# Stock assessment models with graphical user interfaces for key South Australian marine finfish stocks

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SOUTH AUSTRALIAN
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INSTITUTE

Australian Government

Fisheries Research and
Development Corporation

**13 November 2014**

**Project No. 1999/145**

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# Final Report for the Fisheries Research and Development Institute

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Published by SARDI Aquatic Sciences



ISBN 0 7308 5303 9

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# Non Technical Summary

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**NON TECHNICAL SUMMARY:**

The South Australian marine scalefish industry harvests a range of species for Australian markets using several fishing methods, including hand line, haul net, and gill net. A medium-sized catch divided among a relatively high number of operators, together with prices not reaching those obtained by invertebrate fisheries exporting to Asia, mean that stock assessment research must be cost effective.

While of lower value than invertebrates, finfish have the great advantage for stock assessment that they can be aged, via yearly otolith growth rings. Catch-samples-at-age provide relatively direct information on growth and mortality. Otolith ageing techniques had been developed and validated for South Australian snapper and garfish (FRDC Project 97/133). Fish were subsampled for ageing from a larger market length-measured sample. A second principal data source were commercial catch and effort totals, by month, for each species, reported by gear type and by species targeted. Recreational catches were estimated from creel (FRDC Project 93/249) and telephone/diary (FRDC Project 99/158) surveys. The third data input is biological information, notably weight and fecundity versus length.

In this project, these data were used as input to likelihood-fitted stock assessment models for South Australian garfish and snapper, providing estimates of yearly recruitment, and for each model time step, fishable biomass, population numbers, and exploitation rate.

A user interface was also constructed, allowing biologists to run the two models for South Australian garfish and snapper after yearly updates of the catch and effort time series. This Excel interface serves as a front-end to the underlying estimation routines coded in AD Model Builder. A user manual (Chapter 6) is provided.

The dynamic model formalism developed, extending that of a previous FRDC Project (95/008) for King George whiting, is both age- and length-based. The partition of the lengths of fish in each cohort is done by ‘slicing’ the age cohort into length bins. Fish of a given age reaching legal size in each time step are assigned to a single bin, providing a clean separation of legal from sublegal fish in each cohort and model time step. This ‘slice-growth’ model formalism resembles that of ‘growth groups’ (Punt et

al. 2002), one difference being that a single set of mean growth parameters (e.g. $K$ and $L_\infty$) is estimated, along with parameters describing the spread of lengths, rather than separate mean growth parameters for each length group.

A second stock assessment modelling innovation is a method to correct for non-representative subsampling of ages (Chapter 1). Researchers can choose a strategy of subsampling for ageing from the larger sample of fish whose length has been measured representatively, notably to age greater subsamples of larger fish. Larger and thus older fish have been subject to exploitation levels of mortality for longer times. Therefore larger sub-samples of older fish would yield more precise proportions versus age in the upper tail, permitting more precise estimates of fishing mortality, and thus absolute biomass. More generally, using this method, any non-representative age subsampling (intentional or otherwise) can be corrected.

A third feature of the model estimators developed is the fitting to length moments (Chapter 1) rather than to binned numbers, first proposed by Fournier and Doonan. This, in combination with length partition by slices and age subsampling correction factors, permitted fits to the length distributions for each age and sex individually, rather than to overall length samples summed over age and sex. Fitting to separate length distributions by age in turn permitted a dynamic accounting of changes in the predicted length samples of a single cohort due, for example, to variations in mortality over time. This feature also permitted growth estimation to be integrated into the overall stock assessment, correcting for biases in growth that can result from fish samples being of the catch rather than of the population.

**OUTCOMES ACHIEVED**

1. The models developed serve as the basis of stock assessment for garfish and snapper in South Australia and were used by the Marine Scalefish Fishery Management Committee to assess the impact of changes in legal minimum length of garfish, to evaluate snapper management strategies (maximum size versus reduced fishing mortality) and to estimate changes in snapper biomass prior to and following the establishment of seasonal closures.
2. A length- and age-based method of stock assessment modelling (by ‘length slices’) was further developed.
3. A method was developed to give stock assessment researchers the choice of an optimal strategy for subsampling fish to be aged. Previously, age subsamples had to be representative or else induce (large) bias. One strategy could sample roughly equal numbers by length (from larger representative samples by length) which could enhance the precision of stock assessment inference via greater-than-proportional numbers of older fish. More generally, all aged fish can be used.
4. These models suggest that reasonably reliable stock assessment inference can be drawn from sporadic or even one-off programs of age and length sampling, in combination with regular catch and effort time series data.
5. These AD Model Builder estimation routines were made accessible via an Excel front end, permitting biologists to carry out yearly stock assessments of South Australian snapper and garfish.

**KEYWORDS: garfish, snapper, catch-at-age, age- and length-based models, stock assessment, correction for age subsampling, slice growth**

# Acknowledgements

We thank Tony Fowler, Keith Jones, Qifeng Ye and Dave McGlennon for frequent discussion, providing biological insight in model development. Age and length sample data were provided by Drs. Ye (garfish), Fowler and McGlennon (snapper), and collected by teams including Dave Short, Craig Noell, Bruce Jackson, Paul Jennings and Greg Ferguson.

Extensive advice in model development was provided by André Punt (CSIRO Hobart), who consulted and reviewed the work in three visits to SARDI during the project. His review of Chapter 1 (with our responses) is included as Appendix 1.1. We also thank Dave Fournier, whose parameter estimation library, AD Model Builder, permits models of this complexity.

# Background

In South Australian marine scale fisheries, stock assessment documents are now required yearly. Industry, specifically the SA Marine Scalefish Fishery Management Committee (MSFMC) and the state fishery managers (PIRSA), have requested yearly indicators for effective fishery management, notably recruitment, exploitation rate, fishable biomass, and yearly egg production. These would allow management decision makers to assess whether the stock is being overexploited (lower recruitment and higher exploitation rate) or affected by environmental factors (higher or lower recruitment with no upward trend in exploitation rate) and to judge the need for management action which might enhance financial yields from the resource. Currently lacking in South Australian marine scale fisheries are statistically rigorous estimation models for these indicators. These estimation models must be developed and subsequently maintained within increasingly limited cost constraints.

While of lower value, finfish bring the great advantage to stock assessment that they can be aged, via annual otolith growth rings. Catches-at-age provide relatively direct information on growth and mortality. Otolith ageing techniques are now well developed and validated in South Australia for King George whiting, snapper, and garfish. For garfish, a comprehensive FRDC project was completed prior to the beginning of this modelling project, FRDC Project 97/133, "Fisheries biology and habitat ecology of the southern sea garfish (*Hyporhamphus melanochir*) in southern Australia" (Jones et al. 2002). Qifeng Ye directed a weekly Adelaide SAFCOL market catch length sampling program. Subsamples for otolith ageing were taken at a rate of 15% or higher. For snapper, Tony Fowler and Bruce Jackson direct an on-going South Australian catch monitoring program of SAFCOL market length sampling and of fisher (on-board) and in-market age sampling.

The other principal data source are catch and effort totals, by month, for each species. In the South Australian database, fishers report effort daily by gear type and by species they have targeted. Catches are reported by weight.

The third major data input is the extensive biological information on the key finfish species, which have been gathered in recent and on-going programs. Together with otoliths and catch and effort totals, these data now provide the necessary input for a rigorous stock assessment. In FRDC Project 97/133, studies of garfish spawning, fecundity and larval biology were undertaken.

Thus, the South Australian marine scale industry has invested in a range of important data for key fish stocks. Their adoption for effective use in fishery resource management and value optimisation requires two things: (1) to bring these data into a single statistical description of each fishery; (2) to provide answers to questions that managers and industry ask.

Worldwide, the analysis of catch-at-age samples and catch totals have been dominated by various formulations of virtual population analysis (VPA). Several drawbacks of this approach have been documented in the literature, notably the fact that recruitment is inaccurately estimated for the year immediately preceding, and becomes reliable only several years subsequent as the depletion of each cohort is measured and analysed. But management requires information for the year to come from the year preceding, meaning that VPA effectively provides its worst estimate when it is primarily needed for management decision making.

More recently, new statistical methods for age-structured models have been developed which, unlike VPA, do not restrict analysis to each cohort independently. Formulated as a likelihood maximisation, this approach for analysing the otolith and catch and effort data sets, is more statistically rigorous, providing asymptotically best parameter estimates of minimum variance, and allowing quantification of confidence bounds for estimated parameters. A model of this form, with full spatial and monthly dynamic description, was developed under an FRDC program for the primary target marine scale species in South Australia, King George whiting (FRDC Project No. 95/008). The two other key species in South Australia, and those for which data sets are richest, are snapper and garfish.

The South Australian marine scale fishery is undergoing a comprehensive management restructure. An external review was contracted by PIRSA and the Marine Scalefish Fishery Management Committee to assess research priorities. The report of the external reviewers recommended the extension of the King George whiting modelling approaches to provide yearly indicators for resource management.

# Need

In 1998, industry, in consultation with PIRSA, FRDC and the SA FRAB formulated a 5-year plan to specify and rank research priorities in, “South Australian Fisheries and Aquaculture Five Year Research and Development Strategy”, highlighting the need for more accurate and timely stock assessment methods in multi-species marine finfish stocks. For Marine Scalefish, priority item 2 (after allocation issues of User Access) was “Stocks Assessment (A): There is an urgent requirement to identify further biological information relating to key species which will lead to better total management of the fishery”, with the first Key Requirement being to “more accurately assess stocks levels of key species”.

Data for optimal and sustainable management are now available. Needed are cost-effective analysis tools for converting these data to a form that managers and the MSFMC can apply directly to management decision making.

Requested are yearly estimates of stock performance indicators, recruitment, exploitation rate, and stock biomass, for the key species. This need was addressed for King George whiting in a previous FRDC project. Models for estimating performance indicators of other species, notably snapper and garfish are now required.

Cost-effective delivery of indicators to fishery managers and the management committee will be attained by providing the research biologists with a stock assessment model estimation software for analysis of fisheries data. This software should meet three criteria: (1) Use the best available methods of estimating stock management indices, (2) provide confidence bounds for all indicators estimated, and (3) be presented in a user-friendly interface, allowing its use, in conjunction with modellers, by the research biologists who gather the data and write yearly stock assessment documents.

# Objectives:

1. To build a model estimation software structure, which will use (1) monthly catch and effort data, (2) aged catch samples, (3) life history information, and when available (4) recruitment indices, and (5) length-frequency samples to estimate yearly performance indicators, accessed through a graphical user interface, for use in marine scalefish stocks.
2. To build two models for key marine scalefish species in South Australian waters for use in yearly stock assessment.
3. To transfer model outcomes, notably yearly estimated biological performance indicators, to the Marine Scalefish Fishery Management Committee.

# CHAPTER 1. Garfish stock assessment model estimator

## Introduction

The current FRDC project is to develop stock assessment models with user interfaces that will permit the biologists responsible for particular species to carry out yearly stock assessment indicator estimation, with relatively modest inputs from the modellers who created the original estimation software. Most of the work in this project, however, was focused on developing statistically robust and powerful estimators of stock assessment estimates useful for resource management. In this chapter we present the garfish mathematical model. Most of this likelihood model was also implemented for snapper.

The underlying stock assessment estimator to be implemented for both South Australian garfish and snapper extended one developed for King George whiting in FRDC Project 95/008. This King George whiting estimator had the following features: (1) movement among 12 spatial cells; (2) an age- and length-based population description, which partitioned each fish cohort by length into slices, (3) 13 effort types, by gear and 'target' type; (4) effort-conditioned catch equation with associated normal likelihood.

In addition, the external reviewer, Dr André Punt, recommended the following features be implemented: (5) residuals of model fit be plotted and considered for model output evaluation; (6) growth be integrated into the overall stock assessment estimation; (7) that the number of time steps, spatial cells, effort types, and explicit age classes (below the plus group) be reduced to reduce the computation time of model estimation convergence, thereby permitting a more complete assessment of model output uncertainty; (8) a lognormal rather than a normal likelihood be used for fitting catch totals by weight. These modifications have been carried out in the garfish model.

The principal differences between the stock assessments for King George whiting and garfish are threefold: (1) Garfish catches by length need to be fitted in order to explicitly represent logistic mesh selectivity of the two gear types, haul net and dab net. (Unlike King George whiting, mesh selectivity of garfish is more important than legal minimum length in determining relative capture rates by size.) (2) Growth estimation will be integrated. (3) No data or even hypothesis is available to infer or describe the movement of garfish.

Modifications implemented in the garfish model are (4) an integrated submodel was developed, and parameters were estimated, to form the initial (prior to first time step) population array; (5) length distributions were fitted using the first four moment 'properties' (mean, standard deviation, skewness, and kurtosis).

A number of length- and age-based stock assessment model formalisms have been proposed (Fournier and Doonan 1987; Deriso and Parma 1988; Fournier et al. 1990;

Fournier et al 1998; Smith and Botsford 1998; Punt et al. 2002). This class of models which partition the population array by both age and length (rather than just age alone) seek to optimise the sample data obtained from fisheries where individuals can be aged: when subsampling fish whose otoliths are extracted and read, measurements of both age and fish length are usually obtained. Thus it makes the best use of these sample data to fit to both of the independent variables measured, namely both age and length.

The 'slice-growth' approach is advantageous for application to fisheries where a cut-off at a regulated legal minimum length is abrupt. As age increases, the fish in each cohort grow, and the proportion that are legally harvestable, i.e. greater than legal minimum length, increases. The 'slices' are the fish that grow into legal size each model time step. Mathematically, the slice is defined as the integral of the length-at-age probability density function (pdf) over the subinterval of lengths that newly grow above legal minimum length in each time step, due to the growth of the length-at-age distribution. Slices are a canonical and accurate way to model the growth of naturally continuous distributions of numbers with length in a cohort when time is modelled as discrete time steps and it is useful to strictly differentiate fish of legal size from those not subject to harvesting.

Modelling both age and length is advantageous for a number of reasons. (1) Recruitment to legal sizes usually occurs over more than one model time step. Dividing up the cohort into slices (or other length partitions such as regular 1-cm bins) permits a more accurate description of the changes in numbers of fish under harvesting, separating by length those fish of a given age that are subject to harvesting from those that are not. The time-variation over which recruitment occurs can have a large effect on the age-specific numbers available to harvesting, and thus on the observed catch-proportions-at-age for recruiting fish cohorts. In addition, (2) the legal-size fish are further slice-partitioned by length, one slice, i.e. one new length bin, created for each time step that the cohort has been subject to harvesting. Clearly the faster growing fish become subject to harvesting first. Differentiating the amounts of time fish of different slices have been subject to harvesting permits a more accurate description of the changes in numbers of fish under harvesting, both overall and by length. (3) Also, fish of different length are also of different mean weight. In fitting model catches to the important data input of catch-total-by-weight, the slice-length breakdown permits a more accurate model prediction of the total weight of the catch, for any given estimated level of fishing mortality in each time step.

Thus, for models with a discrete time step such as a year or a month, and for fisheries where a legal minimum length is an important cut-off in catch selectivity by length, the slice approach provides a natural way to model the recruitment to legal sizes of each cohort over several time steps and provide an age- and length-based model description of legal sizes in a harvested fish population.

The garfish model implements a length- and age-based approach (via slices) with the following features:

(1) Growth is integrated into the stock assessment model fit. Since the growth submodel (estimating both mean and standard deviations of lengths at age, for all ages) affects the predicted catch numbers and weight in the stock assessment model, and since the stock assessment model generates the estimates of mortality that have a

second-order effect on the predicted growth length-at-age distribution, an unbiased estimate of growth and mortality requires that they be integrated in a single estimation procedure. This obviates what we call 'right-hand asymmetric mortality bias' as elaborated in Discussion.

(2) With garfish, we have integrated a method to correct for non-representative sampling. The two kinds of over- or under-sampling that we correct for are (2.1) the overall market length sampling of garfish by port and month, compared to the relative reported catch totals by port and month, and (2.2) subsampling of fish to be aged from the market catch-at-length samples.

(3) Most length-fitting stock assessments have fit to aggregated sums over age in each length bin. Much or even most age-specific information about growth, and possibly some information about mortality is thereby lost, since the length samples for each age individually are not retained as distinct fitted model quantities. The age-specific information loss that results from aggregating catch length samples is obviated in the garfish model below by not summing over age or sex. Instead individual catch-at-length distributions are fitted, one for each combination of age, sex, and region from which age and length samples are available. The moment properties of the length distribution for each age, sex, and region are calculated using as inputs, the length of each aged fish, and its relative sampling proportion. In particular, this should permit improved accuracy in estimating growth, which in turn provides more accurate measures of recruitment and model predicted catches via the slice-growth description.

# Data

The data sets are aggregated into the two gulfs (Gulf St. Vincent and Spencer Gulf), which are distinct fisheries insofar as the same fishers largely target one gulf or the other, together with the special endorsement that 8 fishers in Gulf St.Vincent (GSV) have to fish with nets in waters deeper than 5 m. (Nets for marine scale fishers are, in general, restricted to use in waters of 5 m or less throughout South Australia). These GSV fishers that are allowed to shoot and haul their nets in deeper water were found, in a 1987 survey, to exercise this option primarily in winter. The partition of the year into summer and winter time steps is suggested by both reproductive biology and associated qualitative difference in the catches between summer and winter: Spawning is protracted through summer, lasting from October through March; during this time mostly females (90%) are captured in spawning aggregations inshore. In winter, roughly even sex ratio is found in the garfish catches and CPUE is roughly double that of summer. To minimise computation times, a minimal number of spatial cells and estimation time steps were employed. Thus, spatially the data were aggregated into the two gulfs, and temporally into half-yearly time-steps (Oct-Mar, Apr-Sep), from Oct 1983 to Sep 2000. Aggregation of age and length samples also followed from that of the model. Ages explicit in the model run in half-years ($y_{1/2}$) from age 3 hy's (1 year olds, at the start of the October time step following the prior summer when these were spawned) to the plus group, age 12 hy's.

The data to be fitted are threefold: (*i*) reported catch and effort totals, by region, effort type, and half-yearly time step; (*ii*) sampled catch numbers-at-length, by region, sex and age, and gear type for one year; (*iii*) subsampled catch numbers-at-age, by region and sex, haul net only, for one year.

*(i) Commercial log catch (by weight, kg) and effort totals.* These are subdivided into categories by sector (commercial and recreational), and for commercials only, by gear and target type. In South Australian marine scale fishery, fishers can choose three target type choices to enter on the catch logs: (a) targeting a species (i.e. garfish) specifically, (b) targeting no species in particular, and (c) targeting another species, garfish in this case being by-catch. We have aggregated these various combinations of category into four effort types: (1.1) commercial haul net, targeting garfish; (1.2) commercial haul net, targeting another species, or declaring no specific target species; (1.3) dab net (and other minor gear types); (1.4) recreational hook and line.

The length and age samples from the catch in South Australia were gathered over a single year (in a weekly random survey at the SAFCOL fish market under FRDC Project 97/133, "Fisheries biology and habitat ecology of the southern sea garfish (*Hyporhamphus melanochir*) in southern Australia" (Jones et al. 2002). The details for how these data were processed to generate final data histograms of (*ii*) and (*iii*) to be fitted, each as a separate likelihood term, are given in the section below.

(*ii*) *Sample catch by length*. Length samples were obtained in a rigorously random market survey, and so were representative of the catches in SA overall. However, raw length histograms were not fitted in the model directly. Instead, the length samples were used to assign a sampling proportion to each aged and thus also sexed garfish. This incorporates the information from length sampling (being a representative and larger sample) by assigning that information to each individual aged garfish. Specifically, we employ (1) the catch sampling proportion by 1-cm length bin of each aged garfish, and (2) the length of the fish itself to the accuracy it was measured (1 mm).

*(iii) Subsample catches by age and sex.* Fish to be aged were obtained from four sources: (1) subsamples from the length sampling at SAFCOL market, and (2) other garfish purchases around the state, (3) garfish gathered in market age sampling prior to the length survey, (4) garfish harvested by researchers primarily investigating garfish reproduction. The sample sizes for the haul net gear type are much larger than for dab net, the latter being a relatively minor gear type for South Australian garfish overall. Moreover, dab nets target only larger garfish, thus providing a less complete sample of the population. Because haul net age and sex samples represent a much larger sample size, and cover a more nearly complete range of harvestable lengths than dab nets, only the haul net age samples were fitted for age composition and sex ratio.

The reasons we adopted this approach of sample correction are twofold. The initial motivation was pragmatic: with a slice-growth partition by length, summing the catches by age and sex to obtain overall model length distributions is difficult. For every age, sex, region (and legal minimum length (LML), when that also changes), a separate slice partition of the fish into lengths is derived and used. Because growth differs (and is separately estimated) by sex and region, and because each time-step growth of the cohort requires a completely new slice partition, a separate set of slice-defining length intervals is derived for each age, sex and region. This provides for a more accurate length partition where legal and sublegal fish are precisely differentiated. But summing by length over sex and age is computationally time-consuming with a slice-length partition because a different set of length bin interval boundaries are defined for each age and sex.

The second reason is that by incorporating the (representative) variation of catch-numbers-at-length (and additionally, for this data set only, by port and month), into the construction of the length distributions by age and sex (for each data half-year and fishery region), the information in the length samples is incorporated without having to sum catch numbers by length over sex and age. This reduces the loss of information that would otherwise occur by retaining separate observed length distributions from each sex and age. Thus, we believe this results in more information being drawn into model inference, namely the individual length distributions of the cohort over its lifespan.

All mathematical symbols are listed, with descriptions, in Tables 1.1-1.5. Array subscripts are enclosed in square brackets. Summation symbols with no explicit upper bound shown imply that the sum was taken over all elements of the summation index indicated.

## Correction for non-representative age subsampling

Dr Qifeng Ye and her team carried out rigorous stratified (by port and month) weekly random sampling for lengths at the SAFCOL fish market which auctions fish from nearly all ports in the two gulfs (Table 1.6). Comparisons of the weight of fish sampled by region ($r$) and half-year ($y_{1/2}$) show the samples are very well correlated with reported catch totals (Figure 1.1). Thus the SAFCOL market samples (numbers captured by length ($l$), to be denoted $\{n_l[r, y_{1/2}, l]\}$) are safely taken as representative of the overall catch in each region and half-year. However, the selection of fish to be aged was not a random subsample from the (single full year) of market length sampling. Some of the aged garfish were gathered prior to the market sampling program and some, notably larger fish in the upper tails of the length distributions, were subsampled for ageing at several times the mean subsample rate of 15%. Originally, we simply removed these additional aged garfish, giving a total sample size of about half the actual number aged. However, in order to make use of all the age otoliths that were read, we subsequently chose to include all aged garfish, and to correct for the resulting over- or under-sampling. Sex can only be determined once the fish is dissected, and this happens at the same time as removal of the otolith. Thus catch sex and age proportions are both derived from the aged samples.

The method for correction follows in two successive stages: (1) correcting for non-representativeness in the market samples, by port and month, (within each region and half-year), and (2) correcting for non-representativeness in the subsamples for ageing, (within each 1-cm length bin).

The correction in (1) was done by calculating the extent of over-sampling (>1) or under-sampling (<1) of the market samples from each port and month relative to reported catch totals (given by weight) in each port and month. These ‘sampling proportions’ ($f_S$) were calculated as a ratio of proportions, namely the proportions of numbers from each port and month (over each region and half-year) of (i) number of aged samples and of (ii) overall reported catches by number:

$$f_S[p,m \mid r,y_{1/2}] = \frac{n_a[p,m \mid r,y_{1/2}] \,/\, n_a[r,y_{1/2}]}{N[p,m \mid r,y_{1/2}] \,/\, N[r,y_{1/2}]} \tag{1.1}$$

Throughout, we shall denote catch and effort totals with upper-case symbols, and sampled data inputs with lower case letters. Thus, $f_S$ calculates the proportion sampled compared to the proportion of total catch in numbers from each port and month. In this context, the catch and effort data were taken as known without error. For instance if, in a given port and month, 5% of the samples were taken, but in the same port and month, only 2.5% of the catch was taken, then the sampling proportion, $f_S$, will be 2. These sampling proportions were calculated for every combination of port and month in both half-years ($y_{1/2}$) and both regions ($r$). Thus the sums ($n_a[r, y_{1/2}]$ and $N[r, y_{1/2}]$) in Eq. (1.1) were taken over all ports and months in each combination of region and half-year, i.e.

$$n_a[r, y_{1/2}] = \sum_{p \in r} \sum_{m \in y_{1/2}} n_a[p, m \mid r, y_{1/2}], \tag{1.2}$$

and

$$N[r, y_{1/2}] = \sum_{p \in r} \sum_{m \in y_{1/2}} N[p, m \mid r, y_{1/2}]. \tag{1.3}$$

The proportion for catch number totals (the denominator in Eq. 1.1) cannot be calculated directly from fishers' catch log data because catches are reported by weight rather than number. Converting weight to numbers is undertaken by noting that

$$N[p, m \mid r, y_{1/2}] = C_w[p, m \mid r, y_{1/2}] \big/ \overline{w}[p, m \mid r, y_{1/2}] \tag{1.4}$$

where $\overline{w}[p, m \mid r, y_{1/2}]$ is the mean weight of an individual fish in the catch from a given port and month, and $C_w[p, m \mid r, y_{1/2}]$ is the total weight of garfish harvested, available from catch logs.

The mean weight of an individual in each port and month could be estimated from the length samples as $\overline{w}[p, m \mid r, y_{1/2}] = w_n[p, m \mid r, y_{1/2}] \big/ n_l[p, m \mid r, y_{1/2}]$. However, the garfish length data was not rigorously representatively sampled on the smallest spatial and temporal units of port and month (being only representative by region and half-year), weekly samples being somewhat variable. Primarily for this reason, the length samples supplied to us by Qifeng Ye were already aggregated over region and half-year. Thus individual mean weights by port and month would not have been from representative samples, and were not, in any event, readily available. An approximation was therefore made to neglect the variation in mean weight of garfish among ports and months (in each region and half-year), and we therefore corrected only for the relative differences (presumed to be generally much larger) in ageing subsample size by port and month.

Substituting Eq. (1.4) into $N[p, m \mid r, y_{1/2}]$ of (1.1), and similarly substituting the analogous numbers-to-weight relationship (not shown) for $N[r, y_{1/2}]$ also in (1.1), and rearranging yields:

$$f_S[p,m\,|\,r,y_{1/2}] = \frac{\dfrac{n_a[p,m\,|\,r,y_{1/2}]}{n_a[r,y_{1/2}]}}{\dfrac{C_w[p,m\,|\,r,y_{1/2}]/\overline{w}[p,m]}{C_w[p,m]/\overline{w}[p,m\,|\,r,y_{1/2}]}}. \qquad (1.5)$$

Neglecting variations in mean weight by port and month implies setting $\dfrac{\overline{w}[p,m]}{\overline{w}[p,m\,|\,r,y_{1/2}]}$=1. This yields the approximate port and month correction formula we employed:

$$f_S[p,m\,|\,r,y_{1/2}] \cong \frac{\dfrac{n_a[p,m\,|\,r,y_{1/2}]}{n_a[r,y_{1/2}]}}{\dfrac{C_w[p,m\,|\,r,y_{1/2}]}{C_w[p,m]}}. \qquad (1.6)$$

This estimate (1.6) for the sampling proportion gives the factor of how much the age sample numbers exceeded ( $f_S$ >1) or fell below ( $f_S$ <1) the level of sampling it should have had to be proportional to commercial catches from each port and month.

Consider the analogy of voters and their elected representatives. The electorate is the entire catch to be represented. The set of sampled fish from a given port and month is the set of their 'representatives'. We wish to assign a legislative voting power to the complete set of representatives from each district which is directly proportional to the size of their electorate. So, for example if the sampling proportion $f_S$ = 2, i.e. if there are twice as many representatives from that electorate, that is aged garfish, as there should be, then each representative from that electorate, each sampled aged fish, should have a vote of ½. In this way the sum of the votes of all the representatives (aged fish) from that electorate will have a legislative voting power proportional to the total number of voters, that is to the total catch. Thus each aged sample is assigned a weighting equal to the reciprocal of the sampling proportion, $1/f_S = f_S^{-1}$. The sum of the $f_S^{-1}$'s from each port and month yields a total corrected sample size proportional to the size of the catch. If $f_S$ = 1, then each representative should have exactly 1 vote. If there were no other aspects of this sampling to correct for other than port and month, then the way to calculate the distributions, (notably of catches by age from all ports and months in a given region and half-year) would be to sum the records from the sample set into bins or moment averages using the value of $f_S^{-1}$ rather than a simple value of 1 for each sampled garfish.

The application to garfish is complicated by the fact that we wish to correct for a second level of non-representativeness in the age samples, namely in subsampling ages from the length samples. We will assume that the non-representativeness of sampling on these two levels is independent. However, we do not know the 'correct' proportion of fish by length bin for the smallest scale of aggregation, namely by port and month. Rather, the garfish samples provide a representative length sample only on the aggregated scale of region and half-year. Therefore, we pursued the following correction procedure to account for subsampling of ages being non-representative on both levels (by port and month within region and season, and among length bins within region and season).

## Catch Sample Histograms by Sex and Age

For any given length bin (and as above, for each distribution over age and sex to be constructed, one for each region and half-year), the relative number aged with the degree of oversampling by port and month taken into account, is simply the sum of $f_S^{-1}$ over all sampled and aged garfish falling in that length bin. In other words, the (purely relative and port and month corrected) number aged in a length bin, call it $\tilde{n}_l$ ('relative age subsample size'), is written

$$\tilde{n}_l[r, y_{1/2}, l] = \sum_{i_a \in r, y_{1/2}, l} f_S^{-1}\left[p[i_a], m[i_a] \mid r, y_{1/2}\right] \tag{1.7}$$

where the sum is over all subsampled aged garfish (indexed by $i_a$) that fell into the given data set ($r, y_{1/2}$) and length bin ($l$). The extent of over- or under-sampling from each port and month ($p[i_a], m[i_a]$) is explicit in the value of $f_S^{-1}$ for each aged garfish ($i_a$), and from each length bin ($l$) by the number of aged garfish summed. Thus, $\tilde{n}_l[r, y_{1/2}, l]$ for all length bins, $l$, gives the age-subsampling length distribution after correcting for port and month. As mentioned above, the only sample catch data used for fitting catches by age and sex were those from haul nets.

Using the same type of correction formula based on a ratio of proportions defined in Eq. (1.1), we now correct for non-representative sampling by 1-cm length bins ($l$). Because the correction for port and month is already expressed in the aged-fish length distribution of $\tilde{n}_l[r, y_{1/2}, l]$, we calculated the sampling proportion which combines both levels of non-representativeness as

$$f_{SS}[r, y_{1/2}, l] = \frac{\tilde{n}_l[r, y_{1/2}, l] \Big/ \sum_l \tilde{n}_l[r, y_{1/2}, l]}{n_l[r, y_{1/2}, l] \Big/ \sum_l n_l[r, y_{1/2}, l]}. \tag{1.8}$$

where we used the random stratified (and thus representative) length samples from the catch ($n_l[r, y_{1/2}, l]$) mentioned at the top of this section. The independence of the corrections by port and month, and by length is assumed for this two-level correction procedure.

Thus $f_{SS}[r, y_{1/2}, l]$ quantifies the extent of over- or under-sampling for each region, half-year, and length bin. To correct for this over- or under-sampling, in forming the data age and sex histograms to be fitted, the contribution from each aged sample will explicitly consider the region, half-year and length bin of that fish, and sum, into the respective age or sex category, the reciprocal of $f_{SS}[r, y_{1/2}, l]$, denoted $f_{SS}^{-1}[r, y_{1/2}, l]$. These data sex and age histograms were constructed and denoted $\{ n_{xa}^{\text{cor}}[r, y_{1/2}, x, a] \}$:

$$n_{xa}^{\text{cor}}[r, y_{1/2}, x, a] = \sum_{i_a \in r, y_{1/2}, x, a, l} f_{SS}^{-1}\left[r, y_{1/2}, l\right] \tag{1.9}$$

where the 'cor' superscript denotes 'corrected' for non-representative subsampling. The sum is over all subsampled aged garfish (indexed by $i_a$) that fell into the given data set ($r, y_{1/2}, x, a$) and length bin ($l$), using haul net samples only. The corresponding data proportions by age and sex, follow directly:

$$P_{xa}^{\text{cor}}[r, y_{1/2}, x, a] = \frac{n_{xa}^{\text{cor}}[r, y_{1/2}, x, a]}{n^{\text{cor}}[r, y_{1/2}]} \tag{1.10}$$

where
$$n^{\text{cor}}[r, y_{1/2}] = \sum_{x} \sum_{a} n_{xa}^{\text{cor}}[r, y_{1/2}, x, a]. \tag{1.11}$$

The principal limitation of these sample data are their short time span, covering, in effect, a single year, though in practice the actual sampling was spread out over two years. Thus, while the model was fitted to catch and effort data for all model half-yearly time steps, catch samples by length and age were fitted for only a single model year (October 1997-September 1998). The model is, to this extent, being applied in a relatively data-poor fishery stock assessment case.

One further mathematical step was undertaken, to rescale the corrected numbers by age and sex, $n_{xa}^{\text{cor}}[r, y_{1/2}, x, a]$, in order that the sum of these over age and sex, for each region and half-year, gives the original sample size of garfish actually aged. Without this rescaling, the corrected numbers summed ($n^{\text{cor}}[r, y_{1/2}]$) would differ slightly from the original true sample size.

The rescaling step is straightforward. A linear equation for each region and half-year (of catch-at-age-and-sex samples) defines the rescaling coefficient $B[r, y_{1/2}]$ we seek. Define the new rescaled $n_{xa}^{\text{cor,B}}[r, y_{1/2}, x, a]$'s (where 'B' denotes 'balanced') as

$$n_{xa}^{\text{cor,B}}[r, y_{1/2}, x, a] = B[r, y_{1/2}] \cdot n_{xa}^{\text{cor}}[r, y_{1/2}, x, a] \tag{1.12}$$

an expression for $B[r, y_{1/2}]$ is derived by equating the corrected and uncorrected sums:

$$\sum_{x} \sum_{a} n_{xa}^{\text{cor,B}}[r, y_{1/2}, x, a] = B[r, y_{1/2}] \cdot \sum_{x} \sum_{a} n_{xa}^{\text{cor}}[r, y_{1/2}, x, a] = \sum_{p \in r}^{n_p[r]} \sum_{m \in y_{1/2}}^{n_m[y_{1/2}]} n_a[p, m \mid r, y_{1/2}]$$
. (1.13)

Solving yields the B-rescaling factor for each region and half-year:

$$B[r,y_{1/2}] = \frac{\sum_{p\in r}^{n_p[r]} \sum_{m\in y_{1/2}}^{n_m[y_{1/2}]} n_a[p,m\,|\,r,y_{1/2}]}{\sum_{x} \sum_{a} n^{\mathrm{cor}}_{x\,a}[r,y_{1/2},x,a]}. \tag{1.14}$$

This rescaling of with $B[r,y_{1/2}]$ will only have an effect in the multinomial fits to these age and sex proportions, Eq. (1.28). It will not affect the proportions themselves ($P^{\mathrm{cor}}_{x\,a}[r,y_{1/2},x,a]$) from which the scaling coefficient, $B[r,y_{1/2}]$, will cancel top and bottom. Thus fits to the length moments are unaltered.

## Catch Sample Length Moment Properties

The length distributions were fitted using the moment properties. Moment 'properties' are the standardised quantities of mean, standard deviation, skewness and kurtosis. These we denoted as $b[i_{mp}, y_{1/2}, r, x, a, g]$, where the 'moment property index', $i_{mp}$, runs from 1 to 4, for the four moment properties, e.g. $b[i_{mp}=1, y_{1/2}, r, x, a]$ denotes the mean length of catches from the specified half-year, region, sex and age. Like the histograms by age and sex, formulas for the moment properties also used the set of corrected age garfish inverse sampling proportions in the sums, for the two reasons given above. Thus, the formula for the mean catch length is:

$$b[1,y_{1/2},r,x,a,g] = \frac{\sum_{i_a\in\, y_{1/2},\,r,x,a,g} f_{SS}^{-1}\left[y_{1/2},r,x,a,l[i_a],g\right]\cdot l\,[i_a]}{\sum_{i_a\in\, y_{1/2},\,r,x,a,g} f_{SS}^{-1}\left[y_{1/2},r,x,a,l[i_a],g\right]} \tag{1.15}$$

where the sum is over all aged sampled garfish ($i_a$) that fell into the given half-year, region, sex, age and gear category whose length moment we seek to calculate, and where the total length of each garfish is $l\,[i_a]$, measured to the nearest mm. Note that for length moments (unlike with catches-at-sex-and-age in the section above) we have made explicit the dependence on gear type ($g$) because length data samples are fitted from both haul net and dab net catches, those two gear types having very different length selectivity profiles. The length bin, $l[i_a]$, that specifies the particular inverse correction factor $f_{SS}^{-1}\left[y_{1/2},r,x,a,l[i_a],g\right]$ in the sum over $i_a$, was determined simply by the particular 1-cm length bin, $l$, that each aged garfish, $i_a$, fell into. In other words, $f_{SS}^{-1}\left[y_{1/2},r,x,a,l[i_a],g\right] = f_{SS}^{-1}\left[y_{1/2},r,l[i_a]\right]$ for all $x,a,g$, where $f_{SS}^{-1}\left[y_{1/2},r,l[i_a]\right]$ was defined in Equation (1.8). This dependence of length bin $l$ on $i_a$ will be assumed but not written in the three subsequent moment formulas below.

The corresponding formulas for the higher moment properties (Abramowitz and Stegun 1970) are:

$$b[2,y_{1/2},r,x,a,g]=\sqrt{\frac{\sum_{i_a\in y_{1/2},r,x,a,g} f_{SS}^{-1}\left[y_{1/2},r,x,a,l,g\right]\cdot\left(\lambda[i_a]-b[1,y_{1/2},r,x,a,g]\right)^2}{\sum_{i_a\in y_{1/2},r,x,a,g} f_{SS}^{-1}\left[y_{1/2},r,x,a,l,g\right]}} \tag{1.16}$$

$$b[3,y_{1/2},r,x,a,g]=\frac{\sum_{i_a\in y_{1/2},r,x,a,g} f_{SS}^{-1}\left[y_{1/2},r,x,a,l,g\right]\cdot\left(\lambda[i_a]-b[2,y_{1/2},r,x,a,g]\right)^3}{\left\{b[2,y_{1/2},r,x,a,g]\right\}^3\times\sum_{i_a\in y_{1/2},r,x,a,g} f_{SS}^{-1}\left[y_{1/2},r,x,a,l,g\right]} \tag{1.17}$$

$$b[4,y_{1/2},r,x,a,g]=\frac{\sum_{i_a\in y_{1/2},r,x,a,g} f_{SS}^{-1}\left[y_{1/2},r,x,a,l,g\right]\cdot\left(\lambda[i_a]-b[2,y_{1/2},r,x,a,g]\right)^4}{\left\{b[2,y_{1/2},r,x,a,g]\right\}^4\times\sum_{i_a\in y_{1/2},r,x,a,g} f_{SS}^{-1}\left[y_{1/2},r,x,a,l,g\right]}. \tag{1.18}$$

We required a minimum number of data points (of aged garfish lengths) for calculation of each moment property. These were chosen to be 1, 4, 8 and 16 aged sampled fish for mean, standard deviation, skewness and kurtosis respectively.

# Population Model

## Population array

The population array, $N[t,r,s,c,i_{sl}]$, dimensioned by time step ($t$), region ($r$), sex ($x$), cohort ($c$), and slice ($i_{sl}$) is structured similarly to that of the King George whiting estimator (Fowler and McGarvey 2000, Chapter 12). The one main difference is that we no longer recombine all the ‘cross-legal’ slices back into a single regular cohort (which we referred to as ‘post-legal’ in the whiting model). Rather we retained the full slice-length description for all ages following recruitment to legal size. Cohorts in the model population array are designated by the year of spawning, so for example, fish spawned in the summer of October 1985 through March 1996, are assigned the cohort subscript designation $c$ = 1985. They recruit to the legal (and thus model) stock at start of their third time step in the population, that is at age 3 hy’s (half-years), in October 1986. A suite of ‘index conversion functions’ allow conversion among different indices for time, age, cohort, and half-year.

## Other Submodels

Four submodels were integrated into the overall stock assessment model: (1) An algorithm was implemented for generating an estimated initial population array from the two estimated levels of steady state fishing mortality, $F_0[r]$ used to construct the initial population age and slice structure. (2) The algorithm that generates the estimated slice growth inputs, based on the estimated growth parameters, is summarised in the King George whiting Final Report, Chapter 10 (though this has been modified for integration into the overall garfish stock assessment estimator described in this report). (3) Prior fits to obtain weight-length relationships followed the algorithm of McGarvey and Fowler (in press), with separate fits done for the two gulfs ($r$) and both sexes ($x$), using the sample data supplied by Qifeng Ye from FRDC Project 1997/133, giving estimated coefficients ($a_w$ and $b_w$) for the standard allometric relationship, $w(l)[r,x] = a_w[r,x] \times l^{b_w[r,x]}$. (4) Similarly, the catch lengths-at-age were earlier fitted for each region and sex to an 8-parameter generalised likelihood model (McGarvey and Fowler, in press). The earlier growth fits used a monthly time step rather than half-yearly, and included all the lengths-at-age, including a large number of fish samples below legal minimum length. However, with the half-yearly time step used in this garfish stock assessment, seasonality was no longer resolvable. Therefore the seasonality component and its two parameters were removed. The distributions of length at age were assumed normal, with a mean length at age written $\overline{l}(a_i) = L_\infty \left\{1 - \exp\left[-K \left\langle \frac{a_i - t_0}{12} \right\rangle\right]\right\}^r$ and where the standard deviation of the observed lengths at each age was given as a power function of the predicted mean length: $\sigma(a_i) = s_0 \cdot \left(\overline{l}(a_i)\right)^{s_1}$.

When this growth (length-at-age pdf) submodel was integrated into the overall garfish stock assessment, only two parameters ($K$, $s_0$) of these six length-at-age parameters (see Tables 1.3 and 1.4), were left freely varying. The other four growth parameters retained their estimated values from the prior length-at-age fits. Integrating the growth model (by fitting to catch length moments) permits correcting for right-hand asymmetric mortality bias (sometimes called Lee's Phenomenon in the context of otolith radius back calculation). This is an underestimation bias for mean length at age that results from the asymmetry in mortality that occurs in populations subject to harvesting (abruptly, as with LML, or gradually, as with logistic selectivity) above a fixed length. Larger fish are harvested sooner and are therefore relatively less abundant, causing the observed sampled length distributions (for the population, not merely the catches) to be compressed to smaller fish sizes, resulting in underestimates of growth and of the spread of mean lengths at age. Eliminating these sources of underestimation bias in growth, caused by harvesting, is a principal reason for integrating growth into the overall stock assessment estimation.

Other ways the catch distributions which are fitted differ from population distributions, notably due to varying selectivity with length, or variations by sex, region, gear and season in the components of the population that are targeted for harvesting are also taken account of, by fitting model catch distributions to the observed data catch distributions.

## Recruitment

Recruitment ($R[r,x,c]$) is estimated for all yearly cohorts ($c$) and for both sexes ($x$) and regions ($r$), from the $c$ = 1983 cohort onwards. Recruitment occurs at the start of age 3 half-years, that is, at the beginning of the summer time step following spawning. From the slice growth submodel, the recruit numbers of each cohort are partitioned into sublegals, i.e. fish below legal minimum length (LML), and those above LML. The latter (legal-size) recruits from each cohort constitute the first slice, $i_{sl} = 1$. This slice index designation for these fish is retained thereafter. As with King George whiting, we assumed a sex ratio at recruitment of 50:50. However, initial examination of fits to catch numbers at age for males were poor. We have therefore allowed the mean estimated recruitment level to be a function of both region and sex. In estimation, this highly significantly improved model fit and yielded recruitment values by sex that diverged from the standard assumed 50:50 recruitment sex ratio.

The yearly recruitment numbers were defined in terms of 'deviation' parameters. The latter being deviations from the geometric mean, it is presumed that this formulation yields a numerically better behaved likelihood than estimating absolute yearly recruitments. Denoted $\varepsilon_R[r,c]$, the recruitment deviations are defined by $R[r,x,c] = \varepsilon_R[r,c] \times \bar{R}[r,x]$, where the mean levels of recruitment by region and sex ($\bar{R}[r,x]$) over years, are also freely estimated parameters. The log of the deviations from each region separately, $\log(\varepsilon_R[r,c])$ are declared in AD Model Builder as 'init_bounded_dev_vectors', meaning that they are constrained so that $\sum_c \log(\varepsilon_R[r,c]) = 0$ for each region, *r*. Thus the product of the deviations themselves in each region, i.e. the geometric mean, $\prod_c \varepsilon_R[r,c] = 1$.

## Survival

The survival equation for all time steps, regions, sexes, cohorts and slices was written in terms of total mortality, $Z[t,r,x,c,i_{sl}]$,

$$N[t+1,r,x,c,i_{sl}] = N[t,r,x,c,i_{sl}] \times \exp\left\{-Z[y_{1/2},r,x,c,i_{sl}]/2\right\}, \tag{1.19}$$

where the factor of ½ reflects the time interval of one half-year for each model time step.

## Natural Mortality

Jones (1990) estimated natural mortality using age samples from a lightly exploited garfish subpopulation in Baird's Bay. The curves of numbers versus age showed a strong dependence on age, with low mortality up to about age 5, and very steep mortality above age 5 for females and above age 7 for males. In the two gulfs, few garfish above age 5 years are caught. Thus, this sample from Baird's Bay gave no evidence of measurable natural mortality in the population ages (5 years and under) that are modelled in this study. Estimating natural mortality in this model itself would be difficult since there is very little contrast through time or between the two gulfs in levels of fishing mortality. For these two reasons, we chose to leave natural mortality fixed at an assumed level of $M = 0.4$. A natural survival factor of $\exp(-M/2)$ is multiplied through the population array in each time step.

Because of the often important influence of the choice of *M*, sensitivity analysis is undertaken to test the effect of the three values for *M* assumed by Jones et al. (1990) in the 'Green Paper', namely $M = 0.4$, 0.55 and 0.7. This sensitivity analysis is presented in Chapter 2.

## Fishing Mortality and the Catch Equation

A Baranov catch formulation is retained from the King George whiting model. Fishing mortality,

$$F[t,r,x,c,i_{sl},i_E] = q_E[r,i_E] \cdot s_{yx}\left[y_{1/2}[t],x\right] \cdot s_l\left[y_{1/2}[t],r,g[i_E],l\left[r,x,a[t,c],i_{sl}\right]\right] \cdot E[t,r,i_E] \quad (1.20)$$

was written as a product of (*i*) $q_E[r,i_E]$, a catchability array that varies with region and effort type, (*ii*) $s_{yx}\left[y_{1/2}[t],x\right]$, relative selectivity by half-year and sex, (*iii*) $s_l\left[y_{1/2}[t],r,g[i_E],l\left[r,x,a[t,c],i_{sl}\right]\right]$, logistic length selectivity as a function of winter or summer, region, and gear, where $l\left[r,x,a[t,c],i_{sl}\right]$ is the midpoint length of each slice specified by its region, sex, age and slice index, and (*iv*) $E[t,r,i_E]$, reported effort for each time step, region, and effort type. Multiplication of these four components of catch rate variation reflects the assumption that they are independent. The strong trends of variation in sex ratio between summer and winter imply a strong linkage between seasonality and sex. Therefore the dependence of relative catchabilities by sex ($x$) and half-year ($y_{1/2}$) were not assumed to be independent and a 2x2 matrix of relative selectivity values was estimated. The first element, $s_{yx}[1,1]$ was set to 1 fixed, and the other three were estimated freely. Note that there is no explicit dependence of catchability on time, apart from half-year. In particular, no attempt was made to infer increasing effective effort with time due to the availability of only a single year of catch length and age samples.

For each element of the population array, $N[t,r,x,c,i_{sl}]$, the total fishing mortality,

$$F_T[t,r,x,c,i_{sl}] = \sum_{i_E} F[t,r,x,c,i_{sl},i_E] \quad (1.21)$$

is the sum of the fishing mortality due to each effort type.

The total mortality is defined in the standard manner as

$$Z[t,r,x,c,i_{sl}] = F_T[t,r,x,c,i_{sl}] + M, \quad (1.22)$$

yielding the Baranov catch equation for model predicted catch:

$$\hat{C}[t,r,x,c,i_{sl},i_E] = \frac{F[t,r,x,c,i_{sl},i_E]}{Z[t,r,x,c,i_{sl}]} \times \left\{1 - \exp\left[-Z[t,r,x,c,i_{sl}]/2\right]\right\} \times N[t,r,x,c,i_{sl}]. \quad (1.23)$$

Logistic length selectivity, parameterised in terms of the 50% and 95% selectivity lengths (Punt and Walker 1998),

$$s_l\left[y_{1/2}, r, g[i_E], \lambda[r,x,a,i_{sl}]\right] =$$

$$\left\{1+\exp\left[\left(\frac{-\log(19)\cdot\left\{\lambda[r,x,a,i_{sl}] - l_{50}\left[y_{1/2},r,g[i_E]\right]\right\}}{l_{95}\left[y_{1/2},r,g[i_E]\right] - l_{50}\left[y_{1/2},r,g[i_E]\right]}\right)\right]\right\}^{-1} \tag{1.24}$$

was estimated independently in the two gulfs for haul net ($g$ = 1), but a single pair of parameters were estimated for dab net ($g$ = 2), with the same values applied across the two regions, i.e. $l_{50}\left[r=1, g=2\right] \equiv l_{50}\left[r=2, g=2\right]$, and similarly for $l_{95}$. This dab net selectivity curve was also assumed to apply for recreational hook and line, the catch length-frequency distributions from dab nets being similar to those of recreational fishers.

## Model Predicted Catches: Totals, and Proportions by Age and Sex

The model-predicted catch outputs, for fitting to data, were formed by summing model catch numbers $\hat{C}[t,r,x,c,i_{sl},i_E]$ over the appropriate independent variables.

Model catch totals by weight, were calculated by summing over sex ($x$), age (cohort, $c$) and length (slice, $i_{sl}$):

$$\hat{C}_w\left[t,r,i_E\right] = \sum_{x,c,i_{sl}} \hat{C}[t,r,x,c,i_{sl},i_E]\cdot a_w[r,x]\cdot \lambda\left[r,x,a[t,c],i_{sl}\right]^{b_w[r,x]}. \tag{1.25}$$

where the weight-length relationship ($a_w l^{b_w}$) is explicit with $l = \lambda\left[r,x,a[t,c],i_{sl}\right]$ being the midpoint length of each slice.

Model catch proportions by both sex ($x$) and age ($a$) (in each region and half-year), for fitting to haul net ($g$=1) catch samples, were calculated as

$$\hat{P}_{xa,g=1}\left[t,r,x,a\right] = \frac{\sum_{i_E(g=1)} \sum_{i_{sl}} \hat{C}[t,r,x,c[t,a],i_{sl},i_E]}{\sum_{x} \sum_{a} \sum_{i_E(g=1)} \sum_{i_{sl}} \hat{C}[t,r,x,c[t,a],i_{sl},i_E]}. \tag{1.26}$$

where the respective cohorts ($c[t,a]$) are calculated using an index conversion function from time step ($t$) and age ($a$).

Recall that for fitting to catch proportions by age and sex we used only haul net ($g$ = 1), both targeted and untargeted, i.e. $i_E$ = 1 and $i_E$ = 2. Recall also that age and length sample data were only available for a single year, October 1997 to September 1998.

## Model Predicted Catches: Length Moment Properties

A normal was assumed for the distributions of lengths-at-age in the population in the slice-growth submodel. When asymmetric catches impinge (i.e. larger fish taken at a higher rate), the length-at-age distributions of the modelled catches will not be normal, and we cannot, in general, postulate what continuous length distribution should be used for model catches. Instead, we fitted the moment ‘properties’, as noted above, which avoids the need to postulate an *a priori* distribution for the observed length-at-age distributions from the catch. Using moments to fit length samples was first proposed by Fournier and Doonan (1987).

The ‘moment properties’ (mean, standard deviation, skewness and kurtosis) rather than the pure or central moments were used because (1) they are more mutually independent (specifically the mean and standard deviation), and (2) vary over a much smaller range of values than pure or central moments. Pure and central moments, being sums of powers from 1 to 4 of total fish length (given in hundreds of mm), would yield values that increased by several orders of magnitude with each higher moment, which could be problematic in model fitting. The moment properties, in particular the mean and standard deviation of the length-at-age distributions, convey important intuitive information about growth. The skewness and kurtosis are zero for a purely normal distribution.

The moment property formulas for model lengths ($\left\{\hat{b}[i_{mp}, y_{1/2}, r, x, a, g]\right\}$) were the same as given for data moment properties (Eqs. (1.15)-(1.18)), except that the midpoints of each model slice were used rather than the observed lengths from each aged garfish, and model catch numbers captured by slice were used as the moment weightings rather than $f_{SS}^{-1}\left[y_{1/2}, r, x, a, l, g\right]$.

The minimum number of slices mathematically required to calculate each moment model property were specified by the degrees of freedom. Ages that had four legal slices or more (6 half-years, i.e. 2.5 years, of age and older) provided sufficient model input to calculate kurtosis, three slices or more were needed for skewness, two slices for standard deviation, and a mean length could be calculated for all model ages, even those with just a single (legal) slice.

# Likelihood

## Catches by weight

The catches by weight were assumed to be lognormally distributed (e.g. Punt and Hilborn 1997; Fournier et al. 1998; see also Quinn and Deriso 1999). A lognormal posits a zero probability of negative catches, a very desirable property not achieved with a normal likelihood, and gives equal probability to observed values that are half or double the model-predicted (median) value. The negative log-likelihood term for fitting catch totals by weight, (catch-log reported totals, in kg) for all model time steps is

$$-\log L_{Cw} = \sum_{t,r,i_E} \log\left[\sigma_{Cw}\right] + \frac{1}{2} \cdot \left\{ \frac{\log\left[C_w[t,r,i_E]\right] - \log\left[\hat{C}_w[t,r,i_E]\right]}{\sigma_{Cw}} \right\}^2 . \qquad (1.27)$$

## Catch Proportions by Both Sex and Age

With garfish, sex selectivity is an important fishery process, with observed raw sex-ratios in the catch changing substantially from summer (~90% females) to winter (~50% females).

Two options were considered for fitting to sex ratios and age proportions. The first option is to have separate log likelihood terms for sampled sex ratios and sampled age proportions. We instead implemented the second option, which is to have a single complete set of proportions (from each region and time step) binned into categories dimensioned by both sex and age simultaneously. This requires only one log-likelihood term to handle both sex ratio and age structure, and avoids fitting to these data twice. The catch at age and sex proportions were fitted using a multinomial likelihood:

$$-\log L_{xa} = -\sum_{t=29}^{30}\sum_{r,x,c} n_{xa}^{\mathrm{cor,B}}[t,r,x,a[t,c]]\cdot\log\left\{\hat{P}_{xa,g=1}\left[t,r,x,a[t,c]\right]\right\}. \qquad (1.28)$$

## Catch Length Moment Properties

In the absence of *a priori* reason to choose any particular distribution, a normal likelihood was applied to fit the data and model moment properties. Fournier and Doonan (1987) followed a similar course.

$$-\log L_{mp} =$$

$$\sum_{i_{mp}=1}^{4}\sum_{t=29}^{30}\sum_{r,x,c,g}\left\{\log\left[\sigma_{mp}\right]+\frac{n_a[y_{1/2}[t],r,x,a[t,c],g]}{2}\cdot\left(\frac{b[i_{mp},y_{1/2}[t],r,x,a[t,c]]-\hat{b}[i_{mp},t,r,x,a[t,c]]}{\sigma_{mp}}\right)^2\right\}$$

(1.29)

Again we weighted each term (by region, sex, age and gear type) in the negative log likelihood by the uncorrected sample size ($n_a[y_{1/2},r,x,a,g]$), that is by the actual number of aged fish. The half-year ($y_{1/2}$) of data sampling (summer or winter) is determined uniquely by the time step ($t$). In the absence of sample data for the dab net gear type from Gulf St.Vincent, we fitted those model moments to the dab net length moments from Spencer Gulf. Length fitting to dab net samples serves mainly to estimate the length selectivity of dab net gear.

The sum over $i_{mp}$ included only terms where both data and model moments had sufficient numbers of data points and slices respectively to meet the minimum criteria specified in those two sections above.

## Minimisation

The model was written and fitted using the AD Model Builder parameter estimation and likelihood analysis software (Fournier 1996). The parameters were estimated by minimising the overall objective function ($O$), written as the sum of the three negative log likelihood terms:

$$O = -\ \log L_{Cw} -\ \log L_{xa} -\ \log L_{mp}\,. \qquad (1.30)$$

# Fits to Four Data Sources

By visual inspection (Figures 1.2a & 1.2b), the catches by weight were satisfactorily fitted. Residuals (open circles) are reasonably well behaved though for minor effort types (in terms of overall catch), and for winter time steps overall, there is a modest tendency towards model overestimation.

While sex and age were fitted simultaneously, we present the fits for sex and age separately (rather than present a 3-D graph of the fits to both). Catch proportions by sex (Figure 1.3) were very closely fitted. This close agreement with sex ratio in the catch is advantageous under the assumption that capture variation by sex and season is an important qualitative feature of garfish fishery dynamics for the model to capture. The fits to (corrected) catch-at-age samples were satisfactory (Figure 1.4) though the fits are closer for summer. The relative catchabilities of males and females and of summer versus winter are estimated by the selectivity coefficients (Table 1.7), which showed lower catchability for males in summer and higher catchability for males in winter.

The model fits to length moments (Figure 1.5a for haul net and 1.5b for dab net samples) express both selectivity by length and growth, in model numbers captured by length, as well as population numbers by length slice. The fits were good for catch mean lengths from both gear types. Thus growth, as mean length at age, is well described. The fits to standard deviations were acceptable at younger ages; however at higher ages data standard deviations declined while model-predicted standard deviations levelled out. The substantial reduction in length-sample standard deviation is unlikely to be representative of the population since the spread of cohort lengths-at-age would not be expected to shrink dramatically and this may, instead, reflect the very small sample sizes that were available for the older ages (see Figure 1.6). Skewness was approximately zero in magnitude for both gear types and sexes, with both model and data, and probably had little influence on the growth and selectivity estimates overall. Kurtosis, on the other hand, yielded good or acceptable fits for haul nets (where the sample was large enough to calculate them, namely combinations of region, gear type and age having at least four legal-size model slices and at least 16 aged sampled fish). Moreover, compared with skewness, the kurtosis absolute values were relatively large. Thus unexpectedly, kurtosis may play a role in conveying length-at-age information.

Because these plotted fits to the four moment properties (Figure 1.5) are not easily interpreted intuitively, we generated more standard plots to compare data and model length frequencies. Specifically we plotted (legal-size) garfish numbers caught in binned (and corrected) data lengths and those from model slices (Figures 1.6a and

1.6b). Because slices are model length bins whose widths and number vary, to make the data and model catch proportions (i.e. the y-axis values) comparable, we presented both as probability densities. Thus we divided each slice proportion by the width of each slice to plot probability density of capture versus length. The data proportions are already naturally scaled as probability densities, the bin widths being constant and equal to 1 unit of total length (that is, 1 cm). The four columns of Figures 1.6a and 1.6b (both sexes, summer and winter) show increasing age from top to bottom thereby illustrating the growth of a length-at-age cohort (as numbers caught) over yearly time intervals. The plotted results are generally encouraging, in particular given that these are not fits per se. While the sample sizes are small so that fewer of the data length-at-age distributions appear normal, the general agreement with the predicted model slice densities is satisfactory.

Some of the properties of the fits observed in Figure 1.5 are reflected in Figure 1.6, notably the small data standard deviations at older ages, and roughly zero skewness. No intuitive explanation for positive values of kurtosis (‘leptokurtic’) observed in Figure 1.5 is evident. However, with data standard deviations that are unrealistically small for the older age groups (Figure 1.5a), observed trends in kurtosis and skewness which depend on standard deviation are difficult to interpret. Also, standard intuitive descriptions of kurtosis more naturally apply to continuous distributions rather than the discrete binned length-slice distributions for which the model-predicted moment properties are defined.

