(iage)));
    L_spr(ff)+=L_age_spr(iage)*wgt_wgtd_L_klb(iage)*1000.0; //in lb
    D_age_spr(iage)=N_age_spr(iage)*(F_D_age_spr(iage)/Z_age_spr(iage))*

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        (1.-mfexp(-1.*Z_age_spr(iage)));
        D_spr(ff)+=D_age_spr(iage)*wgt_wgtd_D_klb(iage)*1000.0; //in lb
    }
}

FUNCTION get_effective_sample_sizes
    neff_survey1_agec_allyr_out=missing;
    neff_fleet1_agec_allyr_out=missing;
    neff_fleet2_agec_allyr_out=missing;

    for (iyear=1; iyear<=nyr_survey1_agec; iyear++)
        {if (nsamp_survey1_agec(iyear)>=minSS_survey1_agec)
            {neff_survey1_agec_allyr_out(yrs_survey1_agec(iyear))=multinom_eff_N(pred_survey1_agec(iyear),obs_survey1_agec(iyear));}
            else {neff_survey1_agec_allyr_out(yrs_survey1_agec(iyear))=-99;}
        }

    for (iyear=1; iyear<=nyr_fleet1_agec; iyear++)
        {if (nsamp_fleet1_agec(iyear)>=minSS_fleet1_agec)
            {neff_fleet1_agec_allyr_out(yrs_fleet1_agec(iyear))=multinom_eff_N(pred_fleet1_agec(iyear),obs_fleet1_agec(iyear));}
            else {neff_fleet1_agec_allyr_out(yrs_fleet1_agec(iyear))=-99;}
        }

    for (iyear=1; iyear<=nyr_fleet2_agec; iyear++)
        {if (nsamp_fleet2_agec(iyear)>=minSS_fleet2_agec)
            {neff_fleet2_agec_allyr_out(yrs_fleet2_agec(iyear))=multinom_eff_N(pred_fleet2_agec(iyear),obs_fleet2_agec(iyear));}
            else {neff_fleet2_agec_allyr_out(yrs_fleet2_agec(iyear))=-99;}
        }

FUNCTION get_projections

    // project using F=Fmsy
    F_proj=F_msy_out*sel_wgtd_L;
    F_D_proj=F_msy_out*sel_wgtd_D;
    Z_proj=M+F_proj+F_D_proj;

    //last year (projection) has no recruitment variability
    N_proj(1)=BiasCor*SR_func(R0, steep, spr_F0, SSB(endyr),SR_switch);
    for (iage=2; iage<=nages; iage++)
        {
            N_proj(iage)=N_proj(iage-1)*mfexp(-1.*Z_proj(iage-1));
        }
    N_proj(nages)+=N_proj(nages)*mfexp(-1.*Z_proj(nages)); //plus group

    for (iage=1; iage<=nages; iage++)
        {
            L_proj(iage)=N_proj(iage)*(F_proj(iage)/Z_proj(iage))*
                (1.-mfexp(-1.*Z_proj(iage)));
            D_proj(iage)=N_proj(iage)*(F_D_proj(iage)/Z_proj(iage))*
                (1.-mfexp(-1.*Z_proj(iage)));
        }

    L_proj_klb=sum(elem_prod(L_proj,wgt_wgtd_L_klb));
    L_proj_knum=sum(L_proj)/1000.0;
    D_proj_klb=sum(elem_prod(D_proj,wgt_wgtd_D_klb));
    D_proj_knum=sum(D_proj)/1000.0;

FUNCTION evaluate_objective_function
    if(optimize_switch<1)
    {
        fval=square(dummy_optimize-0.0);
    }else
    {
        fval=0.0;
    }

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fval_data=0.0;
//---likelihoods-----

//---Indices-----

f_survey1_cpue=0.0;
f_survey1_cpue=lk_lognormal(pred_survey1_cpue, obs_survey1_cpue, survey1_cpue_cv, w_l_survey1);
fval+=f_survey1_cpue;
fval_data+=f_survey1_cpue;

f_fleet1_cpue=0.0;
f_fleet1_cpue=lk_lognormal(pred_fleet1_cpue, obs_fleet1_cpue, fleet1_cpue_cv, w_l_fleet1);
fval+=f_fleet1_cpue;
fval_data+=f_fleet1_cpue;