# Results

The estimated parameter values and confidence intervals as standard deviations about the predicted mean, obtained using the asymptotic approximation (diagonals of the estimated variance-covariance matrix) in A D Model Builder, are given in Table 1.8.

Yearly recruitment values have been left out but are presented immediately below. Further details of model outcomes, plotted, appear in subsequent subsections below.

## Recruitment

The recruitment time series for the two regions (Figure 1.7) show very similar temporal trends, apart from 1984. The two gulfs’ recruitment time series are independent, being essentially separately fitted models, each region using separate data and deriving separate sets of estimated parameters (apart from dab net length data and dab net length selectivity). In particular, estimated yearly recruitment is primarily determined by yearly catch data. The modest temporal correlation of recruitment to the two gulfs (r=0.37, p=0.15, df=15) may suggest a yearly-variable environmental forcing factor in garfish recruitment that is common to both. Also somewhat unexpected is the approximate equivalence of estimated average absolute recruit numbers in the two gulfs.

Estimated female:male recruit proportions were 5:2 in Spencer Gulf and 11:3 in Gulf St.Vincent. These are also relatively similar ratios for essentially two independent models in the two gulfs. Thus, there are two and a half times as many females recruiting in these two populations. The unexpectedly high proportion of females was coincident with a very highly significant improvement in model fit (73.1 log-likelihood units lower, with two additional parameters added; a difference of 3 in log-likelihood units is significant at the 95% level), suggesting this effect is real and strong.

In an earlier version of this model we employed a penalty function on large recruitment deviations from the mean, but changing the relative weighting on (or removing) this log-recruitment-deviation penalty term in the log-likelihood had little effect on model estimates, so it was removed entirely.

## Length selectivity

Gear selectivity is flat above LML (210 mm) for haul nets in summer (Figure 1.8). The logistic length selectivity curves estimated for the other four gear-type/gulf/winter-summer combinations (Figure 1.8) generally concord with prior expectation. In particular, dab nets catch much larger garfish than haul nets. Also, the size selectivity is higher in winter when fishers target both sexes and no spawning aggregations are present. Larger garfish in the population are also present in winter; comparing age-3 with age-4 half-year length-at-age distributions (top rows of Figures 1.6a and 1.6b), the new recruitment year class is more nearly fully recruited with its mode farther above LML by winter.

## Selectivity by sex and season

The estimates for the relative selectivities by sex and season, a 2 x2 matrix, were consistent with the knowledge (Ye et al. 2002) that females dominate summer catches (Table 1.7). In particular the selectivity for males is estimated to be half that of females in summer, and double that of females in winter.

## Maximum Fishing Mortality

By 'maximum fishing mortality', we mean the highest levels of fishing mortality due to each gear type, i.e. assuming maximum selectivity by length, season and sex. The average $F$ for the population overall will be less than $F_{max}$.

Recalling that haul nets are the gear for both effort types 1 and 2, these dominate the overall estimates for $F_{max}$ (Figure 1.9). Among the four effort types, $F_{max}$ underestimates the relative fishing impact of haul nets by comparison to the other 2 effort types (3=dab nets, and 4=recreationals). Haul nets capture most of the fishable length range (Figure 1.7). Thus, the $F_{max}$ estimates plotted for dab nets and recreationals, as illustrated in Figure 1.9 describe the capture rate by those gears only for large garfish which are far less numerous.

## Growth

Two of six growth parameters ($K$ and $s_0$) were freely re-estimated in the integrated garfish model. Integrating growth estimation yielded slightly larger mean lengths at age (Figure 1.10), expressed by a higher estimated instantaneous growth rate, $K$. Slightly larger mean lengths suggests the integration of growth achieved its anticipated effect of correcting for right-hand asymmetric mortality bias caused by fitting to raw catch length-at-age data where larger fish in the length-at-age distribution are removed at a higher rate. However the overall increase in mean length with growth integrated was relatively small (Figure 1.10), amounting to an average of 4.1 and 1.9 mm for females and males in Spencer Gulf, and 8.9 and 9.6 mm in Gulf St.Vincent. By comparison, mean length increment between ages 5 to 6 half-years is about 22 mm. Thus the corrected growth bias is about 1-2 months of growth for garfish in their second year of legal size.

### Biomass

The half-yearly time series of legal size population numbers and biomass (Figure 1.11) exhibit a generally increasing trend. This is inferred by the model from similarly increasing catch rates over that time, a trend which has accelerated in the last several years. Anecdotal reports indicate that this may be due to a rise in capture power of the haul net and dab net gears in recent years, rather than, as the model infers, a larger fishable biomass. This potential confounding of increasing effective effort with rising stock abundance is met in most stock assessments worldwide and remains one of the most challenging problems in fishery population modelling. Rising effective effort can in most cases only be quantified with a second data source, notably fishery-independent indicators, of fishable stock abundance.

A sensitivity analysis was undertaken to determine how much rising effective effort might be biasing the estimated time trajectory of garfish population biomass. This is presented in Chapter 2.

### Exploitation Rate

The exploitation rate is the proportion (as numbers) of legal size fish taken in each (half-yearly) model time step. This has exhibited a variable but consistent trend of decrease over the full length of modelled data time. Currently the exploitation rate is approximately 0.25 per half year in both gulfs.

This value is directly affected by the modeller's choice of natural mortality rate. Sensitivity to choice of *M* is undertaken in Chapter 2.

## Discussion

We seek to estimate 'growth' as the mean and standard deviation of lengths-at-age in the absence of mortality. This is because the model description that uses this growth submodel will subsequently impose mortality on the growing cohort length at-age distributions.

The population cohort lengths-at-age are altered by asymmetric mortality. Since fishing removes the larger individuals in a cohort, the observed cohort mean length at age will, in general, be less than the 'pure growth' mean length at age that would have been observed in the absence of size-dependent mortality. In this garfish stock assessment model, account was taken of the bias induced by asymmetric mortality (namely higher catch rates on larger fish), by (1) following the numbers of garfish by length class, i.e. by slice, in the population array, and (2) fitting to the model numbers generated after mortality impinged, so as to agree with the real population data where asymmetric mortality has also been acting. In garfish we found that the error was not large, about a month or two of growth. Obviating right-hand asymmetric mortality bias is one advantage of a fully length- and age-dependent population array, using slices to partition garfish lengths-at-age.

In fitting to mean lengths-at-age and their standard deviation, we first fit an 8-parameter growth curve using a monthly time step and sinusoidal seasonality, before integrating this growth estimation into the full stock assessment. However, with just two time steps per year in the garfish stock assessment, we found that seasonal variation in growth was poorly resolved so we removed seasonality from the growth description, leaving 6 growth parameters to be fitted. Moreover, since the shift in growth due to accounting for right-hand asymmetric mortality was small, only two parameters were freely estimated in the model above, $K$ and $\sigma_1$. The other 4 growth parameters were taken as estimated by fitting to lengths-at-age prior to integration with the overall stock assessment estimation. These prior fits have the advantage that they can incorporate data (i.e. lengths) for ages that are younger than the youngest age group (3 half-years for garfish, and 5 half-years for snapper) in the stock assessment.

Qifeng Ye gathered the South Australian garfish length samples in highly representative fashion as shown in Figure 1.1. However, ageing was less rigorously representative and approximately 50% more fish were aged (1630) than dictated by representative age subsampling regime under the specific target of 15% (1114) subsampled for ageing. Thus, by correcting for non-representative sampling, mostly at larger sizes of the garfish range, the sample size of usable aged garfish was enhanced.

Exact correction for non-representative sampling could be of value in other fisheries. Fisheries where age sampling from time and space strata is not representative and for which overall catches (here given by port and month) are available to serve as a correction basis are not uncommon. More commonly applicable is the need for correction for non-representative subsampling from length samples to allow all aged fish to be used. Non-representative age subsamples would normally have to be discarded. Thus more age-based information can be sampled for in any length range of interest, without biasing the data for catch numbers-at-age.

One length range of particular interest is the upper tail of the distribution of larger and older fish. Information about mortality from older age samples is richer because those fish have been in the exploited population longer. Moreover, the relatively low numbers present in the older age classes of the population normally result in much lower sample sizes being obtained from older age classes in a representative sample. Thus one potentially powerful stock assessment strategy would be to subsample roughly equal numbers by size to get more precise inference about mortality than a representative aged subsample from a fixed number of otoliths read. This would need to be proven or investigated numerically. But in general, we suspect that more age samples from older fish is likely to bring better estimates of $Z$. Thus an over- and under-sampling correction procedure like that presented above can allow for unbiased use of aged subsamples with any strategically chosen or opportunistically obtained set of aged fish. All this assumes that representative sampling has been undertaken at a higher level (for garfish that being both by port and month, and by length), from which the ages can be understood as subsampled.

Overall, the satisfactory fits (Figures 1.2-1.5), and agreement of model and data length distributions at age (Figure 1.6), suggest that the estimation objectives were probably achieved. Thus, a fully age- and length-based description, with growth integrated and with correction for non-representative sampling was obtained with this garfish version of the slice-growth population description.

It was this correction by length, that is, the assigning of a relative length bin abundance to each aged fish that allowed the calculation and fitting of mean length, and the three higher moment properties, for each age and sex individually. Certainly, better growth estimates were obtained with the mean length (and higher moments) available for each age and sex, rather than confounded together in a sum.

One very valuable recommendation of Dr. Punt was to reduce the number of (1) age classes in the garfish population array, and (2) model time steps per year than we used with King George whiting. Fewer age classes is achieved by choosing a younger age at which to form the 'plus group'. This meant fewer cohorts present in the population array and thus correspondingly shorter computation times. More importantly, this permitted retaining the full slice-length partition for all ages rather than recombining the slices into a single normal cohort as was done, with copious programming, for King George whiting. Reducing the number of time steps per years from 12 to 2 gave even more substantial reductions in model estimation computation times.

In some future implementation of slice-growth, it would be convenient and provide potentially more accurate parameter estimates (with the trade-off of longer or much longer computation times) if the number of time steps per year could be a control parameter that modellers or biologists could specify. We used 2 time steps per year with garfish, but 12 (i.e. a monthly time step) with King George whiting. If the number of time steps per year could be flexibly chosen (notably with values of 1, 2, 3, 4, 6 and 12 as likely choices), the initial fitting runs of the model would use longer time steps thus converging much faster until fundamental parameters were well estimated. Then a more detailed fit with more time steps for year could be attempted.

The slice description may have somewhat limited application because (1) some fisheries may not have a minimum size, (2) the programming of the slice-growth formalism is cumbersome. Moreover, when minimum size changes have occurred during the span of the data time series, programming challenges with the slice-growth description are magnified. However the two recommendations listed in the paragraph above substantially reduce the programming required with a slice-growth model.

The slice approach is probably more computationally efficient, however, once the programming is done, than an age- and length-based model estimator using fixed-length (e.g. 1-cm-wide) bins. With fixed bins, growth in each time step is usually done using a length-transition matrix. If growth is continuous, then the length-transition matrix multiplication would be run every time step, which can involve a lot of computation. Moreover, when a continuous distribution (such as the normal used here) is a better description than finite bins for the actual distribution of fish with length, the slice growth approach should be more accurate.

Another alternative for an age- and length-based description is the fully continuous pdf approach of Deriso and Parma (1988) and Parma and Deriso (1990). To date, however, because of the fairly rigid restrictions on the choices for growth and mortality which the mathematics of this model employ, this approach has not been widely applied, despite a mathematically elegant and computationally efficient formulation.

The one remaining alternative is the 'growth-groups' method of Punt et al. (2001a, 2001b, 2002), which considers each subinterval of lengths in the cohort (which are similar to the slices used above) as a separate population component. This is likely to be more practical in programming, and thus more flexible, but may pose challenges in estimation in that a separate $K$ and $L_\infty$ are estimated for each growth group, and these need to be self-consistent since each cohort is the union of growth groups. Comparing, and possibly combining the best features of these distinct age- and length-based approaches would be useful in future years of stock assessment estimation model research.

## Acknowledgments

We wish to thank Qifeng Ye, Keith Jones, André Punt, and the fishers of the South Australian marine scale fishing industry.

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Table 1.1. Independent variables (i.e. array subscripts) for garfish data and model.

| Subscript symbol | Subscript name | Description |
|---|---|---|
| $p$ | port | ports of landing for garfish, the smallest spatial partition of both sample data and commercial catches |
| $r$ | region | specifically, the two gulfs. Ports are aggregated to give the two regions. |
| $y_{1/2}$ | half-year | Either summer (Oct-Mar) or winter (Apr-Sep). |
| $t$ | model time step | Running in successive half years, 34 time steps total, from Oct-Mar 1983 to Apr-Sep 2000. |
| $a$ | age | Half-yearly (hy) ages, represented in the model from 3 hy's to 12, where a=12 hy (winter of age 5 y) is the plus group. |
| $x$ | sex | |
| $l$ | length bin | Specified by an integer, the lower limit of each bin. Length bins, used for subsampling correction, are 10 mm wide. |
| $g$ | gear | Haul net or dab net only. |
| $i_E$ | effort type | Four types, described in text. |
| $c$ | cohort | A subscript in the population array, specifying the cohort by its summer year of spawning, specifically the year identified by the first three (Oct-Dec) months of that summer. |
| $i_{sl}$ | slice | For each cohort, the length slice designates fish of a given length interval that reached legal fishable size in a particular model time step. |
| $i_a$ | fish subsampled for age | This index runs over all individual fish that were sampled and aged. |

Table 1.2. Data inputs.

| Array symbol | Array name | Description |
|---|---|---|
| $C_w[p,m,i_E]$ | catch total (kg) | From catch logs, for each port, month and effort type since October 1983. |
| $E[p,m,i_E]$ | effort total | From catch logs, in units of fisher-days, for each port, month and effort type since October 1983. |
| $p[i_a]$ | port | The port from which a given market sample was landed. |
| $n_p[r]$ | number of ports by region | Used as upper bound in sums. |
| $m[i_a]$ | month | The month (assumed to be from a single 12-month year) when a given market sample was landed. |
| $n_m[y_{1/2}]$ | number of months per half year | = 6; Used as upper bound in sums. |
| $n_a[p,m\,\|\,r,y_{1/2}]$ | catch numbers-at-age | Uncorrected numbers of fish sampled from the commercial catch that were aged (and sexed), by port and month, within each region and half-year. (Only haul net catch-at-age numbers were fitted.) |
| $\lambda[i_a]$ | length | Understood as a real number, the measured length (to nearest mm) of each aged garfish. |
| $n_l[r,y_{1/2},l]$ | numbers-at-length | From random stratified market length sampling, by region and half-year, binned into 1 cm wide length categories. |
| $f_S[p,m\,\|\,r,y_{1/2}]$ | Over- and under-sampling factor by port and month | Quantifies over- and under-subsampling of garfish for ageing by port and month, within region and half-year, using catch-log reported catch totals. See Eq. 1.9. |
| $f_{S\&SS}[r,y_{1/2},l]$ | Over- and under-sampling factor by region, half-year and length bin | Quantifies over- and under-subsampling of garfish for ageing by region, half-year and 1-cm length bin, using $f_S[p,m\,\|\,r,y_{1/2}]$ above, and the random stratified market catch samples by 1-cm length bin. See Eq. 1.10. |
| $f^{-1}_{S\&SS}[r,y_{1/2},l]$ | Over- and under-sampling correction factor | Corrects for both forms of over- and under-subsampling of garfish for ageing. Calculated as reciprocal of $f_S[p,m\,\|\,r,y_{1/2}]$ above. See Eq. 1.12. |
| $n^{\mathrm{cor}}_{xa}[r,y_{1/2},x,a]$ | corrected catch numbers-at-age | Corrected numbers of fish sampled from the commercial catch and aged, by region, half-year, sex and age. |
| $P^{\mathrm{cor}}_{xa}[r,y_{1/2},x,a]$ | corrected catch proportions-at-age | Corrected proportions of garfish catches in bins partitioned over both sex (*x*) and age (*a*), within each region and half-year. |
| $b[i_{mp},y_{1/2},r,x,a,g]$ | Data length moments | The four moment 'properties' (*m*) of mean, standard deviation, skewness and kurtosis, given by region, sex, gear and age from random stratified catch length samples. |

Table 1.3. Estimated (i.e. ADMB 'init') parameters.

| Parameter symbol | Parameter name | Description |
|---|---|---|
| $\log(e_R[r,c])$ | log-R devs | Used to express yearly recruitment by region and cohort as a difference of logs. |
| $\bar{R}[r,x]$ | R-bar | Mean estimated recruit numbers for each region and sex. |
| $q_E[r,i_E]$ | catchability by effort type | The (not relative) catchability parameter relating reported effort by region $r$ and effort type $i_E$ to fishing mortality due to that effort type. |
| $s_{yx}[y_{1/2},x]$ | selectivity by half-year and sex | The relative selectivity by summer and winter and by sex. A 2x2 matrix containing 3 freely estimated parameters, with the value for summer females, $s_{yx}[1,1] = 1$ fixed. |
| $l_{50}[y_{1/2},r,g]$ | | Logistic selectivity curve parameter, specifying length at which garfish in half-year $y_{1/2}$ (g=1) and region $r$ (g=1) are selected at 50% of maximum by gear type $g$. |
| $l_{95}[y_{1/2},r,g]$ | | As above, but 95% selection. |
| $F_0[r]$ | | Pseudo-fishing mortality used to form initial population array, one for each region. |
| $s_{Cw}$ | Cw-sigma | Free parameter quantifying the spread of the lognormal catch-total-by-weight likelihood. |
| $s_{mp}$ | moment sigma | Free parameter quantifying the spread of moment properties (mean, SD, skewness, kurtosis) in their normal likelihood. |
| $K$ | | Von Bertalanffy instantaneous growth coefficient |
| $s_0$ | | Estimated parameter determining standard deviation (SD) of normally distributed lengths about the mean, SD = $s_0$ * (mean length)$^{s_1}$. |

Table 1.4. Fixed input parameters.

| Parameter symbol | Parameter name | Description |
|---|---|---|
| $a_w[r,x]$ | weight-length linear coefficient | The weight-length data were prior fitted to an allometric power curve, $w[l] = a_w\ l^{bw}$. The fits, and thus inferred weight-length coefficients, $a_w$ and $b_w$, are by region and sex. |
| $b_w[r,x]$ | weight-length exponent | |
| $M$ | natural mortality | Taken as fixed at $M$ = 0.4. |
| $s_1$ | exponent of SD in mean lengths at age | Fixed at –0.35, taken from prior fits to mean lengths-at-age. |
| $t_0$ | | Fixed, by prior fits to mean length-at-age, at 1.8 hy's, i.e. towards the end of the first half year of life, that is, in summer of the year of spawning. |
| $L_\infty$ | L-infinity | Fixed, by prior fits to mean lengths-at-age, at 383 mm for females and 363 for males. |
| $r$ | growth exponent | Exponent applied to generalise the von Bertalanffy model (McGarvey and Fowler, in press), fixed at 0.4 from prior fits to mean lengths-at-age. |

Table 1.5. Index conversion and length or weight functions.

| Subscript symbol | Subscript name | Description |
|---|---|---|
| $l\,[r,x,a,i_{sl}]$ | Slice mid-points | Length (mm) of the midpoint of slice designated by region (*r*), sex (*x*), age (*a*) in half-years, and slice. Calculated from slice growth submodel (see King George whiting report). |
| w[λ] | weight-at-length | Prior fitted. See $a_w$ and $b_w$ parameters in Table 1.4. |
| $g[i_E]$ | gear from effort type | Index conversion function from effort type to its associated gear. Effort type partitions catch and effort data by gear, sector and target type. |
| $y_{1/2}[t]$ | half-year from model time step | Index conversion function from model time step to the half-year. The term "half-year" means either summer (October-March) or winter (April-September). |
| $a[t, c]$ | age from time step and cohort | Index conversion function from model time step (*t*) and cohort (given as its year of spawning, *c*) to age of cohort. |
| $c[t, a]$ | cohort from time step and age | Index conversion function from model time step and age to the corresponding cohort year of spawning. |

Table 1.6. Ports and Marine Fishery Area (MFA) statistical blocks by region (SG = Spencer Gulf; GSV = Gulf St.Vincent).

| MFA block | Port | Region |
|---|---|---|
| 19, 20 | Arno Bay (AB) | SG |
| 22, 23, 32 | Tickera (TK) | SG |
| 33, 40 | Corny Point (CP) | SG |
| 42 | Kangaroo Island (KI) | GSV |
| 36 | Middle Beach (MB) | GSV |
| 29, 30, 31 | Port Lincoln (PL) | SG |
| 35 | Port Wakefield (PW) | GSV |
| 11, 21 | Whyalla / Port Pirie (WH/PP) | SG |
| 34 | Port Vincent Stansbury (PVST) | GSV |
| 44 | Cape Jervis (CJ) | GSV |

Table 1.7. Estimates of relative selectivity by sex and half-year.

| | Females | Males |
|---|---|---|
| Summer | 1 | 0.55 |
| Winter | 0.92 | 2.05 |

Table 1.8. Parameters estimates, and relative confidence intervals. The latter were obtained as asymptotic estimates, as the negative inverse of the Hessian at the likelihood maximum.

| **name** | **value** | **relative std %** | **name** | **value** | **relative std %** |
|---|---|---|---|---|---|
| $K$ [SG,female] | 3.28E-01 | 1.8 | $F_0$[SG] | 1.25E+00 | 14.2 |
| $K$ [SG,male] | 3.47E-01 | 2.7 | $F_0$[GSV] | 1.11E+00 | 14.7 |
| $K$ [GSV,female] | 2.86E-01 | 2.3 | $\bar{R}$[SG,female] | 4.49E+06 | 4.4 |
| $K$ [GSV,male] | 3.14E-01 | 4.7 | $\bar{R}$[SG,male] | 1.77E+06 | 6.8 |
| $s_0$[SG,female] | 1.69E+02 | 4.0 | $\bar{R}$[GSV,female] | 4.38E+06 | 4.6 |
| $s_0$ [SG,male] | 1.64E+02 | 6.6 | $\bar{R}$[GSV,male] | 1.20E+06 | 10.2 |
| $s_0$ [GSV,female] | 1.75E+02 | 5.8 | $r_{sel}$[Win,SG] | 2.20E-01 | 58.9 |
| $s_0$ [GSV,male] | 1.88E+02 | 10.7 | $r_{sel}$[Win,GSV] | 2.40E+01 | 79400.5 |
| $q_E$[SG,HNtarget] | 3.72E-04 | 9.1 | $l_{9550}$[DNrec] | 4.55E+01 | 22.4 |
| $q_E$[SG,HNnon-target] | 1.50E-04 | 9.6 | $l_{95}$[DNrec] | 3.27E+02 | 5.6 |
| $q_E$[SG,DN] | 5.49E-04 | 22.2 | $l_{50}$[HN,Win,SG] | 2.32E+02 | 0.6 |
| $q_E$[SG,Recreational] | 1.18E-06 | 22.1 | $l_{50}$[HN,Win,GSV] | 2.30E+02 | 5.9 |
| $q_E$[GSV,HNtarget] | 3.92E-04 | 10.9 | $s_{yx}$[Sum,male] | 5.50E-01 | 11.7 |
| $q_E$[GSV,HNnon-target] | 1.54E-04 | 10.8 | $s_{yx}$[Win,female] | 9.24E-01 | 5.4 |
| $q_E$[GSV,DN] | 8.32E-04 | 26.2 | $s_{yx}$[Win,male] | 2.05E+00 | 12.1 |
| $q_E$[GSV,Recreational] | 3.67E-06 | 25.9 | $s_{rec}$[Win] | 2.10E-01 | 7.8 |
| $s_{Cw}$ | 2.78E-01 | 4.2 | $s_{mp}$ | 2.65E+01 | 6.3 |

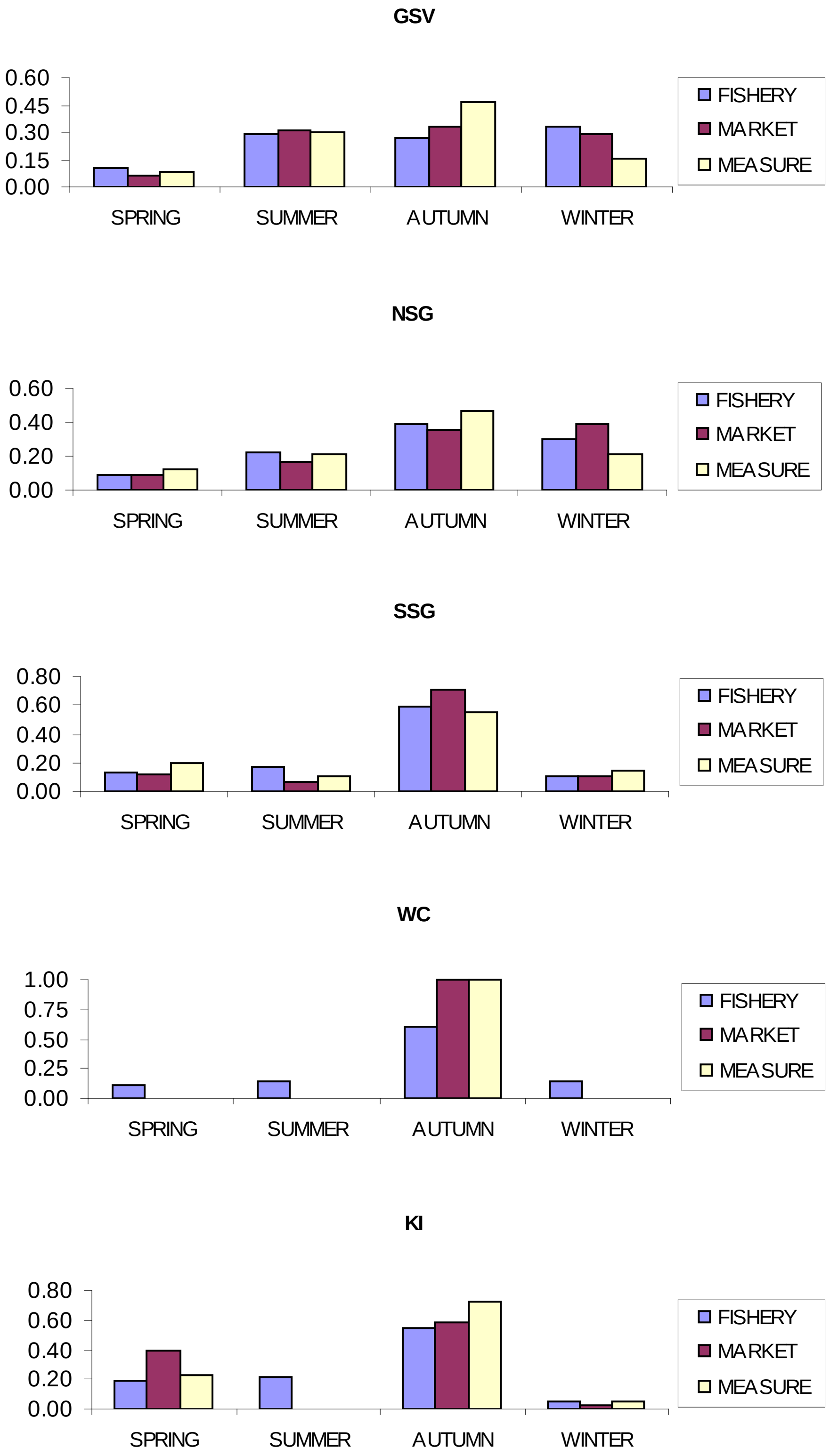



Figure 1.1. Sample sizes of market length sampling compared with the reported catch totals, for five subregions of South Australia and four seasons. (Reprinted, by permission, from Ye et al. 2002.)

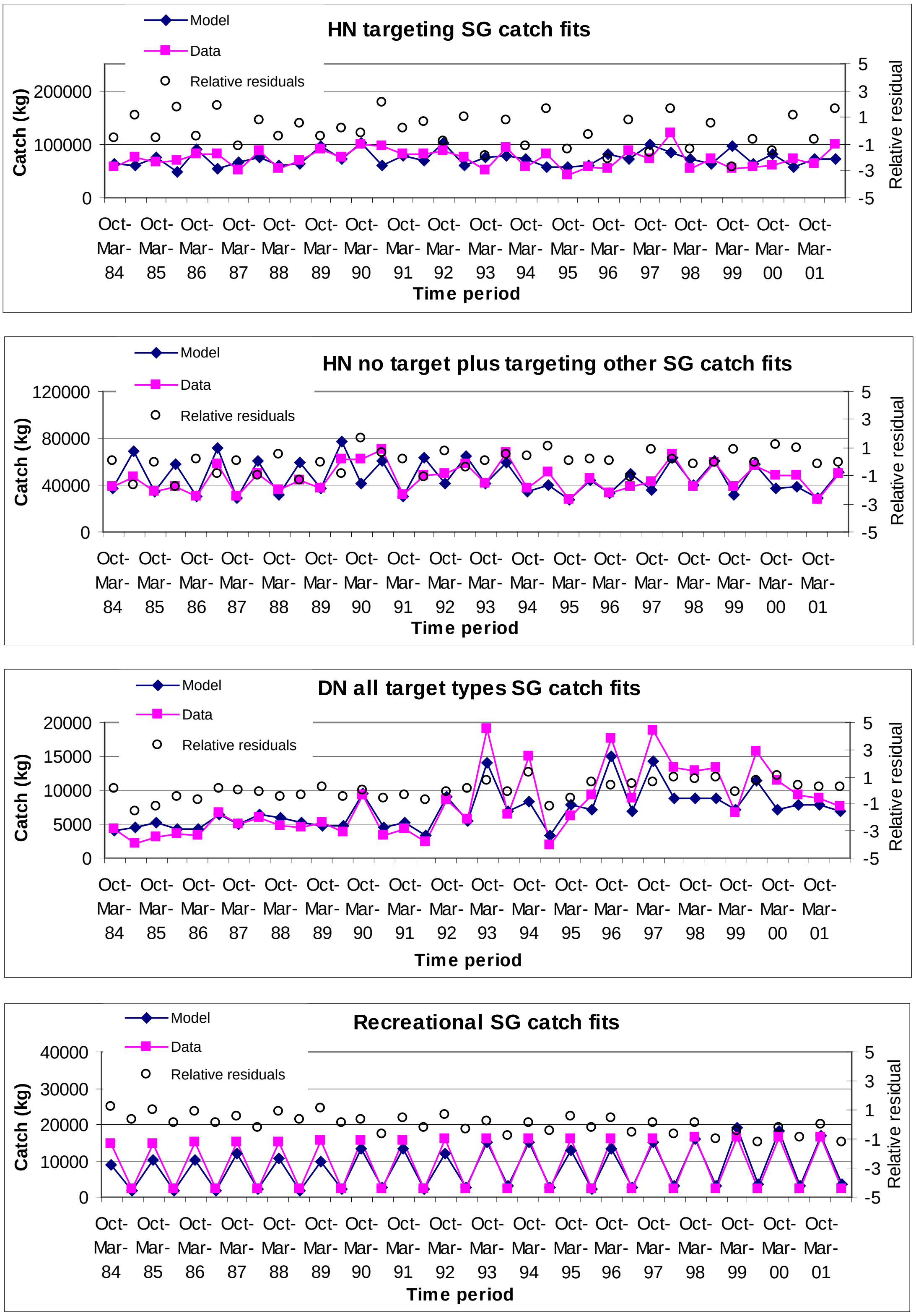



Figure 1.2a. Fits to half-yearly catch totals by weight in Spencer Gulf (SG) for four effort types. HN = Haul nets, DN = Dab nets.

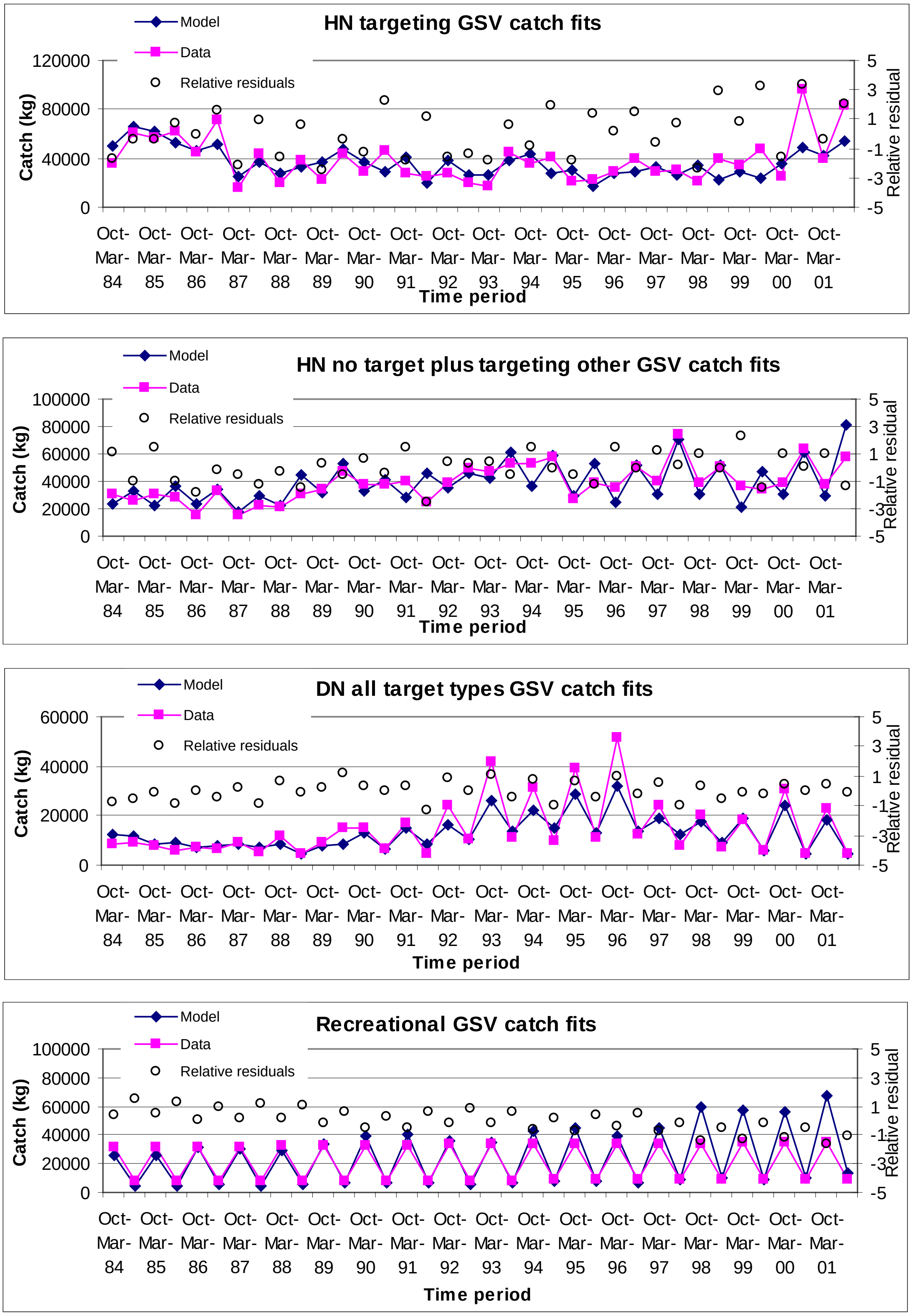



Figure 1.2b. Fits to half-yearly catch totals by weight in Gulf St.Vincent (GSV) for four effort types. HN = Haul nets, DN = Dab nets.

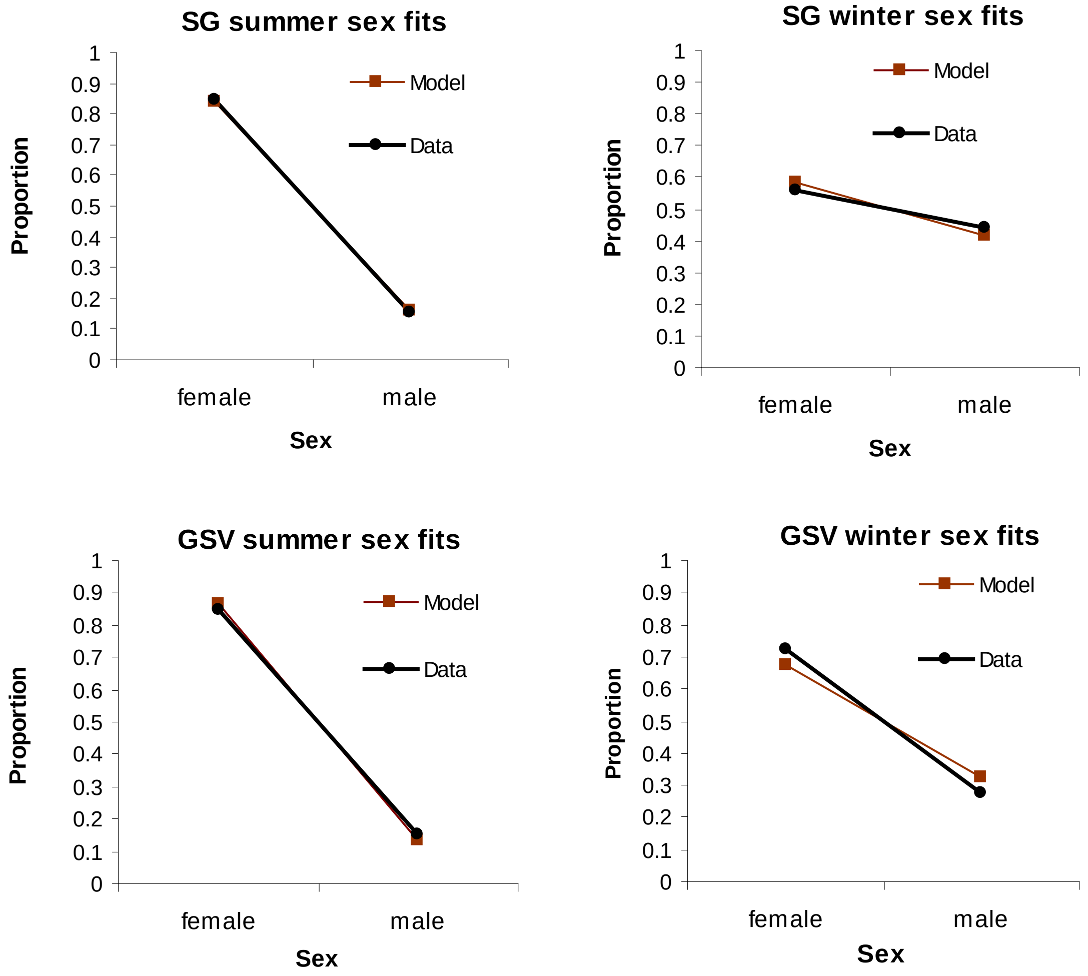



Figure 1.3. Catch-by-sex Haul net fits. The bars are model estimated catch proportions by sex for two model time steps fitted to the single data sample from each half-year (model $t$ = 29 for summer, and model $t$ = 30 for winter). SG = Spencer Gulf, GSV = Gulf St.Vincent.

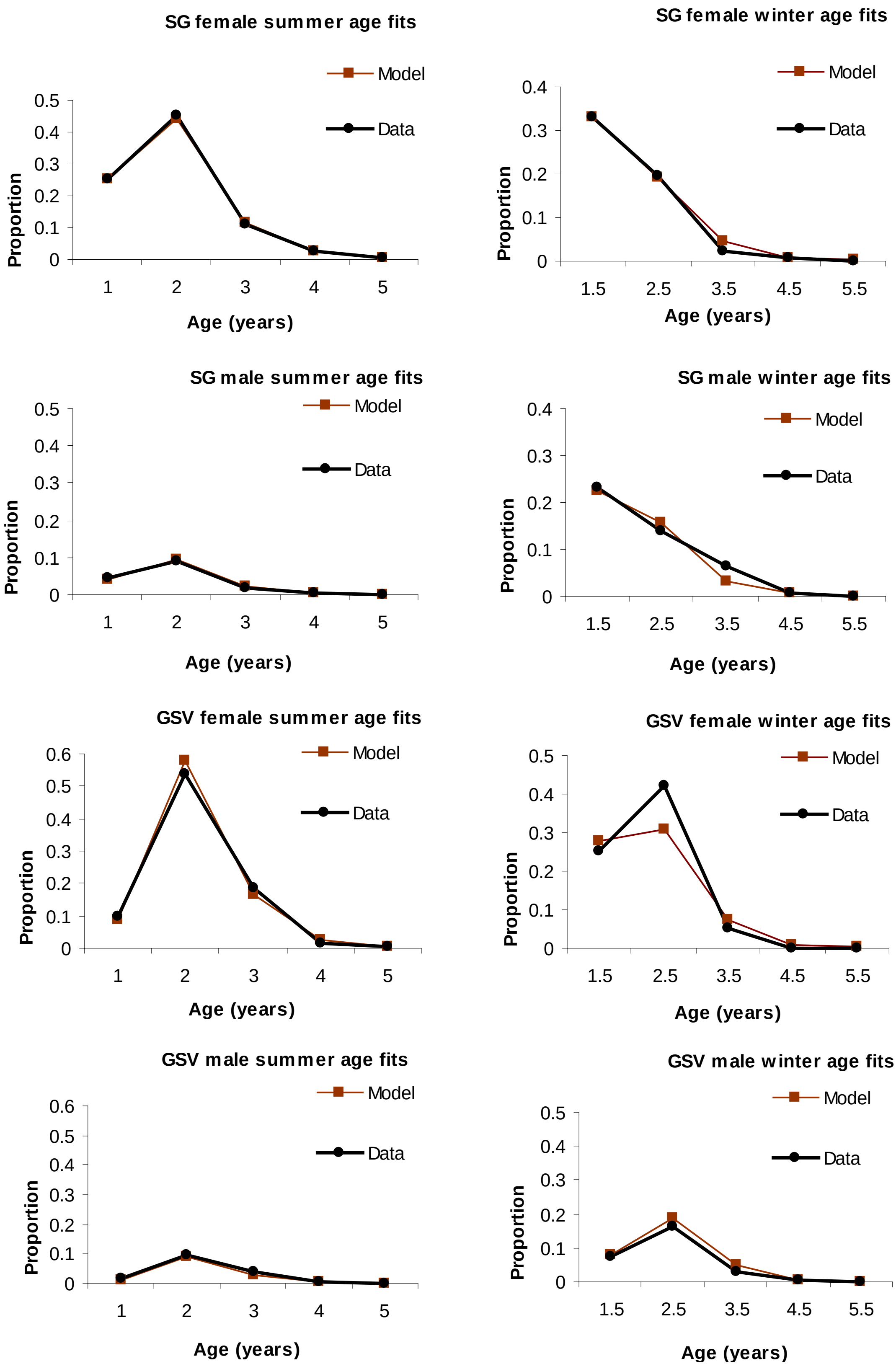



Figure 1.4. Catch-at-age Haul net fits. Model time steps denoted in legend as in Figure 1.3. SG = Spencer Gulf, GSV = Gulf St.Vincent.

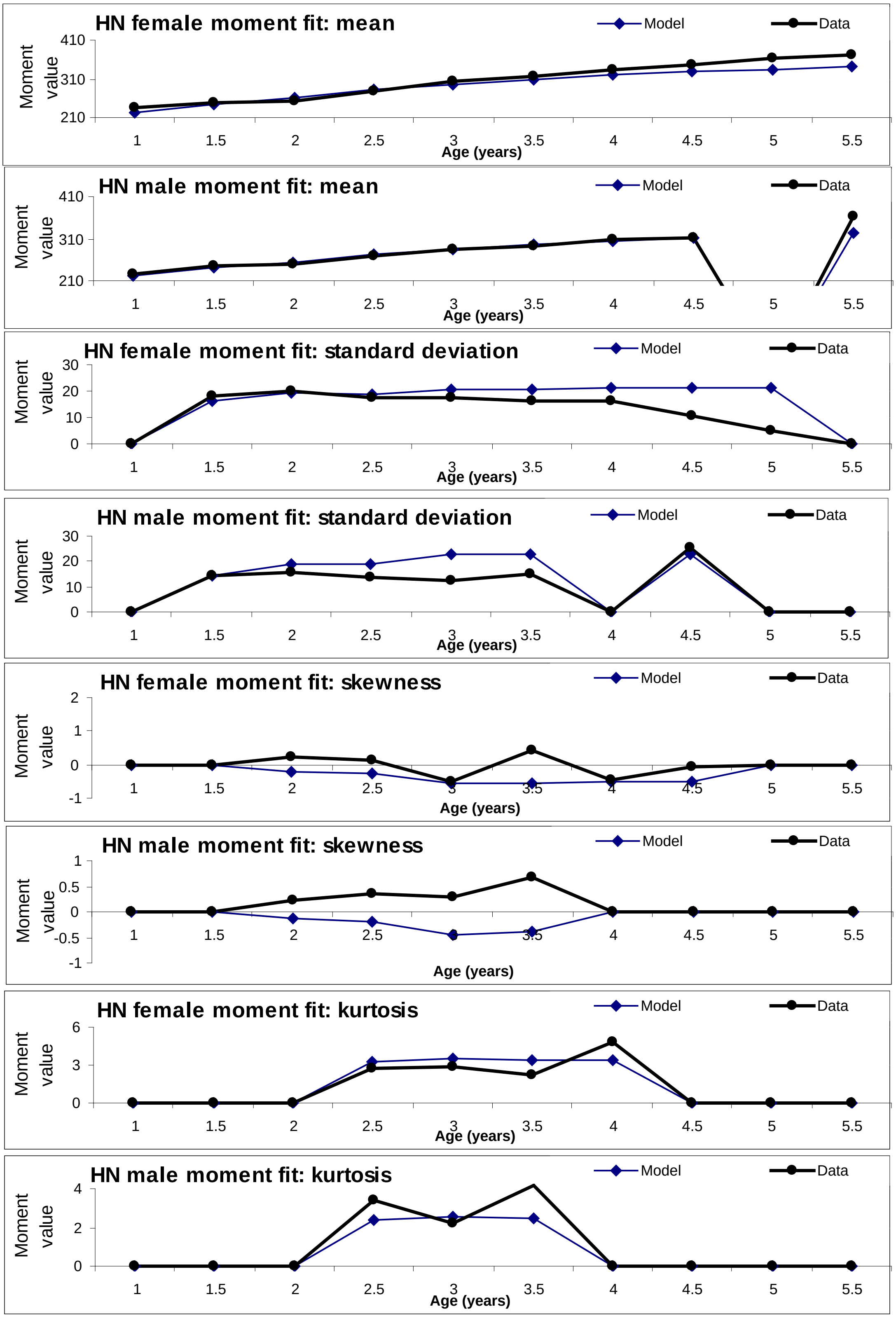



Figure 1.5a. Moment fits for Spencer Gulf gear type = Haul nets (HN).

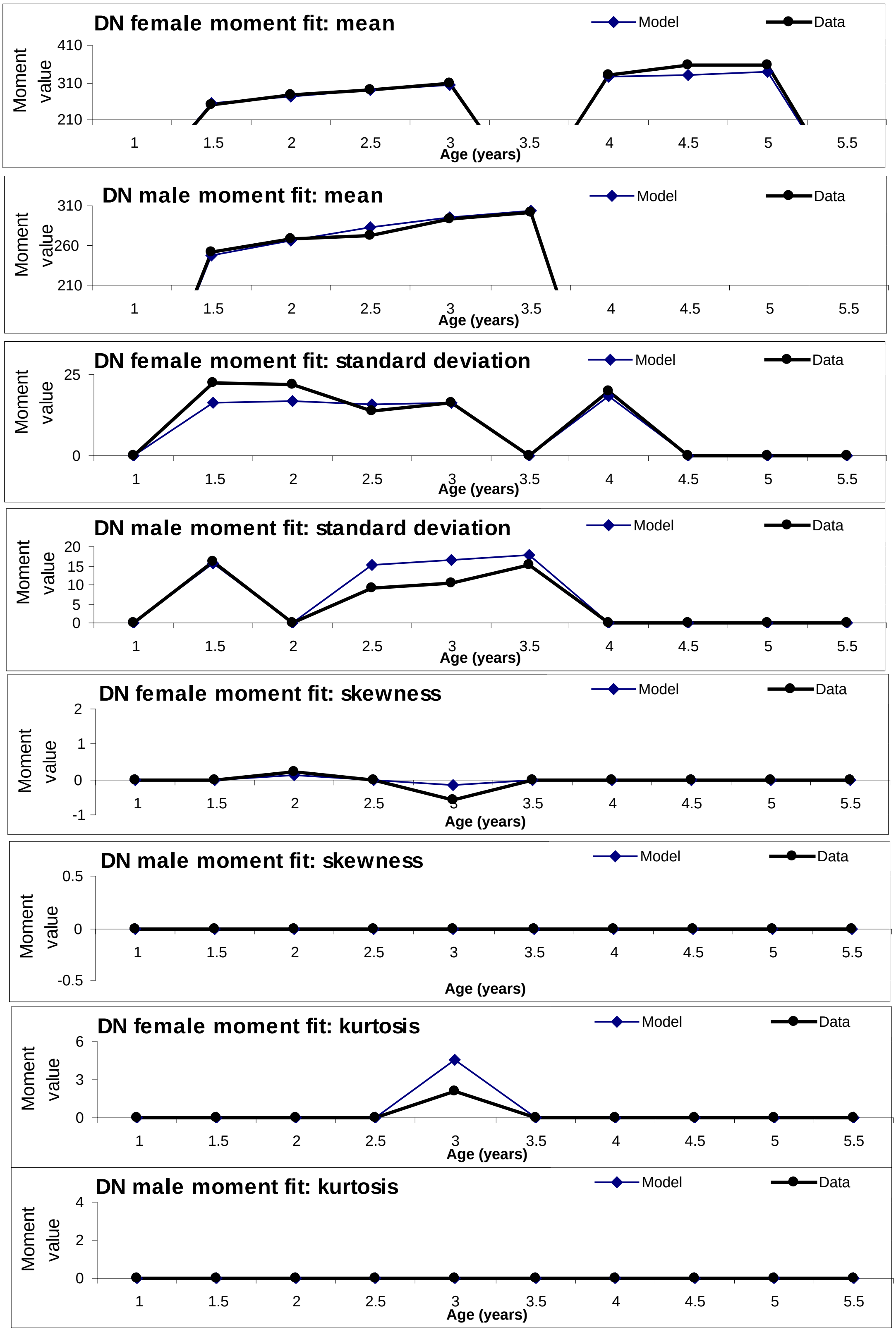



Figure 1.5b. Moment fits for Spencer Gulf gear type = Dab nets (DN).

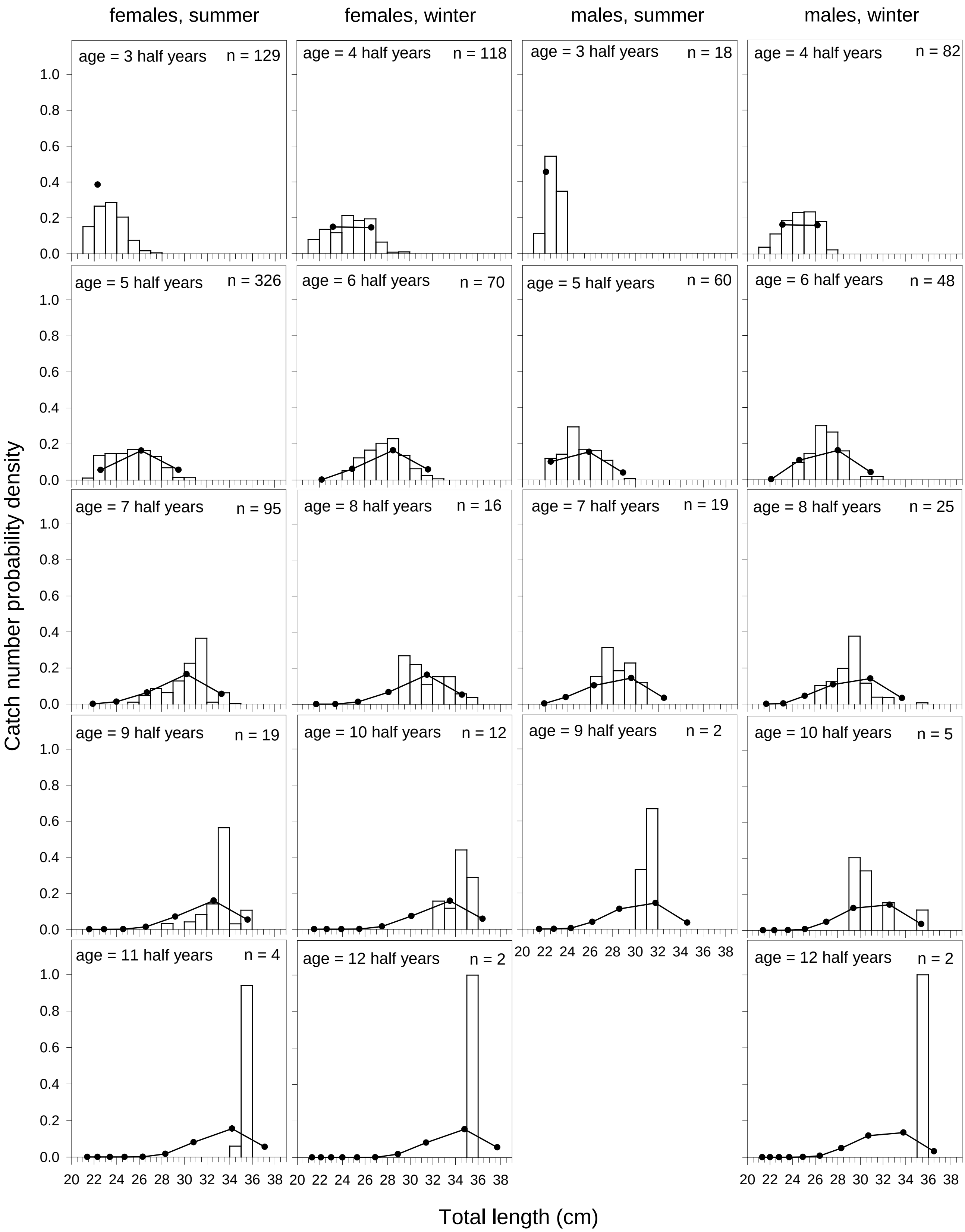



Figure 1.6a. Comparisons of data and model haul net length frequencies: Spencer Gulf. Both data numbers sampled per 1 cm length bin (bars) and model numbers per slice (line and points) are scaled as probability densities, i.e. proportions captured per unit total length.

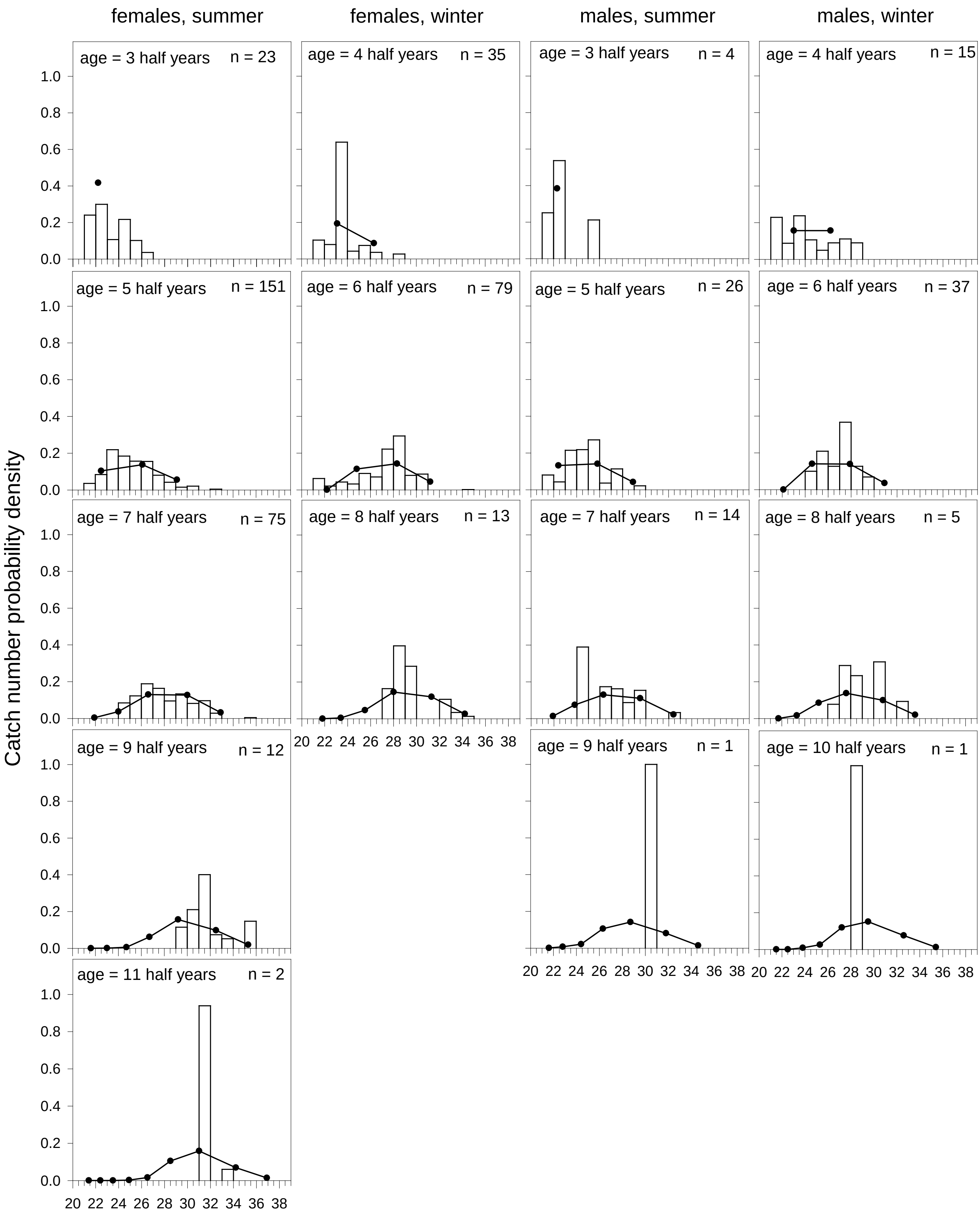



Figure 1.6b. Comparisons of data and model haul net length frequencies: Gulf St.Vincent. Data (bars) and model (lines and points) frequencies scaled as probability densities, as in Figure 1.6a.

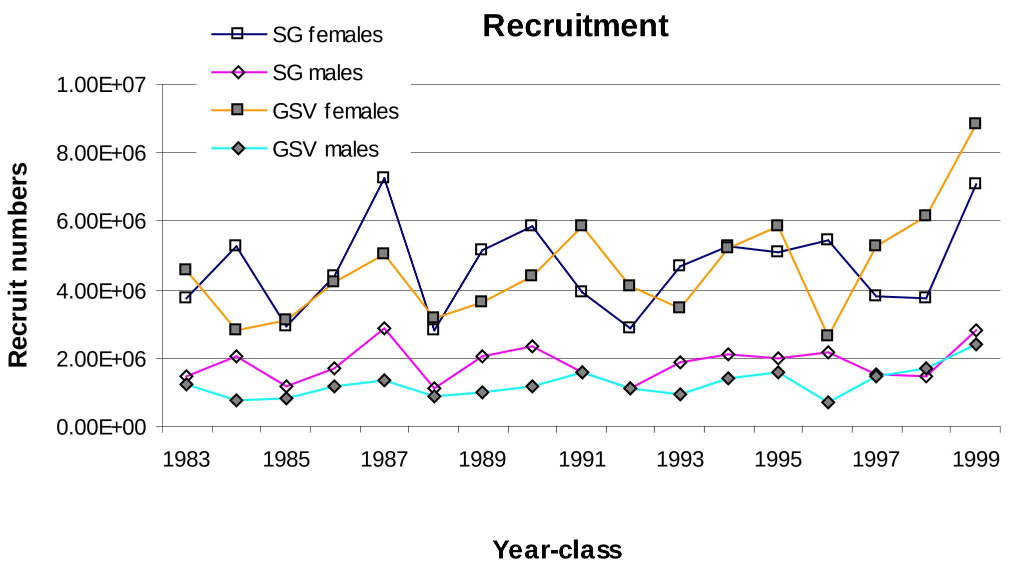



Figure 1.7. Estimated recruitment numbers, by cohort year spawned, for the two regions and sexes. SG = Spencer Gulf, GSV = Gulf St.Vincent.

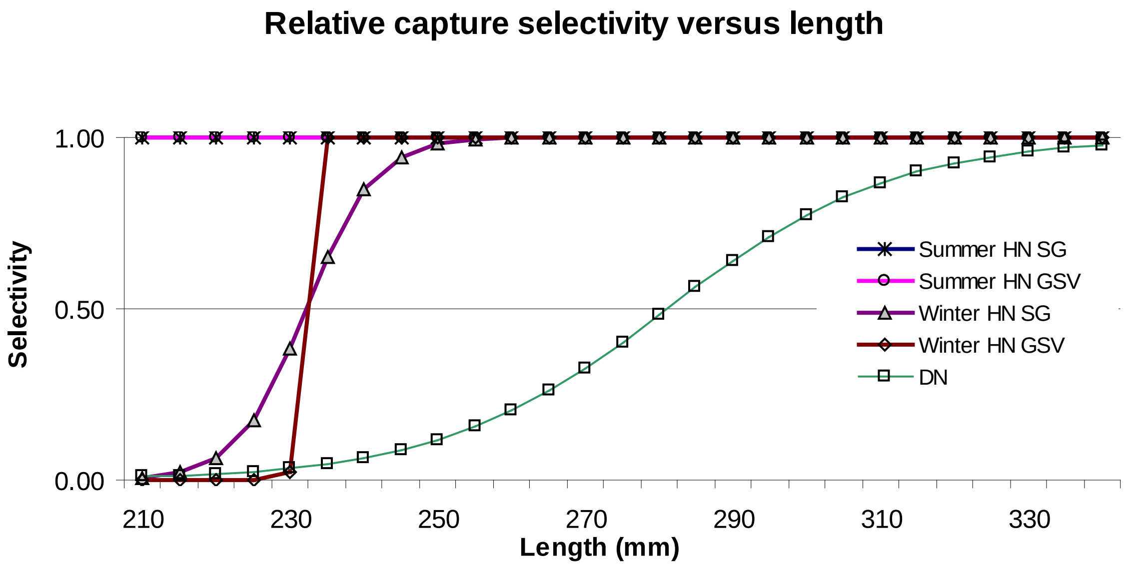



Figure 1.8. Estimated logistic length selectivity curves. SG = Spencer Gulf, GSV = Gulf St.Vincent, HN = Haul nets, DN = Dab nets.

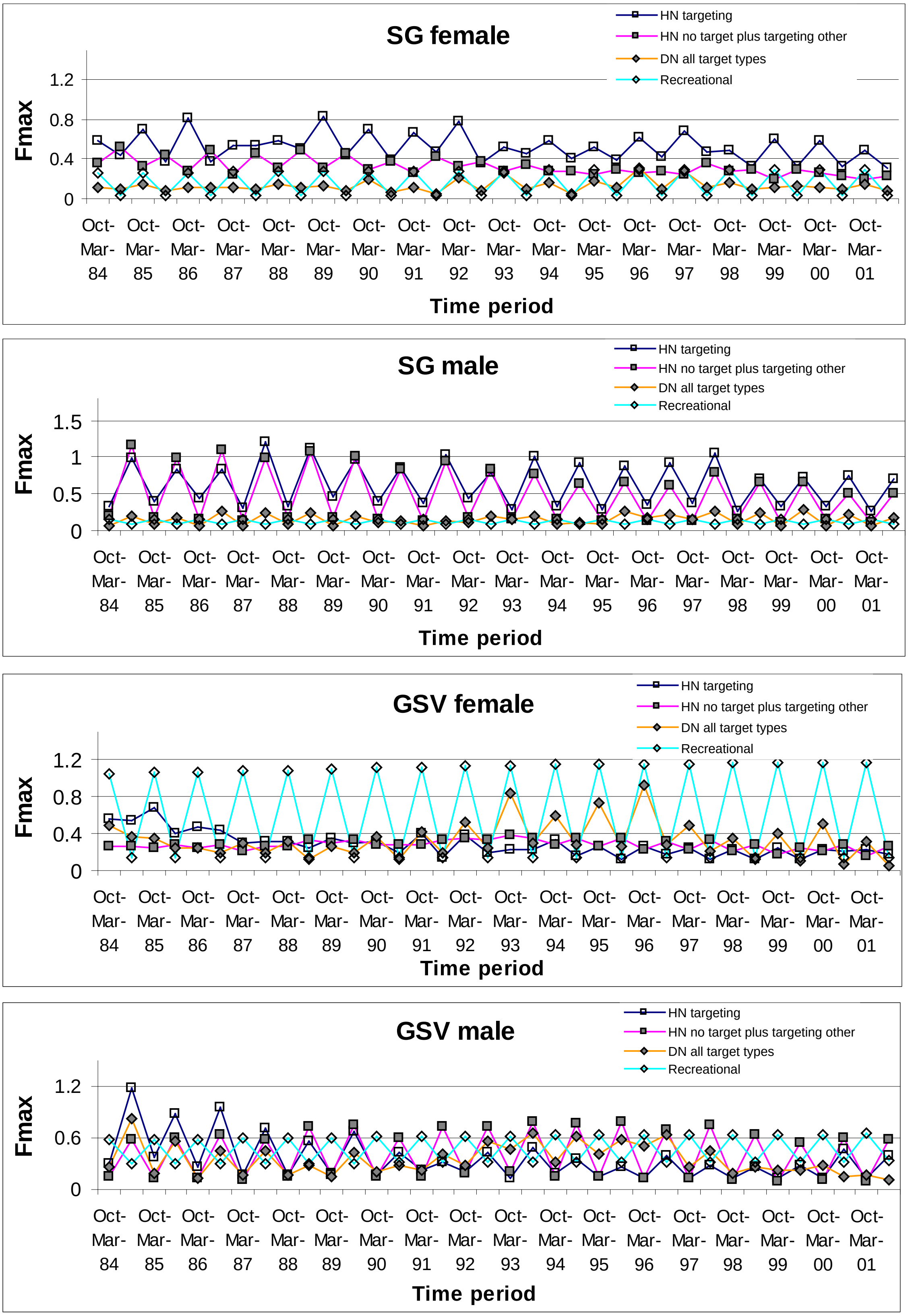



Figure 1.9.  Maximum (i.e. at large garfish size) fishing mortality rates.

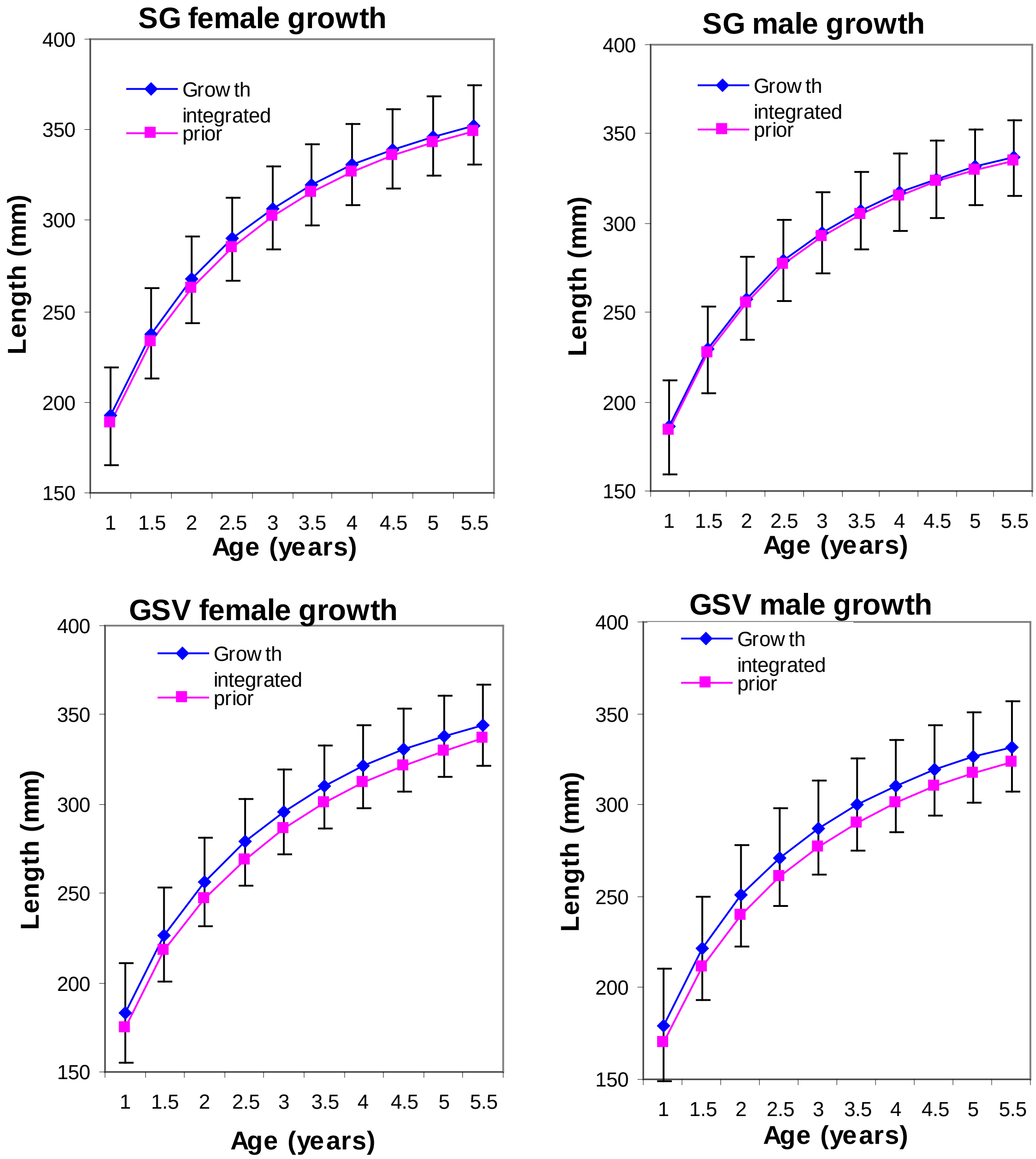



Figure 1.10. Estimated South Australian garfish mean lengths-at-age. 'Prior' were from fits to raw reported catch lengths-at-age externally, prior to integrating growth into the overall estimation. 'Growth integrated' are the current estimates with growth integrated into the stock assessment model presented in this report. Error bars are standard deviations showing the spread of observed lengths-at-age, estimated from the model likelihood $s_1$ and $s_0$ parameters in the growth-integrated estimation. SG = Spencer Gulf, GSV = Gulf St.Vincent

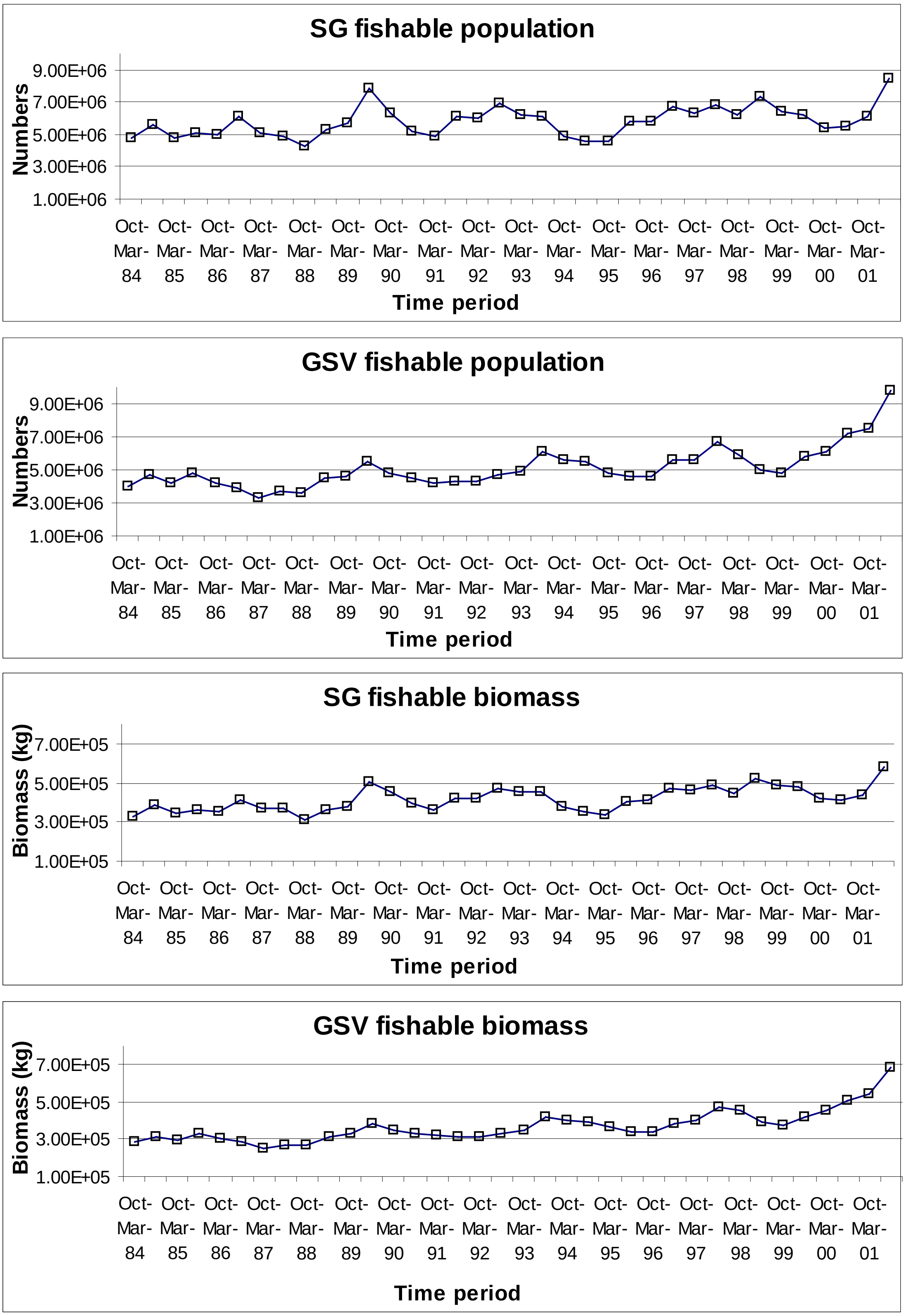
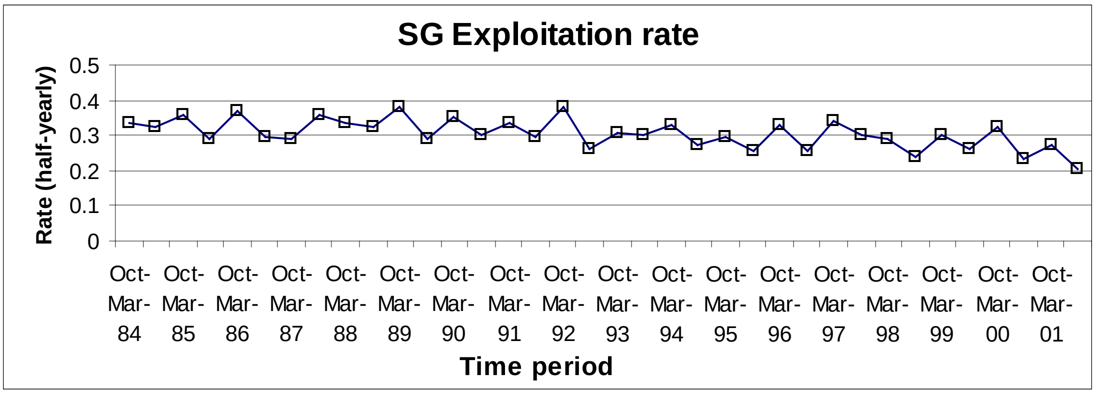



Figure 1.11. Yearly indicators of stock abundance, as fishable (>= LML) biomass and population numbers in the two gulfs. SG = Spencer Gulf, GSV = Gulf St.Vincent.



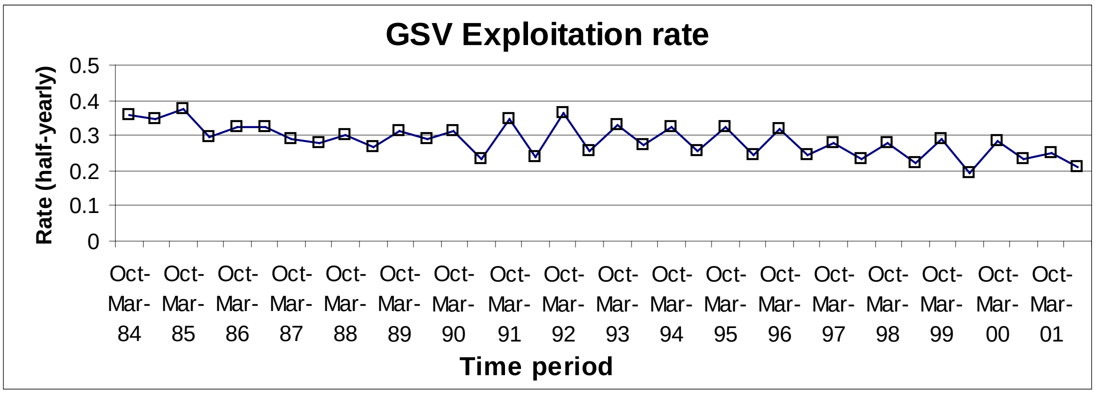




Figure 1.12. Garfish half-yearly exploitation rates for the two gulf fisheries. Exploitation rate is the proportion of fish harvested by all gear types, of those present at the start of each half-yearly model time step.

# Appendix 1.1. Comments on ‘Garfish stock assessment model: Generalizations and modifications from King George whiting” by Richard McGarvey and John E. Feenstra

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(14 August 2002)

*14 Sep 02, Responses by Rick McGarvey, Project PI, and John Feenstra, model development programmer and will appear in italics below. The discussions with Dr Punt have been very valuable over the life of this project. The text discussed is now incorporated as Chapter .*

I have divided my comments on this document into “data”, “model”, “likelihood”, “results” and “future work”. In general, my feeling is that the work conducted to date will provide a defensible framework within which assessments could be conducted for several data-poor species. The use of the ADMB framework should allow rapid and robust parameter estimation and the basic modelling approach seems sufficiently flexible that it should be possible to tailor it to other situations relatively rapidly. I use the (page: paragraph) format to identify my comments in the text. Having commented on the basic methodology several times in the past, my focus for the current review is on the results.

## 1. Comments: Data-related

A) (5:2) should indicate which data are available (and are fitted) by gear-type.
*This is now included in the text.*

B) The “correction” of the age samples by scaling the data for individual fish by the relative probability of their having being sampled provides unbiased estimates of the data on which the model is fitted. However, it is not clear what this process does to the effective sample sizes assumed when fitting the population dynamics model because the data for some individuals are presumably scaled up substantially more than those for other individuals. It would have been useful to have seen a histogram of the relative scaling factors for each fish.
*Plotting histogram of correction factors is a good idea. It is now completed. As expected, the larger/older fish were over-sampled, in some ages, by a large margin.*

C) Further to B), a figure showing the distribution of the values for the $f_S[p,m|t,y_{1/2}]$ and the length-frequency histograms based on the raw and corrected data would help a reader / user understand the impact of the algorithm used to correct for non-random sampling. Given the comments in the text, my guess is that the impact of the $f_S[p,m|t,y_{1/2}]$ factors should be relatively small.

*Yes, Qifeng Ye's garfish sampling by length was representative for most ages of garfish. Only for larger/older ranges of length/age is there an essential need for correction. But as noted in Chapter 1 Discussion, the doubling or tripling the numbers of garfish subsampled for ageing above a pure representative proportion (of 15%) should substantially improve the quality of the overall stock assessment because these older ages contain richer information, perhaps much richer, about mortality and thus also about total stock abundance. Moreover, for other fish stocks in SA, representative sampling has not been achieved.*

*This method of correcting for non-representative subsampling is newly developed in this project, and may find wider application than the two models (garfish and snapper) developed here—non-representative subsampling of fish for ageing from a representative sample of the catch is certainly not uncommon in stock assessment data sets. With these, a correction procedure like the one we present could be of value. This method requires length samples that were representatively sampled from the catch (from which the fish to be aged are subsampled). In practice, the 'subsampling' is often not undertaken with formal survey protocol, but, as often occurs, the fish to be aged are obtained opportunistically. The 'subsampling' in this case is post-facto, i.e. it can be done by modellers given two data sets, one of representative lengths, and another of fish that were aged and whose lengths were also measured.*

D) (10:1) refers to an edge effect. This is the impact of having data for only a short period of years on the behaviour of the model. This effect was noticed for the assessment of King George Whiting. The solution to this problem is to assume that the same age-, sex-, and length-distributions applied for the last four full years of the model fit (October 1997 – September 1998). However, this will bias the estimates of year-class strength. The sensitivity of the assessment results (in particular the estimates of recruitment) to assuming that the age-, sex-, and length-data apply to the period over which they were actually sampled needs to be examined.

*In response to this suggestion, we fitted the age, sex, and length samples to just one year, rather than fitting all of the last four modelled years to the one year of data samples. This suggestion of Dr Punt has resulted in a significant model improvement—no edge effect was, in fact, observed, and the outputs appear more qualitatively realistic.*

E) The moments (Equation 1.15) are computed for both (targeted?) haul net catches and dab net catches. This raises two questions: (1) what about the other two gears (selectivity parameters are estimated for these gears but I don't see that there are any length-frequency data to estimate such parameters), and (2) if data are available to apply Equation (1.15) why were data not available to apply Equation (1.13)? It would seem both equations rely on $f^{-1}_{S\&SS}[y,r,x,a,l,g]$.

*There are three gear types (haul net, dab net, and recreational hook and line). Length moments were fitted for haul net and dab net. Data from recreational catches were not available for either Equation (1.13) or Equation (1.15). Instead we assumed* *the same length selectivity for recreational catches as that estimated for dab net. Both recreational and dab net catch much larger garfish and are relatively minor percentage of total catch, compared to haul net.*

## 2. Comments: Model-related

A) A rationale for the "slice-growth" approach is that "most models fitted to age data consider recruitment of each cohort happening all at once". This isn't totally correct. What is correct, and which the 'slice-growth' approach overcomes, is that most models assume that length-at-age and weight-at-age are independent of exploitation rate. Incidentally, models do exist in which each cohort is divided into "recruited" and "unrecruited" components (e.g. Punt 1999).

*Point taken. We didn't know about Dr. Punt's growth-group length- and age-based method until he came to consult on this project. His 'growth groups', and our 'length-slices' were independently developed. Both are a way to divide up the length-at-age cohort into length bins. Each of Dr Punt's growth groups has a separate K and $L_\infty$, while our 'length-slices' are derived by numerically integrating over length subintervals of each cohort length-at-age distribution. The length-slice approach requires just a single set of growth parameters (including K and $L_\infty$) and two associated parameters that describe the standard deviation of lengths at age. The slice-growth could be considered less avant-garde, providing a more conservative extension of the standard age-based approaches. It is more conservative in that all the quantities for each slice (mean weight, slice bin boundaries, etc.) are defined formally as integrals over a single length-at-age distribution. Further study comparing these two approaches for length- and age-based fishery models would probably be worthwhile. Dr Punt has noted that the two methods are otherwise quite similar. Both partition each recruitment year class into length bins, and both make the simplifying assumption that there is no movement of fish between these (growth-variable) length bins due to variation in growth.*

B) (4:1) argues that the use of 'slice-growth' should lead to "more accurate" estimates of recruitment. However, I see no justification for this statement (see suggestions for future work under section 5).

*We certainly maintain that this approach for age- and length-based modelling is a substantial improvement over standard age-only based models which are still widely used in Australia and New Zealand. This is for three reasons: A purely age-based model does assume a single time, namely at the start of a (usually yearly) model time step, when all the fish of that year class recruit. A slice model makes explicit the arrival of each length 'slice' of fish growing into legal size in each model time step. Secondly, we can accommodate the changing shape of the length-at-age distribution due to larger fish entering the fishery and then experiencing higher mortality sooner. This eliminates 'right-hand (i.e. faster growing fish) asymmetric mortality bias' in estimating growth. Third, this approach can handle length-dependent processes (besides recruitment) such as length selectivity and fitting to length frequency data.*

*However, all of these advantages can be achieved by a growth groups method.*

*The added feature of the garfish model is the ability to fit to length frequencies for each age and sex individually, rather than to the sum of these. By keeping the data* *length samples distinct for each age and sex, the information obtained about length (notably growth) is not confounded by summing all ages and sexes together. In other words, by retaining information in the data about the mean length of each age (and for both sexes), we can fit to mean length-at-age in estimating the growth of the cohort. This latter feature is possible because of (and in model structure closely linked to) the correction for subsampling. It is achieved by taking each aged garfish as being representative of the subset, essentially a stratum, of the catch of fish.*

*We would argue that this should, in most cases, result in a higher quality of information from the length- and age data samples being fitted. We would argue that aggregating over sex and age in each length bins throws away information, namely the individual mean lengths and standard deviations at age (also skewness and kurtosis) for each age and sex independently.*

*Nevertheless, this paragraph has been removed from the text.*

C) Descriptions of the 'growth groups' approach to allowing for variation in length-at-age and hence the impact of exploitation on average length- (and weight-) at-age are given in Punt *et al*. (2001a, 2001b, 2002).

*Yes, growth groups are an important alternative to the slice approach. See above.*

D) Only one parameter of the growth model, *K*, is treated as an estimable parameter during the non-linear minimization. The remaining parameters are set to values estimated externally to the model. It is not clear to me whether this is appropriate because the purpose of integrating the estimation of the parameters of the growth model is to correct for the effects of length-specific selectivity (in particular, the impact of fishing on the perceived value for $L_\infty$ - a parameter that is fixed). Conducting a sensitivity test in which *K* is fixed but $L_\infty$ is estimated would provide a means to examine this issue.

*OK. We undertook several combinations of this sensitivity test. The result suggests very modest sensitivity to freeing up $L_\infty$. When K was fixed at its freely estimated value and $L_\infty$ was freely estimated in its place, the estimated values of $L_\infty$ were nearly identical to the fixed values normally assumed, varying by 1 mm or less. The anti-correlation of K and $L_\infty$ when both were freely estimated was high (at around -0.98) as often occurs. Thus all suggests that allowing just one of these two to vary is advisable, and we have accordingly left the original situation as is, where only K is allowed to freely vary.*

E) The penalty function placed on the recruitment 'deviations' is equivalent to assuming a log-normal prior with standard deviation $1/\sqrt{2}$; it might be appropriate to state this explicitly. The estimated recruitments (Fig. 7) seem to vary less than would be expected given this (assumed) standard deviation.

*Good point. We have now removed this penalty function entirely. Fournier and others have included it in the past with data sets where recruitment was less well determined. We have found, by testing different levels of weighting on this penalty function, that for the garfish model, recruitment estimates are not sensitive to the amount of weighting we give to this penalty, and that, in fact, the estimates are almost identical when it was removed.*

F) What is the basis for assuming that $M$=0.4yr$^{-1}$ given that the data for Baird's Bay seem uninformative? Conducting sensitivity tests in which $M$ is fixed at alternative values would provide a means to assess the impact of an erroneous choice for $M$ for the baseline analysis.

*Yes, testing the sensitivity values of M is worthwhile. We tested assumed values of M = 0.55 and 0.7 as Jones et al (1990) had done. See Chapter 2.*

G) Several ways exist to calculate the "fully selected fishing mortality" (referred to in the report as the "maximum fishing mortality"). Shepherd (1983) outlines some of the problems associated with defining a measure of "overall" fishing mortality and provides two suggestions for how to define this in actual assessments.

H) Per recruit analysis is conducted. What wasn't clear to me was whether the per-recruit analysis was based on the 'slice-growth' model or some simpler model. Also, the description of the per-recruit calculations (21:2) does not specify how the multiple fleets were dealt with and which values for the "fully selected fishing mortalities" were applied to produce Figure 3.4. Figure 3.4 suggests that value per kg is not constant – however, no data are provided on what was assumed for value per kg.

*The per-recruit analysis described was integrated with the dynamic slice-growth model, as Dr Punt had intended to recommend. We acknowledge that the Methods for this per-recruit analysis were not sufficiently detailed in the draft report he read. This has now been elaborated considerably in the text.*

*We will place this material in Chapter 3 in order to separate the management relevant outcomes from the technical details of the garfish estimator presented in Chapter 1.*

# 3. Comments: Likelihood-related

A) A key element of the estimator is that the model is fitted to the first four (central) moments of the (catch) length-at-age distributions. This has been suggested in the past but, to my knowledge, it has not formed the basis for any actual assessments. The variances of the moments are defined by $\sigma_{imp}$, an estimable parameter of the model. However, a more appropriate way to weight the likelihood components would seem to be to use the analytical standard deviations for these moments (perhaps modified by an estimable parameter such as $\sigma_{imp}$ to deal with over-dispersion).

*While this remains a potential point of further analysis, we believe the 'natural' relative weightings of the four likelihood components are appropriate as given. Specifically, the mean length is an order of magnitude larger than the standard deviation, and, assuming residuals proportion to the magnitudes of each quantity, carries approximately an order of magnitude greater weighting in the model fit. The standard deviation of lengths is again, nearly an order of magnitude larger than skewness and kurtosis, and this is intuitively desirable since the spread of values contains more essential information about the length distribution than skewness and kurtosis. Skewness and kurtosis would be zero for a normal distribution, and the observed values in the garfish model were nearly zero for skewness and much smaller than standard deviation for kurtosis. Therefore these 'minor' properties of the distributions, with this weighting as it occurred in the model fits, seems about right.*

B) Equation 3.1 implies that the catch estimates for all eight "fleets" are equally reliable – is this a valid assumption?

*By eight fleets, Dr Punt refers to the two regions and four effort types. At an early stage of garfish model development, we did allow the four sigmas (by effort type only) in Eq (1.27) to vary freely. The model parameter set was subsequently reduced by combining the four sigmas into a single value as shown in (1.27).*

*We would argue that a single value has the advantage that catch/effort types with bigger catches overall, will tend to have bigger variations in magnitude from the predicted, and thus will carry more weight in the objective function and thereby in parameter estimates. This property is thought by us to be desirable because the effort types with larger catches (often one or more orders of magnitude) generally have more reliable information, in particular their catch rates are probably better indicators of abundance (just because they include the summed catches of many more individual fishers and fisher days).*

C) The introduction refers to your having adopted the "robustified" likelihoods of Fournier *et al*. for the age-composition data. However, Equation (1.28) is a standard multinomial distribution likelihood (note that the equation given is for the log-likelihood and not the negative log-likelihood).

*Yes, this sentence was mistakenly left in from previous drafts. In a previous version of the garfish model, we did use the Fournier catch-at-age likelihood formulation. It was shown, subsequently, to yield nearly identical estimates to the multinomial, and invoking Occam, we stuck with the simpler likelihood formulation. Mention of it has now been removed.*

D) The weighting of the age-composition likelihood (Equation (1.28)) involves $n_{x,a}^{cor}$. The average value of this quantity depends on the weighting scheme – furthermore, unlike the situation for Equations (1.27) and (1.29), there is no estimable weighting parameter associated with the age-composition likelihood. Sensitivity should be conducted to changing the emphasis placed on these data to see if the data are contradictory in any way.

*This point is well taken and once again, Dr Punt's insight has proved useful. This factor of* $n_{x,a}^{cor}$ *in the catch-at-age-and-sex multinomial likelihood was one aspect that we had not modified in implementing the oversampling correction method. We have now addressed this oversight. Specifically, we reweighted each of the corrected samples of catch-at-age-and-sex so that the sum of the corrected values equalled the original uncorrected sample size (i.e.* $n_{x,a}^{cor}$ *is now replaced with a new derived quantity* $n_{x,a}^{cor,B}$ *the total number of fished actually aged), for each half-year and region. As Dr Punt suggested, using the true sample size in the multinomial likelihood for catch-at-age-and-sex, gives the correct weighting for each term of log(proportion). This rescaling has no effect on any of the other uses for the catch samples, such as the moment fits, since this rescaling factor ('B', Eq. 1.14) cancels from these.*

E) The weighting scheme used to weight the moments seems arbitrary. Rather use the estimated variances of these moments (see 3.A above).

*See point 3.A above.*

## 4. Comments: Results-related

A) The results focus on only one case. The final report needs to examine the sensitivity of the results to some of the key assumptions (see points 1.D, 2.D, 2.F, 3.D, 4.C, 4.E, and 4.F).

*As Dr Punt suggests above, we have undertaken a wide range of sensitivity tests. Two of these are now reported in Chapter 2.*

B) It is noted (6:1) that constructing the model-predicted catch length-frequencies (by gear-type) is complicated. However, it would have been interesting to see the actual length-frequency distributions (after adjustment for sampling bias) plotted against the model estimates. This would not be used when fitting the model but rather as a diagnostic, computed once following parameter estimation.

*This theme was a dominant one in our discussions with André of this model. We take this opportunity to discuss the underlying issue of whether it is preferable to fit to the individual length samples by age and sex as we have done here, or as is more common, to fit to the aggregated length frequencies.*

*Though this remains a subject for further discussion, as general practice in stock assessment where individuals can be aged, we would argue that summing over age and sex in each length bin should not be done if it can be avoided. Rather, we argue that it is, in general, better to fit to the available length distributions individually, one for each sex and age class. There is considerable information about the most important length-dependent process, growth, in the lengths of individuals at each age which should not, if possible, be summed away.*

*The method we present here for garfish represents one way to achieve this estimation objective, of fitting to length samples that are age- and sex-specific.*

*It needs be stated, however, that this argument we make is not yet resolved, even in our own minds. The growth groups approach does fit to aggregated length frequencies, but also has the information on length distributions by age in the age-length key. Thus all the same information is being brought to bear in the two approaches, but in somewhat different ways.*

*Regarding Dr Punt's suggestion that we generate histograms like those more commonly seen, aggregated over sex and age, we have not had time to carry this out. We have, of course, presented the fits of the individual length distributions by age and sex individually (Figures 1.6a and 1.6b) which Dr Punt found useful and essential. For technical reasons involving the difficulty of summing the slice-partitioned lengths, producing these length frequency histograms aggregated over age and sex would be quite time-consuming.*

*The question arises about interpreting comparisons of model and data for the aggregated length-frequencies. If the fits we undertook to individual-age length distributions (Figure 1.6) were good, and closeness to the overall summed length frequency histogram suggested by Dr Punt were not, then we argue that our method* *should be preferred and that using the summed fit would have generated a less accurate estimation than the one we have produced here where the lengths of each age are fitted individually. Again, the basis for this conclusion is that the age-specific length fits should be the better of the two in describing the fishery population dynamics of growth. And we make this claim, in turn, assuming that some (unquantified amount of) information about dynamically changing length-at-age-and-sex is lost by summing over age and sex.*

C) The reason for the re-weighting system is (essentially) to allow inclusion of large animals that were not sampled randomly. It would have been interesting to see sensitivity tests in which only the randomly sampled data were used to estimate the parameters of the model. In principle, use of the whole data set should not impact the point estimates markedly but should improve the precision of the estimates (i.e. the bias of the estimates should not be impacted but the precision should be).

*We suspect it would be difficult to interpret whether the sensitivity-tested estimates of the model using the reduced randomly sampled data set of ages were less precise, though we would expect, because of the associated smaller sample size, that it would be as Dr Punt notes. Because it is not clear how the outcome of this test might guide future improvements in model structure, and again because of time constraints, we have set this aside for now.*

D) A table of parameter values (with their asymptotic variances and correlations) would help readers determine how many parameters are being estimated, the precision of the estimates, and which parameters are highly correlated. The latter could be used to suggest further model simplifications and alternative (more robust) parameterisations.

*This is another important suggestion of Dr Punt. We have undertaken examination of the correlations, both while Dr Punt was visiting and on previous occasions. Some parameters were seen to have been surplus and were fixed or removed.*

*A table with the parameter variances (asymptotic ) has been added in Chapter 1 (Table 1.8).*

E) Selectivity (catchability) is assumed to asymptotic. It might be appropriate to examine the sensitivity of the results (and fits) to assuming dome-shaped selectivity.

*We and Dr Punt have since discussed this. In the case of garfish, it is more likely that selectivity rises at larger sizes, rather than dropping off in a dome-shape, because the price for larger fish is much higher, as much as 5 times higher.*

F) Sex-specific average recruitment and sex-specific catchability are estimated. I would guess that these parameters are highly confounded. Would the results have changed markedly if only one of these quantities was assumed to be sex-specific?

*Originally, this model had only catchability as sex-specific. The introduction of the sex-specific recruitment substantially improved model fit, and yielded values that were quite a bit different from the standard assumed 50:50 recruitment sex ratio. Specifically, estimated female:male recruit proportions are 70:30 in Spencer Gulf and 74:26 in Gulf St.Vincent. These are relatively similar outcomes for two essentially* *independent models in the two gulfs, and the unexpectedly high proportion of females found in both would explain the substantial improvement in model fit, suggesting this effect is real. The model can be expected to differentiate such large differences of sex ratio in both catch vulnerability and recruitment, notably from the change in catch-proportions-by-sex from early ages, those just recruiting to the legal size of harvest, by comparison to sex ratios of catch of older fish. There is also large contrast in catchability by sex between summer and winter that would assist in this otherwise admittedly confounded inference.*

G) I found the diagnostic plots (Figures 2a and 2b; Figures 5a and 5b) difficult to follow (the figures are much too "cluttered"). Figures 1 and 2 of this review show an example of how diagnostics are computed for some other assessments[1]. Figure 1.4 would be enhanced by including some idea of the expected (based on the assumed sample sizes) variances to assess whether the fits are consistent with assumed error model.

*Dr Punt assisted us with new methods to interpret model diagnostics, including a series of diagnostic graphs that he programmed in S-Plus. We will use these here and probably for other models in the future.*

H) Skewness is argued to be close to zero (18:3). Doesn't this argue against the complexity associated with using the 'slice-growth' approach?

*Dr Punt is suggesting that since compensating for right-hand asymmetric mortality bias in growth is a principal stated objective of the full-scale length- and age-based approach we have adopted, that we should expect to see this effect of higher mortality on the faster growing fish cause the catch length distributions to be skewed.*

*Maybe. But of course it's hard to know what skewness should be or how big when this effect is acting and when it is not. Nevertheless it may be true that since the data distributions are not skewed, that this effect is small. The counter argument is that when skewness and kurtosis fits to lengths were removed from the log-likelihood, a sensitivity test that Dr. Punt helpfully recommended, removing the fit to observed skewness had the larger effect than kurtosis. This would imply that the fit to skewness does usefully influence model estimates.*

I) Estimates of variance are not supplied. This is a major weakness of the current presentation. A variety of ways of representing parameter uncertainty are available. At the simplest level, ADMB provides asymptotic variance estimates; while more complicated approaches such as bootstrapping and the application of Bayesian techniques may provide additional useful insights.

*This point is well taken. These asymptotic variance estimates are now provided in Table 1.8.*

[1] During my visit to SARDI, I developed an Splus script to plot a variety of diagnostics related to the fits to the catch-in-weight data. These revealed structure in the residuals when the data were disaggregated to season (summer and winter).

## 5. Comments: Future work

A) The methods developed in this project are all relatively new. An attempt should be made to test the estimation performance of these methods by means of Monte Carlo simulation. In the first instance, tests should be conducted by applying the model to deterministic data when the model used to generate the artificial data sets is the same as that underlying the estimator. Thereafter, the implications of uncertainty in the data (in particular that catch may be measured with less error than effort) should be considered. Finally, the implications of model error need to be examined (e.g. if the values for parameters considered fixed and known are set to incorrect values).

*Simulated data tests were undertaken at Dr Punt's suggestion. The deterministic data simulation tests showed very close agreement of 'true' simulation parameter values with the estimated parameters, to around 6 significant digits.*

B) The simulation analyses referred to above could also explicitly consider whether the statement (4:4) that using basing a model on 'slice-growth' increases the information content of the data.

*We interpret this to mean that if we claim the garfish modelling formalism gives a more accurate description of the population dynamics, that this claim should be tested with simulated data sets. At the present time we do not have access to alternative stock assessment estimation models, which also are fully length- and age-based, to compare ours to. But this remains listed for future work.*

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# CHAPTER 2. Garfish Model Performance Assessment

## Introduction

In this chapter we summarise two sensitivity analyses undertaken to assess the effect on model estimates of two model assumptions.

One potential source of bias in these model outputs is the possible increasing catching power of a given unit of commercial gear, over the time series of model estimation, namely since October 1983. It is generally supposed that the catchability of the gear, due to technological advances, has increased over time. Since commercial CPUE represents an essential source of information, in fact for garfish, the only information on temporal changes in stock size over time, it is worthwhile double-checking to see what effect any increases in the catching power of a unit of fishing effort would be likely to have on the model's estimates. Of principal interest is to assess the impact of rising effective effort on the estimated temporal, notably yearly, trend in population biomass. In this chapter we present the methods for testing (with simulated data sets) the effect on model outputs of a 1% yearly rising effective effort.

The second sensitivity analysis undertaken in this chapter is to the assumed level of natural mortality (*M*). Previous per-recruit stock assessment work on South Australian garfish (Jones et al. 1990) assumed a medium level of $M$ = 0.55, and tested for the sensitivity to values above and below of $M$ = 0.4 and 0.7. The model of Chapter 1 assumed a value at the low end of $M$ = 0.4. In this chapter we present the estimated values of biomass and exploitation rate assuming the other two values of Jones et al. (1990), namely M = 0.55 and 0.7.

## Methods

### Simulated Data Tests for Rising Effective Effort

The method is to create a fishery simulation that can generate simulated data sets for the model estimator to run, substituting the fake data for the real fishery data that the garfish stock assessment model would normally take as input. This simulated fishery adopted most of the same dynamics that have been modelled and programmed, in the stock assessment model (Chapter 1).

Mathematically the catching power of the gear is estimated and quantified by a set of parameters called 'catchability', one catchability parameter for each gear type. To simulate rising effective effort, a yearly rise in catchability of 1% per year, for all gear types, was programmed into the simulation. The mathematical form of this rising and thus time-dependent catchability ($q(t)$) is written:

$$q(t) = q_{est} \cdot \left[1 + q_t \left(t - t_{midpt}\right)\right].$$

The parameter specifying the rate of increase in catchability was set to be $q_t$ = 0.005, i.e. we simulate a rise of 0.5% per half-yearly model time step ($t$). The level of this increasing catchability time series will equal (pass through on its rise) the estimated catchability value from Chapter 1 of $q_{est}$ at $t_{midpt}$ = 19 half years.

Simulated data are then generated which come from this simulated fishery that we know has rising effective effort. Moreover, because it is a computer simulation, we know the 'true' values of population indicators that the estimator will seek to estimate, notably population biomass. The estimator of Chapter 1 is fitting to data from the simulated fishery so the 'true' parameter values the estimator is trying to estimate are the ones that have been programmed into the simulated fishery at the outset.

The simulated data were thus taken as input data and the fishery indicators (including biomass) were re-estimated using the regular garfish estimation model of Chapter 1. Thus the data came from the simulated fishery where effective effort was programmed to rise at 1% yearly. The biomass and other estimated quantities in this sensitivity analysis were outputs from a fit of the regular garfish model that we currently use (Chapter 1) which makes no assumption of increasing catchability over time. Thus, a formal assessment is presented of the bias in the estimates of population biomass that a 1% rising effective effort would induce.

### Sensitivity Analysis for Three Levels of Natural Mortality ($M$)

The method for testing the sensitivity of different assumed levels of natural mortality ($M$) is simpler than for rising effective effort. We ran the full garfish stock assessment estimation of Chapter 1 with the two additional possible values for $M$ that we seek to test, namely $M$ = 0.55 and 0.7. The estimated time series results for biomass and exploitation rate under all three assumed values of $M$ are plotted for comparison.

## Results

### Simulated Data Tests for Rising Effective Effort

***Recruitment***

Garfish model recruitment appears to be highly robust with respect to rising effective effort. The model yearly recruit numbers differed negligibly from the simulated 'true' numbers that the model sought to estimate. Average estimated recruit numbers were about 0.5% lower than 'true' for females and about 7% higher for males; these percentages being virtually the same in both gulfs.

***Per-recruit analyses***

Yield-per-recruit and value-per-recruit would have been about 2% and 1.5% respectively underestimated if effective effort has been rising at 1% per year. Egg-per-recruit showed a similarly small bias of about 2% overestimation.

***Legal size population biomass***
A rising effective effort when, as in most fisheries, it cannot be estimated will cause an observed rising CPUE to imply a more rapidly rising biomass than is occurring in the real population. This effect is observed in the simulation tests (Figure 2.1), but it is relatively small, and the estimated biomass tracks the 'true' biomass relatively closely despite a 1% rising effective effort in the 'true' simulated fishery.

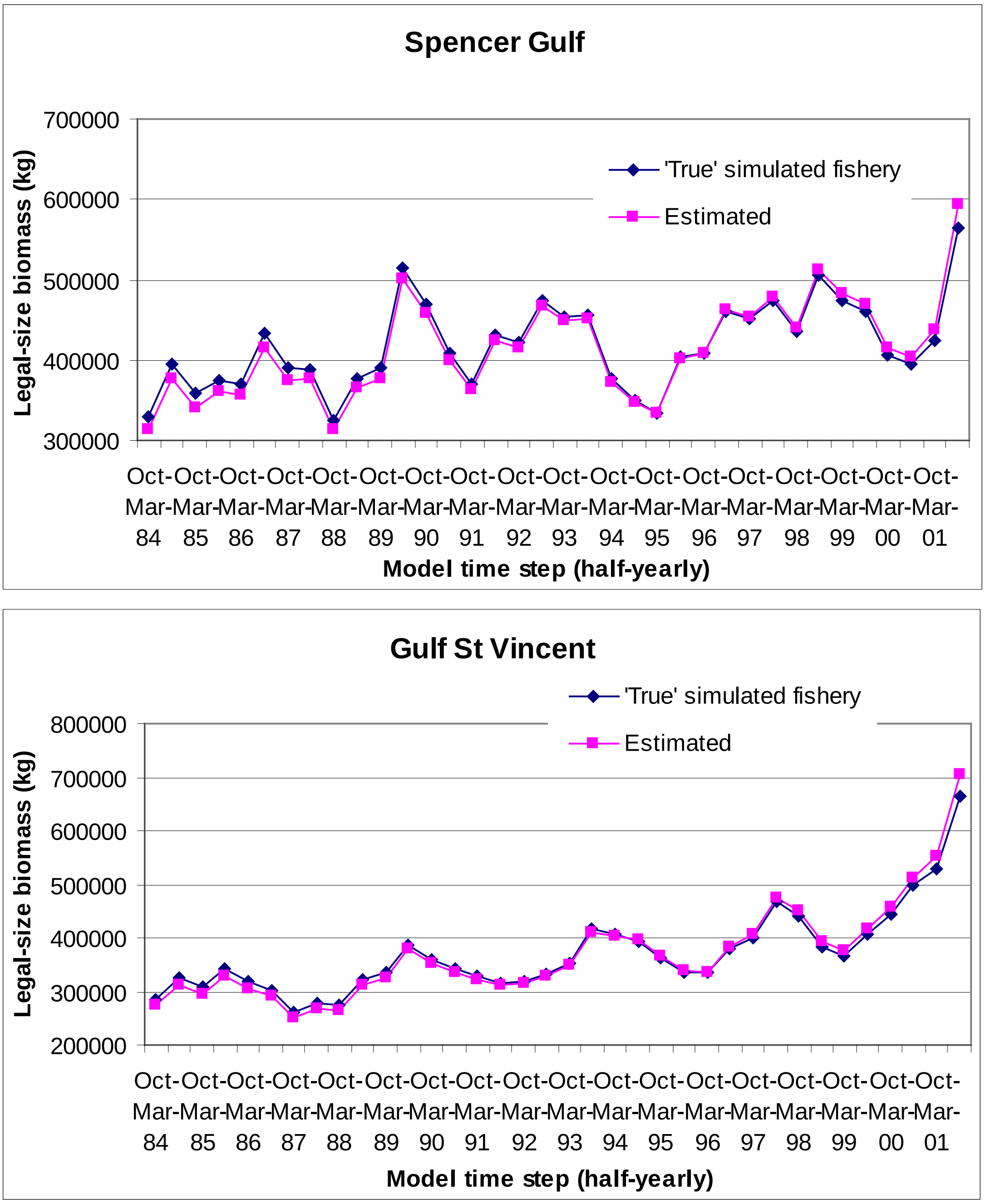



Figure 2.1. Comparisons of garfish model estimates of legal size biomass versus the 'true' levels of biomass from the rising effective effort fishery simulation. (For actual estimates of semi-yearly garfish biomass, see Figure 1.11).

A different plot of these results (Figure 2.2) shows that the bias induced by rising effective effort is relatively small. In Figure 2.2, perfect agreement between estimated biomass and the 'true' simulation biomass is given when those plotted ratios equal a value of 1. Specifically, the proportional bias in biomass (plotted as the 'ratio' of estimated over 'true') induced by rising effective effort, is considerably less than the proportional error in the estimated catchability over the 'true' and rising level of catchability in the simulated fishery itself. Thus to this extent, by comparison to catchability, biomass deviates relatively weakly from its true value when effective effort is modelled to rise over time.

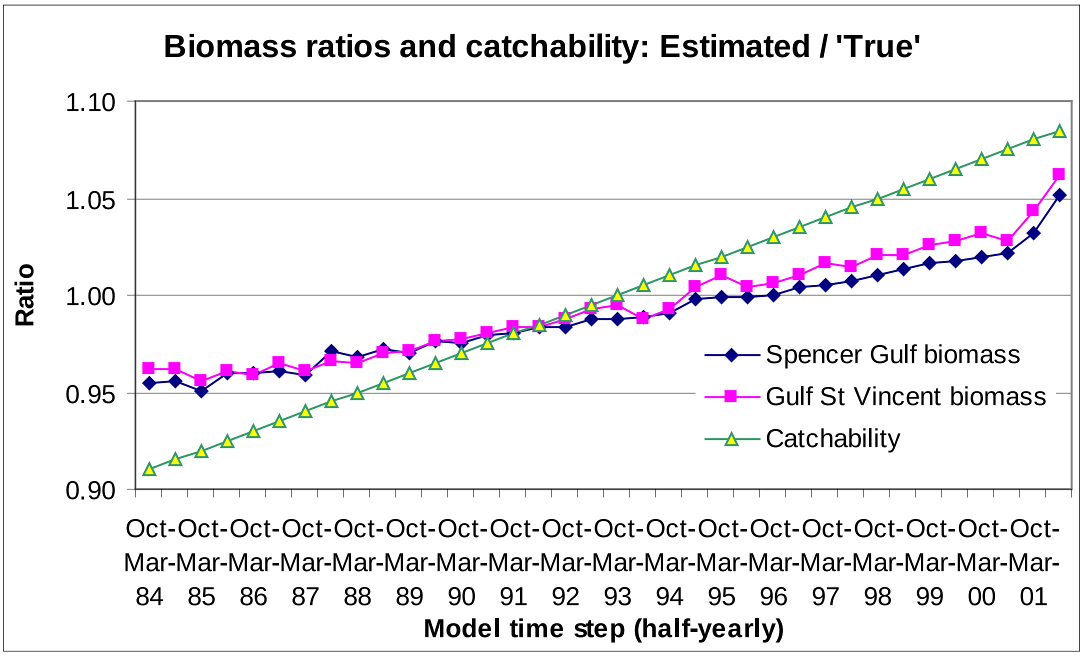



Figure 2.2. Time-varying ratio of the garfish model estimates of legal size biomass over the 'true' levels of legal size biomass from the fishery simulation. Also plotted is the rate of rising catchability in the simulated fishery $\left[1+q_t\left(t-t_{midpt}\right)\right]$.

### *Exploitation Rate*

The effect of rising effective effort on estimates of exploitation rate is similar in magnitude to that of biomass (Figure 2.3), but acts in the inverse direction. Thus (Figure 2.4), a rising effective effort will cause exploitation rate to be overestimated in the early years of the model time, and underestimated in the recently modelled years.

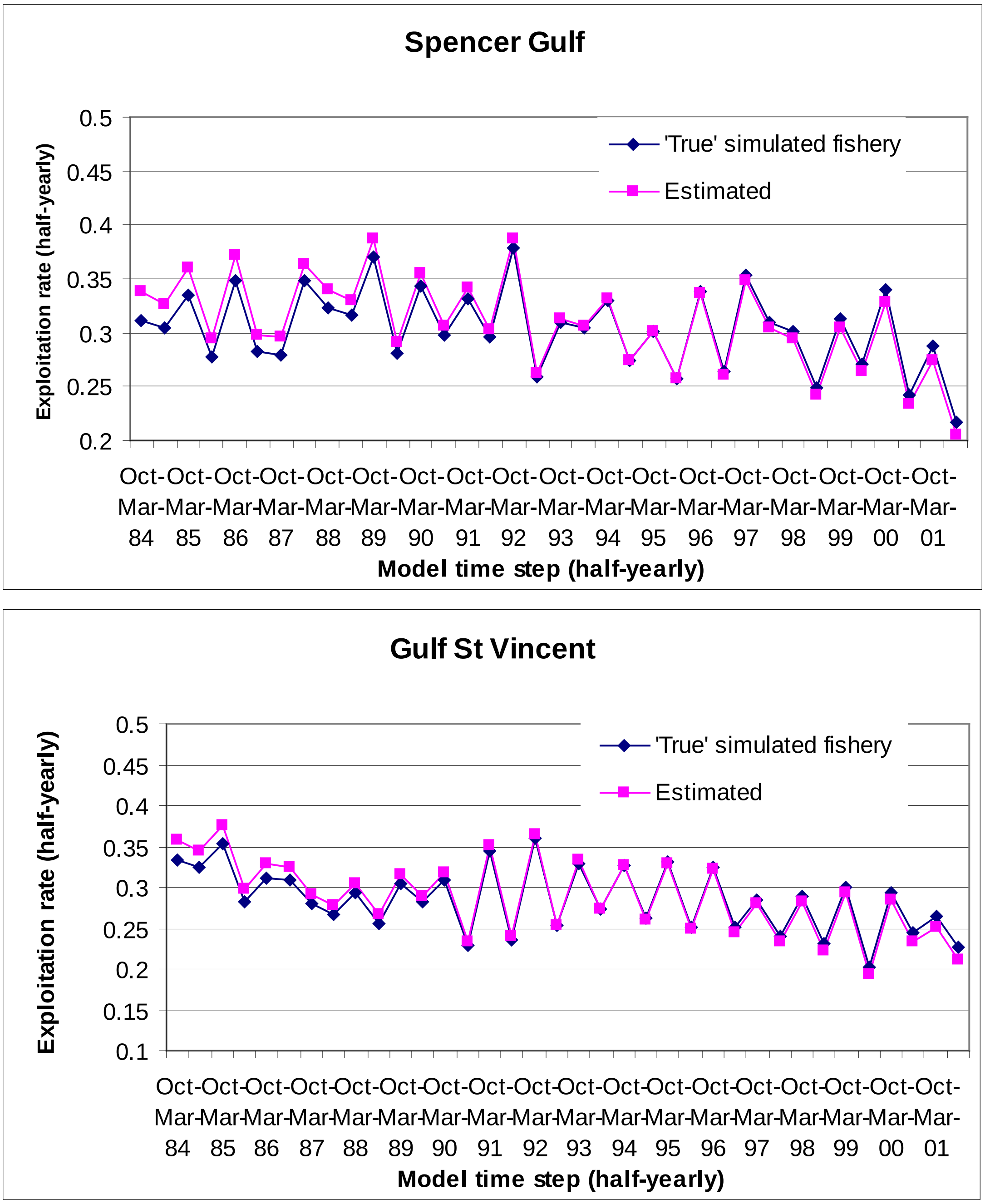



Figure 2.3. Comparisons of garfish model estimates of exploitation rate versus the ‘true’ levels of exploitation rate from the rising effective effort fishery simulation. (For actual estimates of semi-yearly garfish exploitation rate, see Figure 1.12).

The plots for exploitation rate that express the estimation bias as a ratio is given in Figure 2.4. This plot has the same interpretation as Figure 2.2. The outcome shown in Figure 2.4 is that when effective effort is rising over time, exploitation rate essentially the opposite time trend of bias is observed, by comparison with biomass (Figure 2.2). The magnitude of bias is similar, however, and thus, again, less than the deviation of catchability itself from its time variation due to rising effective effort.

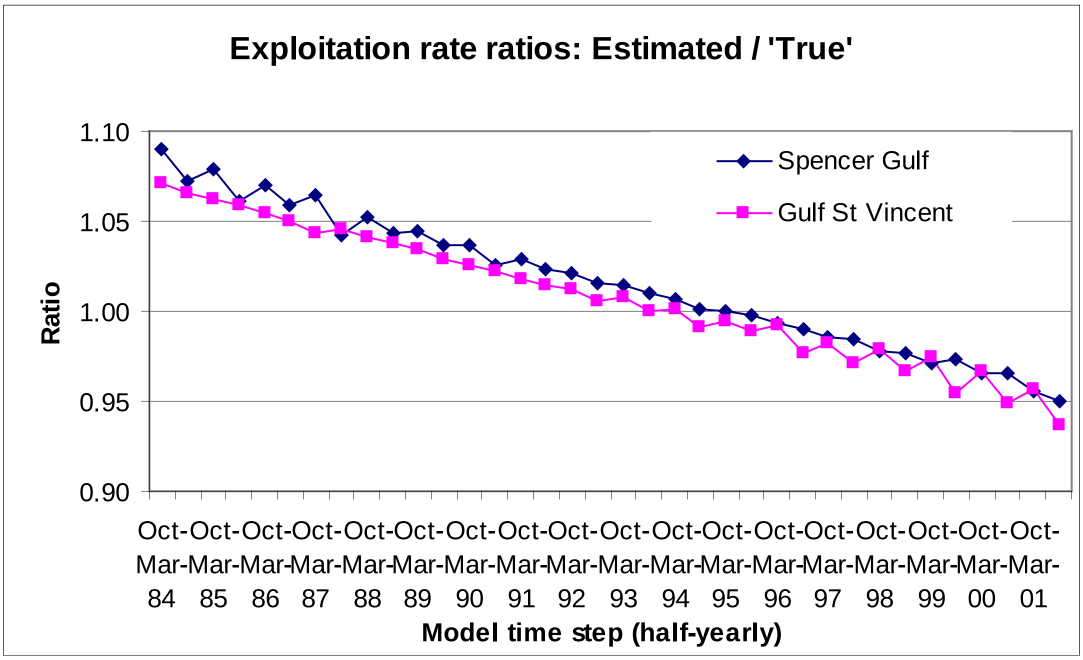



Figure 2.4. Time-varying ratio of the garfish model estimates of exploitation rate over the 'true' levels of exploitation rate from the fishery simulation.

## Sensitivity Analysis for Three Levels of Natural Mortality (*M*)

Here we summarise the results of sensitivity of model outputs, specifically biomass and exploitation rate, to three assumed rates of natural mortality. The estimation of Chapter 1 assumed a value of $M = 0.4$.

***Biomass***

Overall, when *M* is set to a value of 0.55 rather than 0.4, estimates of fishable biomass increased by an average of 19% and 21% in Spencer Gulf and Gulf St.Vincent respectively. A value of $M = 0.7$ results in 44% (SG) and 50% (GSV) increases in estimated biomass.

The time trends of estimated biomass for the three choice of *M* are shown in Figure 2.5. For all three values of *M*, biomass shows a consistent rising trend as reported for the baseline garfish estimation ($M = 0.4$) of Chapter 1 (Figure 1.11). As noted above, this rise appears to have accelerated in the last two years, presumably due to recruitment increases, and again, this more rapid rise in the last two years was obtained for all choices of *M*.