//---Landings-----

//f_fleet1_L in 1000 lb whole wgt
f_fleet1_L=lk_lognormal(pred_fleet1_L_klb(styr_fleet1_L, endyr_fleet1_L), obs_fleet1_L(styr_fleet1_L, endyr_fleet1_L),
                        fleet1_L_cv(styr_fleet1_L, endyr_fleet1_L), w_L_fleet1);
fval+=f_fleet1_L;
fval_data+=f_fleet1_L;

//f_fleet1_D in 1000s
f_fleet1_D=lk_lognormal(pred_fleet1_D_knum(styr_fleet1_D, endyr_fleet1_D), obs_fleet1_D(styr_fleet1_D, endyr_fleet1_D),
                        fleet1_D_cv(styr_fleet1_D, endyr_fleet1_D), w_D_fleet1);
fval+=f_fleet1_D;
fval_data+=f_fleet1_D;

//f_fleet2_L in 1000 lb whole wgt
f_fleet2_L=lk_lognormal(pred_fleet2_L_klb(styr_fleet2_L, endyr_fleet2_L), obs_fleet2_L(styr_fleet2_L, endyr_fleet2_L),
                        fleet2_L_cv(styr_fleet2_L, endyr_fleet2_L), w_L_fleet2);
fval+=f_fleet2_L;
fval_data+=f_fleet2_L;

//f_fleet2_D in 1000s
f_fleet2_D=lk_lognormal(pred_fleet2_D_knum(styr_fleet2_D, endyr_fleet2_D), obs_fleet2_D(styr_fleet2_D, endyr_fleet2_D),
                        fleet2_D_cv(styr_fleet2_D, endyr_fleet2_D), w_D_fleet2);
fval+=f_fleet2_D;
fval_data+=f_fleet2_D;

////---Age comps-----

//f_survey1_agec
f_survey1_agec=lk_robust_multinomial(nsamp_survey1_agec, pred_survey1_agec, obs_survey1_agec, nyr_survey1_agec, double(nages),
minSS_survey1_agec, w_ac_survey1);
//f_survey1_agec=lk_multinomial(nsamp_survey1_agec, pred_survey1_agec, obs_survey1_agec, nyr_survey1_agec, minSS_survey1_agec,
w_ac_survey1);
fval+=f_survey1_agec;
fval_data+=f_survey1_agec;

//f_fleet1_agec
f_fleet1_agec=lk_robust_multinomial(nsamp_fleet1_agec, pred_fleet1_agec, obs_fleet1_agec, nyr_fleet1_agec, double(nages),
minSS_fleet1_agec, w_ac_fleet1);
fval+=f_fleet1_agec;
fval_data+=f_fleet1_agec;

//f_fleet2_agec
f_fleet2_agec=lk_robust_multinomial(nsamp_fleet2_agec, pred_fleet2_agec, obs_fleet2_agec, nyr_fleet2_agec, double(nages),
minSS_fleet2_agec, w_ac_fleet2);
fval+=f_fleet2_agec;
fval_data+=f_fleet2_agec;