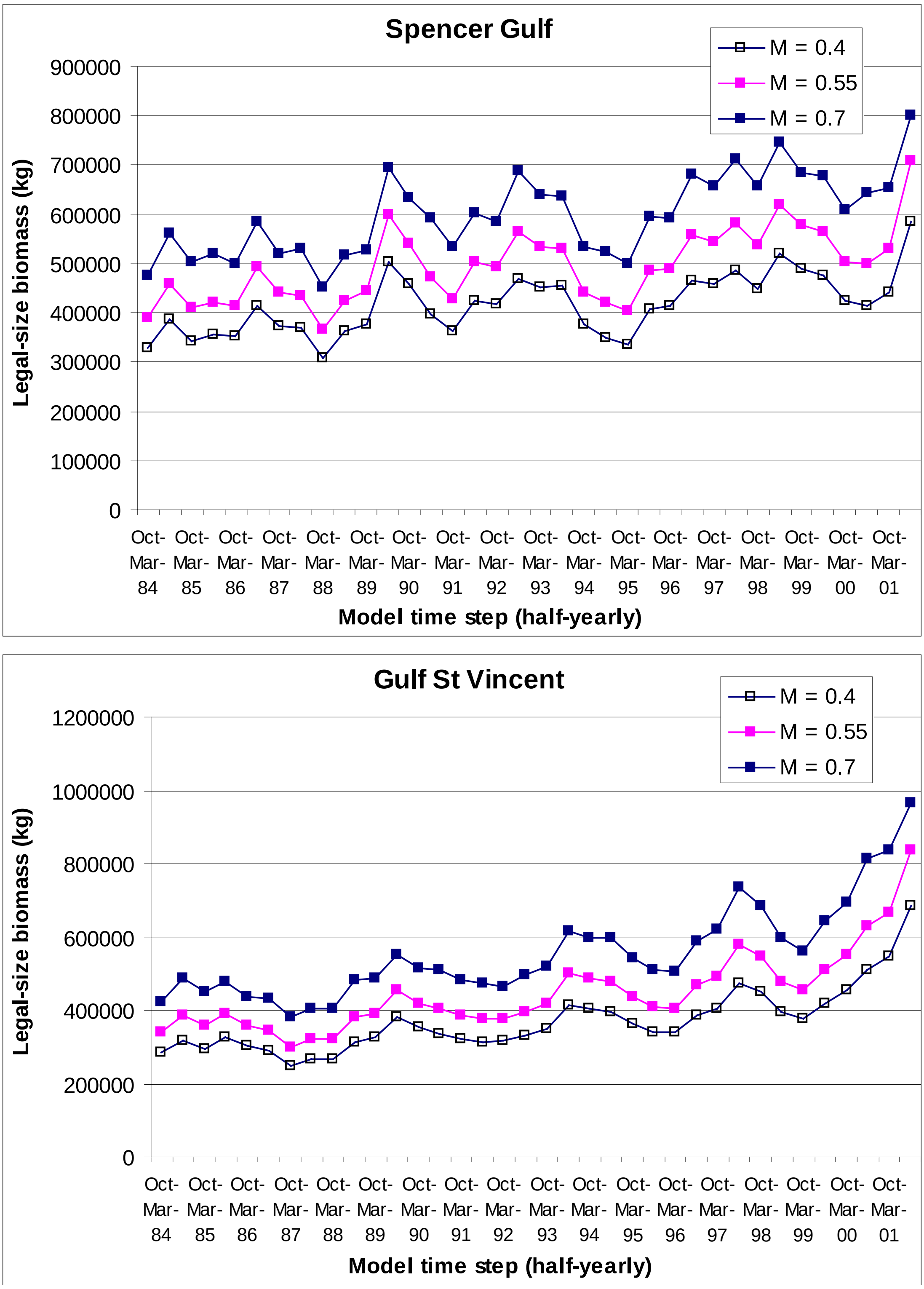
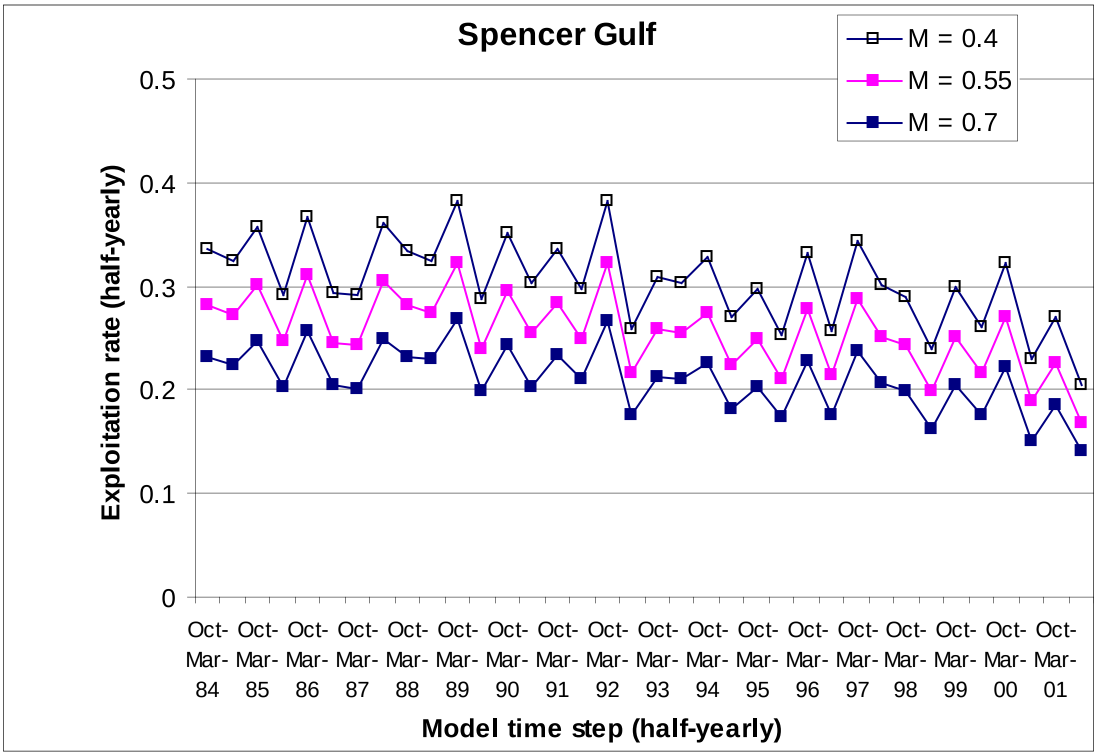



Figure 2.5. Sensitivity analysis testing the effect on estimated legal size biomass of varying assumed levels of natural mortality rate (*M*).

### *Exploitation Rate*

For exploitation rate, as above, the results mirror inversely those of biomass, decreasing with increasing assumed levels of natural mortality. When *M* is set to a value of 0.55 rather than 0.4, estimates of exploitation rate decreased by 16% and 18% in Spencer Gulf and Gulf St.Vincent respectively. A value of *M* = 0.7 results in exploitation rates that were 31% (SG) and 35% (GSV) lower compared with the those estimated in Chapter 1 where M = 0.4.

The time trends of exploitation rate estimates for the three choice of *M* are shown in Figure 2.6. For all three values of *M*, exploitation rate shows a decreasing trend since 1984.



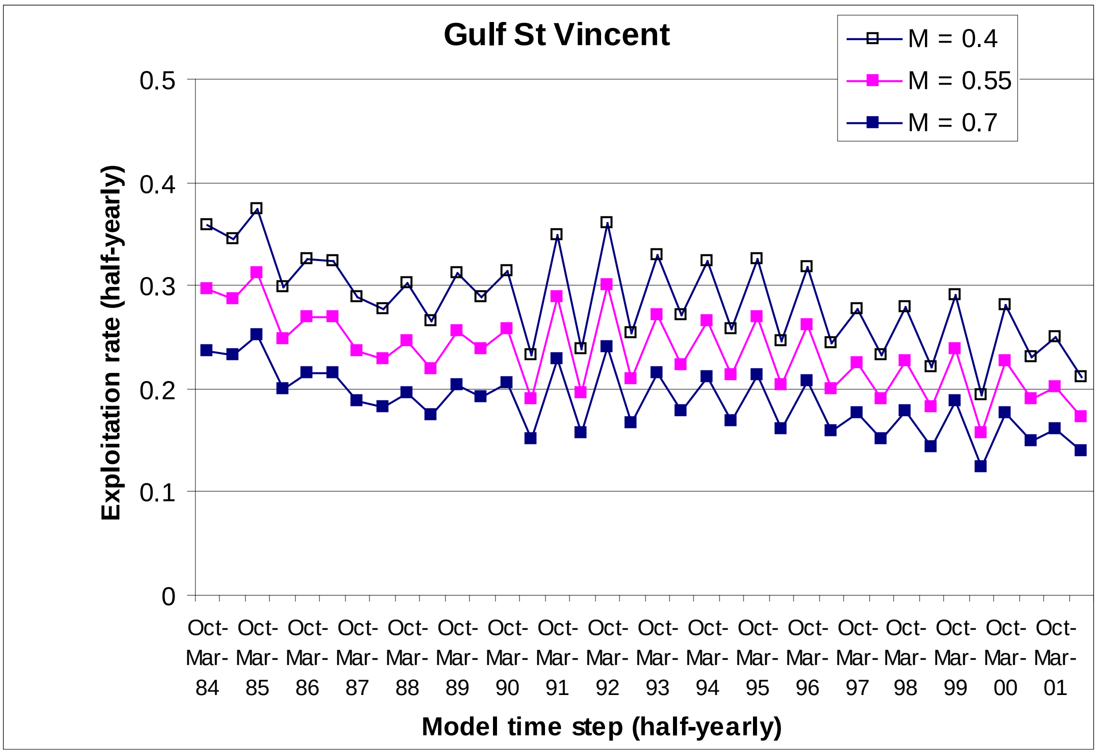




Figure 2.6. Sensitivity analysis testing the effect on exploitation rate estimates of varying assumed levels of natural mortality rate (*M*).

## Discussion

In this chapter, we have investigated the sensitivity of the garfish model stock assessment estimates to two likely sources of error.

(1) The model outputs, notably of garfish population biomass and exploitation rate, are relatively insensitive to rising effective effort. This result was not anticipated. That the biomass time trend varies about half as much as effective effort itself is encouraging, and implies that the model outputs are relatively robust with respect to changes in the fishing power of commercial gear. Since commercial catch per unit effort is the principal source of information on time trends in garfish stock abundance, this is reassuring.

(2) The model outputs were not, however, particularly robust with respect to different choices of natural mortality rate. Biomass estimates are higher for $M = 0.55$, and higher still for $M = 0.7$. Inversely, exploitation rate estimates decline as the assumed value for $M$ increases. Thus estimates of exploitation rate vary from a mean of around 0.3 per half-year (for $M = 0.4$), to about 0.2 per half-year ($M = 0.7$), these averages dropping in the last 4 half-years to about 0.25 ($M = 0.4$), 0.2 ($M = 0.55$) and 0.15 ($M = 0.7$) per half year (Figure 2.6).

However in contrast to average levels, the time trends in both biomass and exploitation rate (Figure 2.6) are essentially unaffected by the choice of M. Exploitation rate has, under all tested choices of $M$, declined through time. Year-to-year variation follows a parallel course for all three choices of $M$. In both gulfs, for M = 0.55, the estimated exploitation rate decreased from about 0.3 to about 0.2.

The choice of $M = 0.4$ for the model of Chapter 1 is on the low side of the range assumed by earlier garfish stock assessment work (Jones et al. 1990). Previous work by Jones (1990) who gathered garfish samples in the relatively unexploited waters of Baird Bay had originally estimated a value of $M = 0.53$ for males and 0.36 for females. Jones et al. (1990) had obtained estimates of 0.57 for males and 0.56 for females using Pauly's method which takes into consideration temperature and growth rates. Thus, a value of $M = 0.55$ is closer to the middle of the range of previously estimated values.

Uncertainty in estimate of $M$ is common to most, or even nearly all, fishery stock assessments. It is less severe for long-lived species because the rate of natural mortality can then safely (though approximately) assumed to be low. Because plus or minus 30% for a value around M = 0.1 would have a much smaller impact on stock assessment estimates than plus or minus 30% around a value around M = 0.55 as Jones et al. had assumed, the estimates are relatively sensitive to this choice for garfish.

# CHAPTER 3. Management Implications of Increased Garfish Legal Minimum Length

## Introduction

With South Australian garfish, a principal management issue under consideration by the Fishery Management Committee is the recent increase in legal minimum length (LML) from 210 to 230 mm. In this chapter we shall assess the impacts of a larger size limit on egg production, catch by weight, and revenue earned, using the garfish stock assessment model described in Chapter 1.

Assessing the performance of size limit change is sensibly addressed by considering these measures of fishery performance (eggs, catch and revenue) on a per-recruit basis. A per-recruit approach for assessing size limit changes is useful for two reasons: (1) Recruitment is likely to vary in the future in ways that cannot be predicted, and managers seek measures of performance that apply regardless of future recruitment variation, and (2) egg-per-recruit (EPR), catch-per-recruit (YPR), and landed-value-per-recruit (VPR) vary less than recruitment itself. Thus measures of the impact of changes in LML can be obtained which are more stable and robust when quantified as per-recruit indicators.

The estimates of growth and mortality obtained in the garfish stock assessment model above permit relatively reliable estimates of per-recruit indicators for stock management. In particular, fishing mortality, often taken as a broad range of possible values in per-recruit analyses, has been estimated by the model of Chapter 1.

## Methods

The calculation of per-recruit population quantities as a function of legal minimum length was integrated into the overall garfish population estimator presented in Chapters 1 and 2. The method was to incorporate the curves (‘ogives’) for fecundity versus length (used for calculating EPR), weight versus length (YPR), and garfish landed price per kg versus length (VPR) with estimates of the numbers of garfish of different age and length in the model population (egg production) or in the model catch (catch by weight and landed value).

These ogives for eggs, harvest weight, and harvest price versus garfish length are needed for per-recruit analyses to evaluate the impact of changes in the legal minimum length of harvest. The input data for these ogives were obtained from the FRDC study of Jones et al. (2002). Relationships of garfish weight versus length are given in Chapter 2 of the FRDC project’s final report (Ye et al. 2002a) and landed price by season was obtained as data from the SAFCOL market samples of that project (Ye, pers. comm.).

Calculating yearly eggs per female involves the incorporation of two processes of reproduction, namely (1) fecundity versus length, that is, the number of eggs produced by a mature female garfish each spawning season, and (2) the proportion of females that are sexually mature, also versus length (Ye et al. 2002b, FRDC report Chapter 5). The eggs-per-female ogives were calculated by multiplying the length-dependent logistic maturity curve for each region (Ye et al. 2002, Chapter 5) by the batch fecundity, also size-dependent. While the knowledge of the number of egg batches produced (i.e. spawning events) by a female per summer season remains somewhat uncertain, assuming this is a constant, this is not likely to create much error because it cancels from the egg-per-recruit calculation when egg-per-recruit is scaled as 'percent virgin egg production', that is, calculated as a percentage of a theoretical unexploited stock. This scaling as the percentage of a 'virgin' fishery is used for the egg-per-recruit results presented below.

The garfish model output provided the estimated population numbers in half-yearly time steps, and for each region, sex, age and length slice. The total eggs produced by each length slice, age, and region was obtained by multiplying model population numbers of females halfway through the summer time step by eggs per female of each slice. Catch is calculated as garfish numbers caught in each model time step multiplied by the weight of each garfish harvested, and landed value takes this catch by weight and multiplies by price per kilo (Table 3.1). Price was considered in the three grades that are used to assign price to fishers, larger garfish bringing a higher price (Table 3.1). The sum of eggs produced by all garfish in the population each summer spawning season (for EPR), and the sum of landed weight and value fish in the yearly catch (for YPR and VPR) are calculated to obtain totals for each region and year.

These yearly estimates of population egg production, catch by weight, and landed value were averaged over the last 5 years.

Finally, mean estimated recruitment over the past 10 years was calculated from each region. Dividing by the recruitment averages, the per-recruit estimates of yearly egg production, catch, and gross value of production in each region were obtained.

This procedure was run for a range of legal minimum lengths, increasing in 5 mm increments. With each tested LML, no new parameters including yearly recruit numbers were estimated. Rather the model fishery time series was re-simulated, using the different levels of LML to protect garfish from harvesting below each tested LML, over the full model time series.

Parameters used are those of the 'baseline' run of Chapter 1. In particular, these include no increasing effective effort, and $M = 0.4$.

Table 3.1. Auction prices to fishers (A$) for garfish from the SAFCOL market. Weekly prices averaged over all weeks of summer and winter, for the months of market length sampling under FRDC Project 97/133 (February 1998-June 1999)

| Length range (mm) | Summer | Winter |
|---|---|---|
| 210-240 | 4.30 | 3.14 |
| 240-270 | 6.55 | 5.12 |
| 270+ | 8.98 | 7.45 |

# Results

## Egg-per-recruit

The model estimates of egg per recruit (along with all other estimates below) are based on a dynamic, rather than steady state model. (That is, the model takes into consideration changes in population size and catch levels with time.) In steady state models, where no year-to-year change is considered, egg-per-recruit is always expected to rise with increasing LML since at a fixed level of fishing mortality, the protection of each cohort from fishing during its additional growth from the old to new LML implies a longer average lifespan before harvesting over the life of that cohort, and thus a longer number of spawning seasons, on average, in the water for females to release eggs. An increase in garfish LML of 20 mm from 210 to 230 implies approximately 2-3 additional months free from harvesting prior to reaching legally harvestable size.

The result for South Australian garfish (Figure 3.1) show a relatively modest increase in lifetime egg-per-female-recruit over the legal minimum lengths from 210 to 230 mm. This low increase in average lifetime female egg production is due to two factors: (1) the relatively lower selectivity of garfish in this size range as quantified by the market length samples of 97-99 and estimated in Chapter 1 (Figure 1.8), and (2) the relatively lower fecundity and less than 100% maturity of female garfish in that size range (210 to 230 mm). Egg-per-recruit rises more rapidly at higher legal minimum lengths than 230 mm where selectivity approaches 100%.

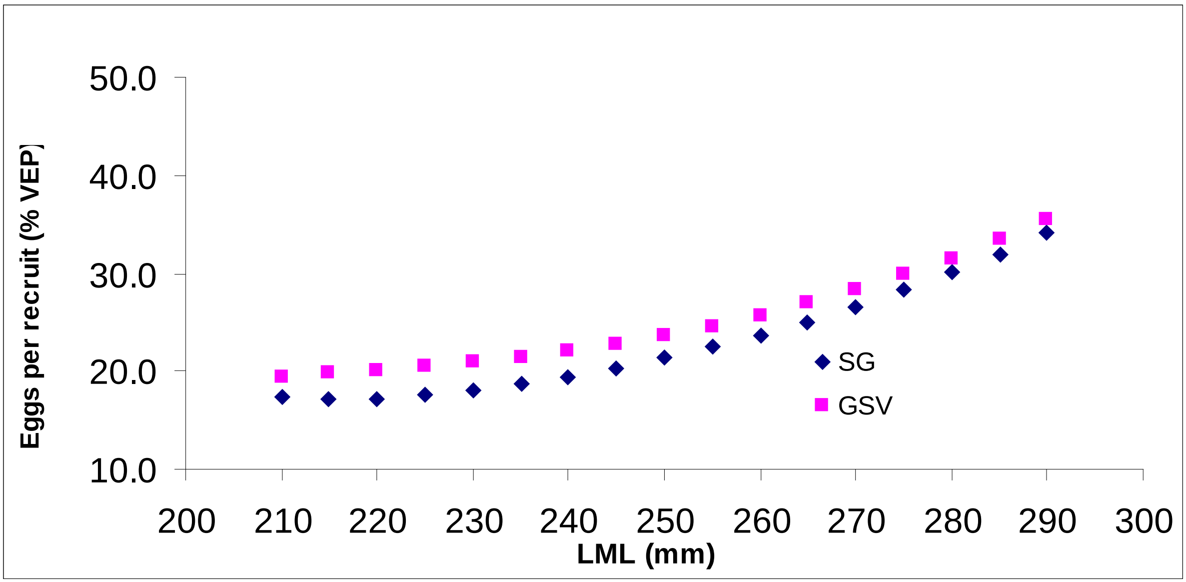



Figure 3.1. Eggs per recruit (i.e. mean number of eggs produced over the average lifetime of a female garfish recruited at age 3 half-years) at a range of modelled choices of legal minimum length. Values shown are given as a percentage of the lifetime eggs produced by a females in an unexploited ('virgin') garfish population (where only natural mortality is non-zero).

Egg production can be partitioned by age into two factors, namely average female garfish population numbers (at each age group) and the numbers of eggs produced by each female. These are plotted along with their product, the total egg production of garfish of each age in Gulf St.Vincent and Spencer Gulf (Figure 3.2). This graph quantifies and illustrates the relative contributions to population reproduction by each age group of female garfish. Assuming no effect of varying levels of exploitation on fertilisation success rate, males can be ignored in quantifying total population egg output. The outcome is that the highest numbers of eggs come from 2-year-old garfish, and that 1-year-olds (newly recruiting around 210 mm) contribute relatively little despite their much greater numbers. Thus this age-specific analysis tends to support the second explanation given above (lower fecundity) for the slow increase in EPR with LML increase from 210 to 230 mm.

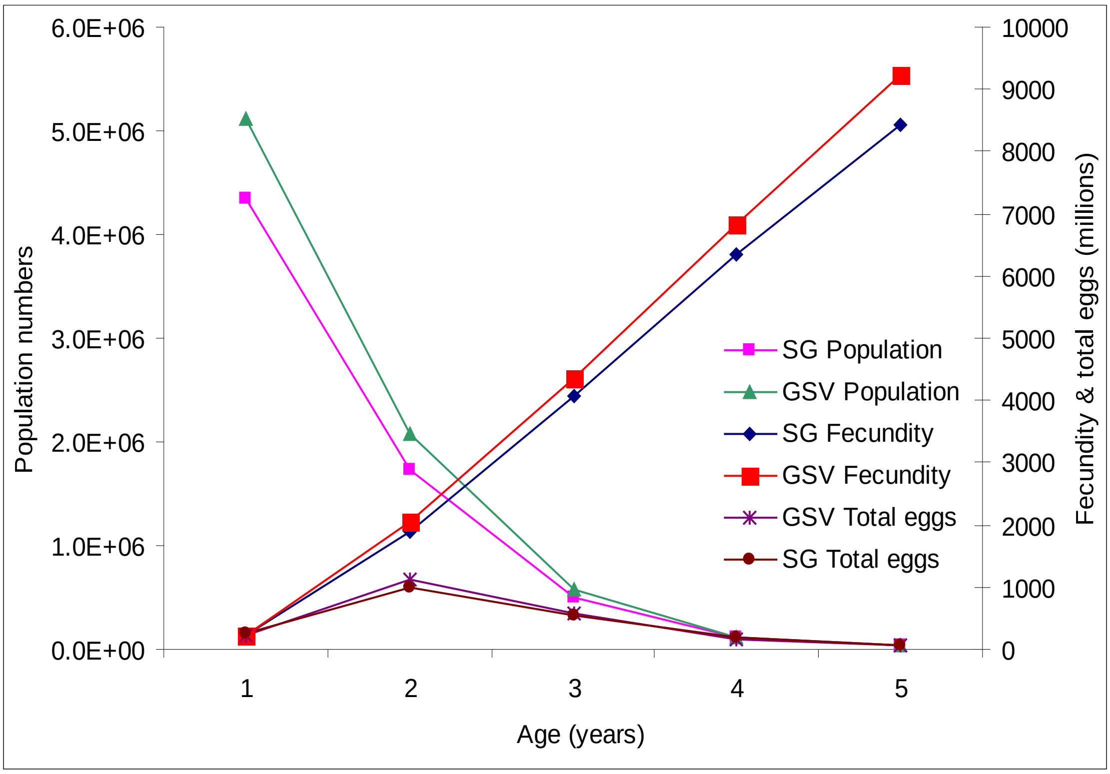



Figure 3.2. Age-specific quantities contributing to yearly egg production: eggs per female, numbers of females, and the resulting total eggs released by each age class, averaged over the last 5 modelled years.

## Yield-per-recruit

Unlike EPR, YPR and VPR can rise or fall, depending on the relative rates of natural mortality and growth by weight. With an increase in LML from 210 to 230 mm, the garfish model estimated an increase of 5.4% and 2.6% in yield-per-recruit for Spencer Gulf and Gulf St.Vincent respectively (Figure 3.3). Thus a relatively modest increase in YPR with increased LML is predicted.

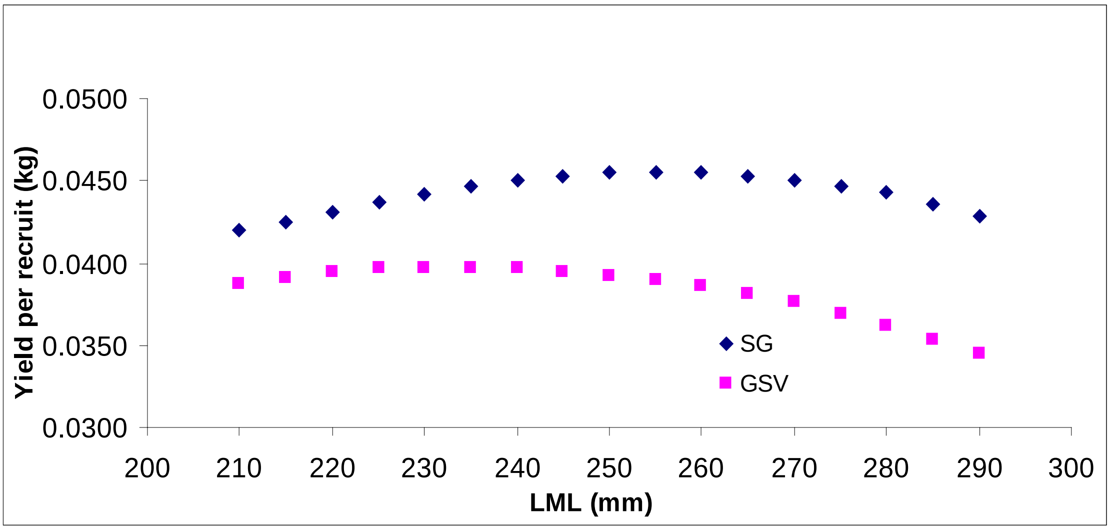



Figure 3.3. Yield per recruit (i.e. mean catch by weight for a garfish recruiting at age 1 year) at a range of modelled choices of legal minimum length.

### Value-per-recruit

The landed price of garfish in South Australia is highly dependent on size. Larger garfish bring a much higher price, roughly doubling in price per kg reported (with substantial weekly variation) from the small to large market size categories. For this reason, garfish value per recruit was more strongly improved by increasing LML (Figure 3.3) than YPR. The modelled increase from 210 to 230 mm yielded increases of 13.9% and 13.3% in value-per-recruit for Spencer Gulf and Gulf St.Vincent respectively.

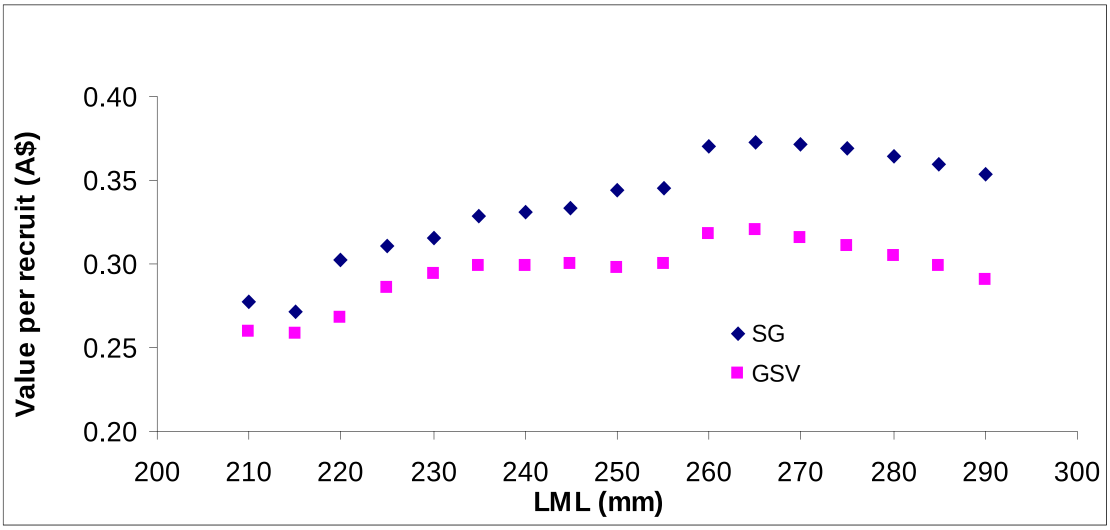



Figure 3.4. Value per recruit (i.e. mean landed value for a garfish recruiting at age 3 half-years) at a range of modelled choices of legal minimum length.

## Discussion

Two prior studies have evaluated the predicted effect of an increase in legal minimum length for South Australian garfish (Jones et al. 1990, p.101-102; and Morison and Presser 2002, Chap 7 of the FRDC report). These two previous studies, and the results summarised above, all estimate relatively low increases in YPR with increased LML. Particularly surprising was the relatively minor increase in egg-per-recruit estimated with increase in legal minimum length. However, due to the higher prices paid for larger garfish, value per recruit does rise with increasing legal minimum length.

All three evaluation studies of increasing legal size (this chapter, Jones et al. 1990, and Morison and Presser 2002) assumed no release mortality of garfish that were captured and then returned to the sea being under the legal minimum length. This release mortality is almost certainly not negligible, and because (1) most garfish from the commercial fishery are caught in haul nets, and (2) garfish are thought to be relatively fragile, this release mortality is likely to be higher, and probably much higher than, for example, King George whiting.

The inclusion of release mortality in garfish on these estimates would imply a relatively lower increase in egg, yield and value per recruit than plotted in Results above. Currently, a 3-month study is being planned for calendar year 2003 to measure release mortality of garfish.

Because the model is fully dynamic (on a half-yearly time step) and provides an integrated estimation of growth and other features of garfish population and fishery (notably variation in vulnerability to different gears by length), the per-recruit estimates from the garfish model should be relatively accurate by comparison to more traditional steady state methods, notably the Beverton-Holt yield equation, commonly used for per-recruit analysis.

As with a majority of fishery stock assessments and per-recruit analyses, one parameter of lower confidence is natural mortality of garfish. Another source of uncertainty for garfish is the still unquantified catch by recreational dab netters. This will be partially rectified with the results from the National Recreational and Indigenous Fishing Survey undertaken in 2000/01.

## References

Jones, G.K, Hall, D.A., Hill, K.L., and Staniford, A.. 1990. The South Australian Marine Scalefish Fishery: Stock Assessment, Economics, and Management. Green Paper of the South Australian Department of Fisheries, unpublished report.

Morison, J.B. and Presser, J. 2002. Chapter 7: An economic analysis of the southern sea garfish fishery in South Australia and marketing prospects. *In*: Fisheries Biology and Habitat Ecology of Southern Sea Garfish (*Hyporhamphus melanochir*) in Southern Australian Waters [*eds.*, Jones, G.K., Ye, Q., Ayvazian, S., and Coutin, P.C.], Australian Fisheries Research and Development Corporation Final Report 97/133.

Ye, Q., Short, D.A., Green, C., and Coutin, P.C. 2002a. Chapter 2: Age and growth rate determination. *In*: Fisheries Biology and Habitat Ecology of Southern Sea Garfish (*Hyporhamphus melanochir*) in Southern Australian Waters [*eds.*, Jones, G.K., Ye, Q., Ayvazian, S., and Coutin, P.C.], Australian Fisheries Research and Development Corporation Final Report 97/133.

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# CHAPTER 4. Snapper Stock Assessment Model Estimator

## Introduction

The stock assessment model estimator used for snapper is based on and is similar to that used for garfish. Thus, most of the model features are as described in Chapter 1. Specifically, the model uses a 'slice-growth' method to describe the lengths and ages of fish in the model population, and thereby to fit snapper catch sample data by both age and length. A half-yearly time step was also employed.

## Data

The data types used as input to the South Australian snapper stock assessment model described below are fourfold:

1. commercial catch and effort data;
2. catch length-frequency samples;
3. catch age samples (read from otoliths);
4. recreational data from the 1994-96 creel survey of boat ramps during daylight hours.

The model considers the catches and associated effort divided into 5 gear types (handline, longline, hauling net, all other commercial gears combined, and recreational). Target type is not differentiated and non-target catches of snapper were, for the most part, low.

The commercial catch sampling (lengths and ages) was undertaken in three separate programs since the early 1990's, namely 1990-91, 1994-95, and 2000 to the present. All catch samples in the first two programs were from Northern Spencer Gulf only. The 2000-2002 samples were larger, more comprehensive, covered both gulfs, and spanned the entire year. The model inferences are most strongly drawn from these latter more complete catch length and age samples. The absence of sampling prior to 1991 will mean that model outputs for years pre-1991 will be less well informed by data.

Model recreational catches employed estimates from a bus-route creel survey of landings at public boat ramps was undertaken under FRDC Project 93/249 (McGlennon and Kinloch 1997). SARDI researchers observed public boat ramps during daylight hours for Gulf St.Vincent in 1994/95 and Spencer Gulf in 1995/96. Skippers returning from day trips were interviewed for landings and time in the water. Effort was also quantified by counting parked boat trailers. The estimated yearly total recreational snapper catch for South Australia state-wide was 47.8 tonnes.

One important limitation of the data set is the absence of information on snapper movements. Tag recoveries (see Section 2.3) have shown that snapper tend to return to a home reef yearly in summer time of spawning, and suggest that they disperse during winters.  Where they go in winter is not known.  Indirect evidence indicates it is plausible that some migrate away from the gulfs over one or a number of years, and thus become uncatchable.  Once results from the current FRDC Project (2002/001) analysing snapper movement by otolith microchemistry become available, they can be incorporated in the snapper stock assessment model described below.

# Methods

Differences between the garfish and snapper models are described in this section.

1. Not sex-specific.  For snapper, there was no evidence of a difference in growth between sexes.  Sex of snapper cannot be distinguished without a dissection, and thus, sex was not known for any length samples.  Thus, in this model, no differentiation by sex is represented in the population array.

2. LML change.  In December 1987, the legal minimum length (LML) of snapper was increased from 280 mm to 380 mm total length.  A new LML implies a new slice partition of each cohort in the snapper population, i.e., the upper and lower bounds of all the slice bins will be different for the post-LML-change population, though the number of bins will not change.  Numbers of snapper in each slice (each length bin), must be reassigned to the overlapping new slices.  An algorithm assigning a linear proportion from each old slice bin, to each new bin was written and implemented.  This algorithm must be integrated into the overall model estimation because growth parameters are freely estimated, and these are used by the slice-bin generation submodel.  Checks on the reliability of this mapping algorithm include summing the total numbers before and after each LML-change reassignment for each cohort to make sure the total numbers remain unchanged.

3. No correction for age subsampling by port and month, only by length.  Garfish age subsamples were partitioned by port and month, while the length samples were aggregated over the whole gulf and half-year.  Thus, for garfish, two levels of subsampling correction were implemented.  For snapper, no such two-level breakdown of the age subsamples was undertaken in the raw data.  Thus with snapper, there was no need for the port and month level of subsampling correction undertaken with garfish.  The age subsampling correction for snapper by 2-cm length bin was undertaken in a manner identical to that described for garfish in Chapter 1.

4. The availability of a single DEPM estimate for one area (NSG) in one summer spawning.  McGlennon and Jones (1999) estimated snapper spawning biomass using the daily egg production method in summer 1994-95 for Northern Spencer Gulf.  Some of the runs incorporated this estimate directly in the model likelihood.  In the end, however, this estimate was removed from the model fits presented below, but that single value is included for comparison in the plots of biomass (Figure 4.1).

5. Highly sporadic yearly recruitment and thus different fishery dynamics.  Snapper recruitment is dominated by very large year classes coming into the fishery approximately once or twice per decade.  Thus, a snapshot of numbers by age contains relatively little information about mortality.  By contrast, for populations

with relatively stable yearly recruitment such as garfish, a single age-composition sample gives information about average mortality in the relative numbers by age. For example, the number of 4 year old snapper compared with 5 year olds does not reflect the declining numbers over that 1-year time interval due to mortality.

6. Age of recruitment was 5 half-years, rather than 3 half-years as it was for garfish.

7. Multiple years of sample data. Data for snapper were available for more than a single year of sampling. Thus, some inferences about recruitment were obtained from the sampling data, notably the presence or absence of large year-class pulses. For garfish, essentially all inference about yearly variation in recruitment would have been drawn from catch and effort totals, specifically yearly change in CPUE.

8. Long life span. There were many more age classes represented in the snapper population array, namely 22 cohorts at any one time, with the oldest age group of the 23+ year-olds being the plus group.

9. Spatial description. The snapper model covers the two gulfs. There were three model regions analysed: Northern Spencer Gulf, Southern Spencer Gulf and Gulf St.Vincent. The West Coast was excluded because essentially no snapper catch samples are available from this region which comprises a small percentage (4.5%) of total South Australian snapper catch.

10. No movement (as with garfish). Because data to quantify movement is not yet available, there is no movement assumed in the model. Thus the results from each region are essentially independent. An FRDC project (2002/001) by Fowler and Hall, using otolith microchemistry, is currently addressing this research need.

11. A 'floor' parameter added to logistic length selectivity. For snapper long lines, there was evidence in the plotted catch length-samples of (1) lower selectivity at smaller sizes, but (2) not so low as to be well approximated by the zero level of selectivity that a standard logistic curve implies. Therefore, to allow long-line length selectivity to vary from an (estimated) lower level up to a maximum of complete selection, a new parameter (the 'floor') was added. Thus, in effect, a generalised logistic selectivity curve, as a function of snapper total length, *l*, was constructed. It has the form

$$s_{generalised}(l) = s_f + \frac{1}{1+\exp\left[-r_{sel}\cdot\left(l-l_{50}\right)\right]+\left[s_f \big/ \left(1-s_f\right)\right]}$$

where $s_f$ is the new floor parameter, and $r_{sel}$ and $l_{50}$ are the two standard logistic curve parameters. This yields the usual logistic S-shape but with a flat asymptote at $s_f$ for small lengths and as usual for logistic curves, reaching an asymptote at 1 for large values of length. We are not aware of previous forms of this generalisation of the logistic curve, though it probably exists somewhere in the literature.

12. Catchability for snapper incorporates simultaneous dependence on both season (winter or summer) and gear. With garfish, seasonality was assumed to affect

catchability for all gears with the same proportional variation. In snapper, hand lines have high catchability in summer, while long lines are dominant in winter, necessitating the separation of these by season.

13. In contrast, the overall catchability parameter of each gear type is not region-specific.

14. Pre-data recruitments estimated for the initial population array. Because snapper recruitment is highly sporadic, the model accuracy can be significantly improved by estimating the size of year classes that are present and dominant in the population at the start of the first model time step, in October 1983. Recruitment for three large year classes evident in the age samples were thus estimated in the initial population array submodel. These cohorts were spawned in January summers of 1969, 1973, 1979.

15. Because of having many more ages (up to 22 yearly age groups for snapper and 5 for garfish) represented in the snapper population array, and thus in the catch, there were fewer aged snapper available for length fitting in each age group. Therefore, we accepted smaller minimum data sample sizes of aged individuals in calculating the data moments. We required a minimum of 1, 4, 8, and 16 aged garfish to calculate mean, standard deviation, skewness and kurtosis, respectively, while for snapper these minimum required sample sizes were reduced to 1, 2, 4, and 8.

# Results

The results will be presented in four sections: First, the principal outputs of the model for fishery management, namely the three principal biological performance indicators, are presented. Second, the fits to the semi-yearly catches, and third the fits to catch proportions-at-age, are shown graphically. The fourth section, fits to snapper catch-age-length samples, are plotted in Appendix 4.1.

## Biological Performance Indicators

The model integrates the four data sources described in the section above to carry out maximum likelihood estimation of three critical stock assessment indicators: yearly recruitment, semi-yearly fishable biomass, and semi-yearly exploitation rate which is the fraction harvested each half-year. Recruit numbers for each cohort are plotted for the January year (i.e. summer) in which they were spawned, but the recruitment values plotted are the estimated numbers reaching age 5 half-years at the start of the summer model time step (1 October). These time series of biological performance indicators, used to assess South Australian snapper stock (Figure 4.1), are presented for the three regions individually.

The results show the following features of the change through time of snapper population indicators:

1. The high yearly variation in recruitment is evident, with a few year classes dominating, notably 1979, 1991 and 1997. This is consistent with (and inferred from) the age-structure catch samples (Figures 4.5-4.8) where those year classes are dominant. The model appears to have identified 1999 as a very good year

class in Northern Spencer Gulf, but this result must be considered preliminary, and will be modified as this year class becomes more fully recruited, making its interpretation much more reliable in future stock assessment years. The 1997 year class is unambiguously strong, and will provide the basis of future catches. The region of highest recruitment is Northern Spencer Gulf, where absolute recruit numbers are higher in all years except 1991. Note that this model estimates the absolute numbers of recruits reaching fishable size (at age 5 half-years), with yearly recruit numbers lying in the hundreds of thousands, or less.

2. Recruitment trends in the two gulfs are highly correlated in time: relatively good and bad years of recruitment occur in the same years (Figure 4.1). Because it is believed that snapper return to their aggregation site of spawning, movement between gulfs is thought to be minimal. Thus, these strong between-gulf correlations in recruitment suggest a common environmental factor which influences both gulfs. One plausible hypothesis, higher-than-average summer temperatures, was examined by Fowler and Jennings (submitted) who showed that timing of spawning in summer is also a factor. Temperature has been shown to be a strong indicator of yearly recruitment success in New Zealand.

3. Fishable biomass, like recruitment and for that reason, is also generally correlated in broad scale trends between the three regions, principally reflecting the arrival of large year classes in 1979 and 1991. Similarly, the shift of abundance downward in the Northern Spencer Gulf in those early years prior to 1993 is in large part due to the decline in the available biomass from the dominant 1979 year class.

4. The 'X' in the fishable biomass graph (Figure 4.1) marks the estimated level of spawning biomass in the Northern Spencer Gulf during summer of 1993-94 using the daily egg production method ('DEPM') (McGlennon and Jones 1999). This DEPM estimate was not used as a data input in the model runs shown. The fact that this DEPM-estimated biomass level falls below the model value (dotted-dashed line 1994) is not necessarily an inconsistency. Recall that the model biomass includes all fish that enter the fishable stock at any time in their life history. Circumstantial evidence has sometimes indicated that snapper may leave the gulf for several years at a time. These would not be counted in the DEPM estimate because those fish are not producing eggs. But they would, if they eventually returned and were captured, be counted in model estimates which infer a more all-inclusive population biomass from catches and changing numbers-at-age over time. Moreover, if there were snapper in the gulf that were not actively spawning at the time the 1994 DEPM survey was undertaken, then they also would be omitted from the DEPM spawning biomass total. Thus taking into consideration these differences in the components of the population being counted by the two methods, comparison of these two entirely independent estimates of absolute biomass in Northern Spencer Gulf suggest that the model estimates are not inconsistent with the estimate obtained using DEPM.

5. The general rising trend in fishable biomass since 1993 for all three regions charts the entry and growth of the 1991 year class, which makes up the majority of the catch in the latter 1990's. The further model biomass rise in Northern Spencer Gulf since around summer 2000, not expressed in Southern Spencer Gulf and Gulf St.Vincent, is due to the much stronger estimate of 1997 year class recruitment in

Northern Spencer Gulf than in the other two regions.

6. One encouraging result is the generally higher estimated levels of biomass in Gulf St.Vincent since the mid 1990's. As noted, this is due to the 1991 year class. One caveat on this outcome is that pre-1990 biomass is inferred entirely from CPUE. The levels of handline effort in Gulf St.Vincent in the first years of the model time series (1983-1986) were much higher and declined rapidly over that time. Total commercial handline effort continued to decline until the mid-1990's and has remained near those record low levels in both Northern and Southern Gulf St.Vincent. If the less skilled fishers left the fishery as catches declined in those years, CPUE as a measure of relative biomass would overestimate in latter years.

7. Exploitation rates shown are by half-year. They are expected to be higher during summer spawning when hand-line fishers target snapper, and the model outputs show this. With caveats about no ability to detect or account for long-term changes in effective effort, the exploitation rates are estimated to be relatively flat over the full time series. One exception is the generally rising trend in exploitation rate in the Southern Spencer Gulf over the last 4 years. Exploitation rates were generally similar among the three regions, with the highest being in the Northern Spencer Gulf over most of the time series.

One caveat on these results is that the model assumes no increase in effective effort of a fisher-day since 1983.

A second caveat, probably a greater source of error in estimating current levels of exploitation, is due to the use of the older recreational creel survey data. The more recent telephone survey, whose results broken down by region are not yet available, has shown that snapper catches by recreationals are much higher than reported from the creel survey. The creel survey (from April 1994 – March 1996) yielded an estimate of 47.8 tonnes per year compared with 470.5 tonnes from the telephone survey for South Australian snapper catch overall. The creel survey estimate was used in the model above, and thus recreational catch is very substantially under-represented. Moreover, the change in both recreational catch and effort over time were assumed to track change in South Australia's state population overall, since no data on changing levels of recreational effort are available.

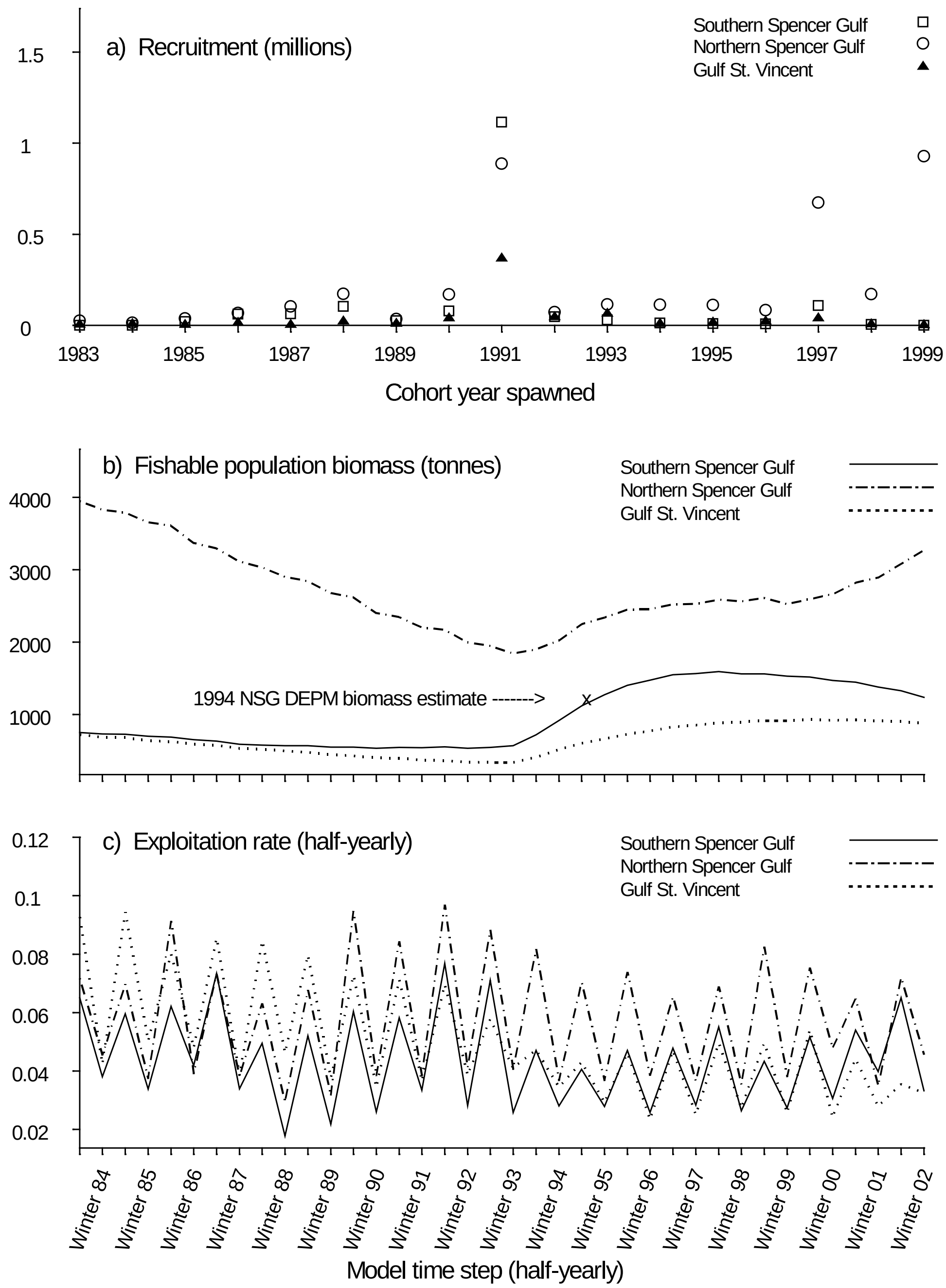


Figure 4.1. Stock assessment indicators for South Australian snapper. The “X” in graph (b) shows the estimated spawning biomass from the daily egg production estimate of McGlennon and Jones (1999) for Northern Spencer Gulf.

## Fits to Catch Totals (by Weight)

The model estimates are obtained by fitting to these four data sources. The closeness of the model predictions is, as for most model estimators, a useful measure of the ability of the model to capture the fishery dynamics in the mathematical (time-step difference) equations that seek to represent change in the snapper population over time.

Catch-log reported commercial catches by weight are a critical data input to the snapper estimation model. Total catch serves as the only ‘extensive’ quantity of data input, without which total biomass and population size cannot be inferred. (In general, total biomass is inferred from catch total by weight divided by fishing mortality.) In addition, because change in catch divided by effort (i.e. CPUE) provides a measure of change in stock abundance, catch total by weight thereby serves this second important role in model stock assessment inference. In the graphed model fits to the first data source, commercial catch totals by weight reported by fishers in their catch logs (Figures 4.2-4.4), the time step is half-yearly, as for garfish.

The model predicted catch totals take account of several processes, notably (1) total reported effort for the five effort types in each half-yearly time step, (2) age compositions, where the arrival and continuing exploitation of the dominant year classes results in rises and eventual declines in the predicted catches over the exploitable history of each large year class, (3) logistic selectivity by length for commercial long-line estimated separately for the two regions and seasons (handline selectivity is taken as flat) and, (4) growth, which gives catch by weight from model catch in numbers.

Generally the fits to catch totals, (Figures 4.2-4.4) are satisfactory, though deviations, predominantly in earlier years, are noted.

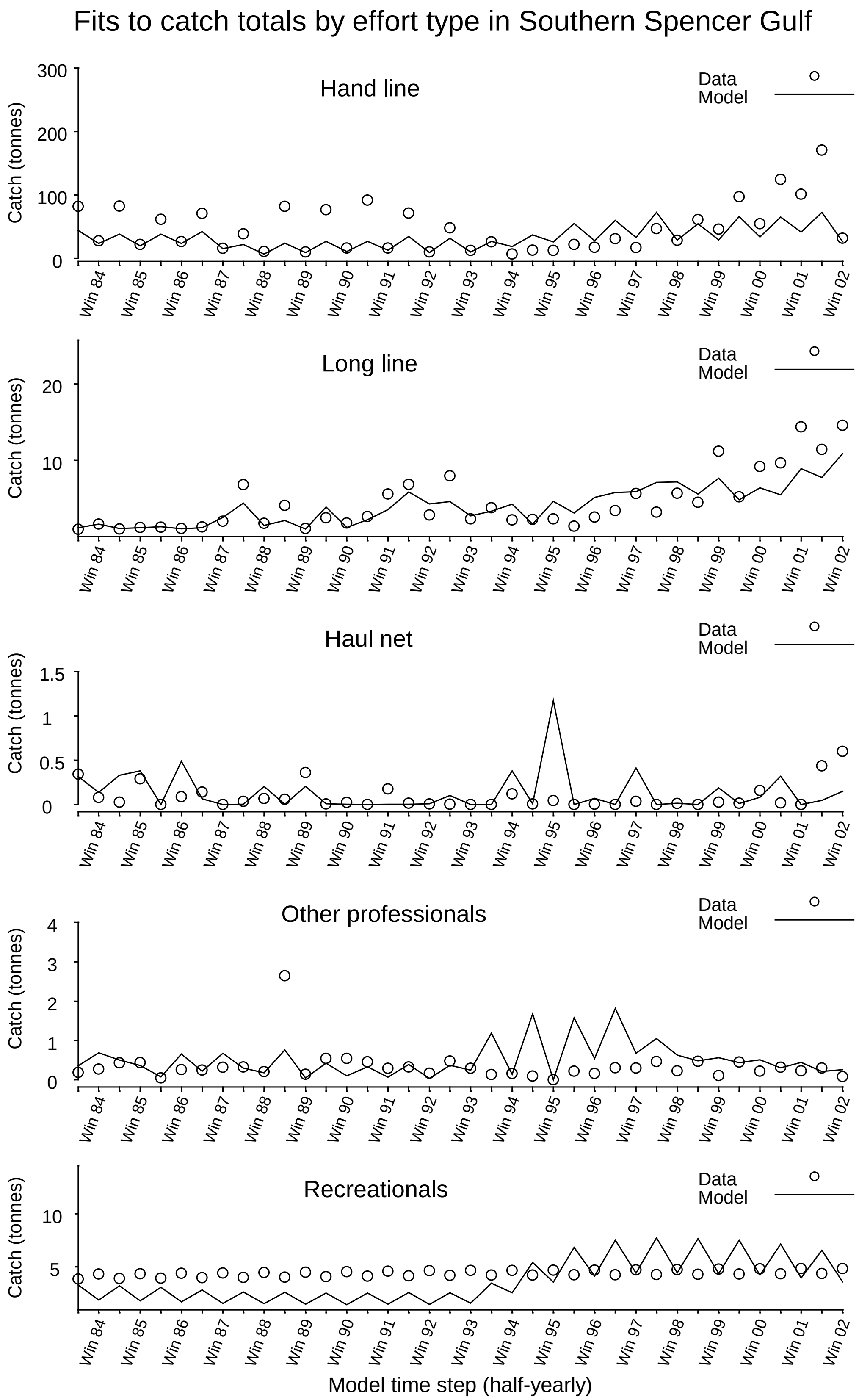


Figure 4.2. Fits of the model-predicted catch totals for the five effort types, and the data totals of snapper catch by weight (tonnes): Southern Spencer Gulf.

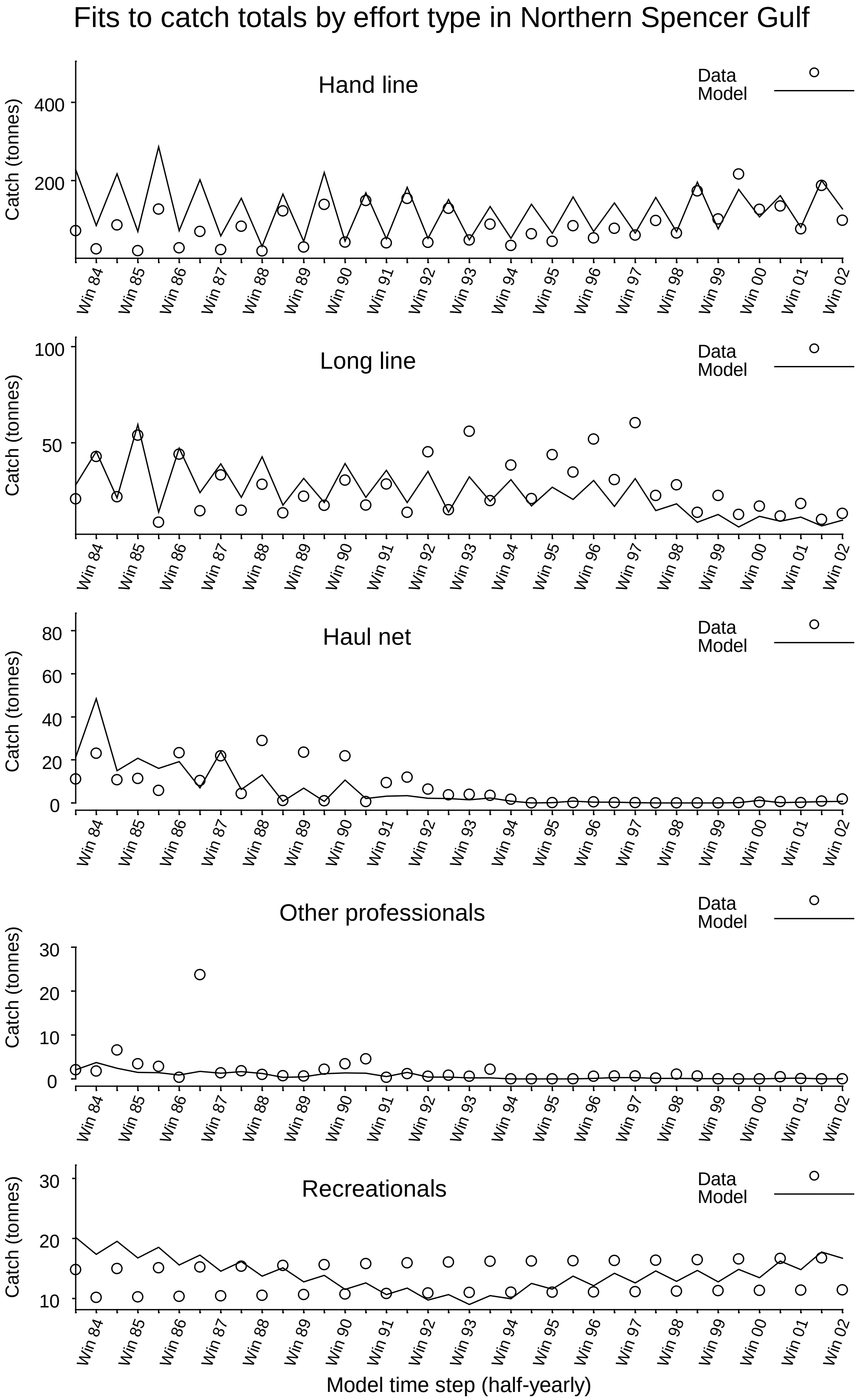


Figure 4.3. Fits of the model-predicted catch totals for the five effort types, and the data totals of snapper catch by weight (tonnes): Northern Spencer Gulf.

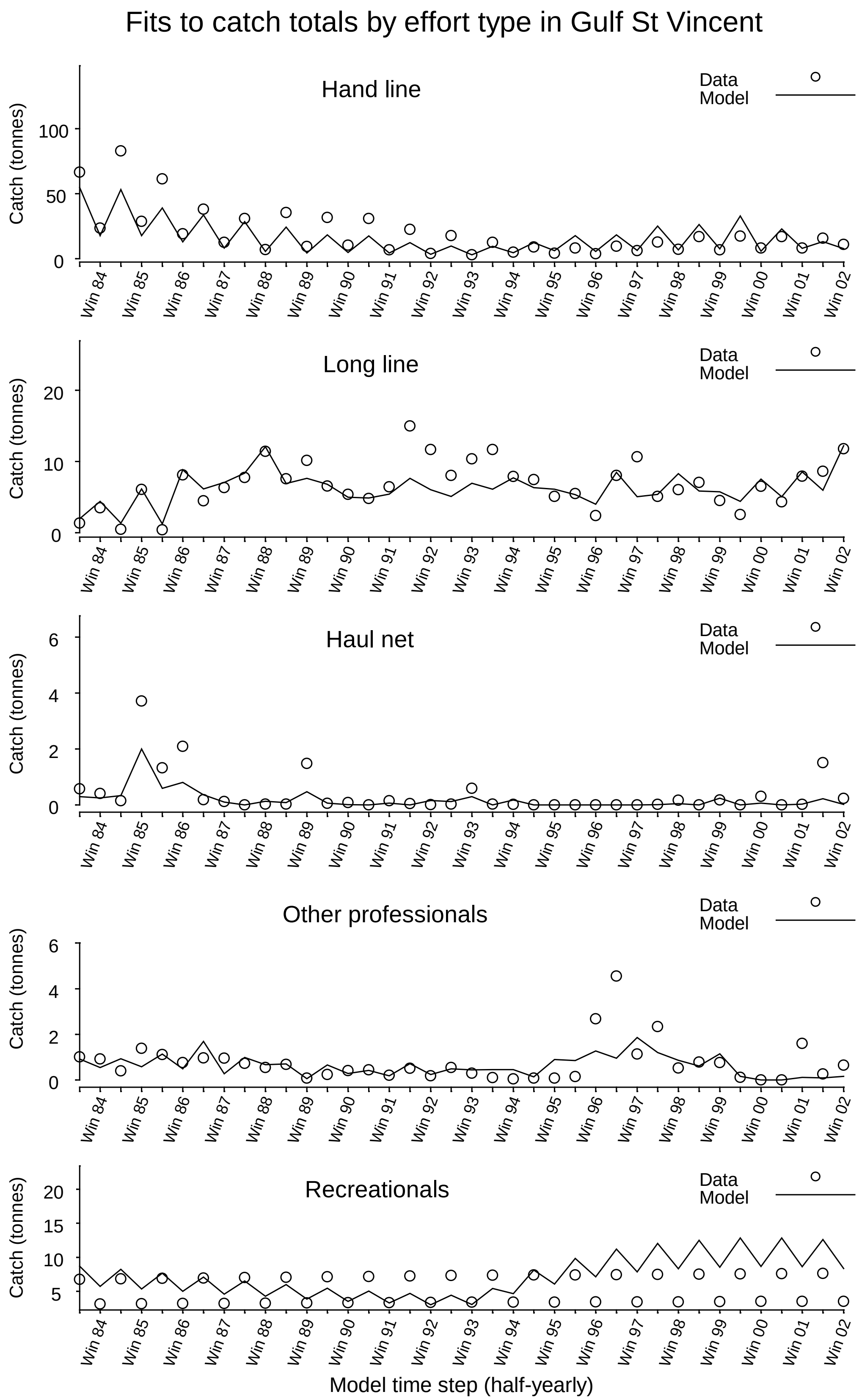


Figure 4.4. Fits of the model-predicted catch totals for the five effort types, and the data totals of snapper catch by weight (tonnes): Gulf St.Vincent.

## Fits to Catch Proportions by Age

This second data source, of catch-numbers-at-age, conveys different information to the stock assessment model inference than it does for garfish, because of the highly sporadic nature of snapper recruitment, as noted in Methods point 5. The large gaps in the age structure between year classes of significant recruitment makes a direct estimate of mortality based on these age compositions difficult or impossible to infer. On the other hand, unlike with garfish, the age samples do provide excellent information on the relative strength of (at least the larger) recruitment year classes.

One caveat on the interpretation of the catch-at-age, as with King George whiting, is that snapper appear to migrate, or otherwise move away from spawning aggregation sites (i.e. fishing 'drops') at certain ages, and in winter. No quantified knowledge of this movement is yet available, so it is not incorporated in the model. In the absence of movement, each region is, in effect, a separate model. Thus, the model implicitly assumes the continuous presence of snapper (within each of the three regions).

The fits to these age structure catch samples are generally good. Deviations are largely due to the fact that the model seeks to fit the predicted size of each recruited year class to a number of samples, that is, to the same cohort of fish but to catch samples from different time periods, and by different gears.

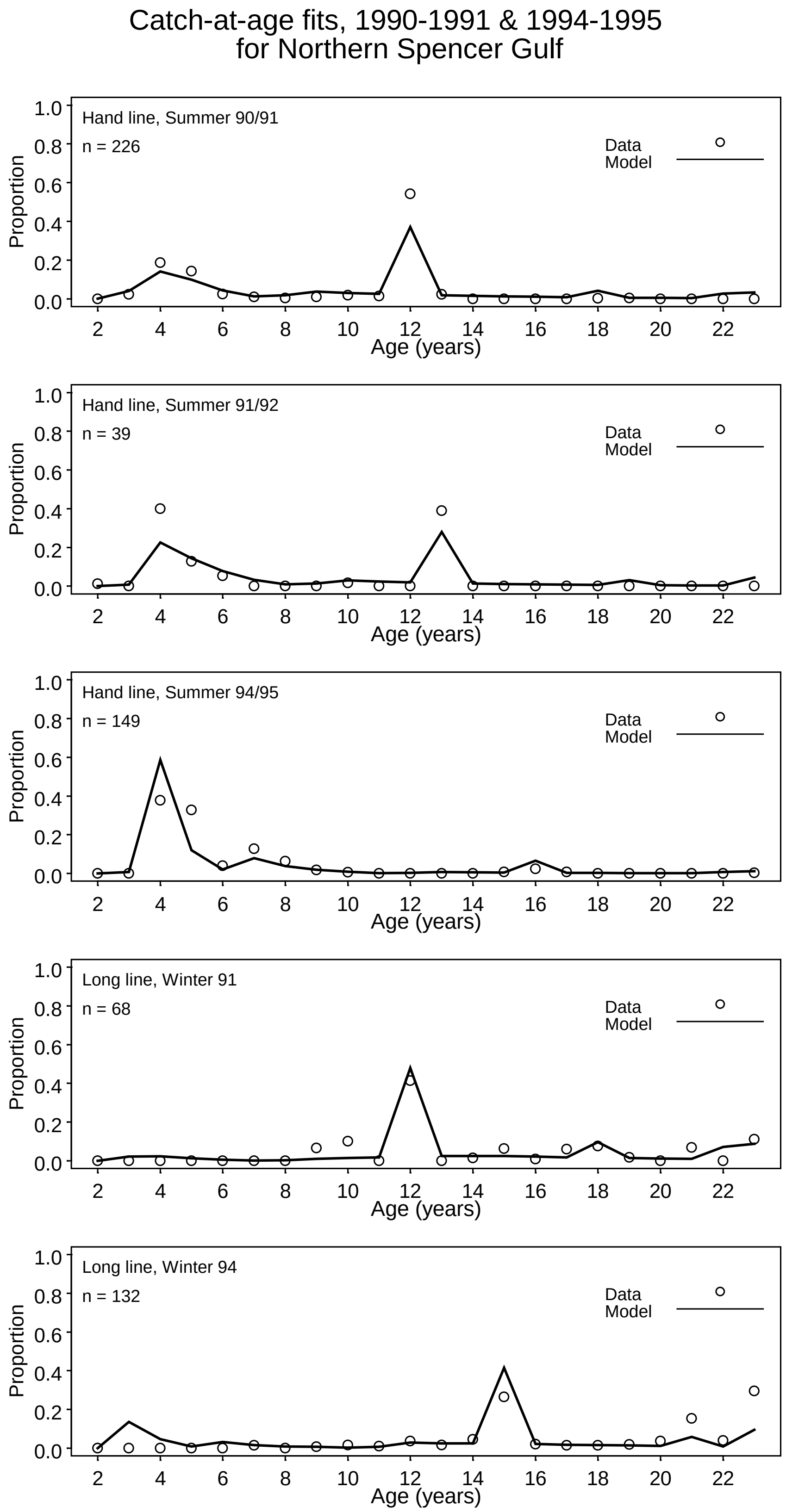


Figure 4.5. Data and model-predicted snapper catch proportions by age for the two earlier programs, 1990-91 and 1994-95, taken in Northern Spencer Gulf only, by both hand line and long line.

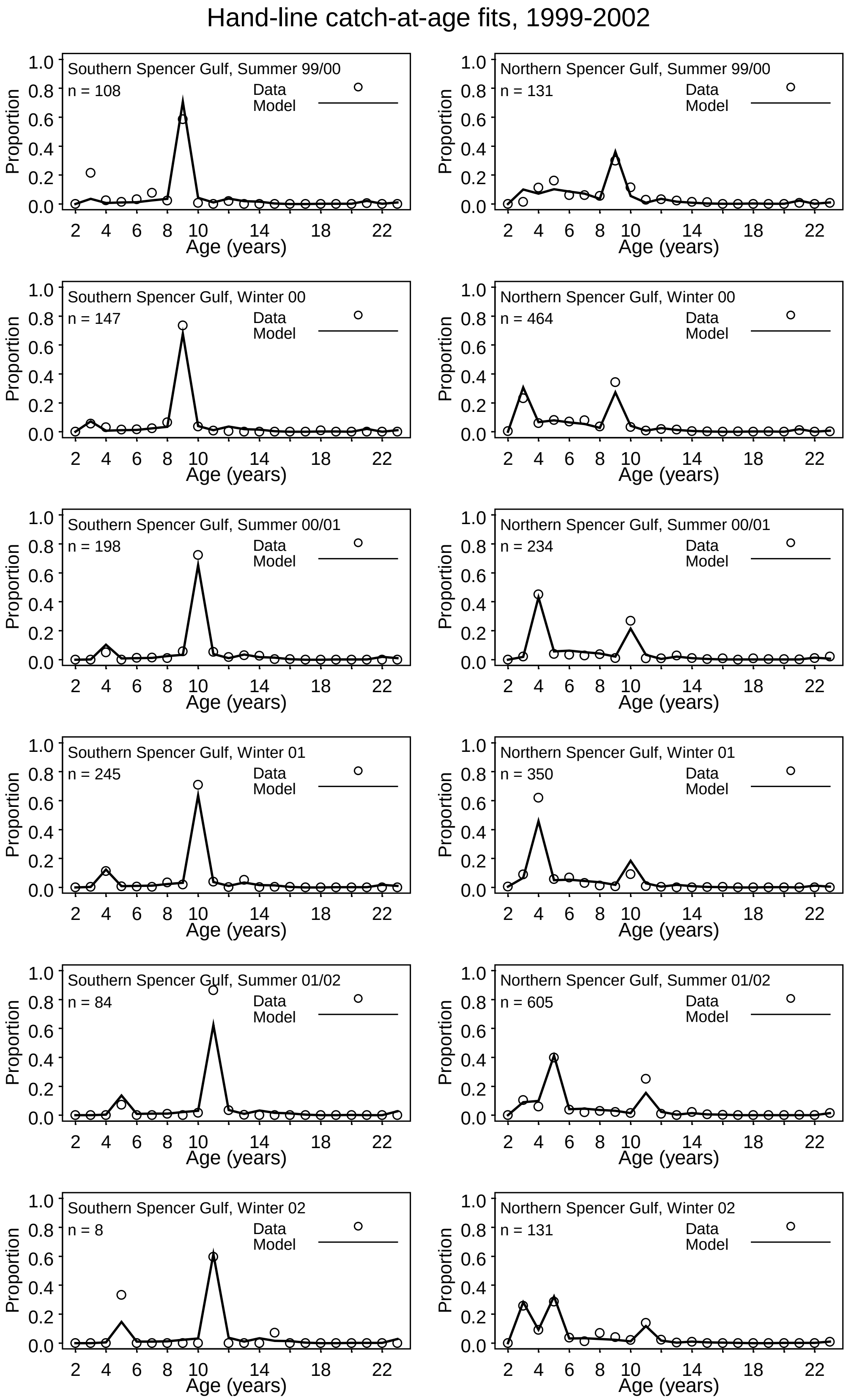


Figure 4.6. Data and model-predicted snapper catch proportions by age in 1999-2002, Northern and Southern Spencer Gulf, hand line only.

Hand-line catch-at-age fits, 1999-2002

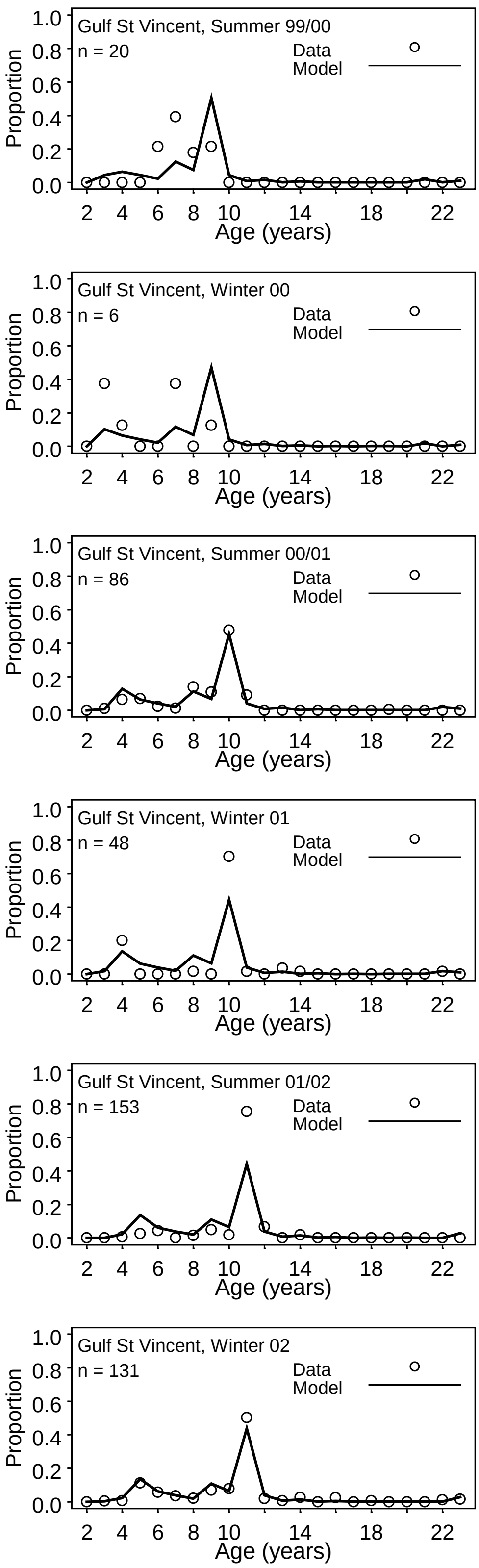


Figure 4.7. Data and model-predicted snapper catch proportions by age in 1999-2002, Gulf St.Vincent, hand lines.

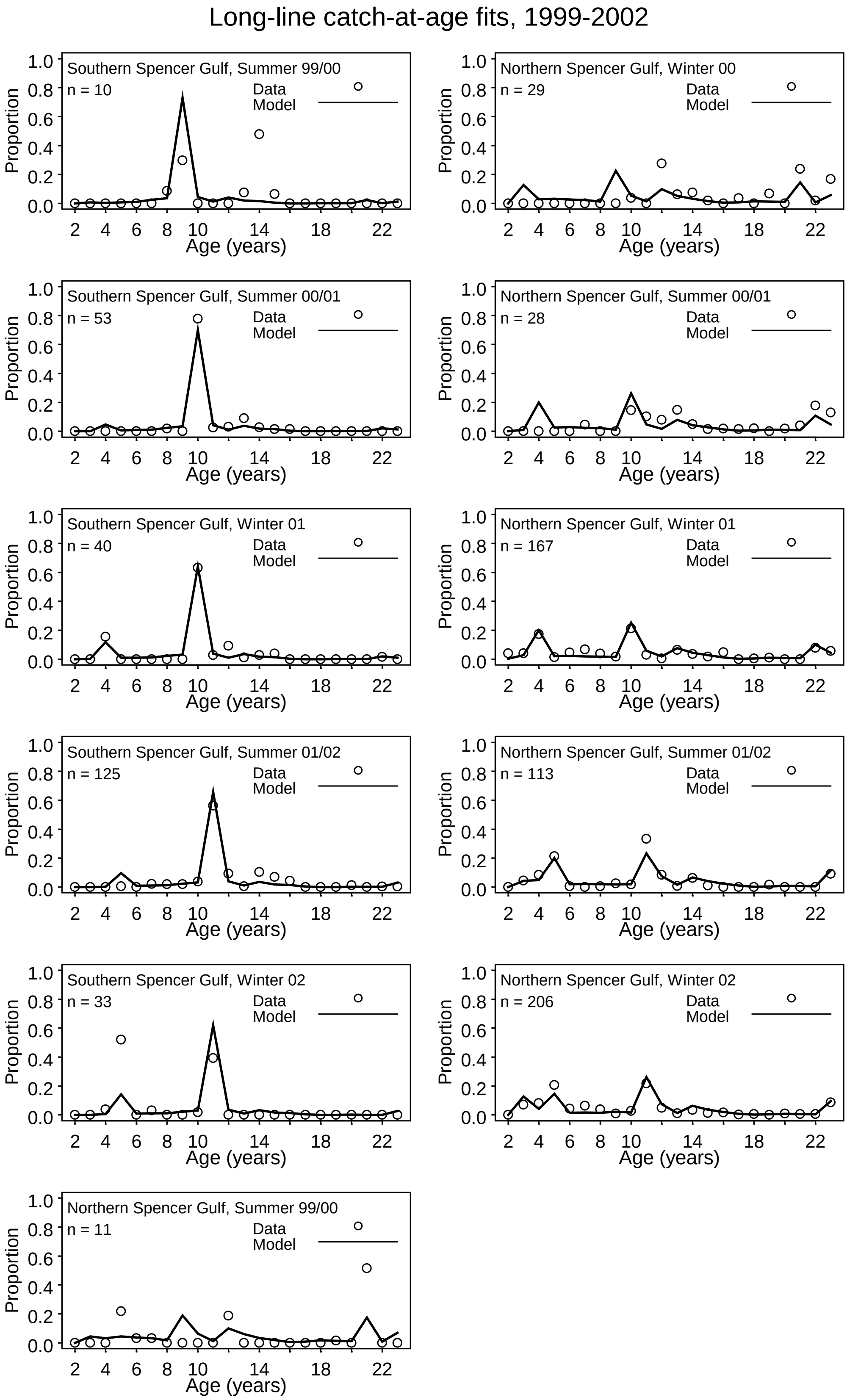


Figure 4.8. Data and model-predicted snapper catch proportions by age taken by long lines in 1999-2002, from Northern and Southern Spencer Gulf.

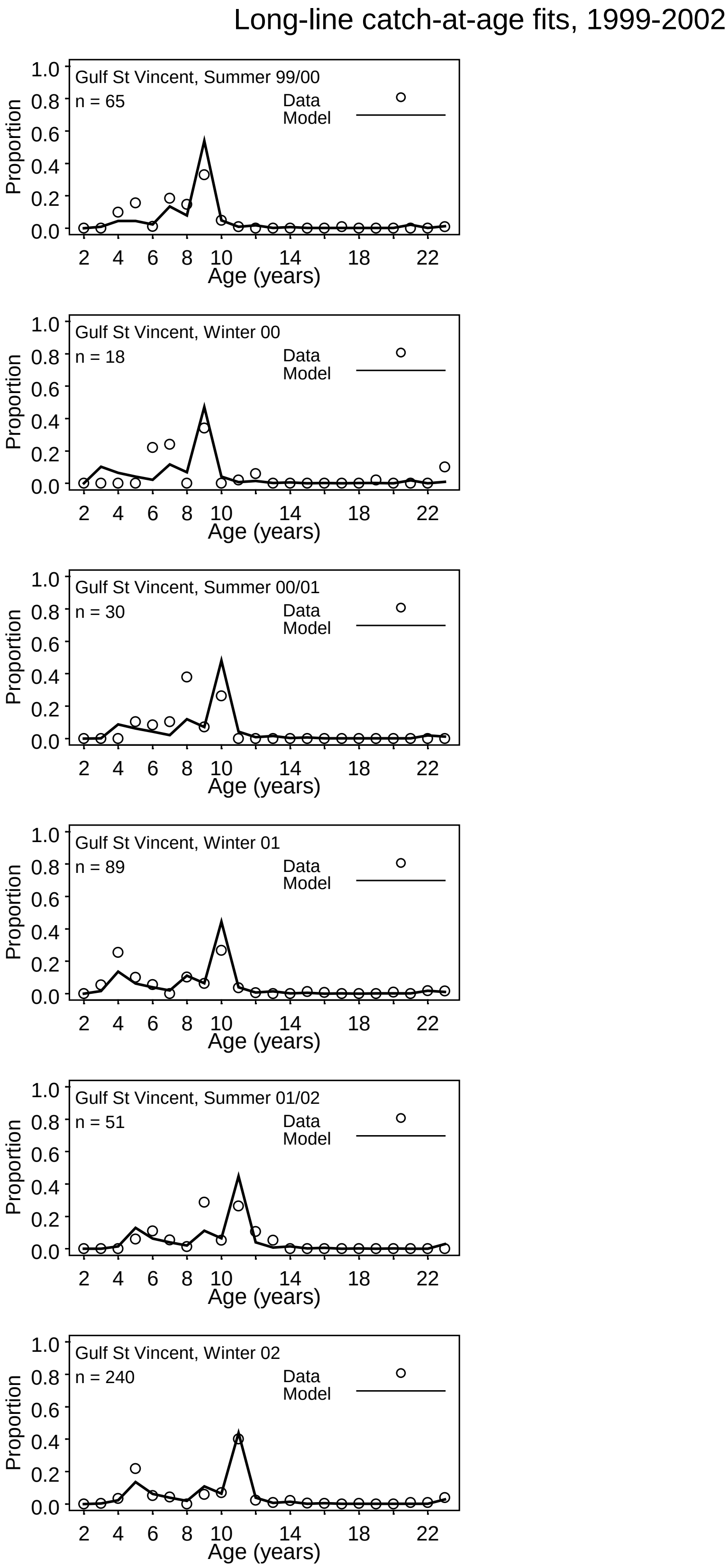


Figure 4.9. Data and model-predicted snapper catch proportions by age taken by long lines in 1999-2002, from Gulf St.Vincent.

## Growth

Growth shows a high degree of variation in South Australian snapper. They grow to fishable length (380 mm) at ages 3-5 years (Figure 4.10). The dotted lines in this graph show the spread of observed lengths about the estimated mean as the standard deviation of the normal likelihood for estimated mean length at age. 95% confidence ranges would be about double the width of the dotted lines shown. Thus, at the peak ages of cohort harvest around age 9-10, that is, at the age when the yearly harvest from that cohort is greatest, the spread of lengths can typically be from 400 mm to about 800 mm.

Growth also exhibits relatively large spatial variation (Figure 4.10). Growth is fastest in Northern Spencer Gulf, followed by Gulf St.Vincent. Growth is considerably slower in the Southern Spencer Gulf for unknown reasons.

The fits to the hand-line catches of mean length at age (Figures 4.11 and 4.12) are close, suggesting three positive outcomes: (1) Mean growth is well fitted by the model. (2) The moment length estimation submodel (developed in this project) is performing as it should by taking account of the observed lengths-at-age properties. (3) The model allows adjustment in growth estimates to correct for right-hand asymmetric mortality bias. This source of bias in estimating growth parameters, also discussed in Chapter 1, results from the fact that the fastest growing fish are removed sooner and in greater numbers from the population due to harvesting. This bias has been accounted for in this model where growth is fully integrated with the predicted changes in numbers by both age and length. Thus, the more rapid removal of faster growing fish is explicit in the model, specifically in the removals of snapper from the faster growing length slices.

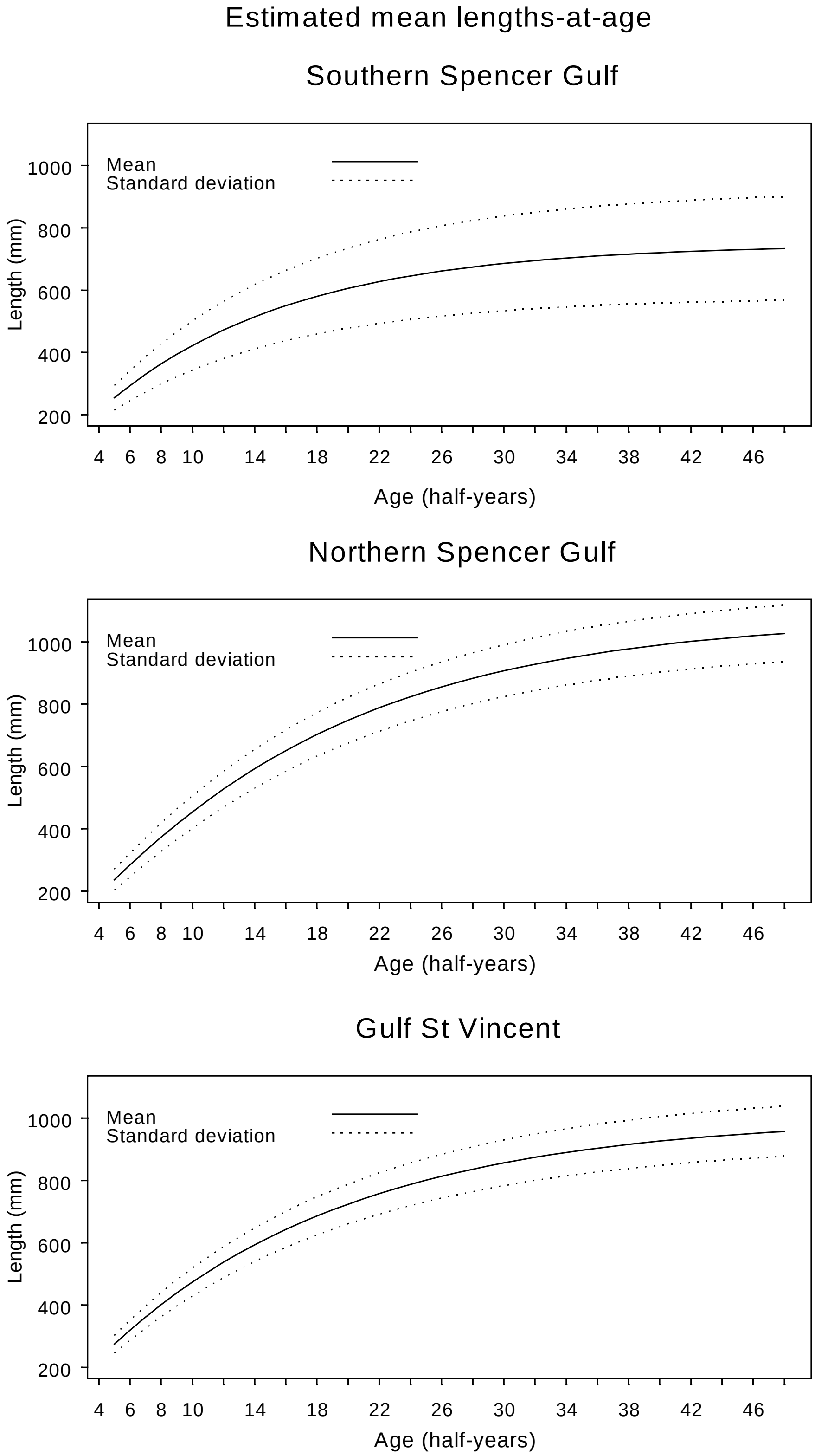


Figure 4.10. Model-estimated mean length at age (in the snapper population), by region. These estimates account for the higher rates of mortality on faster growing fish that would otherwise bias (underestimate) the mean length at age.

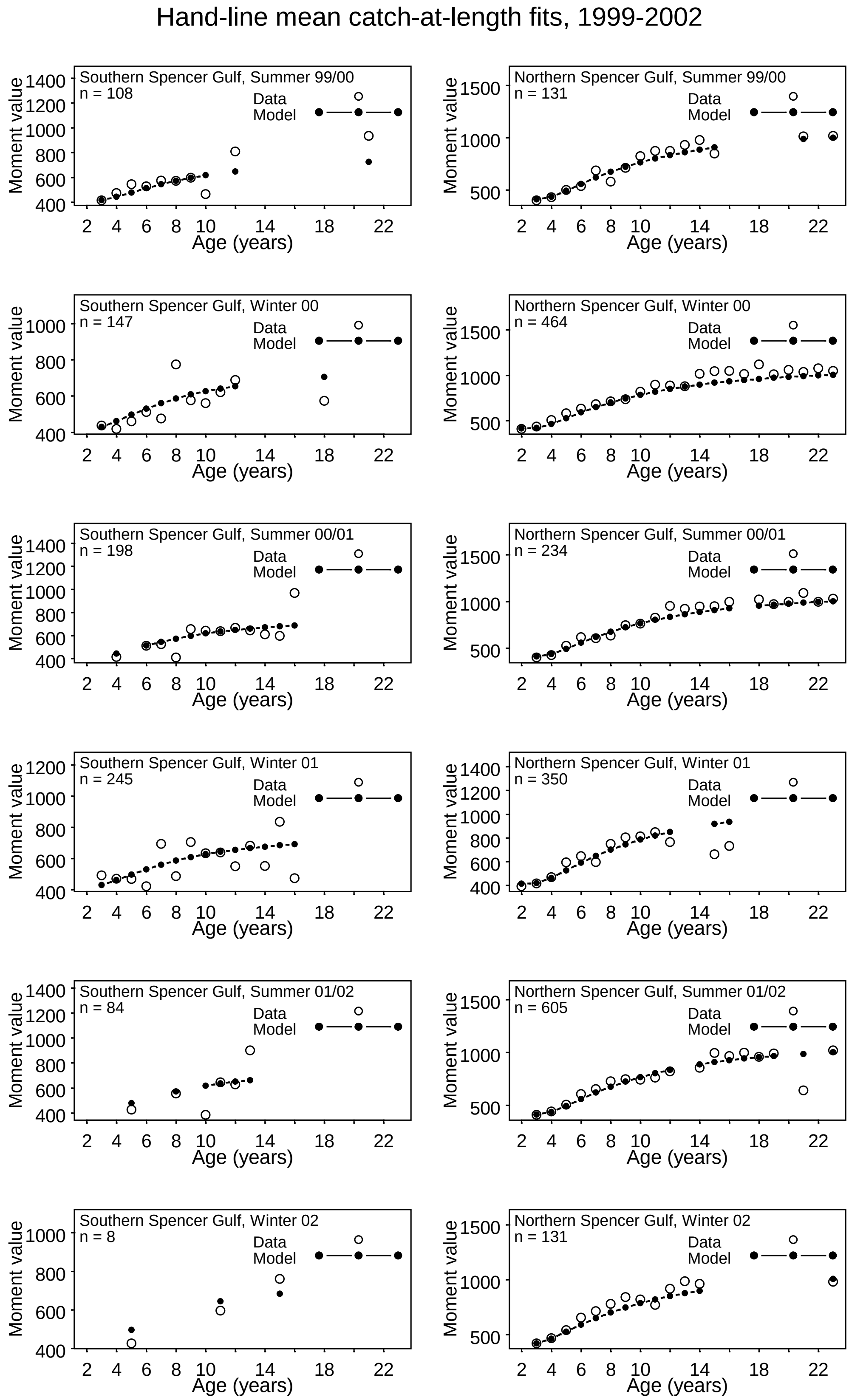


Figure 4.11. Data and model-predicted snapper catch mean lengths by age taken by hand lines in 1999-2002, from Northern and Southern Spencer Gulf.

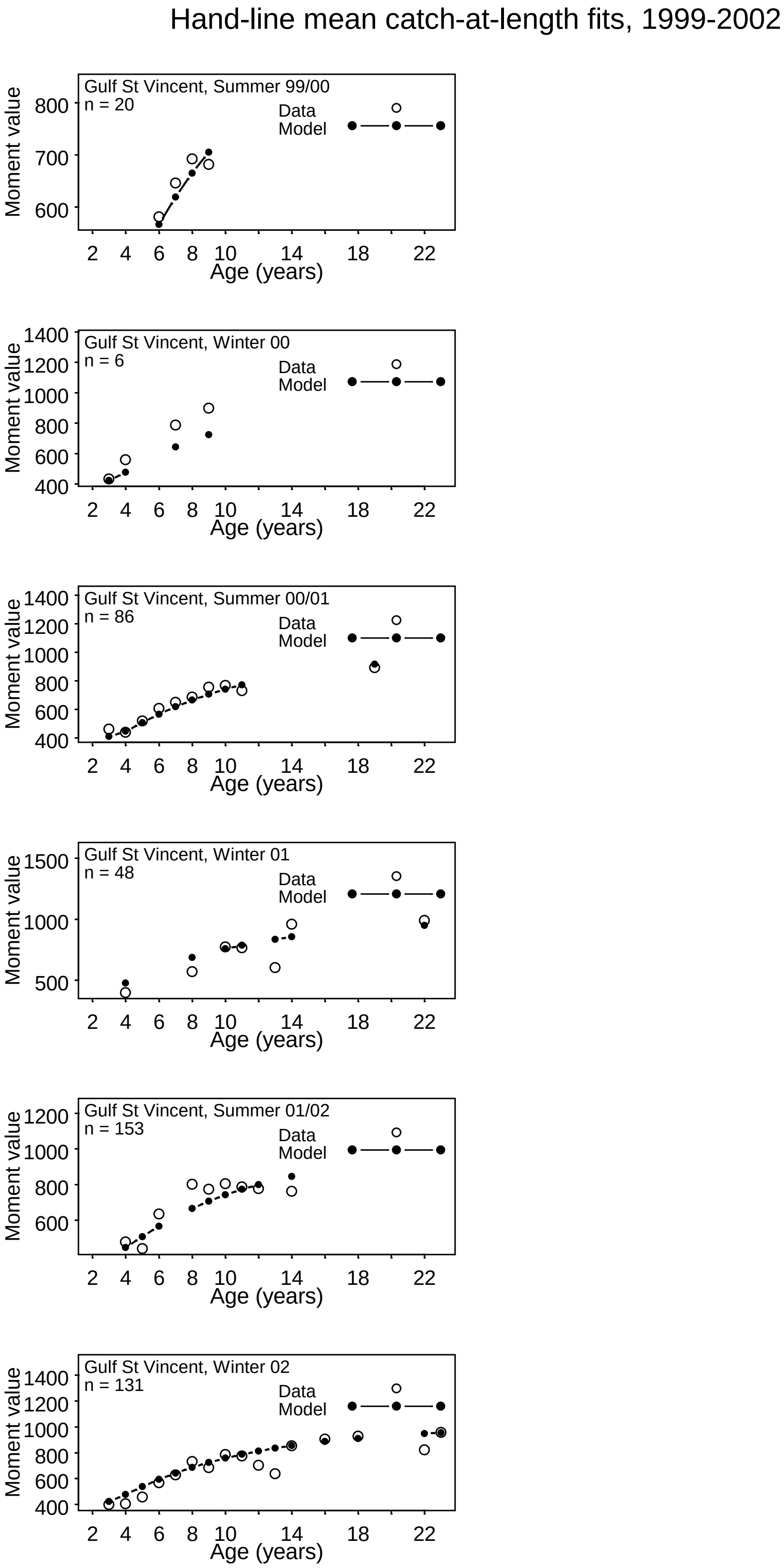


Figure 4.12. Data and model-predicted snapper catch mean lengths by age taken by hand lines in 1999-2002, from Gulf St.Vincent.

## Discussion

Overall, the snapper stock assessment model estimation, like that of garfish, has yielded a relatively smooth path to convergence and the fits are satisfactory or good. The catch sample data, especially for the latter sampling period of 1999-2003, were obtained by regular market sampling, and are thus representative. This is reflected in the self-consistent nature of the fits to both catch-numbers-at-age, notably the peak year classes, and mean-length-at-age among different time periods and gear types.

The principal remaining need is for better knowledge and data on snapper movement. Currently an FRDC Project (2002/001) is underway in South Australia, using otolith microchemistry, to identify ages and destinations of large-scale movements among different water masses.

## References

McGlennon, D. and Jones, G.K. 1999. Snapper (*Pagrus auratus*) South Australian Fisheries Assessment Series No. 99/13. SARDI Aquatic Sciences Report. 23 pp.

McGlennon, D. and Kinloch, M.A. 1987. Resource allocation in the South Australian Marine Scalefish fishery. FRDC Final report. No. 93/249. 105 pp.

## Appendix 4.1. Fits to the Length Moments

In this Appendix, the fits to length moments are shown. Like the garfish model as described in Chapter 1, but unlike previous fishery models that we know, the length data are fitted by age, rather than summing the model numbers in each length bin over all ages and fitting to the summed length data. This is possible because of (1) the explicit partition of the population array, and thus the catches, into length slices, and (2) by the correction algorithm for non-representative age subsampling from the larger sample of lengths. Thus, for all aged fish caught within a given time step, region and gear type, the mean length, and the other three moment properties, are calculated by a weighted sum, the weighting being given by the correction factor for non-representative age subsampling. That is, in the moment sums over all fish of a given age, individual fish are weighted in proportion to the relative size of the length bin that each fish falls into, i.e. more weighting if catch numbers are higher for that corresponding length bin in the (presumably representative) length catch sample.

Four 'central moment properties' were potentially fitted for each combination of age, region and gear (hand line or long line): mean, standard deviation, skewness and kurtosis. However, in practice, we set threshold criteria for fitting to any given moment: (1) A minimum sample size (of aged fish) was required for the data moments, and (2) for the model moments, a minimum number of slices, and thus, of model time steps above age of recruitment, is mathematically required to calculate the successively higher model moments, as summarised in point 13 of Methods . Thus only combinations of age, region, gear and moment that met these two minimum criteria were fitted and are thereby included in the figures to follow.

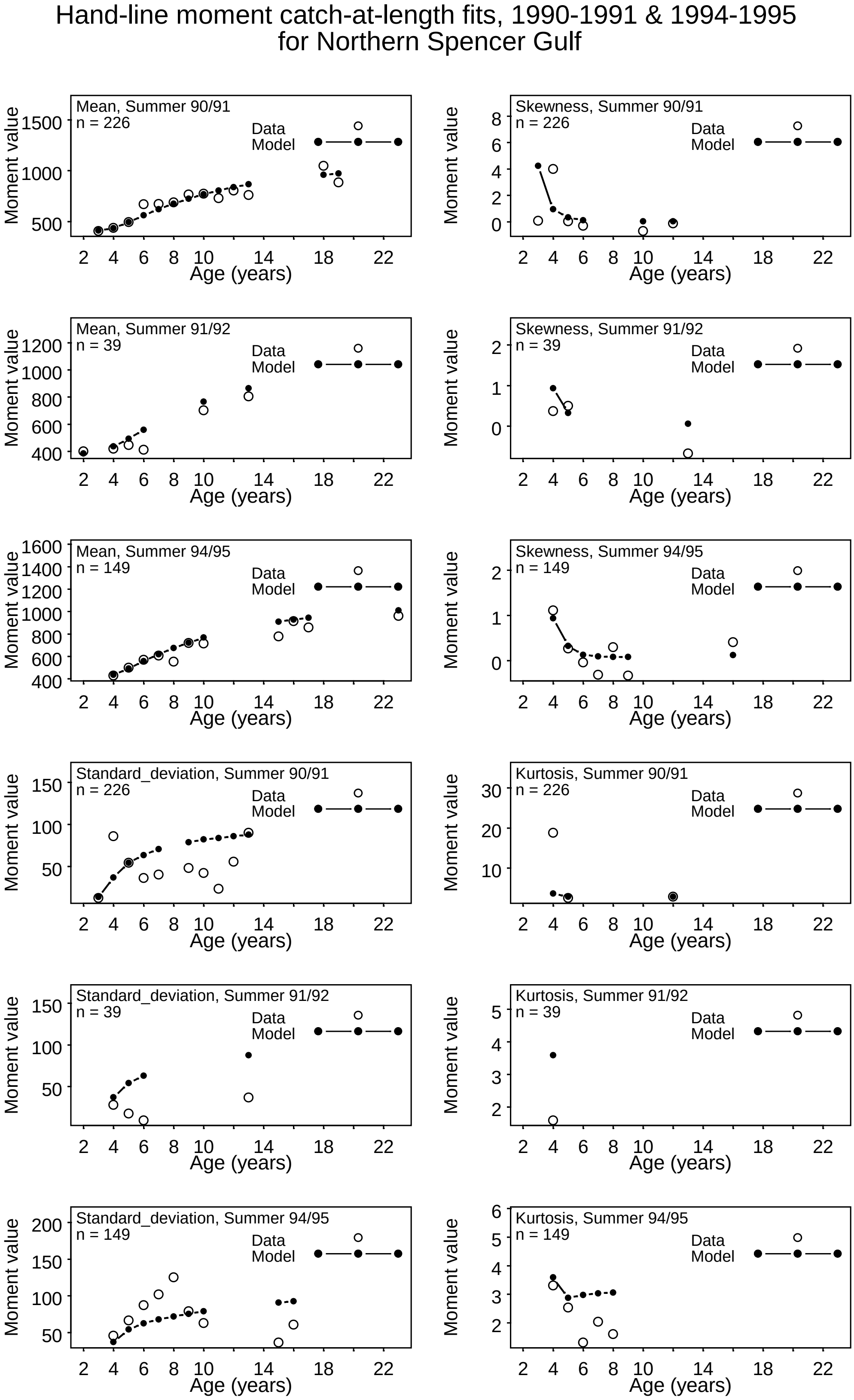


Figure A4.1. Fits of the four central length moments of snapper hand-line catch, by age, for selected half-years in Northern Spencer Gulf, from two sampling periods, 1990-91 and 1994-95.

Hand-line standard deviation catch-at-length fits, 1999-2002

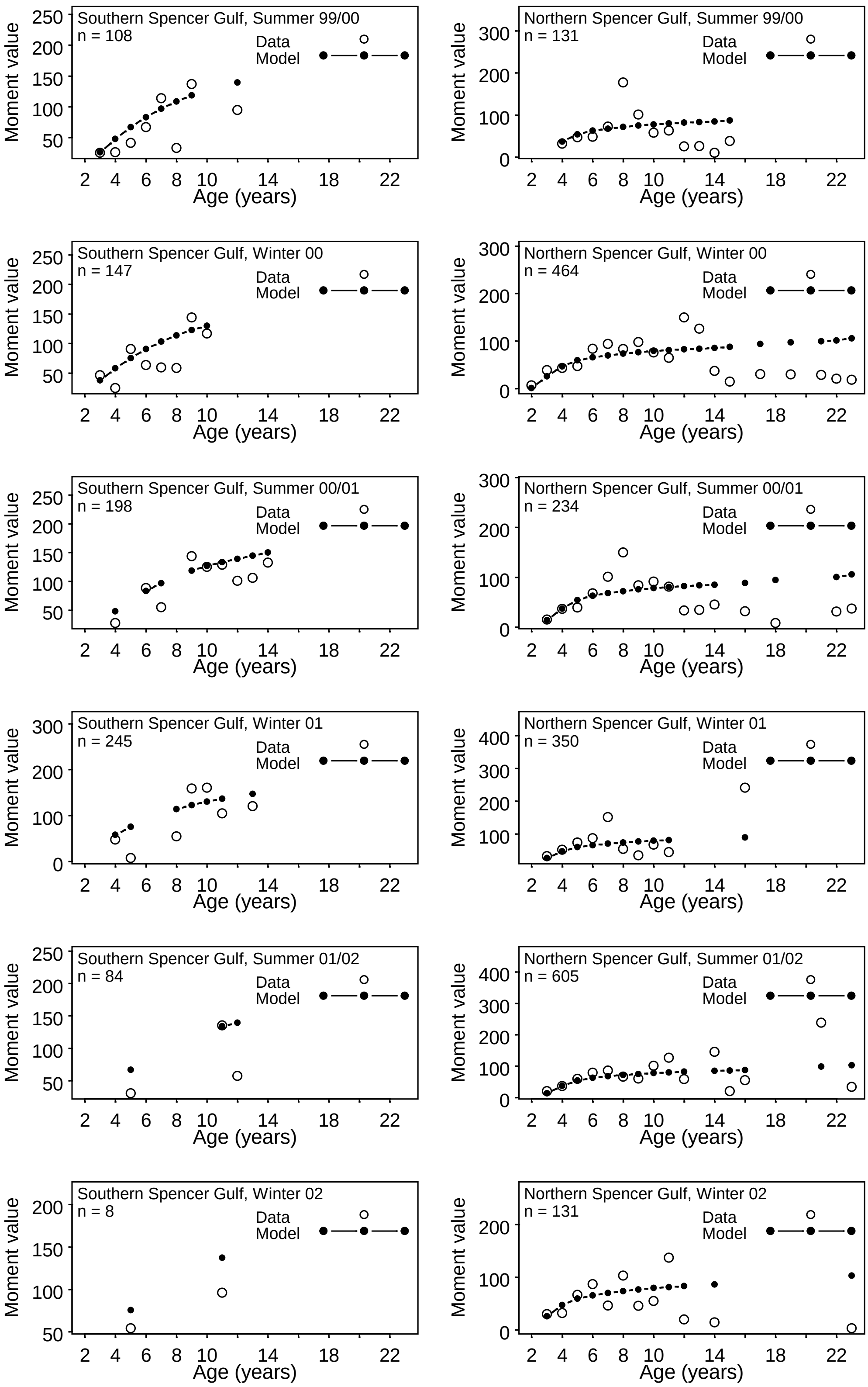


Figure A4.2. Fits of the standard deviation of lengths of snapper hand-line catch, by age, for selected half-years in Northern and Southern Spencer Gulf, from the most recent sampling period, 1999-2002.

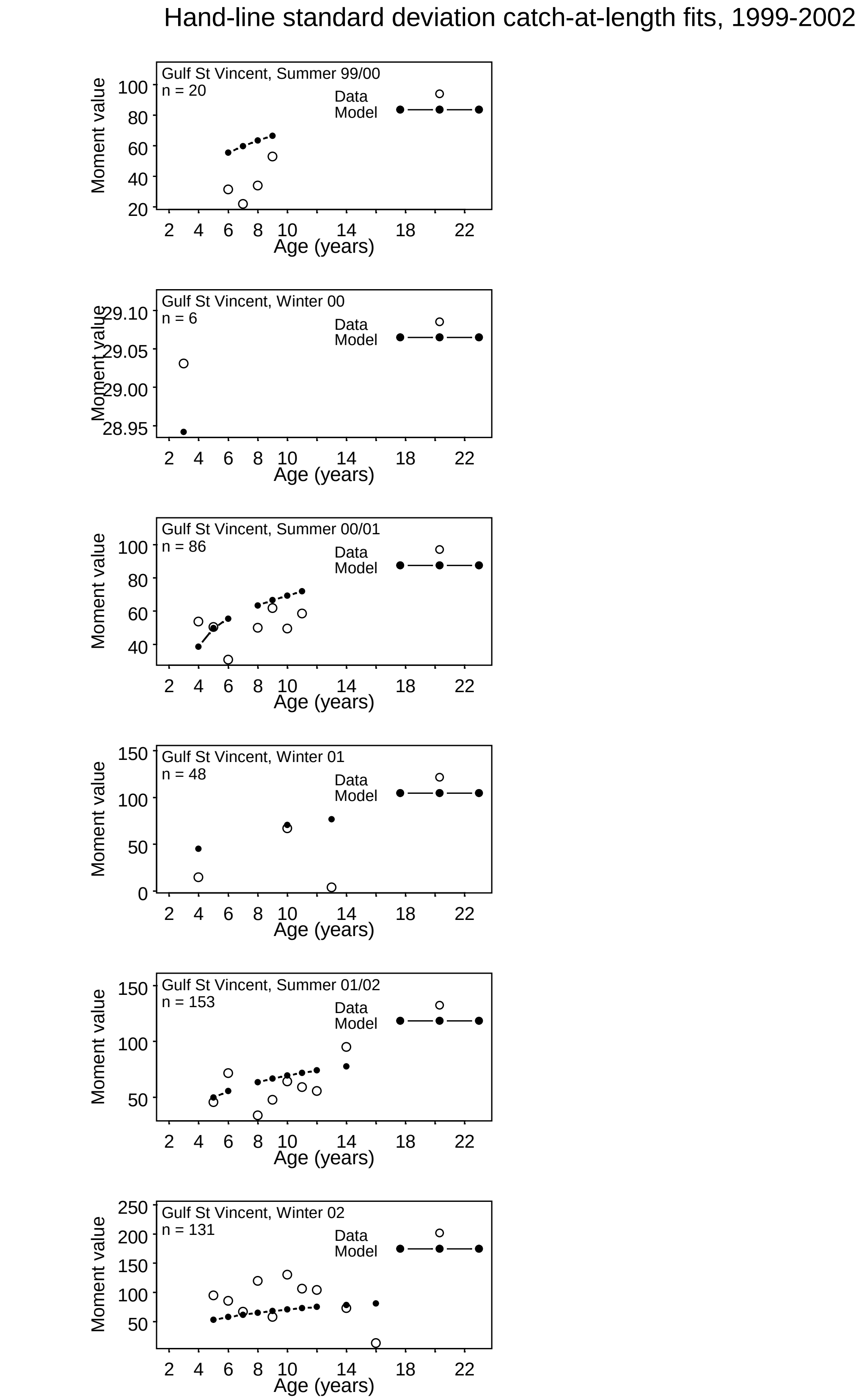


Figure A4.3. Fits of the standard deviation of lengths of snapper hand-line catch, by age, for selected half-years in Gulf St.Vincent, from the most recent sampling period, 1999-2002.

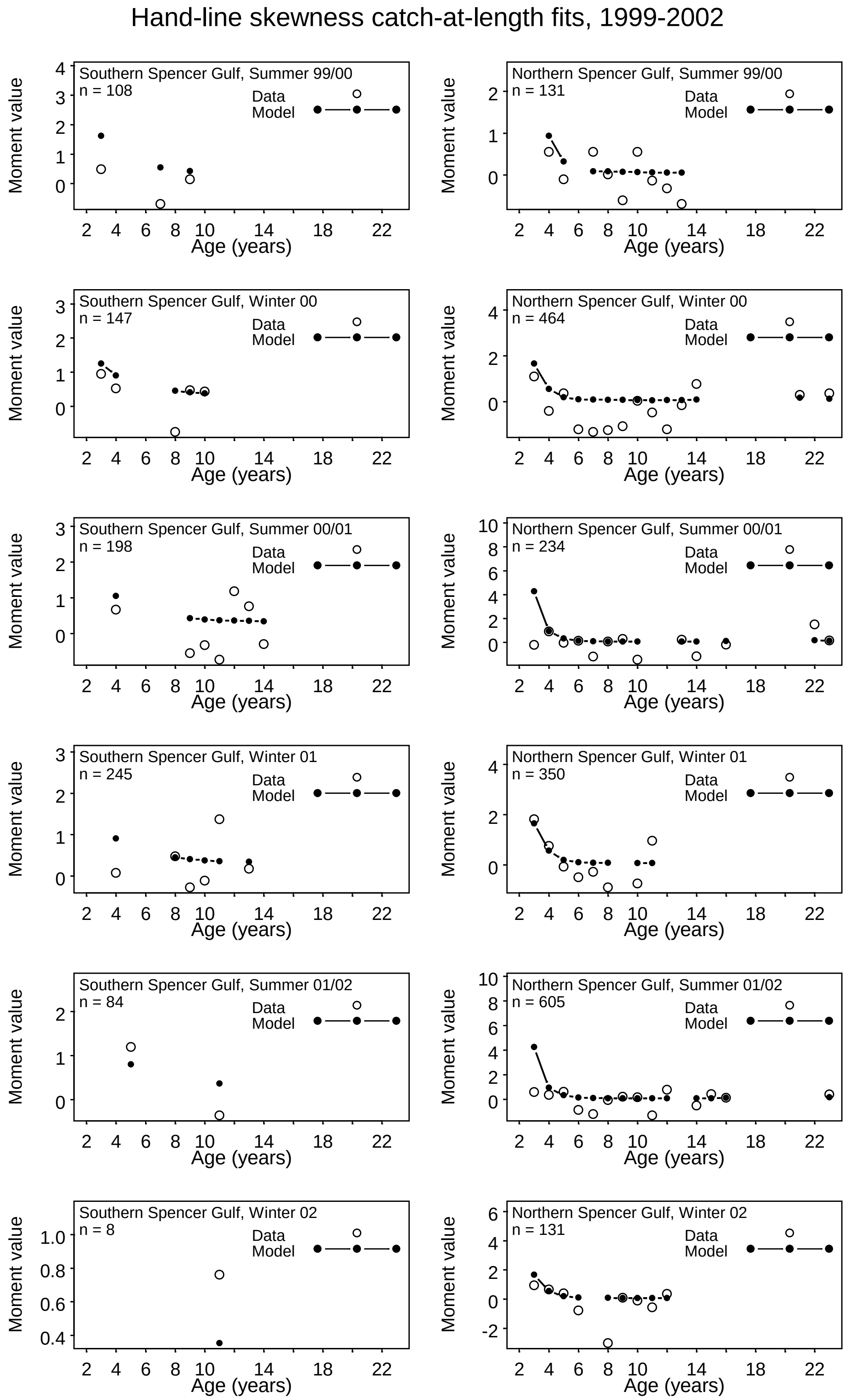


Figure A4.4. Fits of the skewness of lengths of snapper hand-line catch, by age, for selected half-years in Northern and Southern Spencer Gulf, from the most recent sampling period, 1999-2002.

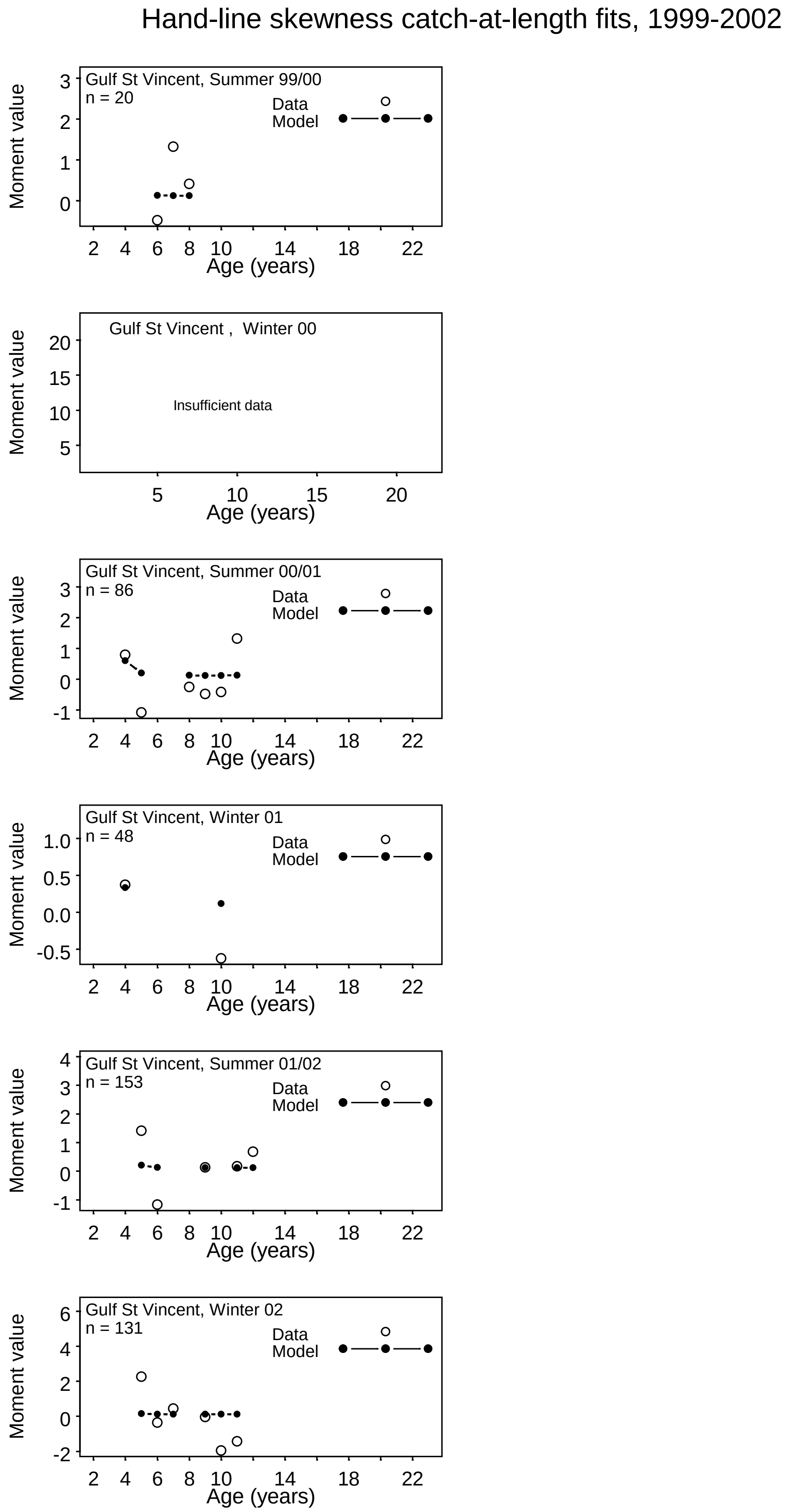


Figure A4.5. Fits of the skewness of lengths of snapper hand-line catch, by age, for selected half-years in Gulf St.Vincent, from the most recent sampling period, 1999-2002.

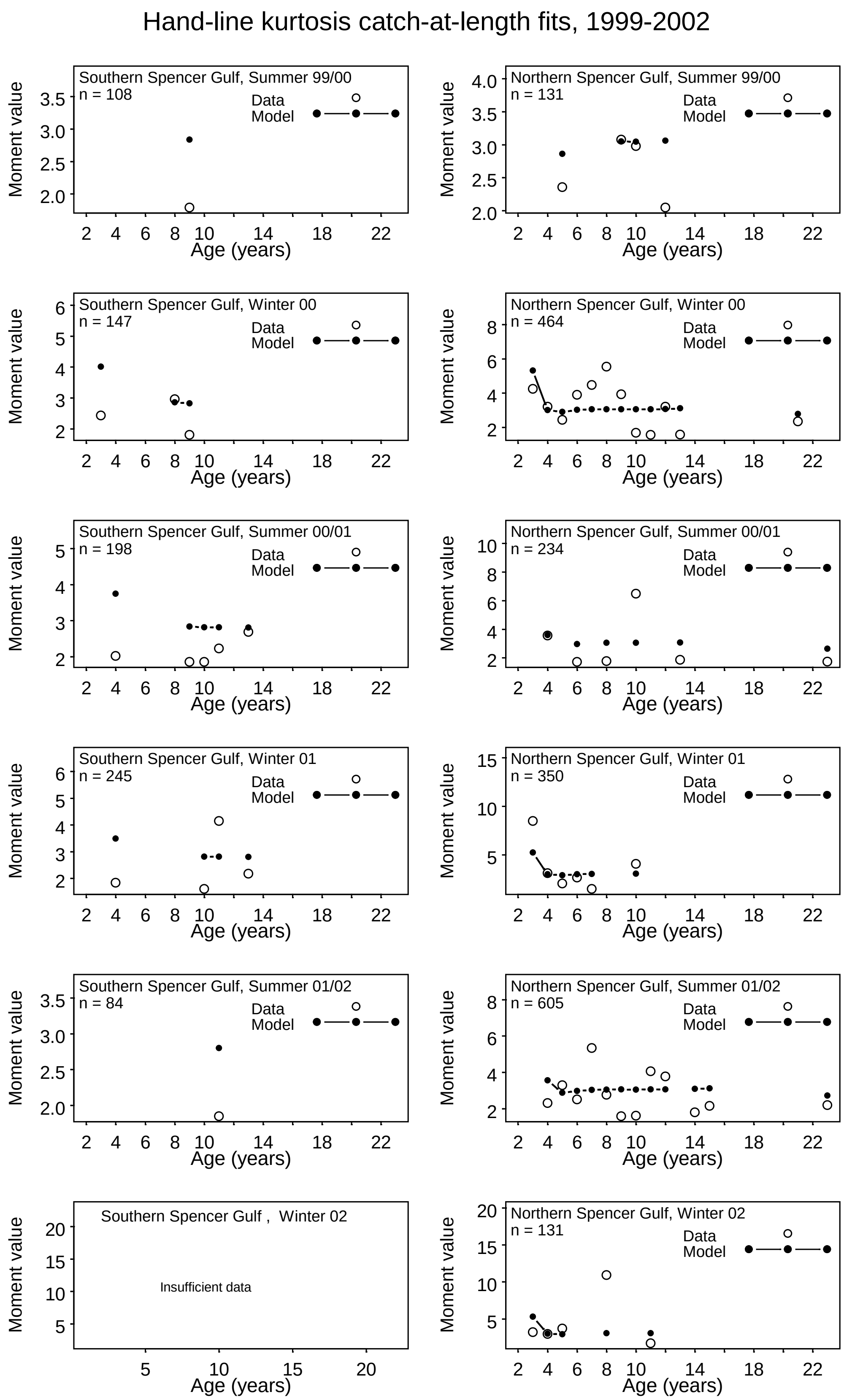


Figure A4.6. Fits of the kurtosis of lengths of snapper hand-line catch, by age, for selected half-years in Northern and Southern Spencer Gulf, from the most recent sampling period, 1999-2002.