//-----Constraints and penalties-----

```

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//Light penalty applied to log_Nage_dev for deviation from zero. If not estimated, this penalty equals zero.
f_Nage_init=norm2(log_Nage_dev);
fval+=w_Nage_init*f_Nage_init;

f_rec_dev=0.0;
//rec_sigma_sq=square(rec_sigma);
rec_logL_add=nyrs_rec*log(rec_sigma);
f_rec_dev=(square(log_rec_dev(styr_rec_dev) + rec_sigma_sq/2.0)/(2.0*rec_sigma_sq));
for(iyear=(styr_rec_dev+1); iyear<=endyr; iyear++)
{f_rec_dev+=(square(log_rec_dev(iyear)-R_autocorr*log_rec_dev(iyear-1) + rec_sigma_sq/2.0)/
  (2.0*rec_sigma_sq));}
f_rec_dev+=rec_logL_add;
fval+=w_rec*f_rec_dev;

f_rec_dev_early=0.0; //possible extra constraint on early rec deviations
if (w_rec_early>0.0)
{ if (styr_rec_dev<endyr_rec_phase1)
  {
    for(iyear=styr_rec_dev; iyear<=endyr_rec_phase1; iyear++)
      {f_rec_dev_early+=square(log_rec_dev(iyear));}
  }
fval+=w_rec_early*f_rec_dev_early;
}

f_rec_dev_end=0.0; //possible extra constraint on ending rec deviations
if (w_rec_end>0.0)
{ if (endyr_rec_phase2<endyr_rec_dev)
  {
    for(iyear=(endyr_rec_phase2+1); iyear<=endyr_rec_dev; iyear++)
      {f_rec_dev_end+=square(log_rec_dev(iyear));}
  }
fval+=w_rec_end*f_rec_dev_end;
}

//Ftune penalty: does not apply in last phase
f_Ftune=0.0;
if (w_Ftune>0.0)
{if (set_Ftune>0.0 && !last_phase()) {f_Ftune=square(Fapex(set_Ftune_yr)-set_Ftune);}
fval+=w_Ftune*f_Ftune;
}

//---Priors-----
//neg_log_prior arguments: estimate, prior mean, prior var/-CV, pdf type
//Variance input as a negative value is considered to be CV in arithmetic space (CV=-1 implies loose prior)
//pdf type 1=none, 2=lognormal, 3=normal, 4=beta
f_priors=0.0;
f_priors+=neg_log_prior(Linf,set_Linf(5),set_Linf(6),set_Linf(7));
f_priors+=neg_log_prior(K,set_K(5),set_K(6),set_K(7));
f_priors+=neg_log_prior(t0,set_t0(5),set_t0(6),set_t0(7));

f_priors+=neg_log_prior(steep,set_steep(5),set_steep(6),set_steep(7));
f_priors+=neg_log_prior(log_R0,set_log_R0(5),set_log_R0(6),set_log_R0(7));
f_priors+=neg_log_prior(R_autocorr,set_R_autocorr(5),set_R_autocorr(6),set_R_autocorr(7));
f_priors+=neg_log_prior(rec_sigma,set_rec_sigma(5),set_rec_sigma(6),set_rec_sigma(7));

f_priors+=neg_log_prior(selpar_L50_survey1,set_selpar_L50_survey1(5), set_selpar_L50_survey1(6), set_selpar_L50_survey1(7));
f_priors+=neg_log_prior(selpar_slope_survey1,set_selpar_slope_survey1(5), set_selpar_slope_survey1(6), set_selpar_slope_survey1(7));

f_priors+=neg_log_prior(selpar_L50_fleet1,set_selpar_L50_fleet1(5), set_selpar_L50_fleet1(6), set_selpar_L50_fleet1(7));
f_priors+=neg_log_prior(selpar_slope_fleet1,set_selpar_slope_fleet1(5), set_selpar_slope_fleet1(6), set_selpar_slope_fleet1(7));

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set_selpar_slope2_fleet1_D(7));
f_priors+=neg_log_prior(selpar_peak_fleet1_D,set_selpar_peak_fleet1_D(5), set_selpar_peak_fleet1_D(6), set_selpar_peak_fleet1_D(7));
f_priors+=neg_log_prior(selpar_top_fleet1_D,set_selpar_top_fleet1_D(5), set_selpar_top_fleet1_D(6), set_selpar_top_fleet1_D(7));
f_priors+=neg_log_prior(selpar_ascwid_fleet1_D,set_selpar_ascwid_fleet1_D(5), set_selpar_ascwid_fleet1_D(6),
set_selpar_ascwid_fleet1_D(7));
f_priors+=neg_log_prior(selpar_deswid_fleet1_D,set_selpar_deswid_fleet1_D(5), set_selpar_deswid_fleet1_D(6),
set_selpar_deswid_fleet1_D(7));