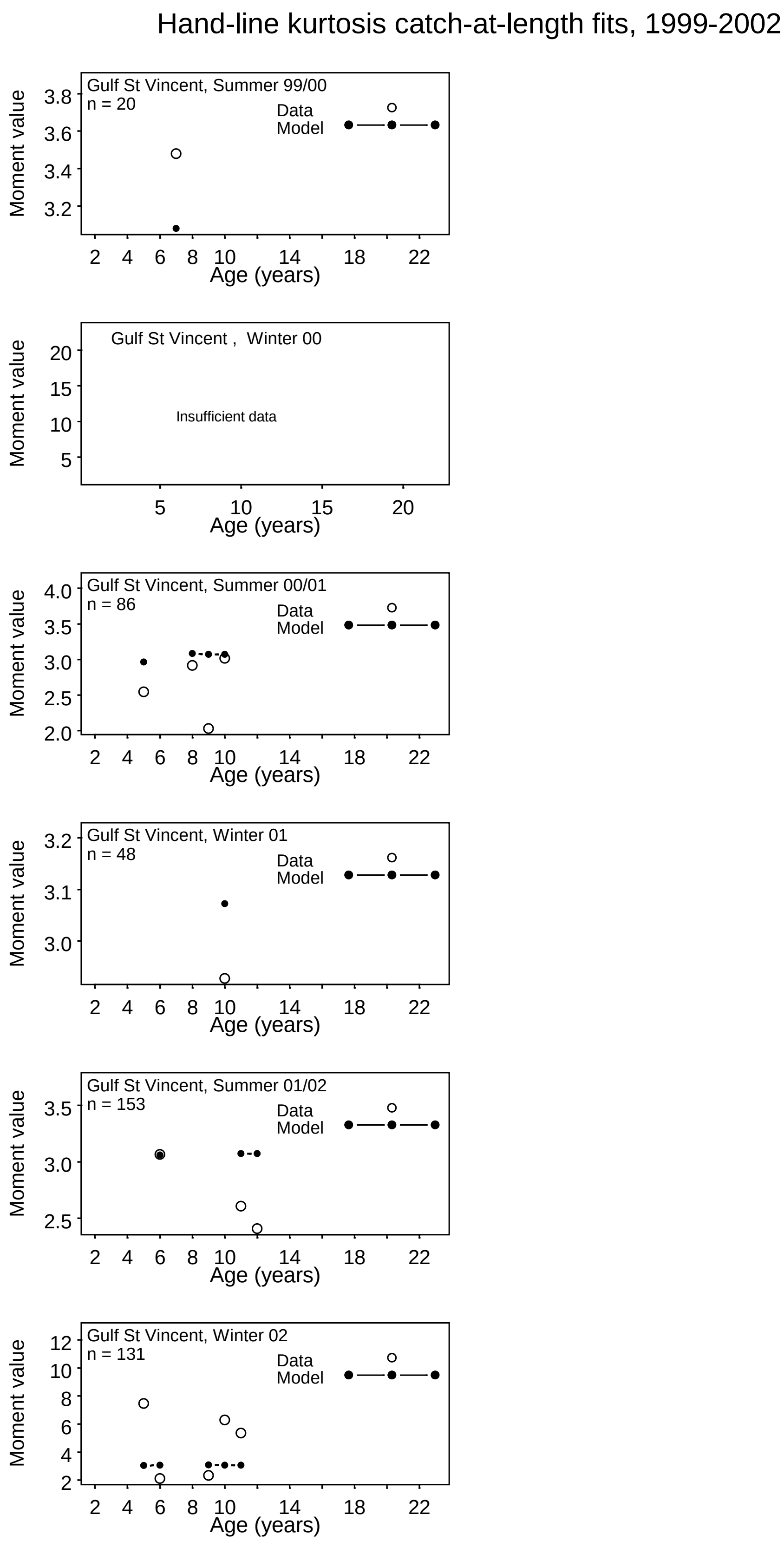


Figure A4.7. Fits of the kurtosis of lengths of snapper hand-line catch, by age, for selected half-years in Gulf St.Vincent, from the most recent sampling period, 1999-2002.

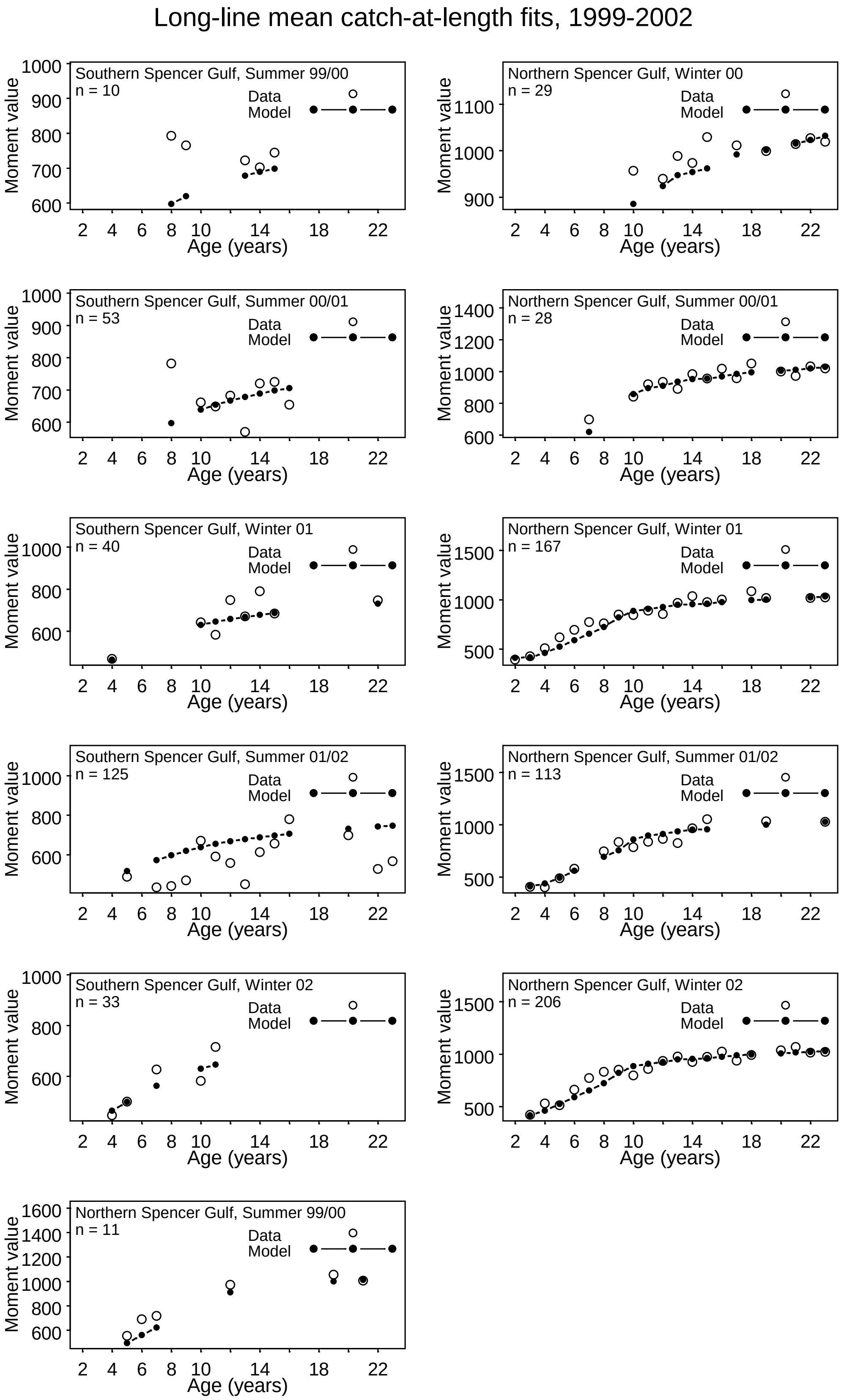


Figure A4.8. Fits of the mean lengths of snapper long-line catch, by age, for selected half-years in Northern and Southern Spencer Gulf, from the most recent sampling period, 1999-2002.

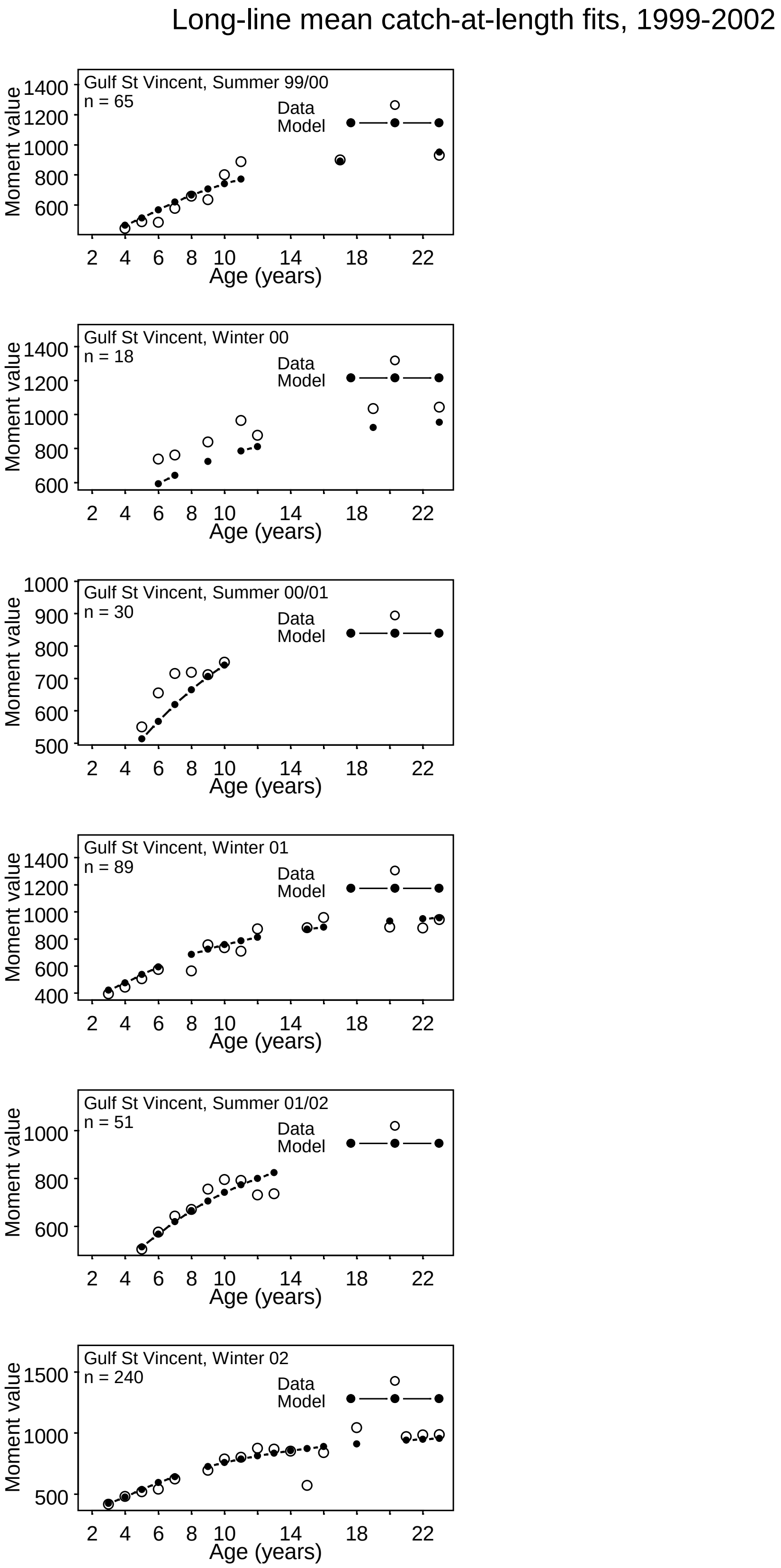


Figure A4.9. Fits of the mean length moments of snapper long-line catch, by age, for selected half-years in Gulf St.Vincent, from the most recent sampling period, 1999-2002.

Long-line standard deviation catch-at-length fits, 1999-2002

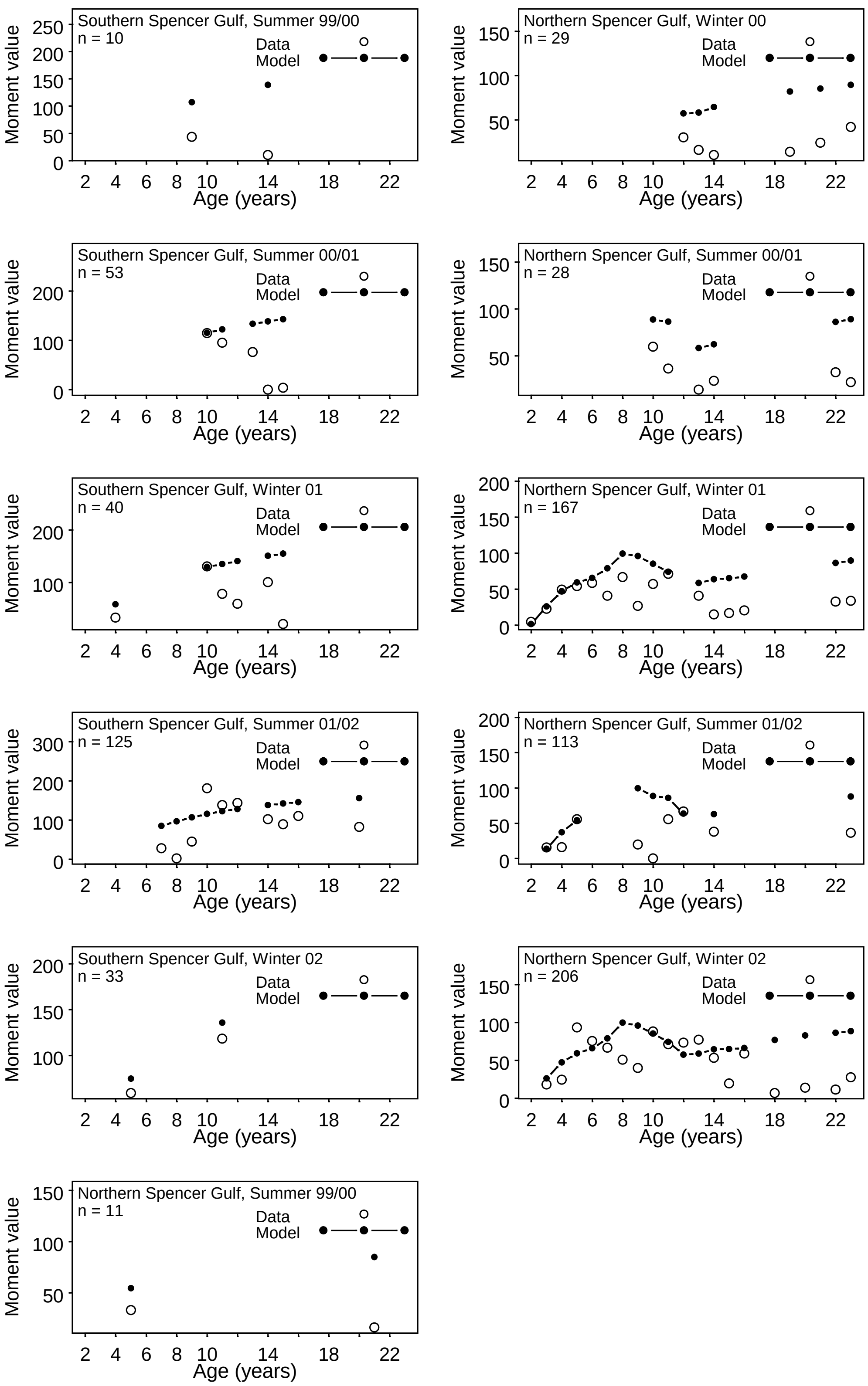


Figure A4.10. Fits of the standard deviation of lengths of snapper long-line catch, by age, for selected half-years in Northern and Southern Spencer Gulf, from the most recent sampling period, 1999-2002.

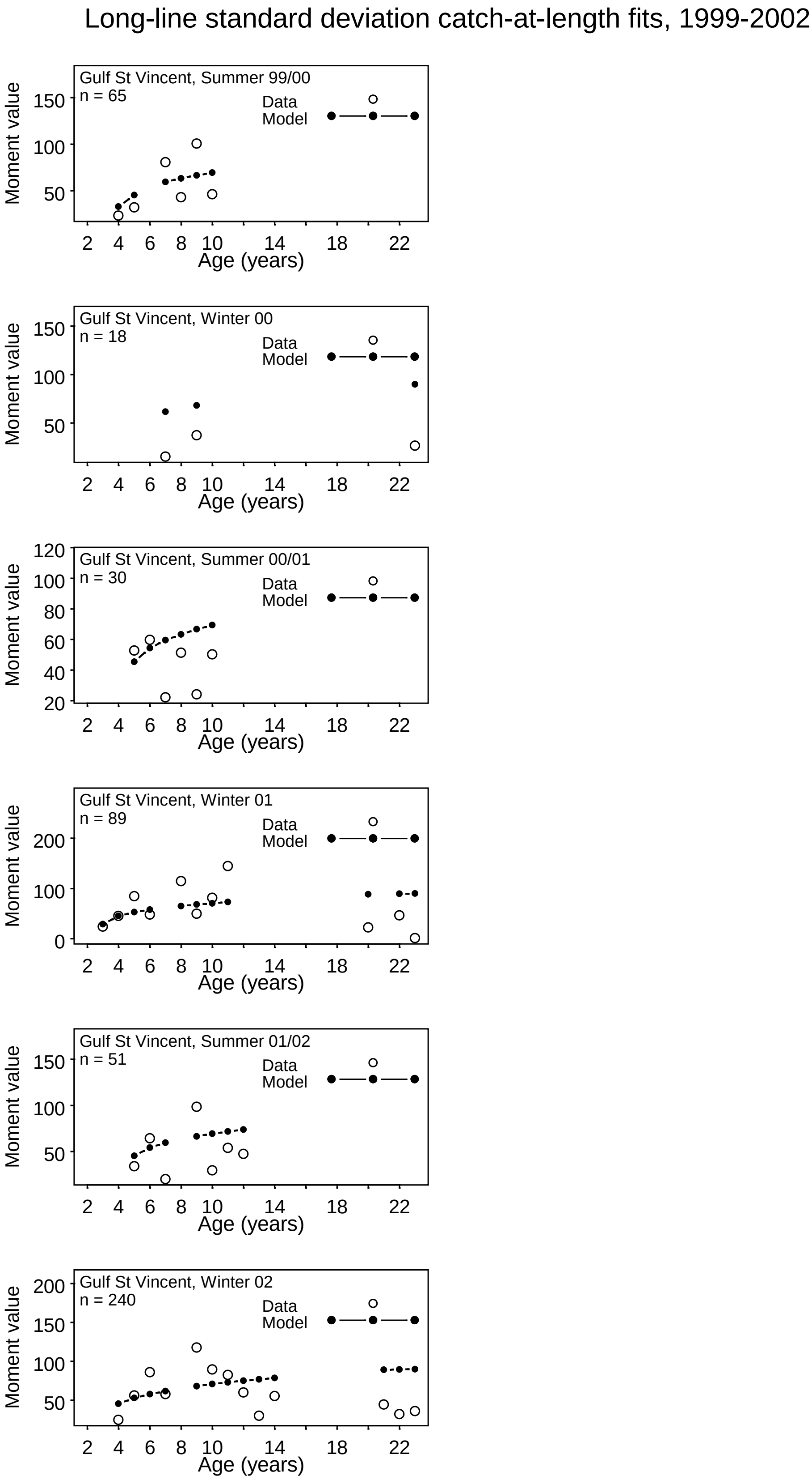


Figure A4.11. Fits of the standard deviation of lengths of snapper long-line catch, by age, for selected half-years in Gulf St.Vincent, from the most recent sampling period, 1999-2002.

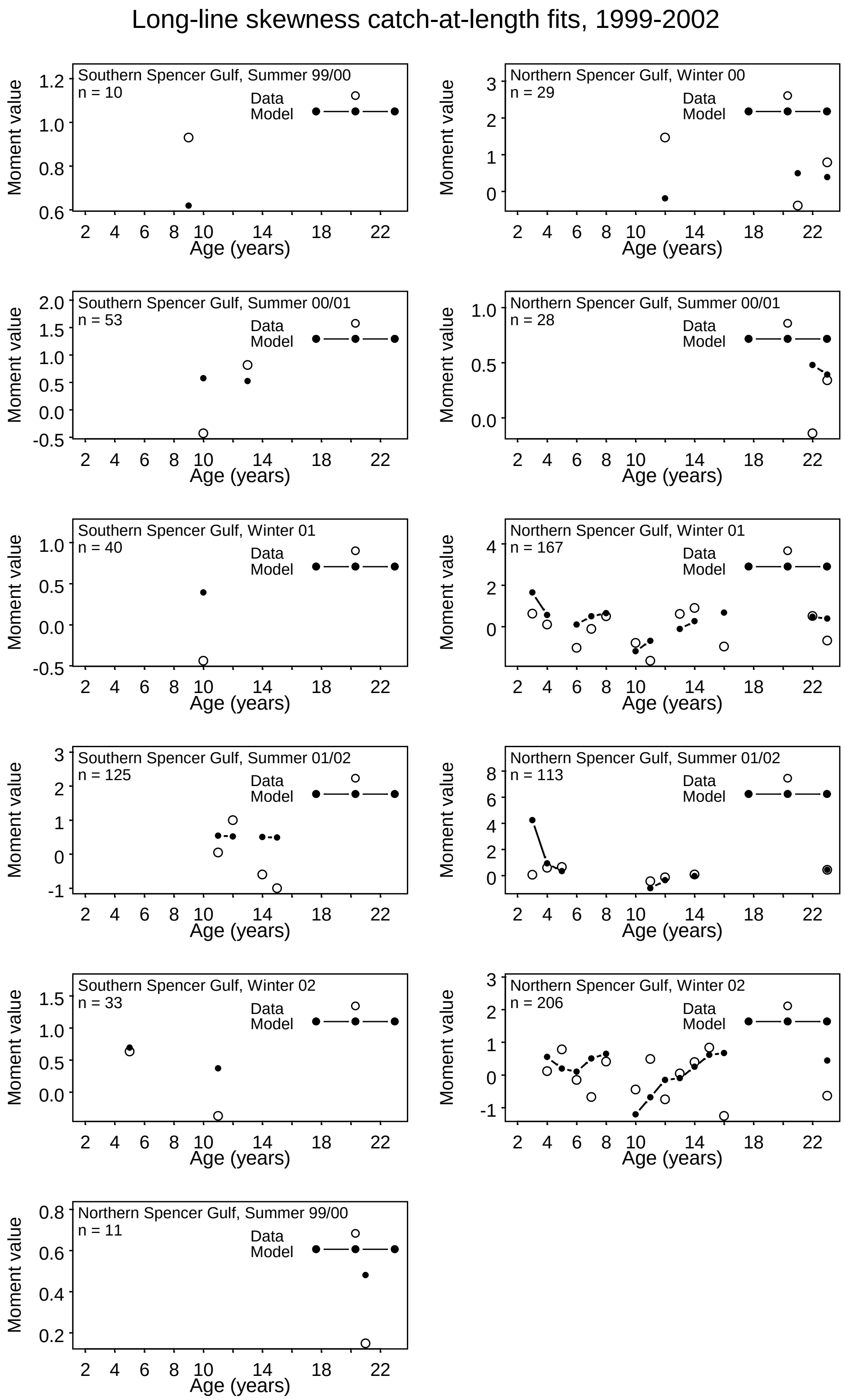


Figure A4.12. Fits of the skewness of lengths of snapper long-line catch, by age, for selected half-years in Northern and Southern Spencer Gulf, from the most recent sampling period, 1999-2002.

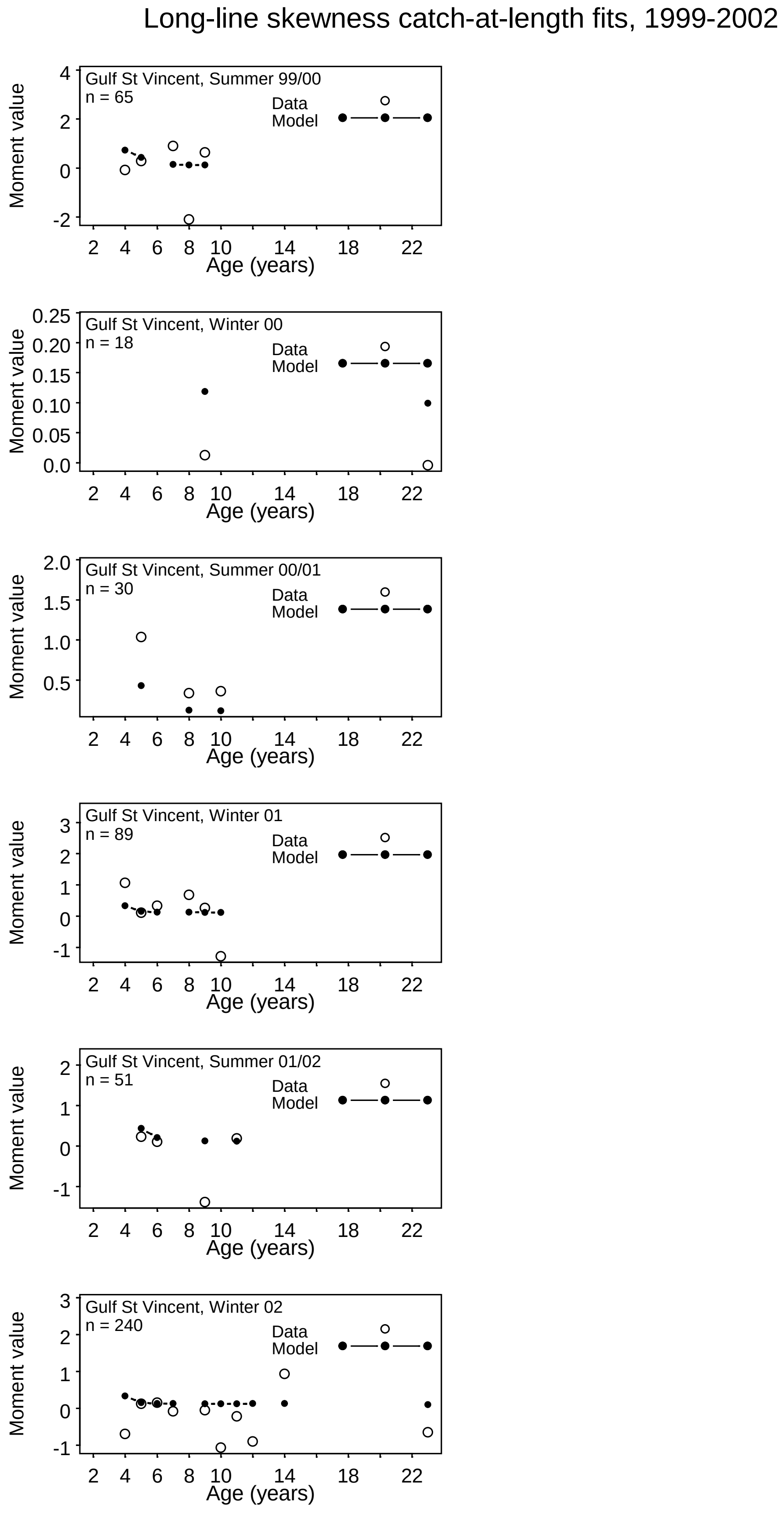


Figure A4.13. Fits of the skewness of lengths of snapper long-line catch, by age, for selected half-years in Gulf St.Vincent, from the most recent sampling period, 1999-2002.

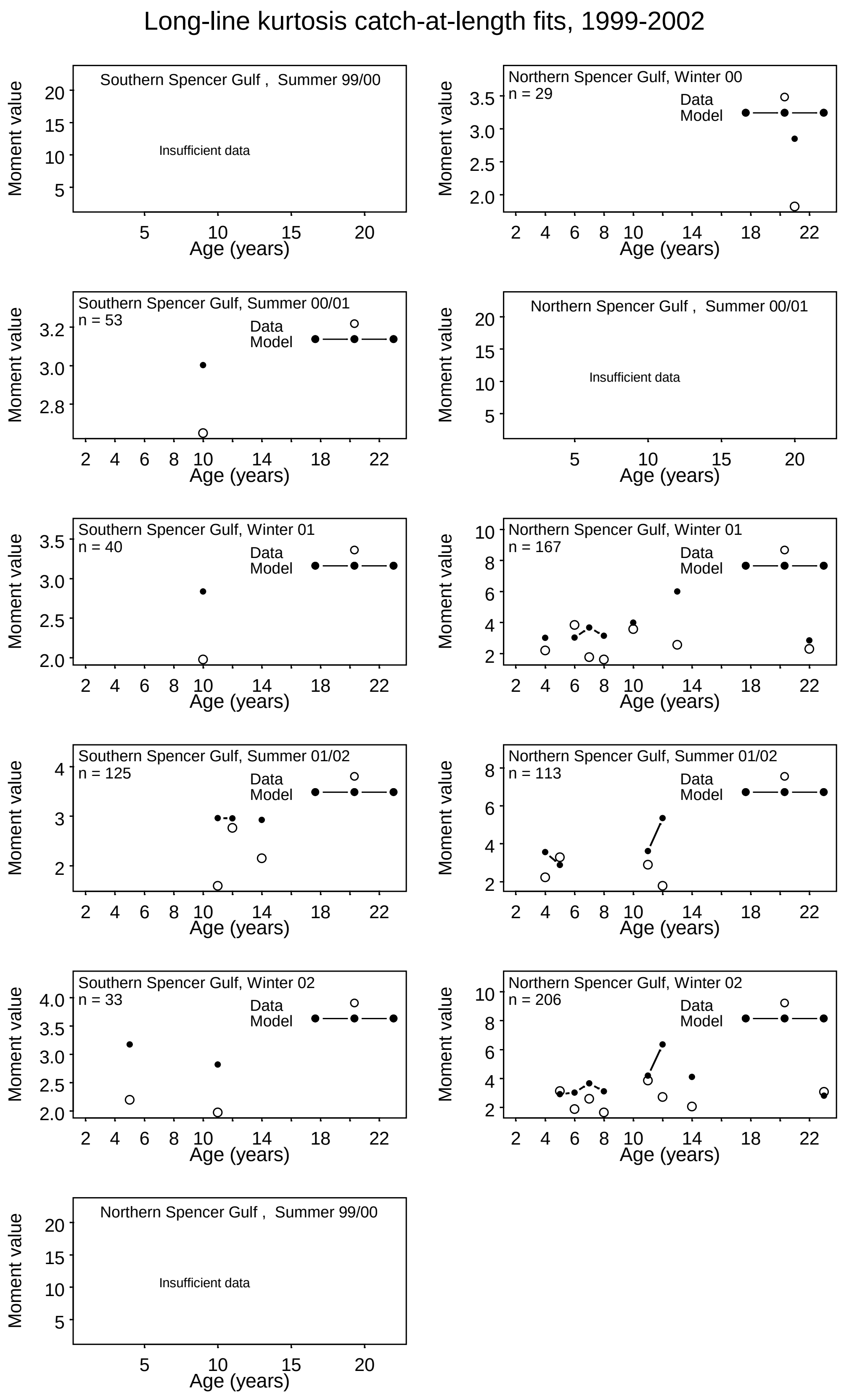


Figure A4.14. Fits of the kurtosis of lengths of snapper long-line catch, by age, for selected half-years in Northern and Southern Spencer Gulf, from the most recent sampling period, 1999-2002.

Long-line kurtosis catch-at-length fits, 1999-2002

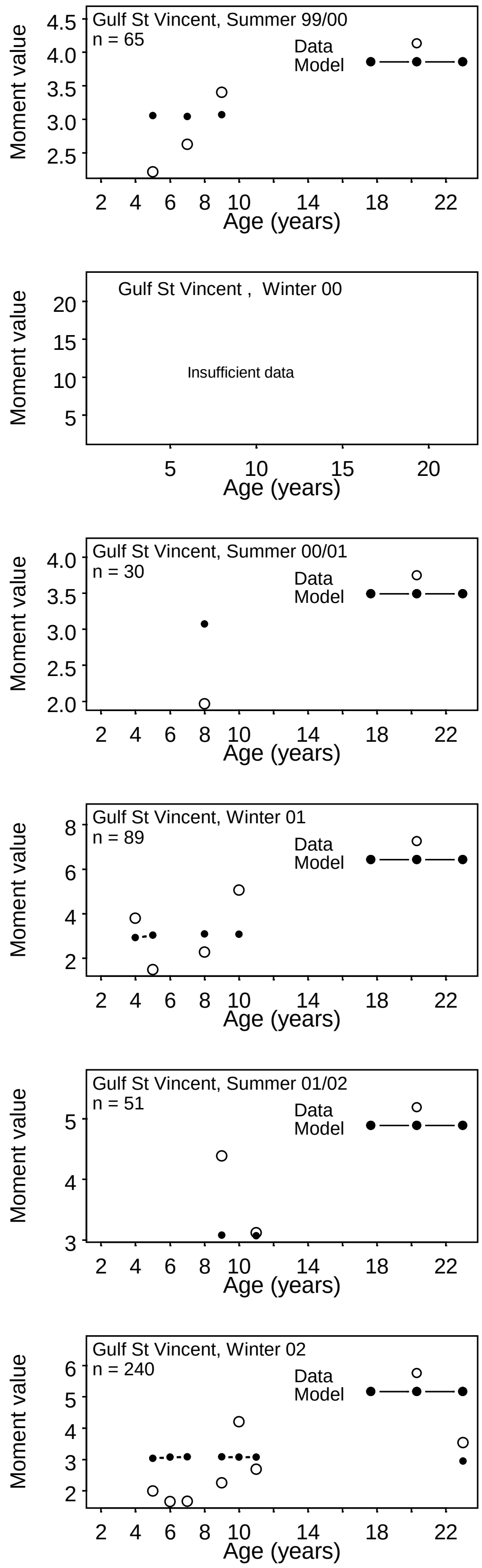


Figure A4.15. Fits of the kurtosis of lengths of snapper long-line catch, by age, for selected half-years in Gulf St.Vincent, from the most recent sampling period, 1999-2002.

# CHAPTER 5: Yield- and Egg-per-Recruit Estimates for Management of the South Australian Snapper Fishery


## Abstract

This chapter summarises the modelling work, specifically yield- and egg-per-recruit analysis undertaken to assist management decision making in the South Australian snapper fishery. In 1998/99 a strong decline occurred in effort and catch-per-unit-effort in the northern Spencer Gulf long-line sector. In the neighbouring Gulf St.Vincent, the snapper stock declined in the 1980's and has not recovered. A number of state-wide regulatory options were taken under consideration. Principal among these were (1) a maximum size limit, and (2) temporal closure. A model was developed to assess these two options. The result is that proposed maximum size limits of 750 mm and 800 mm were shown to yield significant improvements in egg production of 56% and 36% respectively, but would also yield equal (or greater) losses in long-term yearly harvest by weight of -56% and –39%. In contrast, strategies of reduction in the total level of fishing mortality, i.e. an overall reduction in the amount of fishing at all sizes, by 10, 20, 30 and 40%, yielded estimated increases of eggs produced by an average female of 11, 25, 40 and 60% respectively, with slight increases in catch by weight of 1-2%. These yield-per-recruit increases in catch occur because each recruited fish survives to an older average age, and therefore grows in weight to a larger harvested size. Thus, a reduction in total hours of fishing can induce increases in yearly egg production with no loss, and possibly slight increases, in long-term catch. Seasonal closure was the only method under consideration by the Marine Scalefish Fishery Management Committee for reducing overall fishing pressure. These results are robust for a range of reasonable assumed model input values, such as the rate of natural mortality and the current level of fishing mortality on snapper. It is suggested that the timing in the year for a closure to achieve these reductions would be optimal when prices are lowest. This leaves fish in the water for harvest when prices are higher, yielding both greater sustainability via enhanced yearly egg production and a direct economic benefit as higher gross value of production through both higher average prices and slightly higher overall weight of snapper landed. Two time closures per year of three weeks each were then implemented for South Australian snapper, in August and November for the three years since August 2000.


## Introduction

The goal of the model was to assess the expected impacts of the two principal regulatory methods proposed for South Australian snapper: (1) a maximum size limit, and (2) seasonal closure. Both policies would be applied statewide. Spatial closures were not considered, since it was thought probable that this would result in spatial displacement rather than reduction in fishing effort.

The modelling presented in this chapter was completed at an early stage of this FRDC project. As such, while it incorporates features that were subsequently included, these management outcomes were required prior to completion of the complete snapper stock assessment model presented in Chapter 4. As such, this modelling work stands alone as a separate model outcome of this FRDC project.

## Methods

Per-recruit modelling is ideal for fisheries such as snapper which are characterised by highly recruitment events. It is (1) robust with respect to any particular series of yearly recruitments that may occur in the future, and (2) can directly address management questions, and in particular will be used below to compare two potential management regulatory regimes under consideration.

The per-recruit model assumes a constant total mortality (F + M) over all ages, and a constant yearly recruitment of one million age-1 snapper. Dividing by the yearly recruitment, steady state per-recruit estimates of egg production and catch (kg) under a range of the two management policies were generated and are presented below.

Two interpretations of the steady state assumption are possible. First, the sum over all ages can be taken to be the average yearly catch if recruitment is roughly constant. In this fishery, however, recruitment is highly variable, with a single pulse of recruitment passing through the population about every 6-10 years, which comprises the large majority of the (handline) catch while that cohort is in the peak spawning ages of 5-12 years. However, the second interpretation does apply in the case of SA snapper, namely for any given pulse of recruits, the age-specific values calculated represent the egg production and catch by weight of a cohort in each year of age in the fishery. Summing egg production and catch over all ages (divided by the assumed level of recruitment) yields the estimated lifetime average egg production and harvest from each recruit.

A baseline natural mortality level of 10% was assumed and sensitivity to a second assumed rate of 15% (more precisely, instantaneous M = 0.1 and 0.15) were employed (Jones et al. 1990).

Constant fishing mortality (F = 0.15) was taken from the estimate of McGlennon and Jones (1999) estimated from the 1994/95 egg survey, i.e. daily egg production method (Lasker 1985), in the high density snapper spawning areas of the northern Spencer Gulf. Recreational catch from boats launched from public boat ramps (McGlennon and Kinloch 1997) is included. Catches not included in this estimate of 15% annual harvest rate of fishable spawning biomass are those from charter boats and fishing competitions and includes only illegal or non-reported commercial harvest taken in daylight hours from public boat ramps. In order to test the sensitivity of the results to the assumed value of F = 0.15, and in particular, to a potentially higher level of exploitation which includes all forms of non-reported catch and the perceived increase in overall fishing effort since 1994/95, the effect of the two management strategies under a second higher value of F = 0.25 was also tested, as requested by the Snapper Fishery Working Group.

For batch fecundity versus length we employed the linear regression of Crossland (1977) from New Zealand snapper, which closely matches batch fecundity versus length data measured in the course of the 1994/95 northern Spencer Gulf egg survey by McGlennon and Jones (1997, Fig. 60). The relationship is $f_B = 10^{(-3.090)} \cdot LCF^{3.007}$, where $f_B$ = batch fecundity as numbers of eggs in each female spawning, and $LCF$ = caudal fork length (mm).

Von Bertalanffy growth parameters of $t_0$ = 0.8285, $K$ = 0.144, and $L_\infty$ = 930.2 mm (LCF) are taken from the otolith-fitted growth curve of McGlennon and Jones (1997, p. 51) for 1994/95, which closely matched the otolith-derived curve of 1990/91.

Weight versus length was taken from Jones et al. (1990), as weight (kg) = 0.0000156 $LCF^3$.

The conversion from caudal fork length (used in most scientific measurement or monitoring) to total length (used in management for legal minimum or proposed maximum length) is given by TL = (LCF + 1.137) / 0.902 (Jones, unpublished data).

The overall method for egg-per-recruit versus length was (1) calculate steady state numbers at age from assumed mortality (M + F) levels; (2) input fecundity versus length; (3) convert to fecundity versus age using the growth curve mean ages-at-length; (4) calculate age-specific total egg production as the product of female numbers at age times the fecundity-at-age of an average female; (5) sum the calculated age-specific population egg production over all ages to obtain the egg production overall, for each assumed scenario of F, M and chosen maximum size, if applied; and (optionally) divide by assumed constant recruitment of one million per year, to obtain a per-recruit measure.

A similar method was applied for yield-per-recruit. Legal minimum length for snapper was incorporated by simply setting catches to zero for ages whose mean size was below 380 mm.

The strategies of lower fishing mortality (F) were tested by simply comparing the predicted outcomes for eggs and yield under the reductions of 10%, 20%, 30% and 40% with the baseline predictions of F = 0.15.

Maximum size was modelled in the same fashion, except that more explicit account was kept of the mortality of thrown-back fish. These large snapper that would be protected under a maximum size must be returned to the water if captured. For handlines, this mortality is thought to be acceptably low except when the fish swallow the hook and it is lodged in the gills or the gut. In this case, few would survive. Fishers in the Snapper Fishery Working Group meeting (C. Fewster, D. Gill, pers. comm.) guessed that 25-30% are captured with a swallowed hook. Under a maximum size policy, this percentage is likely to rise since the fishers would be targeting smaller (legal) fish and thus the size of the hook would be smaller on average relative to those being thrown back. We chose an incidental fishing mortality coefficient of $M_{hook}$ = 0.3, or 30%. Additionally, the mortality of large fish caught on unattended long lines, (as is the current policy for northern Spencer Gulf), although unquantified, is thought to be significant. This 30% incidental hooking mortality would apply to fish captured (rather than the population overall), so the associated mortality term is written as Z = (M + $M_{hook}$ * F) for these larger fish protected by maximum size.

## Results

Graphs of the predicted numbers of surviving snapper under the assumed levels of mortality are shown versus both age and total length (Figs. 1 and 2). The contribution to the lifetime totals by each year of age are the population numbers shown times the fecundity and weight, also shown. The maximum occurs when these two curves cross, which occurs for the baseline values of F and M at age 8, with the overall peak extending over a very broad range from about ages 5 to 15+ years.

A maximum size of 750 mm would protect ages from about 10+ years, a maximum of 800 mm from about 11+ years. Thus, as indicated on the graphs versus length (Figs. 1b and 2b) a large amount of current egg production is currently contributed by these ages, but also a comparable amount of catch.

Test results for both F-reduction and maximum size strategies are presented in Table 1. The eggs-per-recruit and yield-per-recruit for the estimated 'current' levels of F = 0.15 and M = 0.1 are shown in the left column. Alternative strategies, with predicted percentage changes of egg production and yield from the current for each, are shown to the right.

A maximum size of 750 mm (Table 1) increases egg production by more than half (56%) but a large reduction in yearly long-term catch of the same percentage is predicted. A catch reduction of greater than half would in most cases be unacceptable, unless drastic action were needed, and if no alternatives to this drastic reduction in coastal regional incomes were available. Higher maximum sizes of 800 mm and 850 mm yield commensurately lower reductions in long-term catch, but show a smaller percentage improvement in yearly egg production by comparison to catch. Thus maximum size appears to be a highly unfavourable strategy because of large sacrifices in snapper catch.

The alternative strategy of reductions in overall fishing mortality from 10% to 40% yield a range of egg production increases from 11% to 60%, thus achieving the sustainability objective. Rather than a reduced level of catch, small increases in yield-per-recruit, i.e. is catch by weight, are predicted. These occur because a reduction in fishing mortality tends to shift the numbers at age curve to the right, i.e. the average age and thus weight of capture for each recruit rises.

To test the sensitivity of these results to our assumed levels of F and M, we re-ran these comparisons altering the assumed baseline values of Table 1 to M = 0.15 (Table 2) and F = 0.25 (Table 3). A higher overall level of natural mortality yields reduced benefits for each strategy, with roughly equal effect on maximum size and F-reduction. For maximum size the increases in egg production are now significantly lower than the losses in catch by weight, a high cost / low benefit ratio. The sensitivity results if F is higher (Table 3) at 0.25 than assumed in Table 1 appear to strengthen the outcome in favour of an F-reduction strategy. Now increases in egg production for given levels of F-reduction are higher (e.g., 14% for an F-reduction of 10%, versus 11% in Table 1). Moreover there is, under this higher assumed F, a measurable increase in catch per recruit predicted.

Thus across a range of likely values for the inputs of F and M, the F-reduction strategy yields significant increases in egg production, and either no change or a significant increase in snapper yields by weight.

## Discussion

A maximum size would effectively eliminate three sectors under current exploitation practices of the snapper resource, primarily in northern Spencer Gulf: the long-line commercial fishery, charter boats, and fishing competitions. These target large snapper. A maximum size would cause most or all of this effort to shift to the legal sizes, inducing an increase in the level of effort on these medium sized snapper. Since the principal goal of the management efforts in response to lower long-line CPUE was to protect these sectors, a maximum size would be counter to that objective. A test run was undertaken to account for a shift of effort to the remaining legal stock under a maximum size strategy, which is shown in Tables 1 and 3 by the last column on the top row of results. We assumed that the shift in effort to smaller fish, in particular by those three sectors, would represent a rise by 10% (F = 0.165) in fishing effort on the snapper below maximum size. This results in a substantially less favourable outcome for maximum size, where the percentage reduction in catch is roughly double the increase in egg production.

Snapper prices are highest for the smaller and larger fish. The medium sized snapper, would, under maximum size, make up a substantially greater share of total catch, inducing an overall lower value for those snapper landed. This would be in addition to lower overall catches.

The sharp reductions in long-line CPUE in northern Spencer Gulf which initially drew management attention to the snapper stock may possibly be explained by movement of larger fish to central areas of the Gulf, for reasons which may be related to food abundance. This was made evident only by the intensive catch sampling undertaken in response to the perceived threat which found larger than expected numbers of large snapper in southern and central Spencer Gulf, rather than in the north where they were caught by long lines previously. In addition, the possible appearance of large year-classes of current ages 1 and 3 is also a positive sign, which substantially reduces the evidence for recruitment overfishing in the Spencer Gulf. However, catch rates in the traditional main fishing areas of the northern Spencer Gulf remained low the following year, despite high catches in the central Gulf, causing economic losses for northern Gulf fishers.

The most important area of concern remains the Gulf St.Vincent, where catches of snapper remained low compared to historical levels. The proposed reductions in F were intended to have their most important sustainability impact here.

## Outcome For Snapper Management

After considering the three potential benefits of the two options, maximum size and temporal closure, the Snapper Fishery Working Group, and subsequently the Marine Scalefish Management Committee, recommended that a yearly closure be implemented. The three benefits sought were (1) higher snapper egg production for the state overall, (2) modestly higher yield-per-recruit, (3) targeted fishing mortality reduction, with specific reference to that need for Gulf St.Vincent. Benefits (1) and (2) were identified and quantified by the model above.

Originally the closures were selected to fall at those times of year of lowest South Australian snapper price at the dock. (This is winter, when the relatively large but seasonal catch of Western Australian Shark Bay snapper comes as noticeable pulse into the Australian market.)

A mailed survey poll was sent to all commercial marine scale fishers, who recommended by a strong majority that a snapper time closure be implemented to achieve a 10% reduction in fishing effort. However, strong support was expressed for at least part of the closure to fall in summer, during spawning, to protect spawning fish and achieve a greater reduction in fishing mortality. This recommendation was reiterated by fishers and community members in a tour of all major ports by SARDI and PIRSA and the executive officer of the FMC.

The Minister for PIRSA overseeing fisheries in South Australia, recommended that the two three-week closures be implemented yearly, in August and November.

The stated goal of the closures was a 10% reduction in fishing effort to achieve the benefits specified by the model. Now, after three years of closures, effort data generally confirmed that this objective has been achieved (Fowler et al. 2003) (to the extent a reduction compared with what would have occurred can be quantified).

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Table 1. Snapper Management Scenarios. Baseline parameters: M = 0.1; F = 0.15.

| | Current | LMaxL = 750 | % change | LMaxL = 800 | % change | LMaxL = 850 | % change | LMaxL = 850 | % change |
|---|---|---|---|---|---|---|---|---|---|
| M= | 0.1 | 0.1 | | 0.1 | | 0.1 | | 0.1 | |
| F= | 0.15 | 0.15 | | 0.15 | | 0.15 | | **0.165** | |
| Legal Max Length= | none | **750** | | **800** | | **850** | | **850** | |
| Mhook= | 0.3 | 0.3 | | 0.3 | | 0.3 | | 0.3 | |
| Legal Min Length= | 380 | 380 | | 380 | | 380 | | 380 | |
| Eggs per recruit | 490125 | 765653 | **56%** | 668261 | **36%** | 632238 | **29%** | 570019 | **16%** |
| Yield per recruit | 1.13 | 0.50 | **-56%** | 0.69 | **-39%** | 0.77 | **-32%** | 0.78 | **-31%** |
| Yield (nos.) per recruit | 0.31 | 0.22 | -29% | 0.26 | -17% | 0.27 | -14% | 0.28 | -10% |

| | Current | Reduce F 10% | % change | Reduce F 20% | % change | Reduce F 30% | % change | Reduce F 40% | % change |
|---|---|---|---|---|---|---|---|---|---|
| M= | 0.1 | 0.1 | | 0.1 | | 0.1 | | 0.1 | |
| F= | 0.15 | **0.135** | | **0.12** | | **0.105** | | **0.09** | |
| Legal Max Length= | none | none | | none | | none | | none | |
| Mhook= | 0.3 | 0.3 | | 0.3 | | 0.3 | | 0.3 | |
| Legal Min Length= | 380 | 380 | | 380 | | 380 | | 380 | |
| Eggs per recruit | 490125 | 545161 | **11%** | 610390 | **25%** | 688416 | **40%** | 782687 | **60%** |
| Yield per recruit | 1.13 | 1.15 | **1%** | 1.16 | **2%** | 1.16 | **2%** | 1.14 | **1%** |
| Yield (nos.) per recruit | 0.31 | 0.30 | -3% | 0.29 | -6% | 0.28 | -11% | 0.26 | -16% |

Table 2. Snapper Management Scenarios. Higher level of natural mortality tested: M = 0.15.

| | Current | LMaxL = 750 | % change | LMaxL = 800 | % change | LMaxL = 850 | % change | LMaxL = 850 | % change |
|---|---|---|---|---|---|---|---|---|---|
| M= | **0.15** | **0.15** | | **0.15** | | **0.15** | | **0.15** | |
| F= | 0.15 | 0.15 | | 0.15 | | 0.15 | | **0.165** | |
| Legal Max Length= | none | **750** | | **800** | | **850** | | **850** | |
| Mhook= | 0.3 | 0.3 | | 0.3 | | 0.3 | | 0.3 | |
| Legal Min Length= | 380 | 380 | | 380 | | 380 | | 380 | |
| Eggs per recruit | 293149.97 | 396843 | **35%** | 355281 | **21%** | 340794 | **16%** | 312632 | **7%** |
| Yield per recruit | 0.65 | 0.34 | **-47%** | 0.45 | **-30%** | 0.49 | **-24%** | 0.51 | **-22%** |
| Yield (nos.) per recruit | 0.20 | 0.16 | -22% | 0.18 | -12% | 0.18 | -9% | 0.19 | -5% |

| | Current | Reduce F 10% | % change | Reduce F 20% | % change | Reduce F 30% | % change | Reduce F 40% | % change |
|---|---|---|---|---|---|---|---|---|---|
| M= | **0.15** | **0.15** | | **0.15** | | **0.15** | | **0.15** | |
| F= | 0.15 | **0.135** | | **0.12** | | **0.105** | | **0.09** | |
| Legal Max Length= | none | none | | none | | none | | none | |
| Mhook= | 0.3 | 0.3 | | 0.3 | | 0.3 | | 0.3 | |
| Legal Min Length= | 380 | 380 | | 380 | | 380 | | 380 | |
| Eggs per recruit | 293149.97 | 320227 | **9%** | 351510 | **20%** | 387904 | **32%** | 430564 | **47%** |
| Yield per recruit | 0.65 | 0.65 | **0%** | 0.64 | **-2%** | 0.63 | **-4%** | 0.60 | **-7%** |
| Yield (nos.) per recruit | 0.20 | 0.20 | -4% | 0.19 | -8% | 0.18 | -14% | 0.16 | -20% |

Table 3.  Snapper Management Scenarios.  Higher level of fishing mortality tested:  F = 0.25.

| | Current | LMaxL = 750 | % change | LMaxL = 800 | % change | LMaxL = 850 | % change | LMaxL = 850 | % change |
|---|---|---|---|---|---|---|---|---|---|
| M= | 0.1 | 0.1 | | 0.1 | | 0.1 | | 0.1 | |
| F= | **0.25** | **0.25** | | **0.25** | | **0.25** | | **0.275** | |
| Legal Max Length= | none | **750** | | **800** | | **850** | | **850** | |
| Mhook= | 0.3 | 0.3 | | 0.3 | | 0.3 | | 0.3 | |
| Legal Min Length= | 380 | 380 | | 380 | | 380 | | 380 | |
| Eggs per recruit | 274848 | 431450 | **57%** | 359688 | **31%** | 336710 | **23%** | 294006 | **7%** |
| Yield per recruit | 0.97 | 0.59 | **-39%** | 0.74 | **-23%** | 0.80 | **-18%** | 0.79 | **-19%** |
| Yield (nos.) per recruit | 0.34 | 0.28 | -17% | 0.31 | -9% | 0.32 | -6% | 0.32 | -5% |

| | Current | Reduce F 10% | % change | Reduce F 20% | % change | Reduce F 30% | % change | Reduce F 40% | % change |
|---|---|---|---|---|---|---|---|---|---|
| M= | 0.1 | 0.1 | | 0.1 | | 0.1 | | 0.1 | |
| F= | **0.25** | **0.225** | | **0.2** | | **0.175** | | **0.15** | |
| Legal Max Length= | none | none | | none | | none | | none | |
| Mhook= | 0.3 | 0.3 | | 0.3 | | 0.3 | | 0.3 | |
| Legal Min Length= | 380 | 380 | | 380 | | 380 | | 380 | |
| Eggs per recruit | 274848 | 311961 | **14%** | 357954 | **30%** | 415865 | **51%** | 490125 | **78%** |
| Yield per recruit | 0.97 | 1.01 | **5%** | 1.06 | **9%** | 1.10 | **13%** | 1.13 | **17%** |
| Yield (nos.) per recruit | 0.34 | 0.34 | -1% | 0.33 | -2% | 0.32 | -4% | 0.31 | -7% |

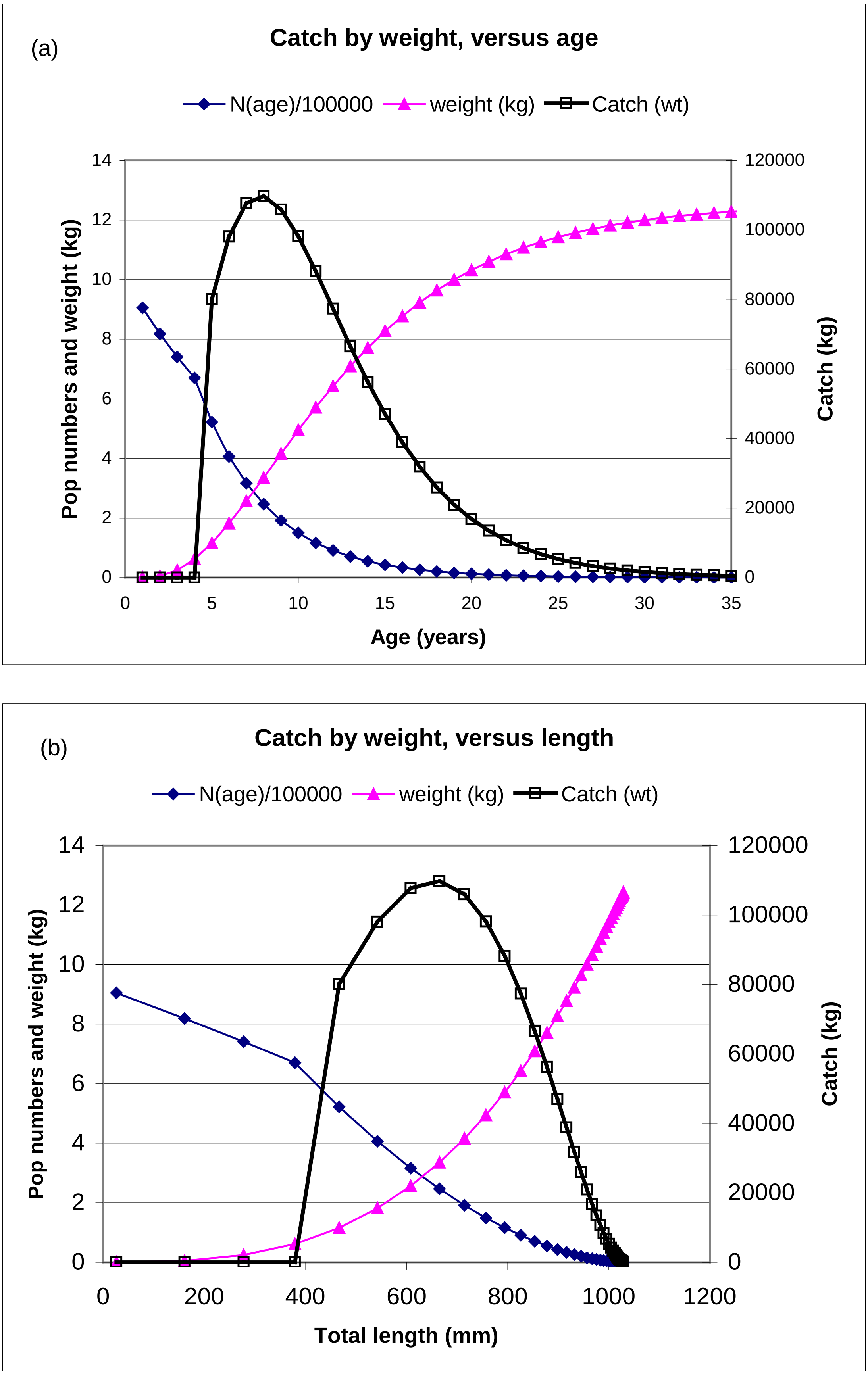


Figure 1. (a) Catch of each yearly cohort age, calculated as the product of numbers at age (from one million age 1 recruits) times mean weight of snapper in each age class. (b) Same, but versus length.

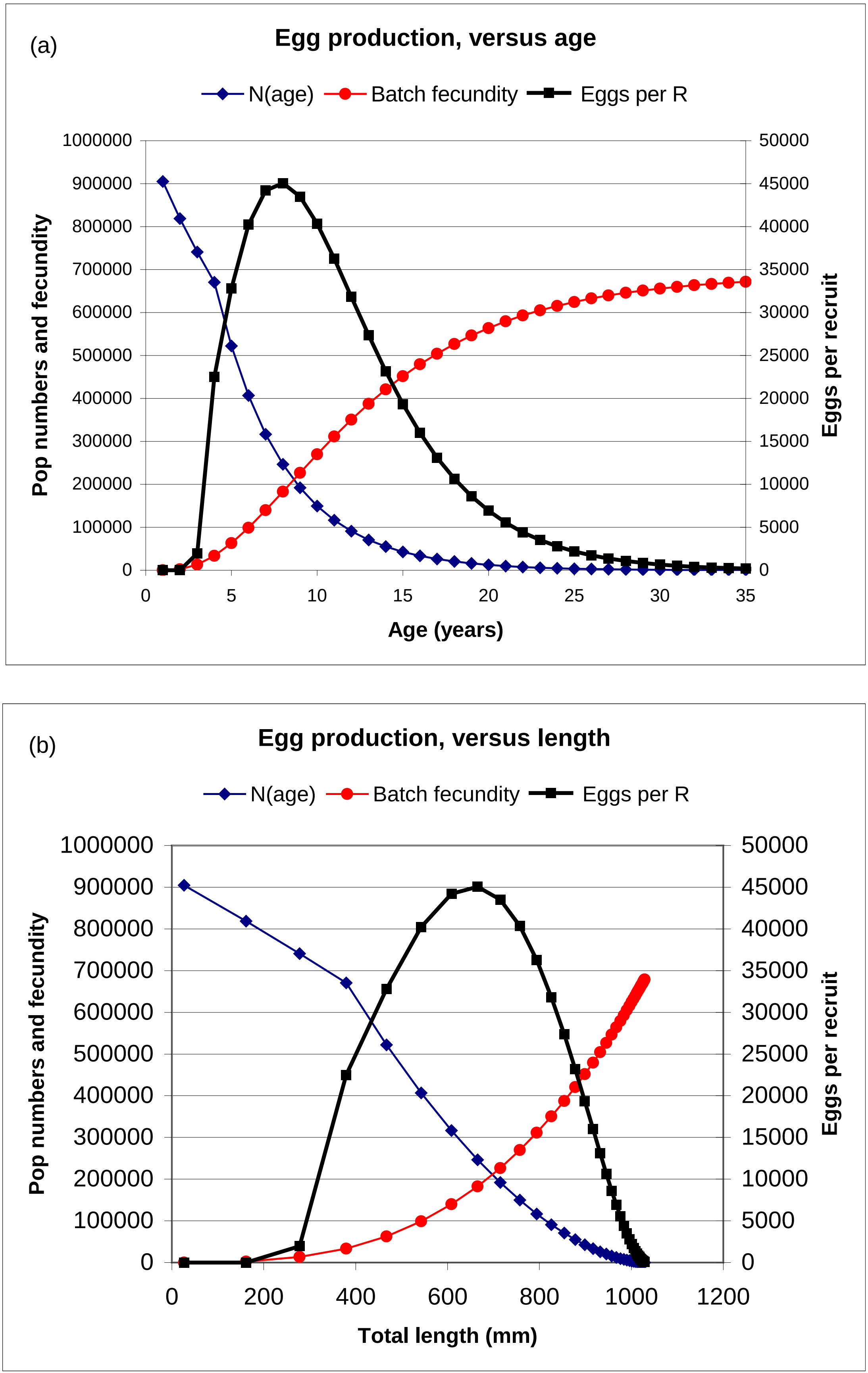


Figure 2. (a) Yearly egg production per recruit versus age, calculated as the product of survival times mean weight of snapper in each age class. (b) Same, but versus length.