f_priors+=neg_log_prior(selpar_init_fleet1_D,set_selpar_init_fleet1_D(5), set_selpar_init_fleet1_D(6), set_selpar_init_fleet1_D(7));
f_priors+=neg_log_prior(selpar_final_fleet1_D,set_selpar_final_fleet1_D(5), set_selpar_final_fleet1_D(6), set_selpar_final_fleet1_D(7));

f_priors+=neg_log_prior(selpar_L50_fleet2,set_selpar_L50_fleet2(5), set_selpar_L50_fleet2(6), set_selpar_L50_fleet2(7));
f_priors+=neg_log_prior(selpar_slope_fleet2,set_selpar_slope_fleet2(5), set_selpar_slope_fleet2(6), set_selpar_slope_fleet2(7));

set_selpar_slope2_fleet2_D(7));
f_priors+=neg_log_prior(selpar_peak_fleet2_D,set_selpar_peak_fleet2_D(5), set_selpar_peak_fleet2_D(6), set_selpar_peak_fleet2_D(7));
f_priors+=neg_log_prior(selpar_top_fleet2_D,set_selpar_top_fleet2_D(5), set_selpar_top_fleet2_D(6), set_selpar_top_fleet2_D(7));
f_priors+=neg_log_prior(selpar_ascwid_fleet2_D,set_selpar_ascwid_fleet2_D(5), set_selpar_ascwid_fleet2_D(6),
set_selpar_ascwid_fleet2_D(7));
f_priors+=neg_log_prior(selpar_deswid_fleet2_D,set_selpar_deswid_fleet2_D(5), set_selpar_deswid_fleet2_D(6),
set_selpar_deswid_fleet2_D(7));
f_priors+=neg_log_prior(selpar_init_fleet2_D,set_selpar_init_fleet2_D(5), set_selpar_init_fleet2_D(6), set_selpar_init_fleet2_D(7));
f_priors+=neg_log_prior(selpar_final_fleet2_D,set_selpar_final_fleet2_D(5), set_selpar_final_fleet2_D(6), set_selpar_final_fleet2_D(7));

f_priors+=neg_log_prior(log_q_survey1,set_log_q_survey1(5),set_log_q_survey1(6),set_log_q_survey1(7));
f_priors+=neg_log_prior(log_q_fleet1,set_log_q_fleet1(5),set_log_q_fleet1(6),set_log_q_fleet1(7));

f_priors+=neg_log_prior(F_init,set_F_init(5),set_F_init(6),set_F_init(7));
f_priors+=neg_log_prior(log_avg_F_fleet1,set_log_avg_F_fleet1(5),set_log_avg_F_fleet1(6),set_log_avg_F_fleet1(7));
f_priors+=neg_log_prior(log_avg_F_fleet1_D,set_log_avg_F_fleet1_D(5),set_log_avg_F_fleet1_D(6),set_log_avg_F_fleet1_D(7));
f_priors+=neg_log_prior(log_avg_F_fleet2,set_log_avg_F_fleet2(5),set_log_avg_F_fleet2(6),set_log_avg_F_fleet2(7));
f_priors+=neg_log_prior(log_avg_F_fleet2_D,set_log_avg_F_fleet2_D(5),set_log_avg_F_fleet2_D(6),set_log_avg_F_fleet2_D(7));

fval+=f_priors;

} // end optimization switch

//-----
//Logistic function: 2 parameters
FUNCTION dvar_vector logistic(const dvar_vector& ages, const dvariable& L50, const dvariable& slope)
//ages=vector of ages, L50=age at 50% selectivity, slope=rate of increase
RETURN_ARRAYS_INCREMENT();
dvar_vector Sel_Tmp(ages.indexmin(),ages.indexmax());
Sel_Tmp=1./(1.+mfexp(-1.*slope*(ages-L50))); //logistic;
RETURN_ARRAYS_DECREMENT();
return Sel_Tmp;

//-----
//Logistic-exponential: 4 parameters (but 1 is fixed)
FUNCTION dvar_vector logistic_exponential(const dvar_vector& ages, const dvariable& L50, const dvariable& slope, const dvariable& sigma,
const dvariable& joint)
//ages=vector of ages, L50=age at 50% sel (ascending limb), slope=rate of increase, sigma=controls rate of descent (descending)
//joint=age to join curves
RETURN_ARRAYS_INCREMENT();
dvar_vector Sel_Tmp(ages.indexmin(),ages.indexmax());
Sel_Tmp=1.0;
for (iage=1; iage<=nages; iage++)
{
if (ages(iage)<joint) {Sel_Tmp(iage)=1./(1.+mfexp(-1.*slope*(ages(iage)-L50)));}
if (ages(iage)>joint){Sel_Tmp(iage)=mfexp(-1.*square((ages(iage)-joint)/sigma));}
}
Sel_Tmp=Sel_Tmp/max(Sel_Tmp);
RETURN_ARRAYS_DECREMENT();
return Sel_Tmp;

```

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```
//-----
//Logistic function: 4 parameters
FUNCTION dvar_vector logistic_double(const dvar_vector& ages, const dvariable& L501, const dvariable& slope1, const dvariable& L502, const
dvariable& slope2)
  RETURN_ARRAYS_INCREMENT();
  dvar_vector Sel_Tmp(ages.indexmin(),ages.indexmax());
  Sel_Tmp=elem_prod( (1./(1.+mfexp(-1.*slope1*(ages-L501)))),(1.-(1./(1.+mfexp(-1.*slope2*(ages-(L501+L502)))))) );
  Sel_Tmp=Sel_Tmp/max(Sel_Tmp);
  RETURN_ARRAYS_DECREMENT();
  return Sel_Tmp;

//-----
//Jointed logistic function: 6 parameters (increasing and decreasing logistics joined at peak selectivity)
FUNCTION dvar_vector logistic_joint(const dvar_vector& ages, const dvariable& L501, const dvariable& slope1, const dvariable& L502, const
dvariable& slope2, const dvariable& satval, const dvariable& joint)
  RETURN_ARRAYS_INCREMENT();
  dvar_vector Sel_Tmp(ages.indexmin(),ages.indexmax());
  Sel_Tmp=1.0;
  for (iage=1; iage<=nages; iage++)
  {
    if (double(iage)<joint) {Sel_Tmp(iage)=1./(1.+mfexp(-1.*slope1*(ages(iage)-L501)));}
    if (double(iage)>joint){Sel_Tmp(iage)=1.0-(1.0-satval)/(1.+mfexp(-1.*slope2*(ages(iage)-L502)));}
  }
  Sel_Tmp=Sel_Tmp/max(Sel_Tmp);
  RETURN_ARRAYS_DECREMENT();
  return Sel_Tmp;

//-----
//Double Gaussian function: 6 parameters (as in SS3)
FUNCTION dvar_vector gaussian_double(const dvar_vector& ages, const dvariable& peak, const dvariable& top, const dvariable& ascwid, const
dvariable& deswid, const dvariable& init, const dvariable& final)
  RETURN_ARRAYS_INCREMENT();
  dvar_vector Sel_Tmp(ages.indexmin(),ages.indexmax());
  dvar_vector sel_step1(ages.indexmin(),ages.indexmax());
  dvar_vector sel_step2(ages.indexmin(),ages.indexmax());
  dvar_vector sel_step3(ages.indexmin(),ages.indexmax());
  dvar_vector sel_step4(ages.indexmin(),ages.indexmax());
  dvar_vector sel_step5(ages.indexmin(),ages.indexmax());
  dvar_vector sel_step6(ages.indexmin(),ages.indexmax());
  dvar_vector pars_tmp(1,6); dvar_vector sel_tmp_iq(1,2);

  pars_tmp(1)=peak;
  pars_tmp(2)=peak+1.0+(0.99*ages(nages)-peak-1.0)/(1.0+mfexp(-top));
  pars_tmp(3)=mfexp(ascwid);
  pars_tmp(4)=mfexp(deswid);
  pars_tmp(5)=1.0/(1.0+mfexp(-init));
  pars_tmp(6)=1.0/(1.0+mfexp(-final));

  sel_tmp_iq(1)=mfexp(-(square(ages(1)-pars_tmp(1))/pars_tmp(3)));
  sel_tmp_iq(2)=mfexp(-(square(ages(nages)-pars_tmp(2))/pars_tmp(4)));

  sel_step1=mfexp(-(square(ages-pars_tmp(1))/pars_tmp(3)));
  sel_step2=pars_tmp(5)+(1.0-pars_tmp(5))*(sel_step1-sel_tmp_iq(1))/(1.0-sel_tmp_iq(1));
  sel_step3=mfexp(-(square(ages-pars_tmp(2))/pars_tmp(4)));
  sel_step4=1.0+(pars_tmp(6)-1.0)*(sel_step3-1.0)/(sel_tmp_iq(2)-1.0);
  sel_step5=1.0/(1.0+mfexp(-(20.0*elem_div((ages-pars_tmp(1)), (1.0+sfabs(ages-pars_tmp(1)))))));
  sel_step6=1.0/(1.0+mfexp(-(20.0*elem_div((ages-pars_tmp(2)), (1.0+sfabs(ages-pars_tmp(2)))))));