# CHAPTER 6. User Manual for ‘Garface’: an Excel user interface

## Preface

An objective of this project was to provide access to the use of the model estimation programs (Garest and Snapest, presented in Chapters 1 and 4) through a graphical user interface. The goal was to permit the use of the parameter estimation models by biologists carrying out yearly (or periodic) stock assessment of garfish and snapper. These models fit to the various data sources, notably including semi-yearly catch and effort totals, and generate performance indicators used in managing South Australian marine scalefish stocks. On a yearly basis, new catch and effort totals are gathered and summarised. The goal of the user interface is to permit stock assessment biologists to carry out this task, of upgrading the catch and effort data set and running the estimation of extended time series of performance indicators, on an annual or periodic basis.

The interface itself is an Excel file. Writing the GUI in Excel permitted three major advantages: (1) All stock assessment biologists are familiar with Excel, and use it frequently in day-to-day numerical work. (2) The data is usually provided in Excel or it can be easily imported from databases. (3) The outputs that assessment biologists currently produce for inclusion in stock assessment reports are also largely or entirely analysed and graphed in Excel. Thus, no further programming or software learning, and minimal additional steps of converting and moving data are needed to use the stock assessment model interface.

In the remainder of this chapter, the text of the User Manual for Garface is attached.

# INTERFACE SOFTWARE FOR THE SOUTH AUSTRALIAN GARFISH STOCK ASSESSMENT ESTIMATION MODEL (GARFACE)

# USER MANUAL

S A R D I

SOUTH AUSTRALIAN
RESEARCH AND
DEVELOPMENT
INSTITUTE

FISHERIES
RESEARCH &
DEVELOPMENT
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SARDI Aquatic Sciences
PO Box 120
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5 November 2003

## Disclaimer

**While to the best of our knowledge, the South Australian Garfish Management Model operates as specified, no warranty, either expressed or implied, is made with respect to the performance or fitness for any particular purpose of the computer programs and written material.**

## Project Sponsorship

This model was developed under the sponsorship and support of the Australian Fisheries Research and Development Corporation (FRDC) Project No. 1999/145, "Stock assessment models with graphical user interfaces for key South Australian marine finfish stocks", Dr. Richard McGarvey, Principal Investigator. Additional data and research support were provided by the South Australian Marine Scalefish Fishery Management Committee, and the marine scale fishers of South Australia. This research was undertaken by the South Australian Research and Development Corporation (SARDI), a division of the Department of Primary Industries and Resources of the state government of South Australia.

## Further Documentation

For further details of the field and laboratory data collection and analysis, model structure and parameter estimation, and further technical information about this user interface and simulation software described herein, please refer to the Final Report of the FRDC project numbered and titled above. This Final Report can be obtained from FRDC (tel: (02) 6285 0400; or email: frdc@frdc.com.au).

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# 1. Introduction

This software runs a stock assessment estimation model for South Australian garfish. The Excel file, “Garface.xls”, serves as the user interface between users, notably biologists carrying out stock assessment, and the underlying model estimation ‘engine’. Similar interface software, named “Snapface”, runs the snapper stock assessment estimation model, for which there is a separate manual contained in file “Snapface_Manual.doc”. The principal purpose of these software interfaces is to permit South Australian biologists to carry out the yearly assessment for garfish and snapper.

It is presumed that each year (or every few years), when a stock assessment is to be carried out on South Australian garfish, that the commercial catch and effort time series data will be updated. The outcome of the estimation run that this package (named ‘Garface’) will permit, is to add in the new catch and effort data thus extending (and necessarily also revising) the time series of basic management indicators for garfish, namely fishable biomass, recruitment, and exploitation rate. This is achieved by (1) adding new year(s) of catch and effort data, and (2) running Garface to estimate a new set of parameters, (3) examining the plots of the (3.1) fits to the data, and of the (3.2) biological performance indicators that comprise the principal output of this stock assessment estimation software.

The estimation engine is coded using the AD Model Builder (abbreviated ADMB) software library. ADMB permits convergence to a solution set of freely estimated model parameters more rapidly than other minimisation packages, sometimes 10 or 100 times faster. It also produces a complete set of confidence intervals on these parameter estimates (via the computation of a ‘Hessian’ matrix).

So another way to think of this Excel workbook interface, is as a way to communicate your wishes to the ADMB estimation executable file, garest.exe.

The tasks that can be carried out using the garface.xls interface include the following:

1. Add a new year of catch and effort data, or revise any data from past years.
    - 1.1. The model time step is semi-yearly, so catch and effort data to be added will cover the two half-yearly time periods of the model, namely, October-March and April-September.
    - 1.2. Yearly updates of catch and effort data must therefore be aggregated (that is, summed to give a total) over these two 6-month periods of each year.
2. Fix some parameters to pre-chosen values, while the rest are freely estimated.
    - 2.1. This feature could be used to do sensitivity analysis.
    - 2.2. For example, you could vary the choice of natural mortality rate, Mnatural, to assess what impact this choice has on the model estimates of biomass.
3. Choose whether or not to calculate the Hessian. The Hessian (a matrix of second derivatives of the maximised likelihood function with respect to each parameter) permits an approximate measure of confidence interval for each of the estimated parameters.
4. Change relative weightings assigned to the three data sources, namely

4.1. catch and effort data,
4.2. catch-proportions-at-age and by sex,
4.3. length moment properties.
The weighting factors instruct Garest to give more influence to some data sources than to others in the fitting process.
5. Alter the range (‘bounds’) on the permitted values of estimated parameters.

## 1.1. Model Description

A detailed description of the data, the model equations and model estimation likelihood, assumptions, sensitivity analysis, simulation testing, and detailed graphic output of the best estimate to date for SA garfish (as of 2003) is found in Final Report Chapter 1 of the FRDC Project (No. 1999/145, “Stock assessment models with graphical user interfaces for key South Australian marine finfish stocks”) under which this software was developed.

In addition to the detailed mathematical description of the Garest stock assessment estimation model given in Chapter 1, we provide a brief overview of the model structure immediately below:

The model considers two regions for garfish in South Australia, namely the two gulf fisheries (St.Vincent and Spencer). As noted, the model time step is half-yearly, starting with the first model time step in October 1983 to March 1984, and continuing (with the current version) to April-September 2001.

The main parameters to be estimated fall into three categories, (1) catchability, (2) growth, and (3) recruitment.

There is a catchability parameter for each of the four ‘effort types’. Similar parameters, which appear explicitly in the catch equation, are also estimated namely relative selectivity parameters by winter/summer (that is, season) and male/female. A logistic length selectivity curve is estimated for the two main gear types, haul net and dab net.

Growth parameters are used to build the length-at-age distribution that describes the mean length for each half-yearly age, as well as the observed spread of lengths at each given half-yearly age. From growth, a ‘slice’ partition of each cohort into length bins is constructed. This ‘slice growth’ description permits a fully dynamic breakdown of the garfish population by both age and length. A slice is defined as those garfish that grow into legal fishable size in each model time step. The first modelled age of garfish is at age 3 half-years, that is, at the start of the summer following the summer season that each cohort is spawned. Some garfish, but not a majority, have reached legal size (of 210 mm, recently increased to 230 mm) at this time. These are then the first ‘slice’ from that cohort. Those that grow past 210 mm by the start of the next model time step (the next April 1), are then assigned to the second slice, and so on.

Two growth parameters (K and sigm) are freely estimated by fitting to the length moments from length-at-age samples. The other growth parameters were fitted prior to inclusion in Garest by fitting directly to lengths-at-age, assuming, as is common, that these lengths-at-age are those of an unexploited population. One important advantage of integrating growth estimation with the overall stock assessment estimation is to avoid any underestimation in estimates of growth that would occur by ignoring that the length-at-age samples are from a population where faster growing fish are taken out by the fishery sooner, because they reach fishable sizes sooner.

Yearly recruit numbers in each of the two regions are estimated freely. No stock-recruitment relationship is assumed.

Other parameter types include (4) the sigma (that is, standard deviation) parameters that are estimated as part of the likelihood components, and (5) the per-region fishing mortality parameter that is estimated to construct the initial population array, that is, the numbers of garfish in each region, sex, age, and length slice at the start of the model time series, on 1 October 1983.

The principal model outputs, namely the three biological performance indicators of semi-yearly biomass, and exploitation rate, and yearly recruit numbers for each region, are computed from the estimated parameters. These time series are found in the worksheet named “BPIcharts” of the model interface once the estimation run is implemented.

## 1.2. What the Interface Cannot Do

Note that there is no facility for the user to add new age and length data. All age and length catch samples were from a single program of sampling, undertaken in an FRDC Project on garfish reproductive biology and population structure (Project 97/133, “Fisheries biology and habitat ecology of the southern sea garfish (*Hyporhamphus melanochir*) in southern Australia”, Jones et al. 2002). Because there are no current plans to undertake further garfish sampling, this facility was not needed.

Thus, the interface does not permit the inclusion of additional age and length samples. These require further detailed programming, notably because of the lengthy calculations needed to correct for over-sampling and under-sampling of fish for ageing from the larger samples of fish whose lengths were measured. (See Chapter 1, subsection entitled, “Correction for non-representative age subsampling“.) In particular, in Project 97/133, a greater-than-representative proportion of larger garfish were subsampled for ageing. Because larger and thus older fish have been in the fishable stock for a longer time, numbers-at-age of older individuals contain better information about fishing mortality, having experienced the higher-than-natural mortality for longer time period. Thus to add new sample data by age or length, or to make any other modifications to underlying Garest estimation program, modellers using AD Model Builder would be employed.

## 1.3. Software Overview

Garface.xls is an Excel workbook that allows a user to interact with and run the garfish stock assessment model parameter estimation program garest.exe, referred to as "Garest", which was created using AD Model Builder. The name "Garface" will be used in this document to refer to the interface software application. The Garest run which produced the results detailed in Final Report Chapter 1 of the FRDC Project (No. 1999/145, "Stock assessment models with graphical user interfaces for key South Australian marine finfish stocks") is referred to here as the "base run".

The files associated with the Garface software should all exist in the one directory of choice. All such files must remain in this directory in order that Garface can assume where to look for information it requires. A warning will be issued to the user if prerequisite files are not present or are renamed. However this directory (with all its files) can be copied or moved to another location, or be renamed.

Initial installation of Garface requires the user to accept a license agreement and disclaimer. Uninstallation is carried out simply by clicking the "Uninstall" button on the "Welcome" worksheet (this button is found a few columns to the right of the "Manual" button).

Opening file Garface.xls presents the user with a control form that serves as the switchboard of Garface. Garface worksheets can be accessed via this control form. Copies can be made of Garface worksheets and either placed in the Garface workbook or else in another workbook. The user can also create additional worksheets of choice. The standard Microsoft Excel functionality remains available while in a worksheet and user input of data and other values to communicate to Garest is done simply by entering values in designated cells.

# 2. The control form

The switchboard form allows the user to go to any of the standard Garface worksheets. Once in one of these worksheets one can return to the switchboard by clicking the button "Back to main form". The contents section of this manual refers to sections in the manual that deal in turn with each of the Garface worksheets.

Clicking the "Save run and close" button allows the user to copy the garface.xls workbook at any stage to any location and name. Then, at some future time this workbook can be copied to a directory with all standard input-output files expected by Garface and opened. When opened it is then possible to continue the estimation run exploration from the settings last saved. This button's functionality mirrors the standard Microsoft Excel "Save As" operation. Note that the directory for this saved Garface workbook, if not the same directory as the current working directory, must have a copy of all other Garface system files too. So another way to accomplish this functionality is by saving to the current working directory and then in Windows Explorer copy this working directory to another location. Saving to the current working directory is simpler however and allows for many runs to be saved (and ready to be continued later) without other files needing to be copied as they are already in the directory. This latter option is efficient but note that only one copy of a Garface workbook application must be in use at any one time.

Alternatively, by clicking the "Produce report workbook" button, Garface allows the user the option to only copy all the standard Garface input and output worksheets at any stage of a user's working session. This copied workbook can also be saved to any directory and name but will not hold the interface software to continue a run. It however allows the user to analyse, plot, and otherwise manipulate Garface's workbook contents (for example, for printing). This button's functionality is not mirrored directly by Microsoft Excel.

The section of controls within the "base run inputs" frame allows the user to select which Garest input file information to restore to the base run settings. Ticking the desired checkboxes and clicking the load button will then fill the corresponding Garface worksheets with the base run input values. The base run input values are the values used to obtain the output results found in Final Report Chapter 1 of the FRDC Project (No. 1999/145). Naturally, if not all base run inputs are loaded then the base run outputs may not be obtained. Also, if a current run involves additional data (for example, an extra year of data) to the base run, then loading (for example, worksheet "ParameterPhases") base values will also need to be followed by extending the logRdev values by one new value of choice for each region in worksheet "ParameterInitialValues".

Clicking the button "Run the estimator" causes Garface to write the contents of the current set of Garface input worksheets to Garest input files and then to execute Garest. While Garest runs Excel is suspended and cannot be used and a black window will popup. This window is the MS DOS window to which Garest outputs its run-time computation information. Note that if Garest is interrupted prematurely (either due to an ADMB error or user interruption) then Garface output worksheets will simply contain whatever resides in the current Garest output files present in the directory. In this case, these files may not have been updated by the latest Garest run and output results should be ignored and the session re-run. For more details see section "Running the estimator program Garest".

Clicking the "Manual" button leads the user into a location within the document containing this manual.

# 3. Input: Data

The worksheet "DataInput" contains the catch-effort data to which the Garest model parameter estimation program (that is, "Garest") will fit its model catch quantities.

Three types of input cells exist. One is headed "ntest" which is an integer value representing the number of half-yearly model time steps. An ntest value is expected to be an even-numbered integer value greater than or equal to 36. This number is an index used by Garest for the last model time step. The first model time step is Oct 83 through Mar 84 (Garest model time step index 1); this never changes. The last model time step is expected to be a winter time step such as Apr-Sep-01 (ntest = 36; model time step index 36), Apr-Sep-02 (ntest = 38; model time step index 38), Apr-Sep-03 (ntest = 40; model time step index 40), etc. The base run has an ntest value of 36.

Summer model time steps cover periods such as Oct-Mar-01 (model time step index 35), Oct-Mar-02 (model time step index 37), etc.

Another type of input on this worksheet are the catch-effort catch data values. Each cell contains a value representing in kilograms how much garfish was caught. 2*ntest*4 cell values are expected to be filled. Each cell represents the catch for one model time step, for one region, for one type of gear-target category. The four columns (columns A, B, C, and D) represent the gear-target combination categories (that is, the effort types) and are respectively from left to right haul net targeted, haul net untargeted (that is, garfish caught but was not targeted), dab net targeted plus untargeted, and recreational. The rows (2*ntest of these) represent a particular model time step in a particular region; there are two regions. The row order of model time step region combination of the data set is as follows: Oct-Mar-84 in SG (Spencer Gulf), Oct-Mar-84 in GSV (Gulf St.Vincent), Apr-Sep-84 in SG, Apr-Sep-84 in GSV, Oct-Mar-85 in SG, Oct-Mar-85 in GSV, etc. The two blue shaded columns on the worksheet enumerate this pattern of indexing of model time step region combination for each row of data (at least for the base run; users may wish to continue this labelling if considered helpful).

The other type of input on this worksheet are the catch-effort effort data values. For the first three effort types the values represent man days of fishing effort spent by commercial fishermen. Fisher day values are a sum of the number of fishermen fishing aboard for each day fished over the period. For example, if three fishers aboard were fishing on the first day and two on the second day then for those two days of fishing five fisher days are recorded. The last effort type values (right-most of the four columns of data) represent boat hours of fishing effort spent by recreational fishermen. The categories of the cells are the same as those of the catch-effort catch data.

## 4. Input: Parameter initial values

The worksheet "ParameterInitialValues" contains the starting Garest parameter values which Garest uses as the initial fix in parameter space from where it commences objective function optimisation (that is, the search for a best-fit set of parameter values). Note that for each new year of catch-effort data added (see section "Input: Data"), exactly one more column value should be added on the right of the two logRdev parameter input rows of cells.

Below each row containing the label of a parameter (indicated by a row starting with a hash (#) symbol) there exists either a one or two row matrix of cells with one or more columns. Each cell within this matrix represents a category of the parameter. For example, parameter F0, which is the initial state array fishing mortality, has one row and two columns with the left column value representing the level of initial state array fishing mortality in Spencer Gulf and the right column value representing the level in Gulf St.Vincent.

Apart from the standard two buttons (that is, "Back to main form" and "Manual") there exists a third button, labelled "Check bounds", on this worksheet. When the user clicks on it Garface will check each of the starting values that currently exist on the worksheet against their corresponding parameter bounds. A cell will be coloured red if it contains a value that lies outside of the interval indicated by the corresponding parameter bounds. The values for the lower and upper bounds of each parameter are found on worksheet "ParameterBounds". Note that when the user clicks the "Check bounds" button after an acceptable value has replaced the out of bounds value then the red colour will be removed.

For an example of a set of typical values that should be acceptable see the initial values used for the base run. For another example see the final estimated parameter output of the base run. Note however that the further away a given proposed run is from the base run's conditions (for example, likelihood component weight factors are different, parameter phases are different) the less reliable the base run's values will be for starting values. In this case a similar approach can still be adopted by replacing the base run with another run that was acceptable and closer to the newly proposed run. Note that, in order to obtain a reasonable fit to data and also to obtain realistic parameter output values, the user may well have to use the parameter output values from one Garest run and use these as initial parameter values in a second execution of the run.

A loose rule of thumb for obtaining an idea of the spread of acceptable values may be obtained by considering values that lie between the two values obtained by subtracting (for the lower value) and adding (for the upper value) the base run's parameter standard deviation value from the base run's parameter output. Values outside of this range may also be suitable as starting values, but this aforementioned method gives a conservative measure. An exception to this occurs when a parameter has a standard deviation value which is larger than the parameter estimate, in which case clearly the method is of little use and the parameter can be considered badly estimated.

For a brief description of each parameter's meaning refer to Appendix A of this manual.

# 5. Input: Parameter bounds

The worksheet "ParameterBounds" contains the parameter bound values which Garest uses as a means to constrain optimisation in its search for suitable parameter values. Parameter estimates that result from a Garest run will not have a value lower than the lower bound value given and will not have a value higher than the upper bound given. Altering the bounds on a parameter can sometimes help in making Garest converge to a realistic solution.

Each parameter label on the worksheet is as found on worksheet "ParameterInitialValues" except that a suffix "_bd" is added. However, unlike worksheet "ParameterInitialValues" in which each category of the parameter has a value, on this sheet, "ParameterBounds", exactly two rows and one column exist for each parameter. These values apply to all categories of the parameter.

For each parameter the first row contains a value representing the lower bound and the second row contains a value representing the upper bound. These values are real numbers (and may be negative depending on the nature of the parameter). For example, parameter F0, which is the initial state array fishing mortality, has label F0_bd with the first row below it containing the value 0.05 (in the base run) and the next row below containing the value 5 (in the base run). So this example would force Garest to produce an initial state array fishing mortality value, one for each region, each lying between 0.05 and 5.

For a brief description of each parameter's meaning refer to Appendix A of this manual.

## 6. Input: Parameter phases

The worksheet "ParameterPhases" contains the parameter phase values which Garest uses as a means to constrain optimisation in its search for suitable parameter values. This is an advanced feature of ADMB and for Garface is mostly likely to be of benefit by allowing the user to fix certain parameters, meaning that they will not be estimated.

Each parameter label on the worksheet is as on worksheet "ParameterBounds" except that "_ph" replaces "_bd". However, unlike worksheet "ParameterBounds" where two rows follow the row containing the parameter label, on this sheet, "ParameterPhases", only one row follows containing the value of the phase. This value applies to all categories of the parameter.

This value is used to indicate in which "phase" of the optimisation the parameter becomes active and is estimated. The ADMB default value is 1. When all parameters have a phase value of 1 it means they are all estimated in the one phase (that is, the one estimation process). Any parameters that have a phase value of –1 are not estimated but remain fixed throughout the optimisation run at their values set in worksheet "ParameterInitialValues". At the end of the run any parameter not set to phase –1 will have been estimated by Garest. Apart from values –1 and 1 the only other values that are acceptable are 2, 3, 4, etc. For example, if one starts with the base run value, then changing the phase value for parameter Rbar to 2 results in Garest's optimisation process initially keeping Rbar fixed while it estimates values for the other parameters (the ones that have a phase value of 1) before introducing Rbar into the follow-up optimisation process estimating all parameters (except those that have a phase value of –1).

For a brief description of each parameter's meaning refer to Appendix A of this manual.

## 7. Input: Sundry control options

The worksheet "SundryControlOptions" contains six values which are Garest's settings as to how much strength it should give to data sets and how refined should be the search for parameters during objective function optimisation. Each type of value is described below.

logRdev weight
This value is a number by which the recruitment penalty component in the overall model log-likelihood objective function multiplies. The recruitment penalty is the sum of squares of the logRdev parameters. If this value is zero then the recruitment penalty has no influence. Enter only non-negative values. The base run value is 0.

catch-effort catch fit mll weight
This value is a number by which the catch-effort catch log-likelihood objective function components are multiplied. The catch-effort catch log-likelihood is in the form of a log-Normal log-likelihood. If this value is zero then the catch-effort catch data is not being fit; garfish fishable population numbers and fishable biomass will not be calculated well. Enter only non-negative values. For example, setting this value to 0.005 will cause quite different values to be produced than using a value of 1 as in the base run; if all else is the same, fits to catch-effort catch should look worse and fits to catch-at-age-sex should look better than in the base run.

catch-at-age-sex mll weight
This value is a number by which the catch-at-age-sex log-likelihood objective function components are multiplied. The catch-at-age-sex log-likelihood is in the form of a multinomial log-likelihood function. If this value is zero then the catch-at-age data is not being fit; fishing mortality will not be calculated well. Enter only non-negative values. For example, setting this value to 0.005 will cause quite different values to be produced than using a value of 1 as in the base run; if all else is the same, fits to catch-at-age-sex should look worse and fits to catch-effort catch should look better than in the base run.

moment fit mll weight
This value is a number by which the length distribution moment log-likelihood objective function components are multiplied. If this value is zero then length data is not being fit; slicegro parameters will not be estimated well. Enter only non-negative values. For example, setting this value to 0.005 will cause quite different values to using a value of 1 as in the base run; if all else is the same, fits to the length moments should look worse and fits to catch-effort catch or catch-at-age-sex, or both, should look better than in the base run.

option for generating matrix of parameter standard deviations and correlations subsequent to likelihood maximisation (that is, Hessian to be calculated).
This value is expected to be a number that indicates to Garest whether or not to update the "ParameterStdOutput" and "ParameterCorrOutput" worksheet values. A value of 0 will cause this current estimation run not to produce new parameter confidence information; any other number will enable production. If this feature is enabled (that is, non-zero value) it can result in the Garest run taking several times longer than when it is disabled. Note that if the parameter standard deviations and correlations are not calculated in a run then, in order to avoid any confusion, Garface will colour red a cell in the first row of worksheets "ParameterStdOutput" and "ParameterCorOutput" alerting the user that the results in these two sheets are possibly unrelated to results in the rest of the workbook.

Yearly natural mortality rate
This value is simply a constant number representing the level of natural mortality assumed by Garest. It is a positive real number. Note that this is not estimated.

convergence criteria
This value helps to determine at what point in the parameter estimation process the optimisation should stop. If the largest parameter derivative value is less than this value the optimisation phase can end. The size of the maximum parameter derivative value is a measure (but not the only one) of how far away in parameter space, at a given stage in the optimisation process, the current set of parameters is from an optimum set of estimates. A larger value of the convergence criteria can mean quicker run times but less efficient optimisation and hence less reliable results. However this value can be made too small resulting in little improvement in result reliability. The base run value is 0.001.

maximum function evaluations
This number helps to determine at what point in the parameter estimation process the optimisation should stop. It represents the maximum number of times in a given optimisation phase that the estimation process can compute the objective function. Larger values can mean longer run times but can also result in better estimates. The base run value is 500.

# 8. Running the estimator program Garest

When the user clicks the "Run the estimator" button on the control form, Garface makes many assumptions about user input before calling the program Garest. Clicking the "Run the estimator" button causes Garface to write the contents of the current set of Garface input worksheets to Garest input files and then to execute Garest. Garface waits for Garest to finish before copying relevant Garest output values to Garface output worksheets.

While Garest runs the current Microsoft Excel spreadsheet application is suspended and cannot be used; however Garest runs should only last a few minutes depending on operating system software and PC hardware. Note that if Garest is interrupted prematurely (either due to an ADMB run-time error or user interruption) then Garface output worksheets will simply contain whatever resides in the current Garest output files present in the directory. In this case, these files may not have been updated by the latest Garest run and output results should be ignored and the session re-run. If Garest's parameter estimation failed (for example an interruption to Garest) then the output values found in this worksheet may not relate to the run input settings found in the workbook. The user will be alerted of this parameter estimation failure by means of a popup message box appearing after the run.

Two main types of prematurity of the Garest run may occur. One type involves the run aborting before the parameters have been estimated. In this case not only the Garface output worksheets "ParameterStdOutput" and "ParameterCorOutput" but also all other output worksheets will not reflect results associated with the run settings that the user has last set in the input worksheets. As mentioned above, the user will be alerted of this situation. The other type of Garest run prematurity may occur when the user has enabled the option for generating the matrix of parameter standard deviations and correlations in worksheet "SundryControlOptions" but the run aborts during the stage when the Hessian matrix rows are being calculated (that is, aborts while the parameter standard deviations and correlations are being calculated but after the parameter value estimates are calculated). In this case no cell in the first row of worksheets "ParameterStdOutput" and "ParameterCorOutput" (see section "Input: Sundry control options") may be coloured red. This would occur if the run preceding the run suffering this second type of interruption had a specification to calculate the parameter standard deviations and correlations and finished successfully (in which case this previous run would not have the first row cell coloured red). An indication that this problem of a Hessian matrix not having been calculated is signalled by Garface via colouring red a cell in the first row of worksheets "ParameterStdOutput" and "ParameterCorOutput".

The user may recognise that Garest has entered the Hessian matrix row calculation stage by observing Garest's MS DOS output window and looking for lines such as "Estimating row 3 out of 87 for hessian". The Hessian matrix is a square matrix whose elements are the second-order derivatives, with respect to the vector of parameters, of the objective function being optimised, diagonal values of which are used in the process of computing parameter standard deviations and off-diagonal elements of which are used in the process of computing parameter correlations.

The parameter value calculation stage may be recognised by observing in the aforementioned MS DOS output window lines such as
"funcount:
15
TotalObj, mLLCEWt*mllWt, mLLCnLWt*mllLen, mLLCnASxWt*mllAgeSx, logRdevWt*Rpenalty
2653.71 -225.172 513.891 2364.99 0
Here "funcount" followed by 15 means that Garest has finished its 15$^{th}$ objective function evaluation and the two lines immediately following is output of the negative log-likelihood components of the objective function related to data source. So "TotalObj" represents total objective function, "mLLCEWt*mllWt" represents the catch-by-weight (that is, Catch-effort catch) negative log-likelihood component ("mllWt") multiplied by "catch-effort catch fit mll weight", "mLLCnLWt*mllLen" represents the length moment negative log-likelihood component ("mllLen") multiplied by "moment fit mll weight", and "mLLCnASxWt*mllAgeSx" represents the catch-at-age-sex negative log-likelihood component ("mllAgeSx") multiplied by "catch-at-age-sex mll weight". "logRdevWt*Rpenalty " represents the recruitment penalty component ("Rpenalty") multiplied by "logRdev weight". "moment fit mll weight", "catch-at-age-sex mll weight", and "logRdev weight" are explained in section "Input: Sundry control options".

Regarding the input worksheets of Garface, if the user fails to properly enter values then Garest's MS DOS output window will probably not be visible for long and the run should terminate very quickly; the user may only see a flash of a black screen for a couple of seconds. This kind of behaviour is a fair indication of the existence of

Garface input worksheet problems. The same caveats as mentioned above for premature run terminations applies with respect to the output worksheets. For example, if the user deletes a cell value and leaves it blank that should have a value in it on one of the input worksheets, then this can result in this behaviour. It may also occur if the user happens to have selected a very small number of maximum function evaluations (for example 1 or 2). Off course deleting columns or shifting cells will also result in problems.

Depending on what settings plus data and parameter inputs for Garest have been set in the Garface input worksheets, an ADMB run-time error may occur that does not result in automatic exiting (or at least not quick exiting as above) of the Garest MS DOS output window. Instead the window may hang and an error message with options (possibly involving white and red colours in the box display) will popup. In this event just choose the option that allows the program to terminate. It is the result of numerical difficulties deep inside Garest computations. This type of error is usually resolvable by trial and error choosing of different initial parameters, parameter bounds, and maybe parameter phases. Otherwise perhaps unusually unrealistic data entries may be responsible.

## 9. Output: estimated parameter values

The worksheet "ParameterEstOutput" contains the estimated parameter values produced by Garest and is copied directly from the Garest output text file "garest.par". The ".par" extension to this text file indicates that it is a standard feature of ADMB output for the parameter estimates values. These values are the result of ADMB's numerical computations which involves a numerical process called AUTODIF (automatic differentiation) and a statistical process known as the "Maximum Likelihood" estimation method of estimating parameters.

The layout and meaning of the information on this worksheet are identical to the worksheet "ParameterInitialValues". The one exception to this is the line that looks something like "# Number of parameters = 68 Objective function value = 2.65E+03 Maximum gradient component = 1.32E+01". This line indicates how many parameters were actually estimated, as opposed to being kept fixed in phase –1. It also contains the objective function value at the end of the run and the largest value of the parameter derivative vector, that is, the maximum gradient component.

If Garest's parameter estimation failed (for example an interruption to Garest) then the output values found in this worksheet may not relate to the run settings. The user will be alerted of this parameter estimation failure by means of a popup message box appearing after the run.

For a brief description of each parameter's meaning refer to Appendix A of this manual.

# 10. Output: report

The report quantities produced by Garest are presented to the user in three views via worksheets "ReportOutput", "BPIcharts", and "FITcharts". As with the other worksheets, the information including charts on these worksheets can be copied to another worksheet or workbook, either manually or by clicking the "Produce report workbook" button on the control form. The display of this information can then be modified for presentation purposes by the user according to requirements. Refer to Appendix D for a definition of the model time periods; Garest defined integers were used for the time period labelling for chart display format reasons.

Worksheet "ReportOutput" contains a direct copy of the Garest output text file "garest.rep". The ".rep" extension to this text file indicates that it is an ADMB report output file containing ADMB programmer defined quantities. It contains extensive information on model fits, biological performance indicators (BPIs), and other model structure outputs (which are all ultimately derived from the estimated parameters). Charts and a more intuitive presentation of the information on model fits and BPI information is presented in worksheets "BPIcharts" and "FITcharts".

Additional information provided in worksheet "ReportOutput" includes, at the top of the worksheet, a breakdown of objective function components consisting of TotalObj, mLLCEWt*sum(mLLCwt_RgSnEt), mLLCnLWt*sum(mLLCnL_MomRgSx), mLLCnASxWt*sum(mLLCnACsx_RgSn) and logRdevWt*norm2(logRdev). The objective function component's weight factor values are also displayed as mLLCEWt, mLLCnLWt, mLLCnASxWt, logRdevWt. All these quantities have identical meaning to that explained in section "Running the estimator program Garest" in the paragraph on the parameter value calculation stage. The yearly natural mortality rate value chosen by the user is also output next to label "Mnatural". Standardised residuals for the catch-effort catch fits (same category format as explained in section "Input: Data"), various slicegro array structures (whose format can be deduced from array label arguments displayed), yearly Fmax for each model region, time-step, and effort type, length selectivity curves, growth curves, yield-per-recruit (YPR), value-per-recruit (VPR), and egg-per-recruit (EPR) with labelling information is also displayed.

Worksheet "BPIcharts" contains the output as charts of the biological performance indicators recruitment, fishable population, fishable biomass, and half-yearly exploitation rates which are often of interest to fishery managers. The recruitment chart plots, for each region and sex, recruit numbers against recruit cohort year where cohort year value is the model-defined year of spawning. For each of the two regions a chart exists plotting model computed fishable population numbers in a region against model time period (that is, model half-years). Similarly, there exist corresponding charts for model computed biomass (in kilograms) and half-yearly exploitation rate. Note that the per-recruit quantities of yield-per-recruit (YPR), value-per-recruit (VPR), and eggs-per-recruit (EPR) are also given in this workbook. For each of these three quantities there is one value per gulf (plus some related information) and they were computed using the last 5 years in the model.

Worksheet “FITcharts” contains the output as charts of the fits to the various data sources of the model. The contents of this worksheet together with parameter uncertainty information can give an idea to the user of the success of a Garest run. Generally speaking the closer the fit the better. The first eight charts near the top of this workbook display catch-effort catch (in kilograms) values. Each of the eight charts contains a plot of the data and a plot of the model computed catch values for a particular region and effort type. Catch-at-age proportions against years of age of the haul net catch, for both data and model-computed values, are plotted in the next eight charts, one chart for each region-sex-season combination. For given region and season, proportions summed across sex should sum to one. The next four charts contain plots of data and model proportions against sex for haul net catch, one chart for each region-season combination with proportions summing to one for each plot within each chart. The last 16 charts contain plots of data and model computed length moment values against half-years of age (expressed as fraction of a year of age). The left side of the chart lattice displays the haul net information and the right side the dab net information. Each chart depicts information for a gear (haul net or dab net), sex, and moment in Spencer Gulf; the Gulf St.Vincent information is also present in the cells of this worksheet.

If Garest’s parameter estimation failed (for example an interruption to Garest) then the output values found in this worksheet may not relate to the run settings. The user will be alerted of this parameter estimation failure by means of a popup message box appearing after the run.

# 11. Output: parameter standard deviations

The worksheet “ParameterStdOutput” contains the computed parameter standard deviation values produced by Garest and is copied directly from the Garest output text file “garest.std”. The “.std” extension to this text file indicates that it is a standard feature of ADMB output for the parameter standard deviation values.

There are four columns on this worksheet. The first row contains the labels and are “index”, “name”, “parameter estimate”, and “parameter standard deviation”. Column “index” simply contains ADMB’s sequential numbering (ascending order from top to bottom) of parameters that were actually estimated, as opposed to being kept fixed in phase –1; parameters that are kept fixed during the run are not listed. Column “name” contains the names of the parameters as they are known in Garest and also Garface. Column “parameter estimate” contains the estimates for the parameters. Column “parameter standard deviation” contains the standard deviations on the parameters. For a description of each parameter sub-category as it appears listed in the “ParameterStdOutput” and “ParameterCorOutput” worksheets refer to Appendix B of this manual.

As mentioned in section “Input: Sundry control options” Garface will colour red a cell in the first row of the worksheet alerting the user that the results are possibly unrelated to results in the rest of the workbook. Note that as explained in section “Running the estimator program Garest” an interruption to the Garest program’s execution during the Hessian row calculation stage (or offcourse also during the parameter estimation stage) may result in the values in worksheets "ParameterStdOutput" and "ParameterCorOutput" not representing values related to values found in the rest of the workbook. An indication that this problem of a Hessian matrix not having been calculated is signalled by Garface via colouring red a cell in the first row of worksheets "ParameterStdOutput" and "ParameterCorOutput".

However, even if both the parameter estimation and the Hessian calculation stages were not interrupted it may still be that the values found in worksheets "ParameterStdOutput" and "ParameterCorOutput" do not represent values found in the rest of the workbook. The reason for this is due to ADMB internal requirements for the Hessian matrix (for example, mathematical suitability for matrix inversion) not having been met by the Hessian matrix calculated in the current Garest run. In this case, even though the user specified in Garface to have parameter standard deviations and correlations produced, ADMB was not able to carry out the needed calculations, and as a consequence Garface simply loaded the "garest.std" and "garest.cor" files (which would be from a previous run) that were present in the Garface directory. Note that this problem with an unsuitable Hessian matrix is less likely to occur if the Garest run has been allowed to run long enough. Setting the maximum function evaluations (see section "SundryControlOptions") high enough can result in a longer Garest run as will setting the convergence criteria small enough. An indication that this problem of an unsuitable Hessian matrix having occurred is signalled by Garface via colouring red a cell in the first row of worksheets "ParameterStdOutput" and "ParameterCorOutput".

The parameter standard deviation values are derived from the diagonal elements of the Hessian matrix which is a square matrix whose elements are the second-order derivatives, with respect to the vector of parameters, of the objective function being optimised. A given parameter's standard deviation value is the square root of the negative of the diagonal element of the inverse Hessian matrix calculated at the maximum likelihood parameter estimate values. These parameter standard deviation values are a measure of the uncertainty in the parameter estimates associated with the maximum likelihood estimation process that produced these estimates.

These can be used in conjunction with the parameter estimate to form a confidence interval for the parameter based on the intrinsic assumption of the process that these parameter estimates are a stochastic quantity distributed approximately according to the Normal probability density function. For example, if a parameter value is 20 and its standard deviation value is 3 then an approximate 95% confidence interval for the parameter would be [20 - 1.64*3, 20 + 1.64*3] where 20 – 1.64*3 is the lower limit and 20 + 1.64*3 is the upper limit of the interval.

## 12. Output: parameter correlation matrix

The worksheet "ParameterCorOutput" contains the same columns as in worksheet "ParameterStdOutput" but additionally contains a lower diagonal matrix region of cells directly to the right. It is copied from the Garest output text file "garest.cor". The ".cor" extension to this text file indicates that the file is a standard feature of ADMB output for the parameter correlation matrix values. As can be seen from the labelling the rows and columns correspond to the estimated parameters and each cell within this lower diagonal matrix region contains a value. This value is the computed row-column pair parameter correlation value.

The statistical definition of correlation defines the meaning of each such quantity and ADMB's computation process uses the Hessian matrix to produce it within the same numerical and statistical framework as described in section "Output: parameter standard deviations". For example, if cell F9 on the worksheet contains a value of 0.1609 then this means that the parameter sigm for Southern Spencer Gulf males is positively correlated with parameter K for Southern Spencer Gulf females by about 16%. Note that a value of 1 lies on the diagonal of the matrix since a parameter is by definition perfectly correlated with itself (in the absence of auto-correlation modelling).

As mentioned in section "Input: Sundry control options" Garface will colour red a cell in the first row of the worksheet alerting the user that the results are possibly unrelated to results in the rest of the workbook. Also, for further caveats see section "Output: parameter standard deviations".

# 13. Miscellaneous

The <u>"Back to main form"</u> buttons (and associated macros) won't work from user added worksheets or from copies of standard Garface worksheets, but only from Garface standard worksheets. This is expected behaviour and is done in an effort to maintain application integrity. The user perhaps may add worksheets or copy standard Garface worksheets for purposes of aiding manipulation of inputs or analyses of outputs.

<u>Renaming or deleting Garface application worksheets</u> will naturally result in failure of Garface. In this event a message will be displayed to the user plus a suggestion as to what went wrong and how to remedy the situation. If it is renamed then the user may be able to name it back to the original name, or else he or she may either attempt to copy it back from a master and modify it for the current estimation, or start afresh with a new Garface workbook.

Garface was made to run, and has been tested, on Microsoft Windows 2000 Version 5.0. <u>VBA and Microsoft Office object libraries</u> may be different in non Windows 2000 environments. Relevant object libraries existing at the time of Garface's construction are as follows: "Visual Basic For Applications", "Microsoft Excel 9.0 Object Library", "OLE Automation", "Microsoft Forms 2.0 Object Library", "Microsoft Office 9.0 Object Library", "Microsoft Scripting Runtime". These items may be viewed by accessing the Microsoft Visual Basic (VBA) editor (by pressing and holding key Alt and then F11 or by selecting the option in Microsoft Excel's macro submenu) and clicking the "Tools" menu and selecting menu "References". This will bring up the available references list box and the above mentioned object libraries should be ticked and listed at the top of the list of references. If some are not ticked then simply scroll down the list box until they are found and tick them. Note that in future editions of Microsoft Windows some of these object libraries may have a slightly different name, such as for example “Microsoft Excel 10.0 Object Library” perhaps. In this case it may have no effect on Garface’s performance due to software backwards compatibility, however an error message may be raised and the suggestions above should be attempted. If this fails the user can call the Help Desk for the names of object libraries that are compatible with the object libraries mentioned above.

The regions, Spencer Gulf (abbreviated SG) and Gulf St.Vincent (abbreviated GSV), are spatial aggregations of MFA blocks (that is, South Australian marine fishing areas) defined as follows:
SG: 11, 19, 20, 21, 22, 23, 29, 30, 31, 32, 33
GSV: 34, 35, 36, 40, 41, 42, 43, 44

# Appendix A: Descriptions of each type of estimated parameters

Note: refer to Final Report Chapter 1 of the FRDC Project (No. 1999/145), for further details, including equations.

Phase = - 1 means that the parameter is not estimated. Rather the value given in the “ParameterInitialValues” worksheet will be used and taken as fixed.

The first line provides the mathematical symbol notation for each type of parameter as found in Final Report Chapter 1 of the FRDC Project (No. 1999/145, “Stock assessment models with graphical user interfaces for key South Australian marine finfish stocks”); however for some parameters no explicit description is given in the report.. The second line below each parameter heading indicates the category values as pertaining to the “ParameterInitialValues” worksheet.

# Linf:
$L_\infty$
row = region = SG,GSV; column = sex = FEMALE,MALE
Phase = - 1 for the base run. Growth parameter (as defined by the slicegro model description).

# K:
K
row = region = SG,GSV; column = sex = FEMALE,MALE
Growth parameter (as defined by the slicegro model description).

# t0:
$t_0$
row = region = SG,GSV; column = sex = FEMALE,MALE
Phase = - 1 for the base run. Growth parameter (as defined by the slicegro model description).

# u:
row = region = SG,GSV; column = sex = FEMALE,MALE

Phase = - 1 for the base run.  Growth parameter (as defined by the slicegro model description).

# w:
row = region = SG,GSV; column = sex = FEMALE,MALE
Phase = - 1 for the base run.  Growth parameter (as defined by the slicegro model description).

# sigm:
$s_0$
row = region = SG,GSV; column = sex = FEMALE,MALE
Growth parameter (as defined by the slicegro model description).

# sigexp:
$s_1$
row = region = SG,GSV; column = sex = FEMALE,MALE
Phase = - 1 for the base run.  Growth parameter (as defined by the slicegro model description).

# r:
$r$
row = region = SG,GSV; column = sex = FEMALE,MALE
Phase = - 1 for the base run.  Growth parameter (as defined by the slicegro model description).

# F0:
$F_0[r]$
column = region = SG,GSV
Initial state array fishing mortality.

# Rbar:
$\overline{R}[r,x]$
row = region = SG,GSV; column = sex = FEMALE,MALE
Average recruitment.  This parameter, together with the yearly logRdev parameters below define recruit numbers as Rbar*exp(logRdev).

# logRdevSG:
$\log(e_R[r,c])$
column = cohort year = 1983, 1984, …, maximum cohort year
Spencer Gulf yearly-cohort recruitment component; recruits = Rbar*exp(logRdev).

# logRdevGSV:
$\log(e_R[r,c])$
column = cohort year = 1983, 1984, …, maximum cohort year
Gulf St.Vincent yearly-cohort recruitment component; recruits = bar*exp(logRdev).

# qEt0:
$q_E[r,i_E]$

row = region = SG,GSV; column = haul net targeted, haul net untargeted, dab net all, Recreational
Catchability parameter (as defined by the catch-equation).

# summale_sl:
$s_{yx}\left[y_{1/2}[t], x\right]$
Summer male relative selectivity parameter (as defined by the catch-equation). Summer-female relative selectivity is defined within the model at a value of 1. Parameters summale_sl, winfemale_sl, and winmale_sl have values relative to the summer-female value of 1.

# winfemale_sl:
$s_{yx}\left[y_{1/2}[t], x\right]$
Winter female relative selectivity parameter (as defined by the catch-equation).

# winmale_sl:
$s_{yx}\left[y_{1/2}[t], x\right]$
Winter male relative selectivity parameter (as defined by the catch-equation).

# winrec_sl:
$s_{yx}\left[y_{1/2}[t], x\right]$
Winter recreational relative selectivity parameter (as defined by the catch-equation). This parameter has a value relative to the summer value defined within the model at 1.

# l5095Dnrec:
$l_{95}\left[y_{1/2}, r, g\right]$ - $l_{50}\left[y_{1/2}, r, g\right]$.
Dab net length selectivity parameter (as defined by a logistic length selectivity curve).

# l95Dnrec:
$l_{95}\left[y_{1/2}, r, g\right]$
Dab net length selectivity parameter (as defined by a logistic length selectivity curve).

# l50HN_SumSg:
$l_{50}\left[y_{1/2}, r, g\right]$
Phase = - 1 for the base run. Summer Spencer Gulf haul net length selectivity parameter (as defined by a logistic length selectivity curve).

# l50HN_SumGsv:
$l_{50}\left[y_{1/2}, r, g\right]$
Phase = - 1 for the base run. Summer Gulf St.Vincent haul net length selectivity parameter (as defined by a logistic length selectivity curve).

# l50HN_WinSg:
$l_{50}\left[y_{1/2}, r, g\right]$
Winter Spencer Gulf haul net length selectivity parameter (as defined by a logistic length selectivity curve).

# l50HN_WinGsv:
$l_{50}[y_{1/2}, r, g]$
Winter Gulf St.Vincent haul net length selectivity parameter (as defined by a logistic length selectivity curve).

# rSelHN_SumSg:
Phase = - 1 for the base run.  Summer Spencer Gulf haul net length selectivity parameter (as defined by a logistic length selectivity curve).

# rSelHN_SumGsv:
Phase = - 1 for the base run.  Summer Gulf St.Vincent haul net length selectivity parameter (as defined by a logistic length selectivity curve).

# rSelHN_WinSg:
Winter Spencer Gulf haul net length selectivity parameter (as defined by a logistic length selectivity curve).

# rSelHN_WinGsv:
Winter Gulf St.Vincent haul net length selectivity parameter (as defined by a logistic length selectivity curve).

# sigCw1:
$s_{Cw}$
Log-likelihood objective function sigma parameter for the catch-effort fit (as defined by the objective function formulae).

# sigCl1:
$s_{mp}$
Log-likelihood objective function sigma parameter for the length moment fit (as defined by the objective function formulae).

# Appendix B:  Descriptions of each type of estimated parameter sub-category as it appears in the ParameterStdOutput and ParameterCorOutput worksheets

Note: depending on which parameters are set to phase –1, some of these values below may not appear on the two spreadsheets.  In this case a subset of these values will appear (and the index column values will differ), but the details below will still indicate the category breakdown for a given estimated parameter.  (Note also that all growth parameters Linf, K, t0, u, w, sigm, sigexp, and r have the same category breakdown by region and sex.)  The case for the base run appears below.  SG = Spencer Gulf, GSV = Gulf St.Vincent

| index | name | category |
|---|---|---|

| | | |
|---|---|---|
| 1 | K | SG, FEMALE |
| 2 | K | SG, MALE |
| 3 | K | GSV, FEMALE |
| 4 | K | GSV, MALE |
| 5 | sigm | SG, female |
| 6 | sigm | SG, male |
| 7 | sigm | GSV, female |
| 8 | sigm | GSV, male |
| 9 | F0 | SG |
| 10 | F0 | GSV |
| 11 | Rbar | SG, female |
| 12 | Rbar | SG, male |
| 13 | Rbar | GSV, female |
| 14 | Rbar | GSV, male |
| 15 | logRdevSG | SG,1983 |
| 16 | logRdevSG | 1984 |
| 17 | logRdevSG | 1985 |
| 18 | logRdevSG | 1986 |
| 19 | logRdevSG | 1987 |
| 20 | logRdevSG | 1988 |
| 21 | logRdevSG | 1989 |
| 22 | logRdevSG | 1990 |
| 23 | logRdevSG | 1991 |
| 24 | logRdevSG | 1992 |
| 25 | logRdevSG | 1993 |
| 26 | logRdevSG | 1994 |
| 27 | logRdevSG | 1995 |
| 28 | logRdevSG | 1996 |
| 29 | logRdevSG | 1997 |
| 30 | logRdevSG | 1998 |
| 31 | logRdevSG | 1999 |
| 32 | logRdevGSV | GSV, 1983 |
| 33 | logRdevGSV | 1984 |
| 34 | logRdevGSV | 1985 |
| 35 | logRdevGSV | 1986 |
| 36 | logRdevGSV | 1987 |
| 37 | logRdevGSV | 1988 |
| 38 | logRdevGSV | 1989 |
| 39 | logRdevGSV | 1990 |
| 40 | logRdevGSV | 1991 |
| 41 | logRdevGSV | 1992 |
| 42 | logRdevGSV | 1993 |
| 43 | logRdevGSV | 1994 |
| 44 | logRdevGSV | 1995 |
| 45 | logRdevGSV | 1996 |
| 46 | logRdevGSV | 1997 |
| 47 | logRdevGSV | 1998 |
| 48 | logRdevGSV | 1999 |
| 49 | qEt0 | SG, haul net targeted |
| 50 | qEt0 | SG, haul net untargeted |
| 51 | qEt0 | SG, dab net all |
| 52 | qEt0 | SG, Recreational |
| 53 | qEt0 | GSV, haul net targeted |
| 54 | qEt0 | GSV, haul net untargeted |

| | | |
|---|---|---|
| 55 | qEt0 | GSV, dab net all |
| 56 | qEt0 | GSV, Recreational |
| 57 | summale_sl | Summer, male |
| 58 | winfemale_sl | Winter, female |
| 59 | winmale_sl | Winter, male |
| 60 | winrec_sl | Winter recreational |
| 61 | l5095Dnrec | dab net & recreational |
| 62 | l95Dnrec | dab net & recreational |
| 63 | l50HN_WinSg | haul net, winter , SG |
| 64 | l50HN_WinGsv | haul net, winter, GSV |
| 65 | rSelHN_WinSg | haul net, winter, SG |
| 66 | rSelHN_WinGsv | haul net, winter GSV |
| 67 | sigCw1 | No category |
| 68 | sigCl1 | No category |

# Appendix C: Sundry control option settings for the "base run"

Sundry control option settings for the "base run":
# logRdev weight
0
# catch-effort catch fit mll weight
1
# catch-at-age-sex mll weight
1
# moment fit mll weight
1
# option for parameter standard deviation and correlation matrix
0
# Yearly natural mortality rate
0.4
# convergence criteria
1.00E-03
# maximum function evaluations
500

# Appendix D: Model time step definition for the base run

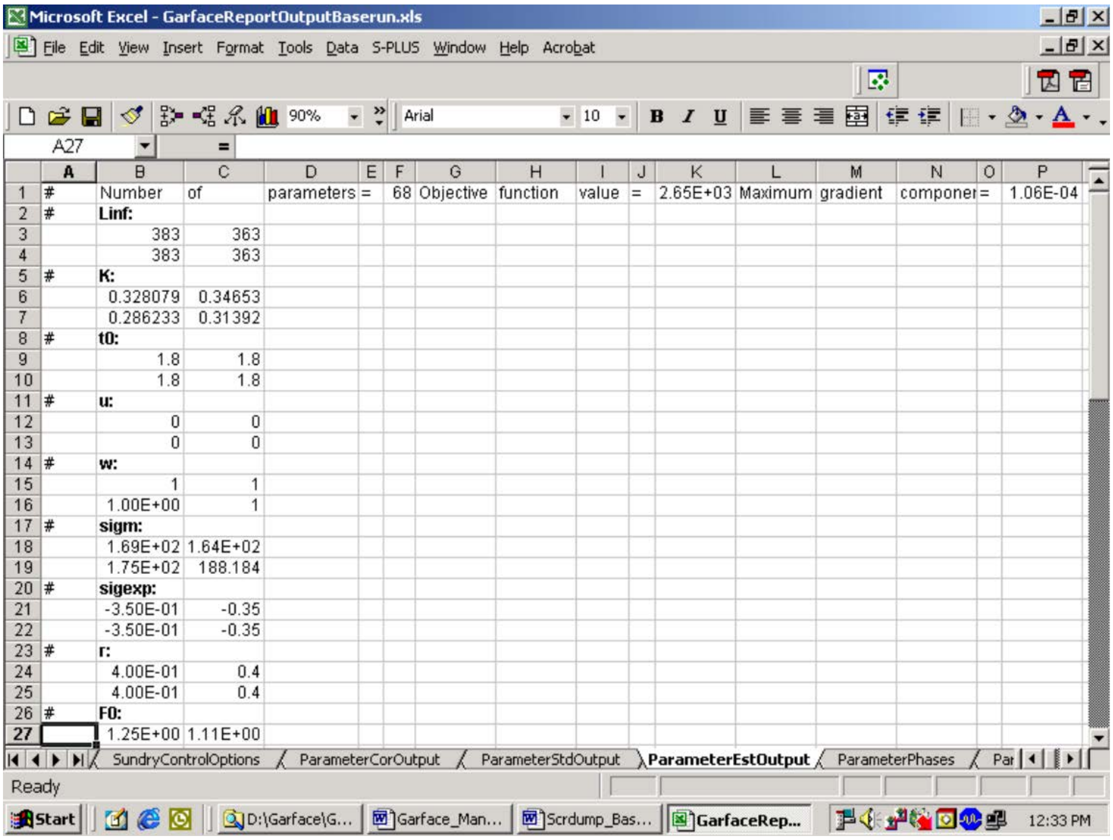
Garest works with numbers and the "integer" value below indicates the value Garest assumes represents the corresponding time period shown beneath "period".

| period | integer |
|---|---|
| Oct-Mar-84 | 1 |
| Apr-Sep-84 | 2 |
| Oct-Mar-85 | 3 |
| Apr-Sep-85 | 4 |
| Oct-Mar-86 | 5 |

| | |
|---|---|
| Apr-Sep-86 | 6 |
| Oct-Mar-87 | 7 |
| Apr-Sep-87 | 8 |
| Oct-Mar-88 | 9 |
| Apr-Sep-88 | 10 |
| Oct-Mar-89 | 11 |
| Apr-Sep-89 | 12 |
| Oct-Mar-90 | 13 |
| Apr-Sep-90 | 14 |
| Oct-Mar-91 | 15 |
| Apr-Sep-91 | 16 |
| Oct-Mar-92 | 17 |
| Apr-Sep-92 | 18 |
| Oct-Mar-93 | 19 |
| Apr-Sep-93 | 20 |
| Oct-Mar-94 | 21 |
| Apr-Sep-94 | 22 |
| Oct-Mar-95 | 23 |
| Apr-Sep-95 | 24 |
| Oct-Mar-96 | 25 |
| Apr-Sep-96 | 26 |
| Oct-Mar-97 | 27 |
| Apr-Sep-97 | 28 |
| Oct-Mar-98 | 29 |
| Apr-Sep-98 | 30 |
| Oct-Mar-99 | 31 |
| Apr-Sep-99 | 32 |
| Oct-Mar-00 | 33 |
| Apr-Sep-00 | 34 |
| Oct-Mar-01 | 35 |
| Apr-Sep-01 | 36 |

# Appendix E: Example outputs from running the base run

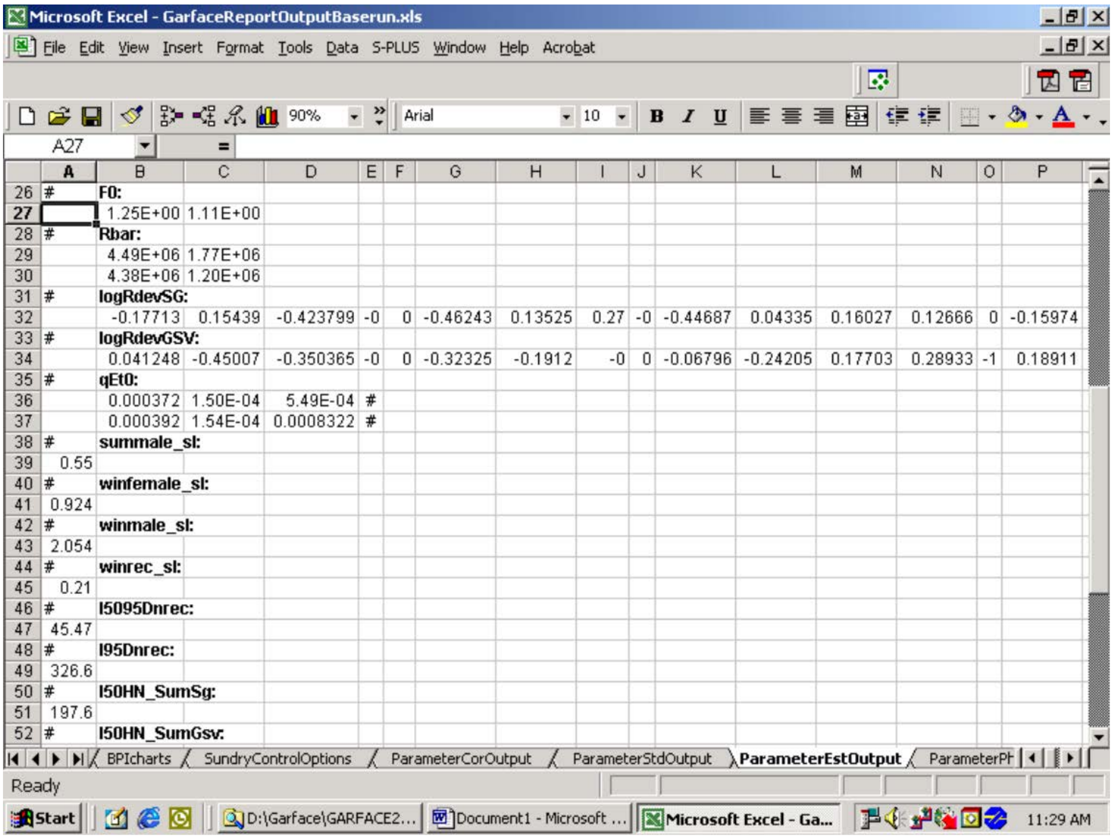
<u>Worksheet “ParameterEstOutput”</u>



Microsoft Excel - GarfaceReportOutputBaserun.xls

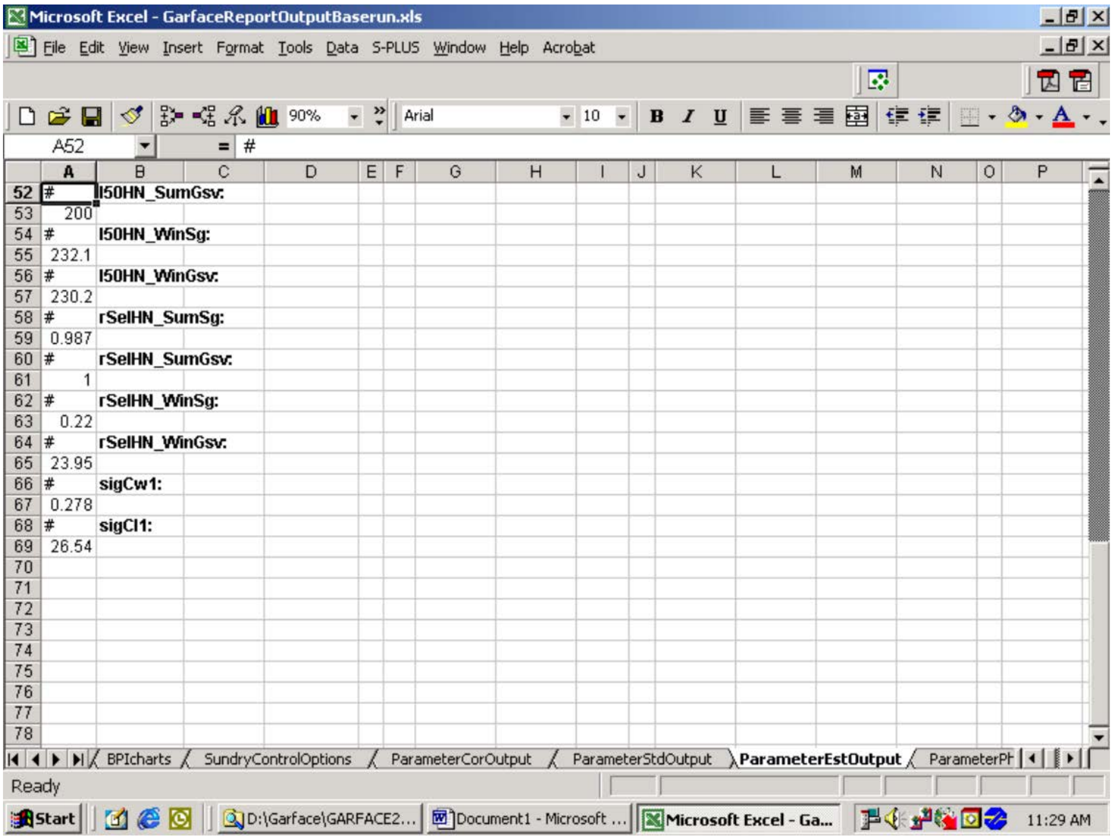
| | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | # | Number | of | parameters | = | 68 | Objective | function | value | = | 2.65E+03 | Maximum | gradient | componer | = | 1.06E-04 |
| 2 | # | **Linf:** | | | | | | | | | | | | | | |
| 3 | | 383 | 363 | | | | | | | | | | | | | |
| 4 | | 383 | 363 | | | | | | | | | | | | | |
| 5 | # | **K:** | | | | | | | | | | | | | | |
| 6 | | 0.328079 | 0.34653 | | | | | | | | | | | | | |
| 7 | | 0.286233 | 0.31392 | | | | | | | | | | | | | |
| 8 | # | **t0:** | | | | | | | | | | | | | | |
| 9 | | 1.8 | 1.8 | | | | | | | | | | | | | |
| 10 | | 1.8 | 1.8 | | | | | | | | | | | | | |
| 11 | # | **u:** | | | | | | | | | | | | | | |
| 12 | | 0 | 0 | | | | | | | | | | | | | |
| 13 | | 0 | 0 | | | | | | | | | | | | | |
| 14 | # | **w:** | | | | | | | | | | | | | | |
| 15 | | 1 | 1 | | | | | | | | | | | | | |
| 16 | | 1.00E+00 | 1 | | | | | | | | | | | | | |
| 17 | # | **sigm:** | | | | | | | | | | | | | | |
| 18 | | 1.69E+02 | 1.64E+02 | | | | | | | | | | | | | |
| 19 | | 1.75E+02 | 188.184 | | | | | | | | | | | | | |
| 20 | # | **sigexp:** | | | | | | | | | | | | | | |
| 21 | | -3.50E-01 | -0.35 | | | | | | | | | | | | | |
| 22 | | -3.50E-01 | -0.35 | | | | | | | | | | | | | |
| 23 | # | **r:** | | | | | | | | | | | | | | |
| 24 | | 4.00E-01 | 0.4 | | | | | | | | | | | | | |
| 25 | | 4.00E-01 | 0.4 | | | | | | | | | | | | | |
| 26 | # | **F0:** | | | | | | | | | | | | | | |
| 27 | | 1.25E+00 | 1.11E+00 | | | | | | | | | | | | | |