  Sel_Tmp=elem_prod(sel_step2,(1.0-sel_step5))+
    elem_prod(sel_step5,((1.0-sel_step6)+ elem_prod(sel_step4,sel_step6)));

  Sel_Tmp=Sel_Tmp/max(Sel_Tmp);
  RETURN_ARRAYS_DECREMENT();
```

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```

return Sel_Tmp;

//-----
//Spawner-recruit function (Beverton-Holt or Ricker)
FUNCTION dvariable SR_func(const dvariable& R0, const dvariable& h, const dvariable& spr_F0, const dvariable& SSB, int func)
RETURN_ARRAYS_INCREMENT();
dvariable Recruits_Tmp;
switch(func) {
case 1: //Beverton-Holt
  Recruits_Tmp=((0.8*R0*h*SSB)/(0.2*R0*spr_F0*(1.0-h)+(h-0.2)*SSB));
  break;
case 2: //Ricker
  Recruits_Tmp=((SSB/spr_F0)*mfexp(h*(1-SSB/(R0*spr_F0))));
  break;
}
RETURN_ARRAYS_DECREMENT();
return Recruits_Tmp;

//-----
//Spawner-recruit equilibrium function (Beverton-Holt or Ricker)
FUNCTION dvariable SR_eq_func(const dvariable& R0, const dvariable& h, const dvariable& spr_F0, const dvariable& spr_F, const dvariable&
BC, int func)
RETURN_ARRAYS_INCREMENT();
dvariable Recruits_Tmp;
switch(func) {
case 1: //Beverton-Holt
  Recruits_Tmp=(R0/((5.0*h-1.0)*spr_F))*(BC*4.0*h*spr_F-spr_F0*(1.0-h));
  break;
case 2: //Ricker
  Recruits_Tmp=R0/(spr_F/spr_F0)*(1.0+log(BC*spr_F/spr_F0)/h);
  break;
}
RETURN_ARRAYS_DECREMENT();
return Recruits_Tmp;

//-----
//compute multinomial effective sample size for a single yr
dvariable EffN_Tmp; dvariable numer; dvariable denom;
RETURN_ARRAYS_INCREMENT();
numer=sum( elem_prod(pred_comp,(1.0-pred_comp)) );
denom=sum( square(obs_comp-pred_comp) );
if (denom>0.0) {EffN_Tmp=numer/denom;}
else {EffN_Tmp=-missing;}
RETURN_ARRAYS_DECREMENT();
return EffN_Tmp;

//-----
//Likelihood contribution: lognormal
FUNCTION dvariable lk_lognormal(const dvar_vector& pred, const dvar_vector& obs, const dvar_vector& cv, const dvariable& wgt_dat)
RETURN_ARRAYS_INCREMENT();
dvariable LkvalTmp;
dvariable small_number=0.00001;
dvar_vector var(cv.indexmin(),cv.indexmax()); //variance in log space
var=log(1.0+square(cv/wgt_dat)); // convert cv in arithmetic space to variance in log space
LkvalTmp=sum(0.5*elem_div(square(log(elem_div((pred+small_number),(obs+small_number))))),var) );
RETURN_ARRAYS_DECREMENT();
return LkvalTmp;

//-----
//Likelihood contribution: multinomial
FUNCTION dvariable lk_multinomial(const dvar_vector& nsamp, const dvar_matrix& pred_comp, const dvar_matrix& obs_comp, const
double& ncomp, const double& minSS, const dvariable& wgt_dat)

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//nsamp=vector of N's, pred_comp=matrix of predicted comps, obs_comp=matrix of observed comps, ncomp = number of yrs in matrix,
minSS=min N threshold, wgt_dat=scaling of N's
RETURN_ARRAYS_INCREMENT();
dvariable LkvalTmp;
dvariable small_number=0.00001;
LkvalTmp=0.0;
for (int ii=1; ii<=ncomp; ii++)
{if (nsamp(ii)>=minSS)
  {LkvalTmp+=wgt_dat*nsamp(ii)*sum(elem_prod((obs_comp(ii)+small_number),
    log(elem_div((pred_comp(ii)+small_number), (obs_comp(ii)+small_number)))));
  }
}
RETURN_ARRAYS_DECREMENT();
return LkvalTmp;

//-----
//Likelihood contribution: multinomial
FUNCTION dvariable lk_robust_multinomial(const dvar_vector& nsamp, const dvar_matrix& pred_comp, const dvar_matrix& obs_comp, const
double& ncomp, const dvariable& mbin, const double& minSS, const dvariable& wgt_dat)
RETURN_ARRAYS_INCREMENT();
dvariable LkvalTmp;
dvariable small_number=0.00001;
LkvalTmp=0.0;
dvar_matrix Eprime=elem_prod((1.0-obs_comp), obs_comp)+0.1/mbin; //E' of Francis 2011, p.1131
dvar_vector nsamp_wgt=nsamp*wgt_dat;
for (int ii=1; ii<=ncomp; ii++)
{if (nsamp(ii)>=minSS)
  {LkvalTmp+= sum(0.5*log(Eprime(ii))-log(small_number+mfexp(elem_div((-square(obs_comp(ii)-pred_comp(ii))),
(Eprime(ii)*2.0/nsamp_wgt(ii))))));
  }
}
RETURN_ARRAYS_DECREMENT();
return LkvalTmp;

//-----
//-----
//Likelihood contribution: priors
FUNCTION dvariable neg_log_prior(dvariable pred, const double& prior, dvariable var, int pdf)
//prior=prior point estimate, var=variance (if negative, treated as CV in arithmetic space), pred=predicted value, pdf=prior type (1=none,
2=lognormal, 3=normal, 4=beta)
dvariable LkvalTmp;
dvariable alpha, beta, ab_iq;
dvariable big_number=1e10;
LkvalTmp=0.0;
// compute generic pdf's
switch(pdf) {
case 1: //option to turn off prior
  LkvalTmp=0.0;
  break;
case 2: // lognormal
  if(prior<=0.0) cout << "YIKES: Don't use a lognormal distn for a negative prior" << endl;
  else if(pred<=0) LkvalTmp=big_number=1e10;
  else {
    if(var<0.0) var=log(1.0+var*var); // convert cv to variance on log scale
    LkvalTmp= 0.5*( square(log(pred/prior))/var + log(var) );
  }
  break;
case 3: // normal
  if(var<0.0 && prior!=0.0) var=square(var*prior); // convert cv to variance on observation scale
  else if(var<0.0 && prior==0.0) var=-var; // cv not really appropriate if prior value equals zero
  LkvalTmp= 0.5*( square(pred-prior)/var + log(var) );
  break;
case 4: // beta

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    if(var<0.0) var=square(var*prior); // convert cv to variance on observation scale
    if(prior<=0.0 || prior>=1.0) cout << "YIKES: Don't use a beta distn for a prior outside (0,1)" << endl;
    ab_iq=prior*(1.0-prior)/var - 1.0; alpha=prior*ab_iq; beta=(1.0-prior)*ab_iq;
    if(pred>=0 && pred<=1) LkvalTmp= (1.0-alpha)*log(pred)+(1.0-beta)*log(1.0-pred)-gammln(alpha+beta)+gammln(alpha)+gammln(beta);
    else LkvalTmp=big_number;
    break;
default: // no sufleet1 prior pdf currently available
    cout << "The prior must be either 1(lognormal), 2(normal), or 3(beta)." << endl;
    cout << "Presently it is " << pdf << endl;
    exit(0);
}
return LkvalTmp;

//-----
//SDNR: age comp likelihood (assumes fits are done with the robust multinomial function)
FUNCTION dvariable sdnr_multinomial(const double& ncomp, const dvar_vector& ages, const dvar_vector& nsamp,
    const dvar_matrix& pred_comp, const dvar_matrix& obs_comp, const dvariable& wgt_dat)
RETURN_ARRAYS_INCREMENT();
dvariable SdnrTmp;
dvar_vector o(1,ncomp);
dvar_vector p(1,ncomp);
dvar_vector ose(1,ncomp);
dvar_vector res(1,ncomp);
SdnrTmp=0.0;
for (int ii=1; ii<=ncomp; ii++)
{
    o(ii)=sum(elem_prod(ages,obs_comp(ii)));
    p(ii)=sum(elem_prod(ages,pred_comp(ii)));
    ose(ii)=sqrt((sum(elem_prod(square(ages),pred_comp(ii)))-square(p(ii)))/(nsamp(ii)*wgt_dat));
}
res=elem_div((o-p),ose);
SdnrTmp=sqrt(sum(square(res-(sum(res)/ncomp)))/(ncomp-1.0));
RETURN_ARRAYS_DECREMENT();
return SdnrTmp;

//-----
//SDNR: lognormal likelihood
FUNCTION dvariable sdnr_lognormal(const dvar_vector& pred, const dvar_vector& obs, const dvar_vector& cv, const dvariable& wgt_dat)
//nyr=number of years of data, pred=vector of predicted data, obs=vector of observed data, cv=vector of cv's, wgt_dat=likelihood weight for
data source
RETURN_ARRAYS_INCREMENT();
dvariable SdnrTmp;
dvariable small_number=0.00001;
dvariable n;
dvar_vector res(cv.indexmin(),cv.indexmax());
SdnrTmp=0.0;
res=elem_div(log(elem_div(obs+small_number,pred+small_number)),sqrt(log(1+square(cv/wgt_dat))));
n=cv.indexmax()-cv.indexmin()+1;
SdnrTmp=sqrt(sum(square(res-(sum(res)/n)))/(n-1.0));
RETURN_ARRAYS_DECREMENT();
return SdnrTmp;

//-----
REPORT_SECTION

if (last_phase())
{
    get_weighted_current();

    get_msy();
    get_miscellaneous_stuff();
    get_per_recruit_stuff();
    get_effective_sample_sizes();
}

```

[illegible]

Supplementary Material

```
selpar_ascwid_fleet2_D_out(8)=selpar_ascwid_fleet2_D; selpar_ascwid_fleet2_D_out(1,7)=set_selpar_ascwid_fleet2_D;  
selpar_deswid_fleet2_D_out(8)=selpar_deswid_fleet2_D; selpar_deswid_fleet2_D_out(1,7)=set_selpar_deswid_fleet2_D;  
selpar_init_fleet2_D_out(8)=selpar_init_fleet2_D; selpar_init_fleet2_D_out(1,7)=set_selpar_init_fleet2_D;  
selpar_final_fleet2_D_out(8)=selpar_final_fleet2_D; selpar_final_fleet2_D_out(1,7)=set_selpar_final_fleet2_D;
```

```
log_q_survey1_out(8)=log_q_survey1; log_q_survey1_out(1,7)=set_log_q_survey1;  
log_q_fleet1_out(8)=log_q_fleet1; log_q_fleet1_out(1,7)=set_log_q_fleet1;
```

```
log_avg_F_fleet1_out(8)=log_avg_F_fleet1; log_avg_F_fleet1_out(1,7)=set_log_avg_F_fleet1;  
log_avg_F_fleet1_D_out(8)=log_avg_F_fleet1_D; log_avg_F_fleet1_D_out(1,7)=set_log_avg_F_fleet1_D;  
log_avg_F_fleet2_out(8)=log_avg_F_fleet2; log_avg_F_fleet2_out(1,7)=set_log_avg_F_fleet2;  
log_avg_F_fleet2_D_out(8)=log_avg_F_fleet2_D; log_avg_F_fleet2_D_out(1,7)=set_log_avg_F_fleet2_D;  
F_init_out(8)=F_init; F_init_out(1,7)=set_F_init;
```

```
log_rec_dev_out(styr_rec_dev, endyr_rec_dev)=log_rec_dev;  
log_F_dev_fleet1_out(styr_fleet1_L, endyr_fleet1_L)=log_F_dev_fleet1;  
log_F_dev_fleet1_D_out(styr_fleet1_D, endyr_fleet1_D)=log_F_dev_fleet1_D;  
log_F_dev_fleet2_out(styr_fleet2_L, endyr_fleet2_L)=log_F_dev_fleet2;  
log_F_dev_fleet2_D_out(styr_fleet2_D, endyr_fleet2_D)=log_F_dev_fleet2_D;
```

```
#include "BAM-SIM-MSE.cxx" // write the R-compatible report
```

```
} //endl last phase loop
```

Draft