SundryControlOptions / ParameterCorOutput / ParameterStdOutput / **ParameterEstOutput** / ParameterPhases / Par



Microsoft Excel - GarfaceReportOutputBaserun.xls

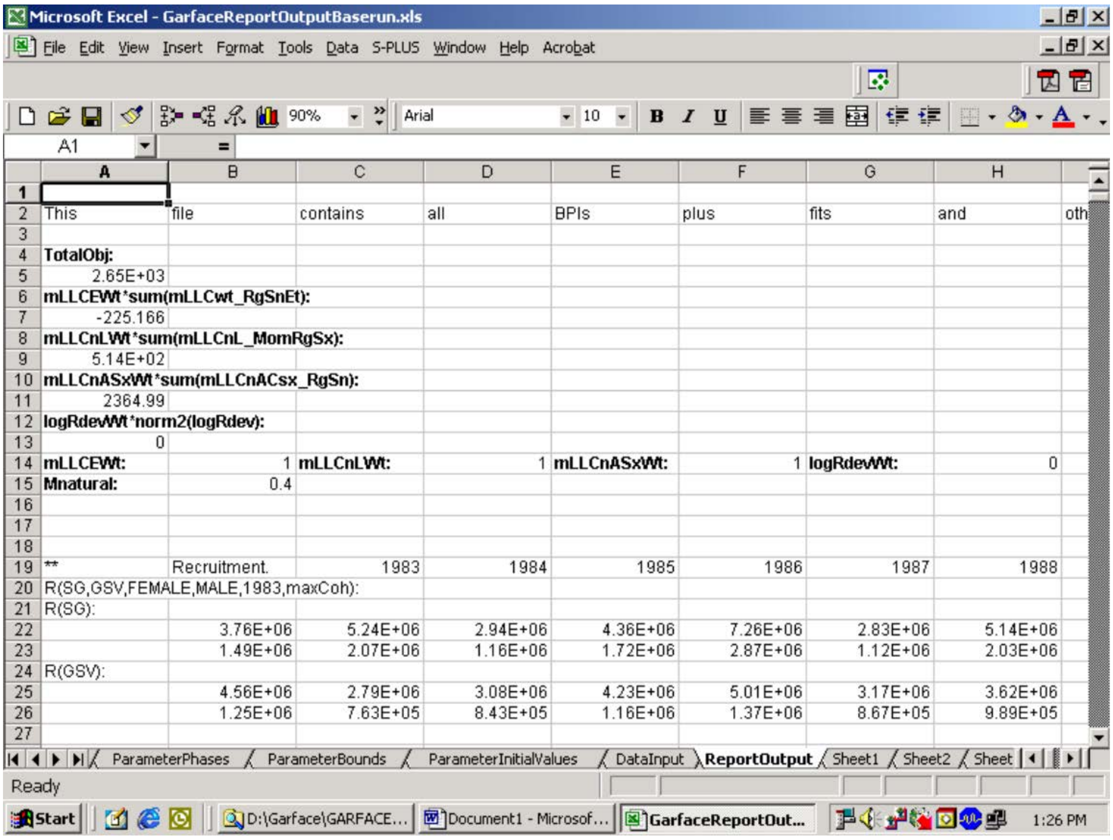
| | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 26 | # | F0: | | | | | | | | | | | | | | |
| 27 | | 1.25E+00 | 1.11E+00 | | | | | | | | | | | | | |
| 28 | # | Rbar: | | | | | | | | | | | | | | |
| 29 | | 4.49E+06 | 1.77E+06 | | | | | | | | | | | | | |
| 30 | | 4.38E+06 | 1.20E+06 | | | | | | | | | | | | | |
| 31 | # | logRdevSG: | | | | | | | | | | | | | | |
| 32 | | -0.17713 | 0.15439 | -0.423799 | -0 | 0 | -0.46243 | 0.13525 | 0.27 | -0 | -0.44687 | 0.04335 | 0.16027 | 0.12666 | 0 | -0.15974 |
| 33 | # | logRdevGSV: | | | | | | | | | | | | | | |
| 34 | | 0.041248 | -0.45007 | -0.350365 | -0 | 0 | -0.32325 | -0.1912 | -0 | 0 | -0.06796 | -0.24205 | 0.17703 | 0.28933 | -1 | 0.18911 |
| 35 | # | qEt0: | | | | | | | | | | | | | | |
| 36 | | 0.000372 | 1.50E-04 | 5.49E-04 | # | | | | | | | | | | | |
| 37 | | 0.000392 | 1.54E-04 | 0.0008322 | # | | | | | | | | | | | |
| 38 | # | summale_sl: | | | | | | | | | | | | | | |
| 39 | 0.55 | | | | | | | | | | | | | | | |
| 40 | # | winfemale_sl: | | | | | | | | | | | | | | |
| 41 | 0.924 | | | | | | | | | | | | | | | |
| 42 | # | winmale_sl: | | | | | | | | | | | | | | |
| 43 | 2.054 | | | | | | | | | | | | | | | |
| 44 | # | winrec_sl: | | | | | | | | | | | | | | |
| 45 | 0.21 | | | | | | | | | | | | | | | |
| 46 | # | I5095Dnrec: | | | | | | | | | | | | | | |
| 47 | 45.47 | | | | | | | | | | | | | | | |
| 48 | # | I95Dnrec: | | | | | | | | | | | | | | |
| 49 | 326.6 | | | | | | | | | | | | | | | |
| 50 | # | I50HN_SumSg: | | | | | | | | | | | | | | |
| 51 | 197.6 | | | | | | | | | | | | | | | |
| 52 | # | I50HN_SumGsv: | | | | | | | | | | | | | | |



Microsoft Excel - GarfaceReportOutputBaserun.xls

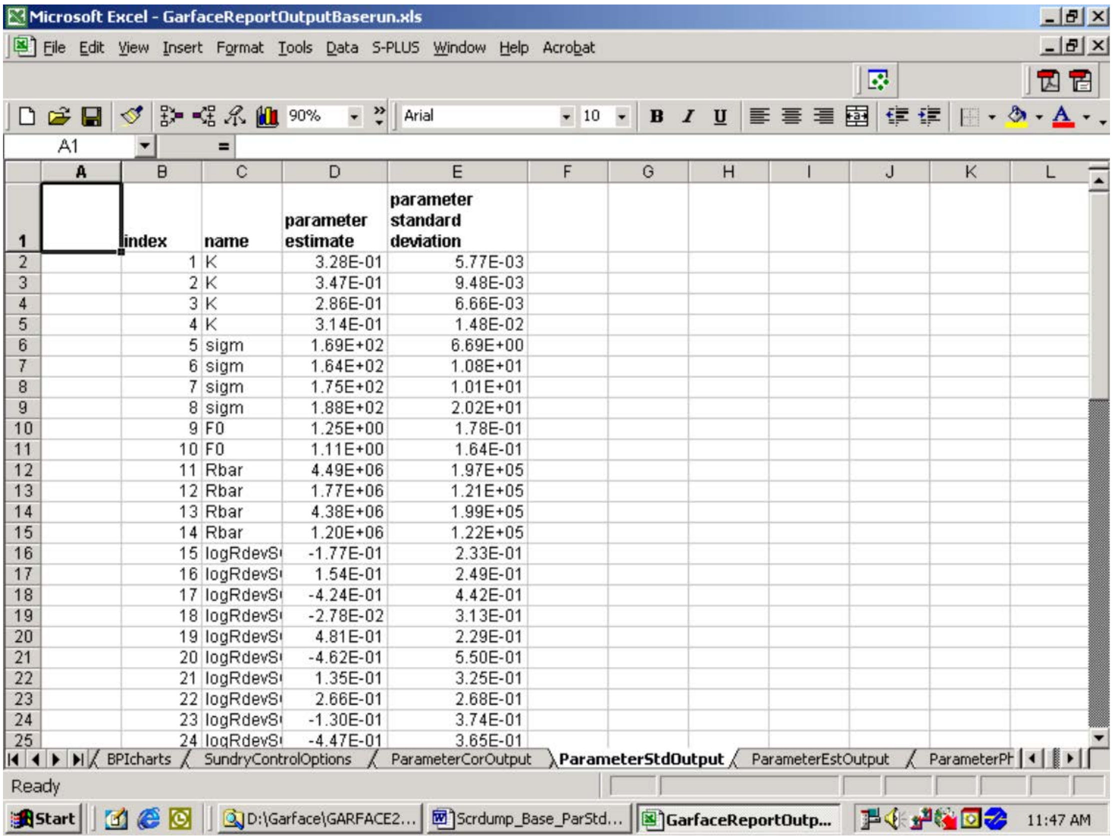
| | A | B | C | D | E | F | G | H | I | J | K | L | M | N | O | P |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 52 | # | I50HN_SumGsv: | | | | | | | | | | | | | | |
| 53 | 200 | | | | | | | | | | | | | | | |
| 54 | # | I50HN_WinSg: | | | | | | | | | | | | | | |
| 55 | 232.1 | | | | | | | | | | | | | | | |
| 56 | # | I50HN_WinGsv: | | | | | | | | | | | | | | |
| 57 | 230.2 | | | | | | | | | | | | | | | |
| 58 | # | rSelHN_SumSg: | | | | | | | | | | | | | | |
| 59 | 0.987 | | | | | | | | | | | | | | | |
| 60 | # | rSelHN_SumGsv: | | | | | | | | | | | | | | |
| 61 | 1 | | | | | | | | | | | | | | | |
| 62 | # | rSelHN_WinSg: | | | | | | | | | | | | | | |
| 63 | 0.22 | | | | | | | | | | | | | | | |
| 64 | # | rSelHN_WinGsv: | | | | | | | | | | | | | | |
| 65 | 23.95 | | | | | | | | | | | | | | | |
| 66 | # | sigCw1: | | | | | | | | | | | | | | |
| 67 | 0.278 | | | | | | | | | | | | | | | |
| 68 | # | sigCl1: | | | | | | | | | | | | | | |
| 69 | 26.54 | | | | | | | | | | | | | | | |

Worksheet “ReportOutput”

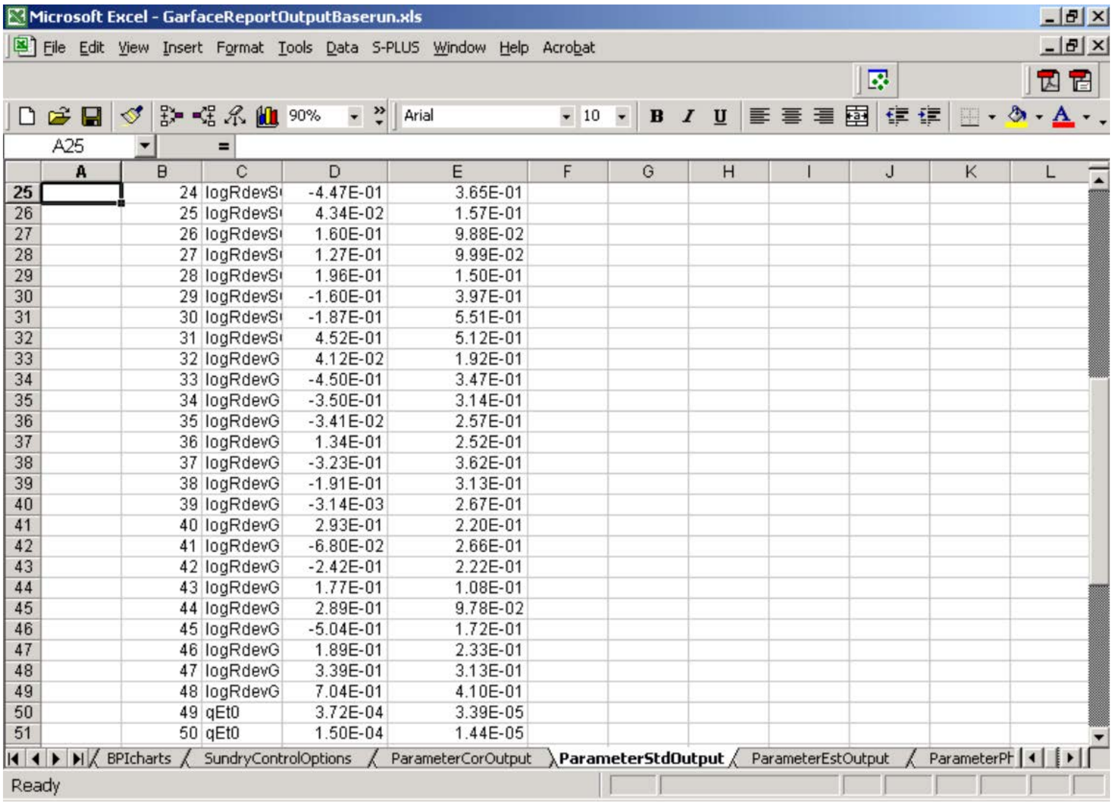

Microsoft Excel - GarfaceReportOutputBaserun.xls

| | A | B | C | D | E | F | G | H | |
|---|---|---|---|---|---|---|---|---|---|
| 1 | | | | | | | | | |
| 2 | This | file | contains | all | BPIs | plus | fits | and | oth |
| 3 | | | | | | | | | |
| 4 | TotalObj: | | | | | | | | |
| 5 | 2.65E+03 | | | | | | | | |
| 6 | mLLCEWt*sum(mLLCwt_RgSnEt): | | | | | | | | |
| 7 | -225.166 | | | | | | | | |
| 8 | mLLCnLWt*sum(mLLCnL_MomRgSx): | | | | | | | | |
| 9 | 5.14E+02 | | | | | | | | |
| 10 | mLLCnASxWt*sum(mLLCnACsx_RgSn): | | | | | | | | |
| 11 | 2364.99 | | | | | | | | |
| 12 | logRdevWt*norm2(logRdev): | | | | | | | | |
| 13 | 0 | | | | | | | | |
| 14 | mLLCEWt: | 1 | mLLCnLWt: | 1 | mLLCnASxWt: | 1 | logRdevWt: | 0 | |
| 15 | Mnatural: | 0.4 | | | | | | | |
| 16 | | | | | | | | | |
| 17 | | | | | | | | | |
| 18 | | | | | | | | | |
| 19 | ** | Recruitment. | 1983 | 1984 | 1985 | 1986 | 1987 | 1988 | |
| 20 | R(SG,GSV,FEMALE,MALE,1983,maxCoh): | | | | | | | | |
| 21 | R(SG): | | | | | | | | |
| 22 | | 3.76E+06 | 5.24E+06 | 2.94E+06 | 4.36E+06 | 7.26E+06 | 2.83E+06 | 5.14E+06 | |
| 23 | | 1.49E+06 | 2.07E+06 | 1.16E+06 | 1.72E+06 | 2.87E+06 | 1.12E+06 | 2.03E+06 | |
| 24 | R(GSV): | | | | | | | | |
| 25 | | 4.56E+06 | 2.79E+06 | 3.08E+06 | 4.23E+06 | 5.01E+06 | 3.17E+06 | 3.62E+06 | |
| 26 | | 1.25E+06 | 7.63E+05 | 8.43E+05 | 1.16E+06 | 1.37E+06 | 8.67E+05 | 9.89E+05 | |
| 27 | | | | | | | | | |

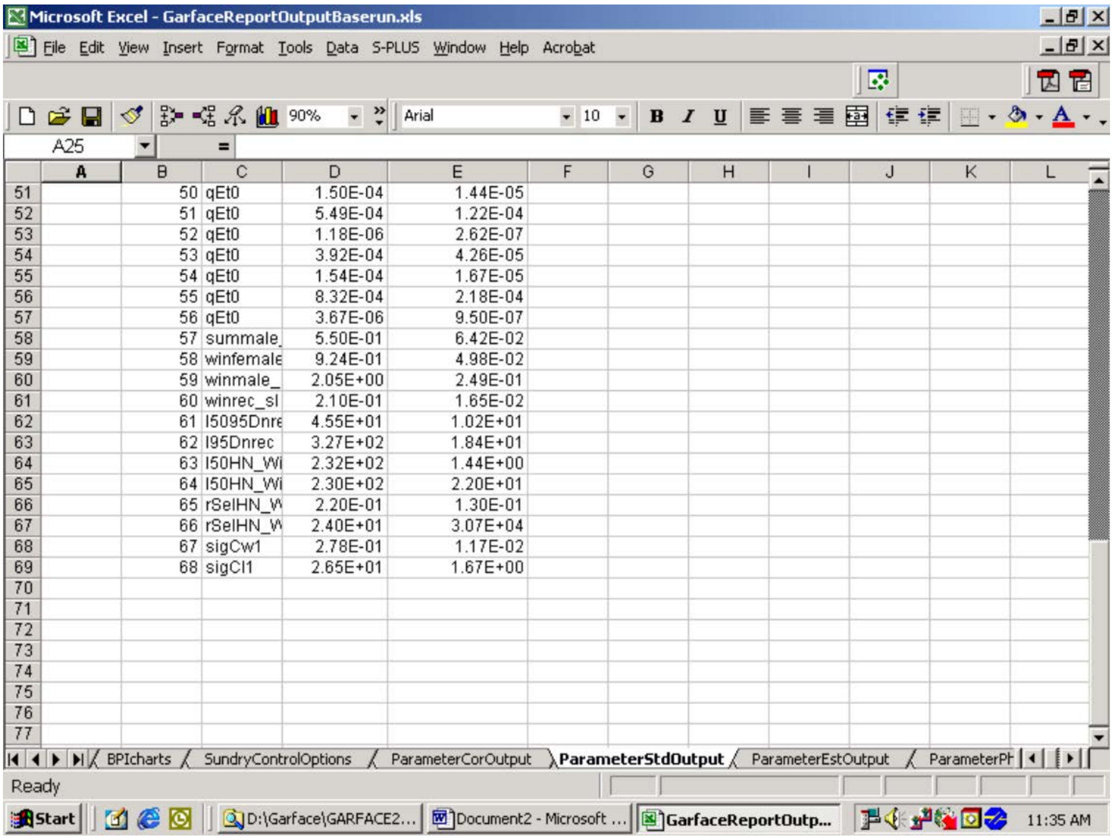
Worksheet “ParameterStdOutput”


Microsoft Excel - GarfaceReportOutputBaserun.xls

| | A | B (index) | C (name) | D (parameter estimate) | E (parameter standard deviation) |
|---|---|---|---|---|---|
| 2 | | 1 | K | 3.28E-01 | 5.77E-03 |
| 3 | | 2 | K | 3.47E-01 | 9.48E-03 |
| 4 | | 3 | K | 2.86E-01 | 6.66E-03 |
| 5 | | 4 | K | 3.14E-01 | 1.48E-02 |
| 6 | | 5 | sigm | 1.69E+02 | 6.69E+00 |
| 7 | | 6 | sigm | 1.64E+02 | 1.08E+01 |
| 8 | | 7 | sigm | 1.75E+02 | 1.01E+01 |
| 9 | | 8 | sigm | 1.88E+02 | 2.02E+01 |
| 10 | | 9 | F0 | 1.25E+00 | 1.78E-01 |
| 11 | | 10 | F0 | 1.11E+00 | 1.64E-01 |
| 12 | | 11 | Rbar | 4.49E+06 | 1.97E+05 |
| 13 | | 12 | Rbar | 1.77E+06 | 1.21E+05 |
| 14 | | 13 | Rbar | 4.38E+06 | 1.99E+05 |
| 15 | | 14 | Rbar | 1.20E+06 | 1.22E+05 |
| 16 | | 15 | logRdevS( | -1.77E-01 | 2.33E-01 |
| 17 | | 16 | logRdevS( | 1.54E-01 | 2.49E-01 |
| 18 | | 17 | logRdevS( | -4.24E-01 | 4.42E-01 |
| 19 | | 18 | logRdevS( | -2.78E-02 | 3.13E-01 |
| 20 | | 19 | logRdevS( | 4.81E-01 | 2.29E-01 |
| 21 | | 20 | logRdevS( | -4.62E-01 | 5.50E-01 |
| 22 | | 21 | logRdevS( | 1.35E-01 | 3.25E-01 |
| 23 | | 22 | logRdevS( | 2.66E-01 | 2.68E-01 |
| 24 | | 23 | logRdevS( | -1.30E-01 | 3.74E-01 |
| 25 | | 24 | logRdevS( | -4.47E-01 | 3.65E-01 |

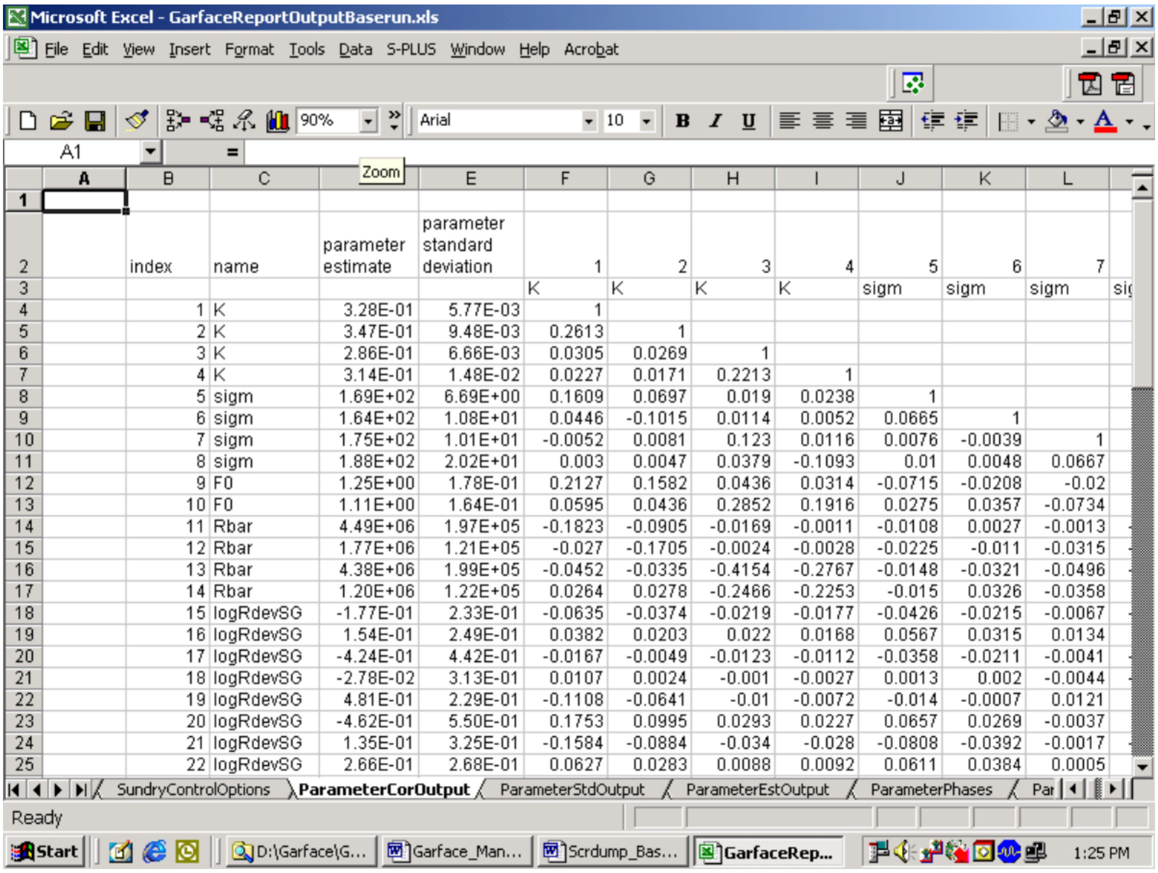



| Row | B | C | D | E |
|---|---|---|---|---|
| 25 | 24 | logRdevS | -4.47E-01 | 3.65E-01 |
| 26 | 25 | logRdevS | 4.34E-02 | 1.57E-01 |
| 27 | 26 | logRdevS | 1.60E-01 | 9.88E-02 |
| 28 | 27 | logRdevS | 1.27E-01 | 9.99E-02 |
| 29 | 28 | logRdevS | 1.96E-01 | 1.50E-01 |
| 30 | 29 | logRdevS | -1.60E-01 | 3.97E-01 |
| 31 | 30 | logRdevS | -1.87E-01 | 5.51E-01 |
| 32 | 31 | logRdevS | 4.52E-01 | 5.12E-01 |
| 33 | 32 | logRdevG | 4.12E-02 | 1.92E-01 |
| 34 | 33 | logRdevG | -4.50E-01 | 3.47E-01 |
| 35 | 34 | logRdevG | -3.50E-01 | 3.14E-01 |
| 36 | 35 | logRdevG | -3.41E-02 | 2.57E-01 |
| 37 | 36 | logRdevG | 1.34E-01 | 2.52E-01 |
| 38 | 37 | logRdevG | -3.23E-01 | 3.62E-01 |
| 39 | 38 | logRdevG | -1.91E-01 | 3.13E-01 |
| 40 | 39 | logRdevG | -3.14E-03 | 2.67E-01 |
| 41 | 40 | logRdevG | 2.93E-01 | 2.20E-01 |
| 42 | 41 | logRdevG | -6.80E-02 | 2.66E-01 |
| 43 | 42 | logRdevG | -2.42E-01 | 2.22E-01 |
| 44 | 43 | logRdevG | 1.77E-01 | 1.08E-01 |
| 45 | 44 | logRdevG | 2.89E-01 | 9.78E-02 |
| 46 | 45 | logRdevG | -5.04E-01 | 1.72E-01 |
| 47 | 46 | logRdevG | 1.89E-01 | 2.33E-01 |
| 48 | 47 | logRdevG | 3.39E-01 | 3.13E-01 |
| 49 | 48 | logRdevG | 7.04E-01 | 4.10E-01 |
| 50 | 49 | qEt0 | 3.72E-04 | 3.39E-05 |
| 51 | 50 | qEt0 | 1.50E-04 | 1.44E-05 |




| Row | B | C | D | E |
|---|---|---|---|---|
| 51 | 50 | qEt0 | 1.50E-04 | 1.44E-05 |
| 52 | 51 | qEt0 | 5.49E-04 | 1.22E-04 |
| 53 | 52 | qEt0 | 1.18E-06 | 2.62E-07 |
| 54 | 53 | qEt0 | 3.92E-04 | 4.26E-05 |
| 55 | 54 | qEt0 | 1.54E-04 | 1.67E-05 |
| 56 | 55 | qEt0 | 8.32E-04 | 2.18E-04 |
| 57 | 56 | qEt0 | 3.67E-06 | 9.50E-07 |
| 58 | 57 | summale_ | 5.50E-01 | 6.42E-02 |
| 59 | 58 | winfemale | 9.24E-01 | 4.98E-02 |
| 60 | 59 | winmale_ | 2.05E+00 | 2.49E-01 |
| 61 | 60 | winrec_sl | 2.10E-01 | 1.65E-02 |
| 62 | 61 | l5095Dnre | 4.55E+01 | 1.02E+01 |
| 63 | 62 | l95Dnrec | 3.27E+02 | 1.84E+01 |
| 64 | 63 | l50HN_Wi | 2.32E+02 | 1.44E+00 |
| 65 | 64 | l50HN_Wi | 2.30E+02 | 2.20E+01 |
| 66 | 65 | rSelHN_W | 2.20E-01 | 1.30E-01 |
| 67 | 66 | rSelHN_W | 2.40E+01 | 3.07E+04 |
| 68 | 67 | sigCw1 | 2.78E-01 | 1.17E-02 |
| 69 | 68 | sigCl1 | 2.65E+01 | 1.67E+00 |

Worksheet “ParameterCorOutput”



Microsoft Excel - GarfaceReportOutputBaserun.xls

| | A | B | C | D | E | F | G | H | I | J | K | L |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | | | | | | | | | | | | |
| 2 | | index | name | parameter estimate | parameter standard deviation | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 3 | | | | | | K | K | K | K | sigm | sigm | sigm |
| 4 | | 1 | K | 3.28E-01 | 5.77E-03 | 1 | | | | | | |
| 5 | | 2 | K | 3.47E-01 | 9.48E-03 | 0.2613 | 1 | | | | | |
| 6 | | 3 | K | 2.86E-01 | 6.66E-03 | 0.0305 | 0.0269 | 1 | | | | |
| 7 | | 4 | K | 3.14E-01 | 1.48E-02 | 0.0227 | 0.0171 | 0.2213 | 1 | | | |
| 8 | | 5 | sigm | 1.69E+02 | 6.69E+00 | 0.1609 | 0.0697 | 0.019 | 0.0238 | 1 | | |
| 9 | | 6 | sigm | 1.64E+02 | 1.08E+01 | 0.0446 | -0.1015 | 0.0114 | 0.0052 | 0.0665 | 1 | |
| 10 | | 7 | sigm | 1.75E+02 | 1.01E+01 | -0.0052 | 0.0081 | 0.123 | 0.0116 | 0.0076 | -0.0039 | 1 |
| 11 | | 8 | sigm | 1.88E+02 | 2.02E+01 | 0.003 | 0.0047 | 0.0379 | -0.1093 | 0.01 | 0.0048 | 0.0667 |
| 12 | | 9 | F0 | 1.25E+00 | 1.78E-01 | 0.2127 | 0.1582 | 0.0436 | 0.0314 | -0.0715 | -0.0208 | -0.02 |
| 13 | | 10 | F0 | 1.11E+00 | 1.64E-01 | 0.0595 | 0.0436 | 0.2852 | 0.1916 | 0.0275 | 0.0357 | -0.0734 |
| 14 | | 11 | Rbar | 4.49E+06 | 1.97E+05 | -0.1823 | -0.0905 | -0.0169 | -0.0011 | -0.0108 | 0.0027 | -0.0013 |
| 15 | | 12 | Rbar | 1.77E+06 | 1.21E+05 | -0.027 | -0.1705 | -0.0024 | -0.0028 | -0.0225 | -0.011 | -0.0315 |
| 16 | | 13 | Rbar | 4.38E+06 | 1.99E+05 | -0.0452 | -0.0335 | -0.4154 | -0.2767 | -0.0148 | -0.0321 | -0.0496 |
| 17 | | 14 | Rbar | 1.20E+06 | 1.22E+05 | 0.0264 | 0.0278 | -0.2466 | -0.2253 | -0.015 | 0.0326 | -0.0358 |
| 18 | | 15 | logRdevSG | -1.77E-01 | 2.33E-01 | -0.0635 | -0.0374 | -0.0219 | -0.0177 | -0.0426 | -0.0215 | -0.0067 |
| 19 | | 16 | logRdevSG | 1.54E-01 | 2.49E-01 | 0.0382 | 0.0203 | 0.022 | 0.0168 | 0.0567 | 0.0315 | 0.0134 |
| 20 | | 17 | logRdevSG | -4.24E-01 | 4.42E-01 | -0.0167 | -0.0049 | -0.0123 | -0.0112 | -0.0358 | -0.0211 | -0.0041 |
| 21 | | 18 | logRdevSG | -2.78E-02 | 3.13E-01 | 0.0107 | 0.0024 | -0.001 | -0.0027 | 0.0013 | 0.002 | -0.0044 |
| 22 | | 19 | logRdevSG | 4.81E-01 | 2.29E-01 | -0.1108 | -0.0641 | -0.01 | -0.0072 | -0.014 | -0.0007 | 0.0121 |
| 23 | | 20 | logRdevSG | -4.62E-01 | 5.50E-01 | 0.1753 | 0.0995 | 0.0293 | 0.0227 | 0.0657 | 0.0269 | -0.0037 |
| 24 | | 21 | logRdevSG | 1.35E-01 | 3.25E-01 | -0.1584 | -0.0884 | -0.034 | -0.028 | -0.0808 | -0.0392 | -0.0017 |
| 25 | | 22 | logRdevSG | 2.66E-01 | 2.68E-01 | 0.0627 | 0.0283 | 0.0088 | 0.0092 | 0.0611 | 0.0384 | 0.0005 |

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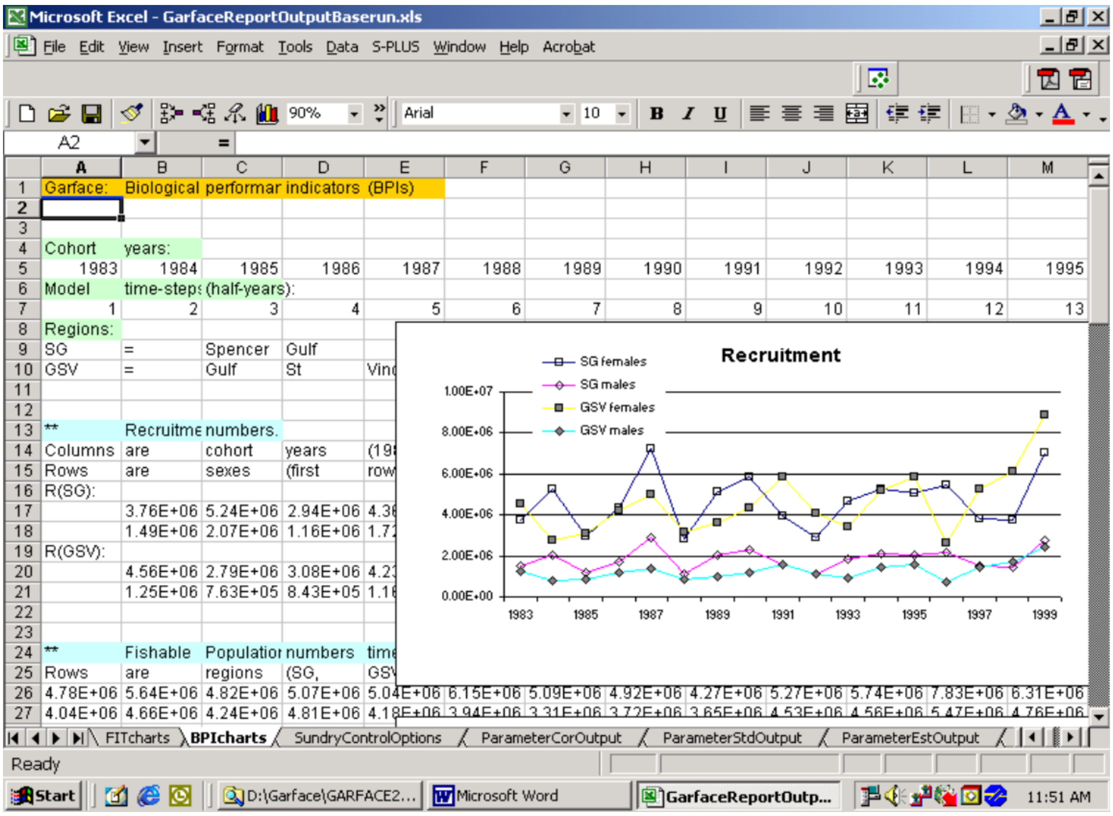
Worksheet “BPIcharts”



Microsoft Excel - GarfaceReportOutputBaserun.xls

| | A | B | C | D | E | F | G | H | I | J | K | L | M |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Garface: | Biological | performar | indicators | (BPIs) | | | | | | | | |
| 2 | | | | | | | | | | | | | |
| 3 | | | | | | | | | | | | | |
| 4 | Cohort | years: | | | | | | | | | | | |
| 5 | 1983 | 1984 | 1985 | 1986 | 1987 | 1988 | 1989 | 1990 | 1991 | 1992 | 1993 | 1994 | 1995 |
| 6 | Model | time-step | (half-years): | | | | | | | | | | |
| 7 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 |
| 8 | Regions: | | | | | | | | | | | | |
| 9 | SG | = | Spencer | Gulf | | | | | | | | | |
| 10 | GSV | = | Gulf | St | Vinc | | | | | | | | |
| 11 | | | | | | | | | | | | | |
| 12 | | | | | | | | | | | | | |
| 13 | ** | Recruitme | numbers. | | | | | | | | | | |
| 14 | Columns | are | cohort | years | (19 | | | | | | | | |
| 15 | Rows | are | sexes | (first | row | | | | | | | | |
| 16 | R(SG): | | | | | | | | | | | | |
| 17 | | 3.76E+06 | 5.24E+06 | 2.94E+06 | 4.3 | | | | | | | | |
| 18 | | 1.49E+06 | 2.07E+06 | 1.16E+06 | 1.7 | | | | | | | | |
| 19 | R(GSV): | | | | | | | | | | | | |
| 20 | | 4.56E+06 | 2.79E+06 | 3.08E+06 | 4.2 | | | | | | | | |
| 21 | | 1.25E+06 | 7.63E+05 | 8.43E+05 | 1.1 | | | | | | | | |
| 22 | | | | | | | | | | | | | |
| 23 | | | | | | | | | | | | | |
| 24 | ** | Fishable | Populatio | numbers | time | | | | | | | | |
| 25 | Rows | are | regions | (SG, | GS | | | | | | | | |
| 26 | 4.78E+06 | 5.64E+06 | 4.82E+06 | 5.07E+06 | 5.04E+06 | 6.15E+06 | 5.09E+06 | 4.92E+06 | 4.27E+06 | 5.27E+06 | 5.74E+06 | 7.83E+06 | 6.31E+06 |
| 27 | 4.04E+06 | 4.66E+06 | 4.24E+06 | 4.81E+06 | 4.18E+06 | 3.94E+06 | 3.31E+06 | 3.72E+06 | 3.65E+06 | 4.53E+06 | 4.56E+06 | 5.47E+06 | 4.76E+06 |



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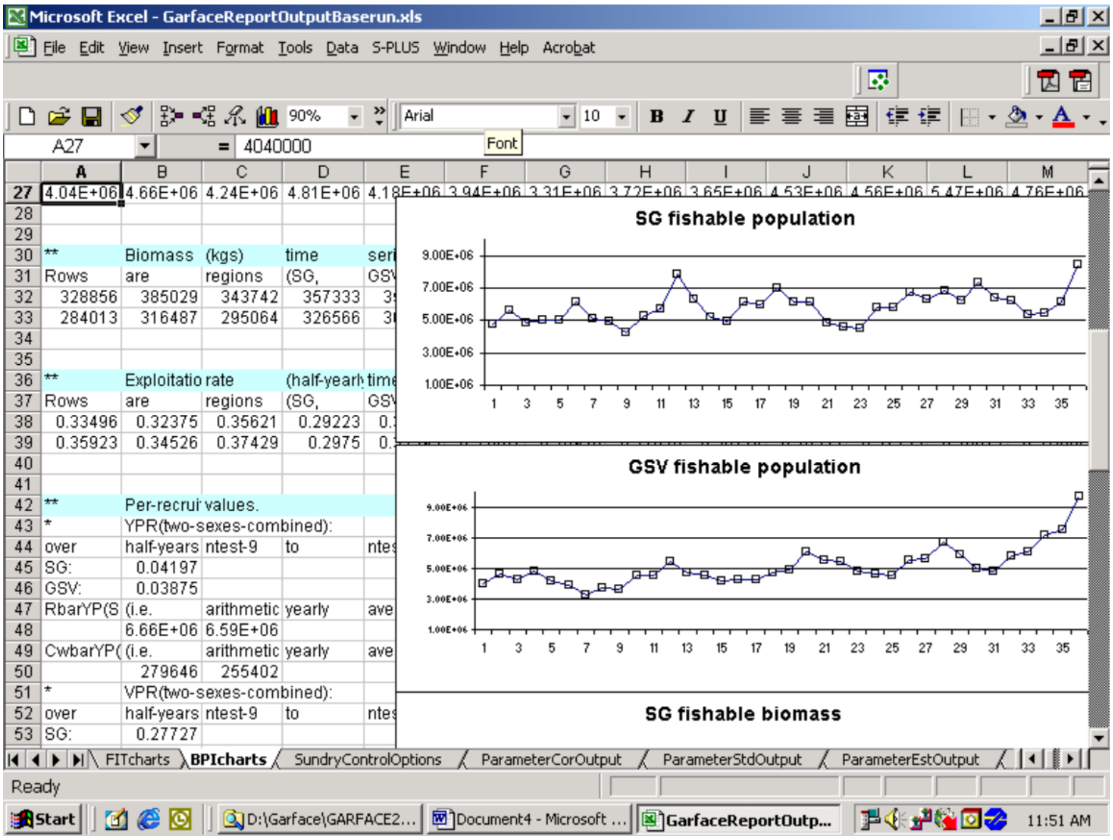
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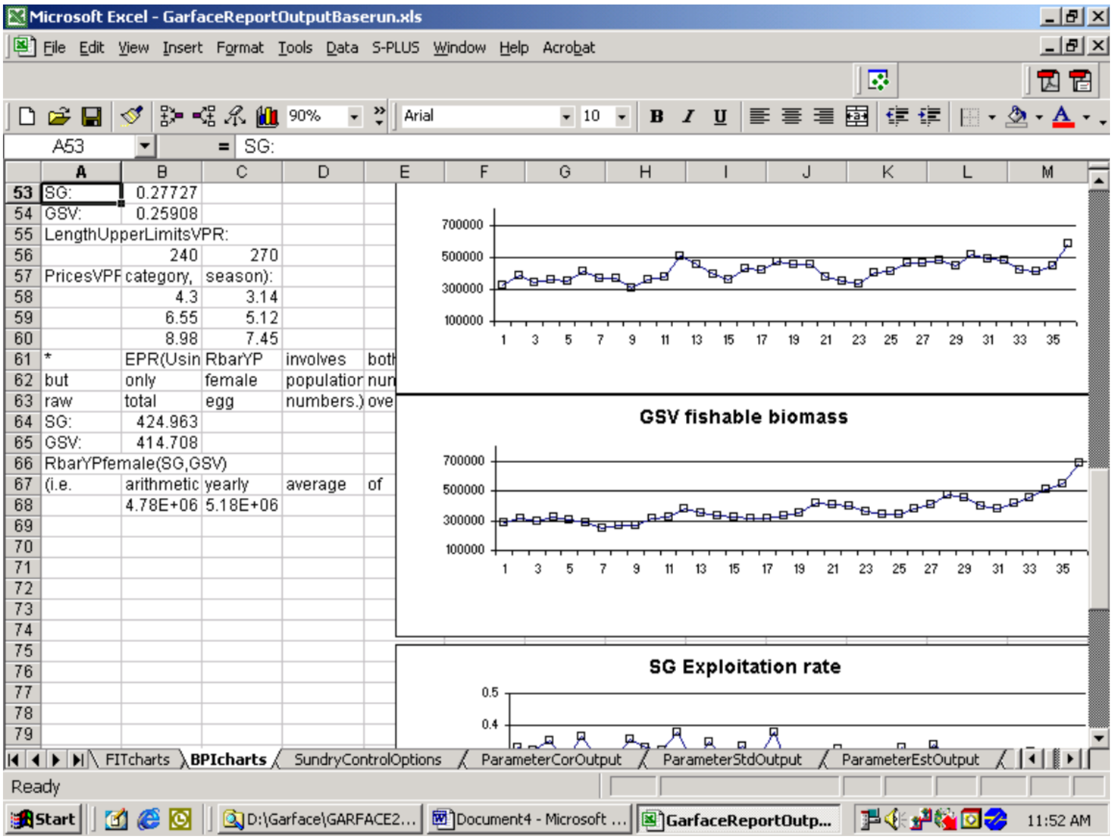
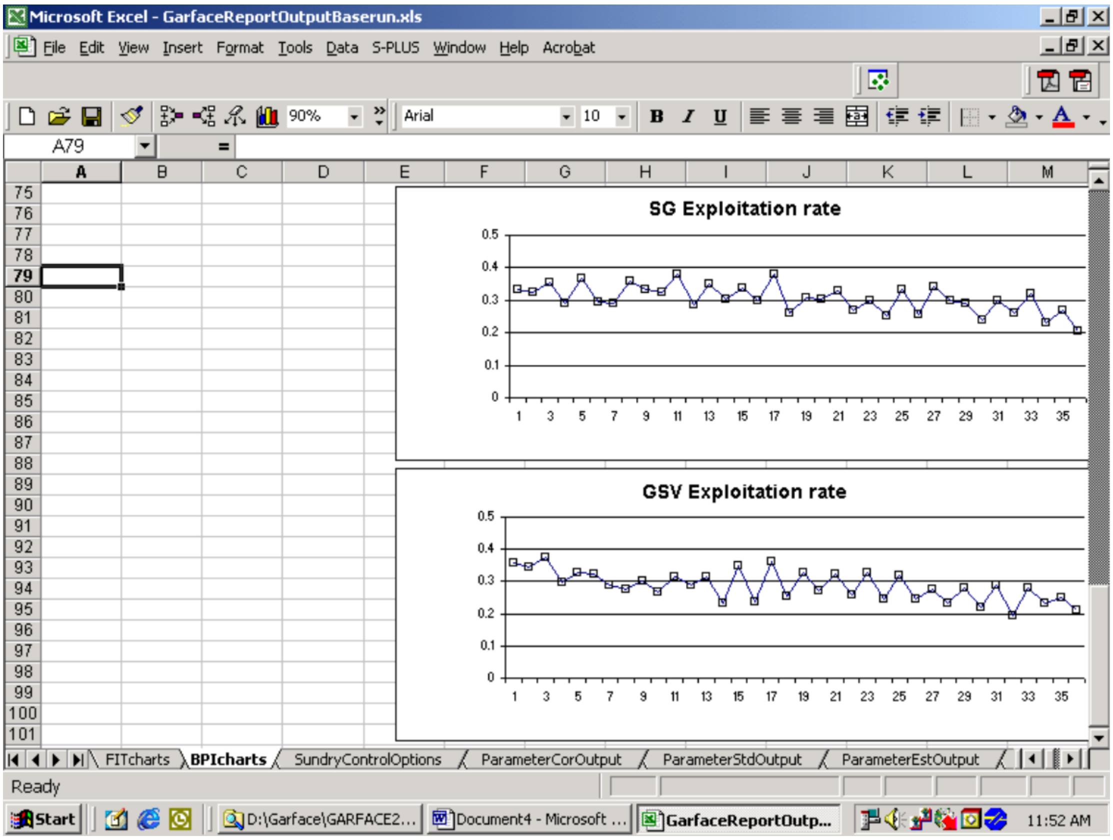
File Edit View Insert Format Tools Data S-PLUS Window Help Acrobat
A27 = 4040000
27 4.04E+06 4.66E+06 4.24E+06 4.81E+06
30 ** Biomass (kgs) time seri
31 Rows are regions (SG, GSV
32 328856 385029 343742 357333
33 284013 316487 295064 326566
36 ** Exploitatio rate (half-yearl time
37 Rows are regions (SG, GSV
38 0.33496 0.32375 0.35621 0.29223
39 0.35923 0.34526 0.37429 0.2975
42 ** Per-recrui values.
43 * YPR(two-sexes-combined):
44 over half-years ntest-9 to ntes
45 SG: 0.04197
46 GSV: 0.03875
47 RbarYP(S (i.e. arithmetic yearly ave
48 6.66E+06 6.59E+06
49 CwbarYP( (i.e. arithmetic yearly ave
50 279646 255402
51 * VPR(two-sexes-combined):
52 over half-years ntest-9 to ntes
53 SG: 0.27727
SG fishable population
GSV fishable population
SG fishable biomass
FITcharts BPIcharts SundryControlOptions ParameterCorOutput ParameterStdOutput ParameterEstOutput
Ready
11:51 AM


Microsoft Excel - GarfaceReportOutputBaserun.xls
A53 = SG:
53 SG: 0.27727
54 GSV: 0.25908
55 LengthUpperLimitsVPR:
56 240 270
57 PricesVPF category, season):
58 4.3 3.14
59 6.55 5.12
60 8.98 7.45
61 * EPR(Usin RbarYP involves both
62 but only female population nun
63 raw total egg numbers.) ove
64 SG: 424.963
65 GSV: 414.708
66 RbarYPfemale(SG,GSV)
67 (i.e. arithmetic yearly average of
68 4.78E+06 5.18E+06
GSV fishable biomass
SG Exploitation rate
FITcharts BPIcharts SundryControlOptions ParameterCorOutput ParameterStdOutput ParameterEstOutput
Ready
11:52 AM



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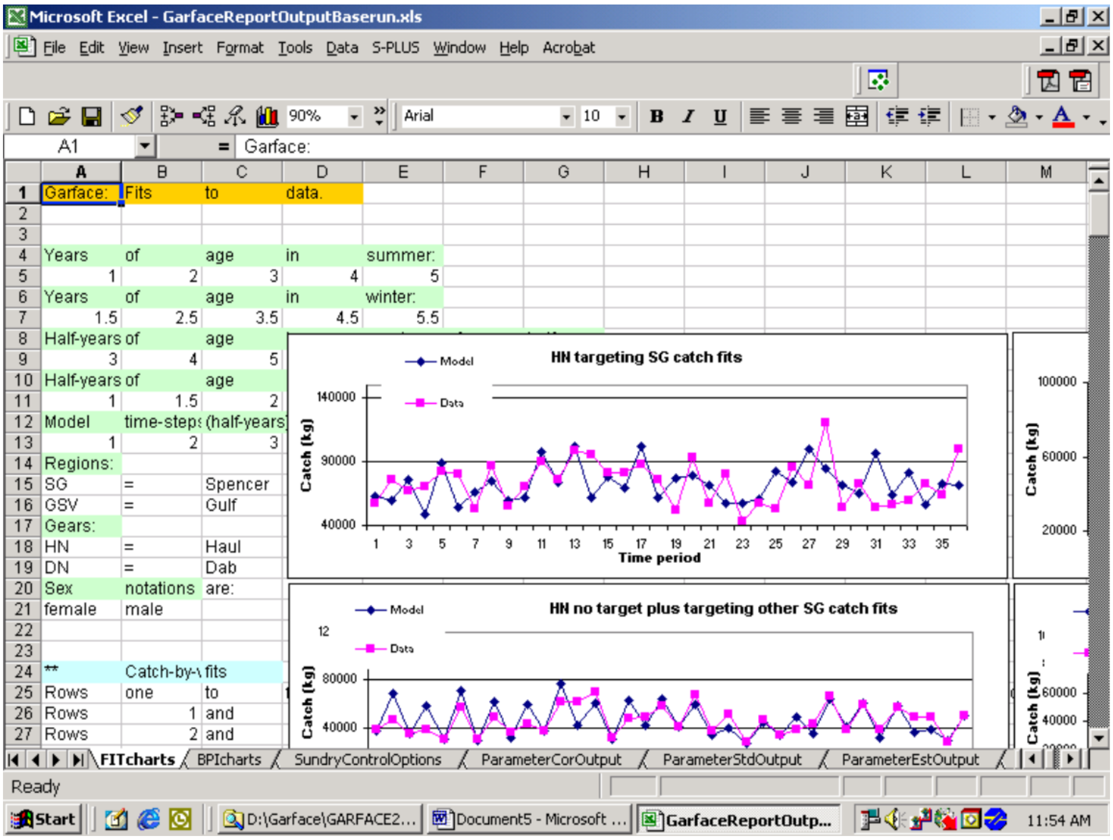
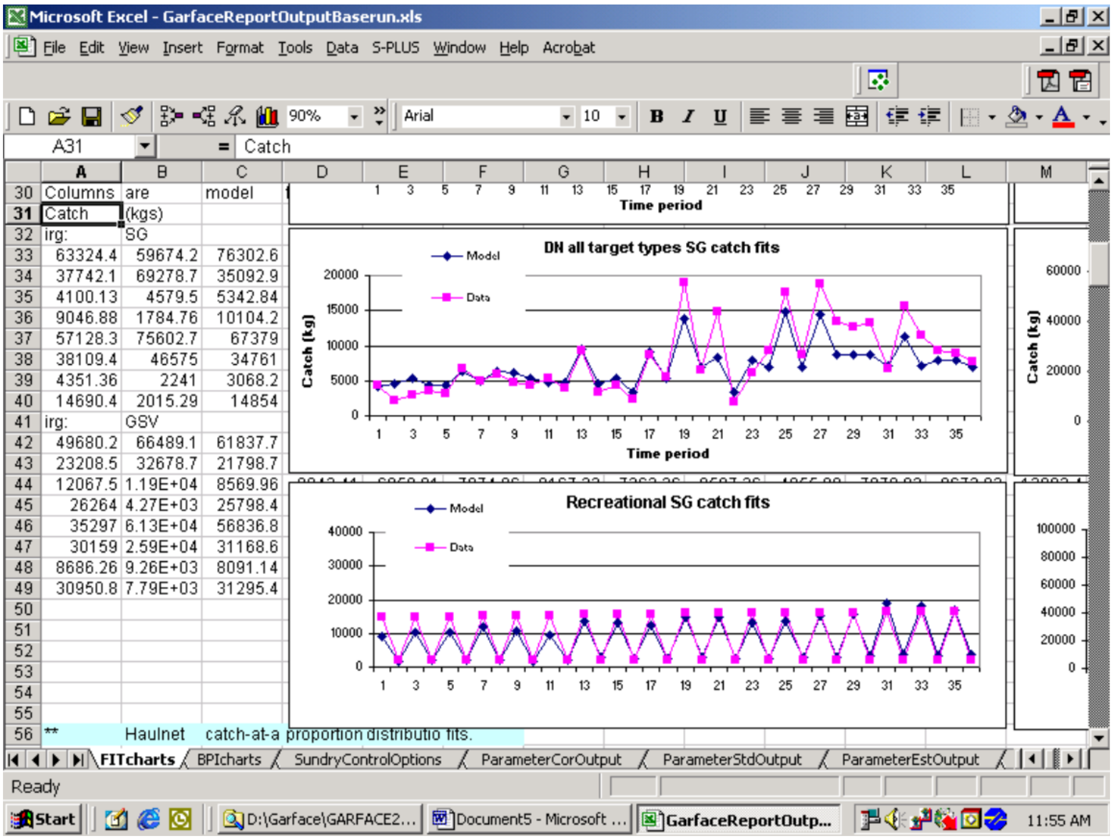
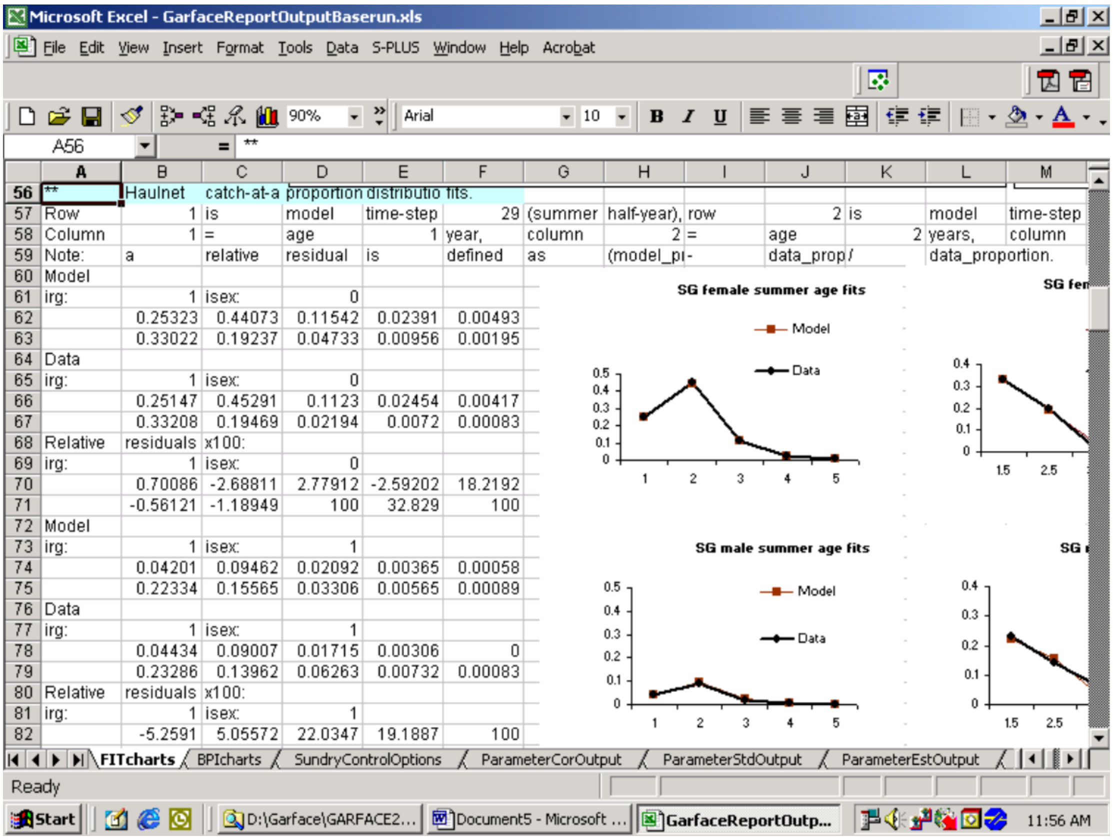
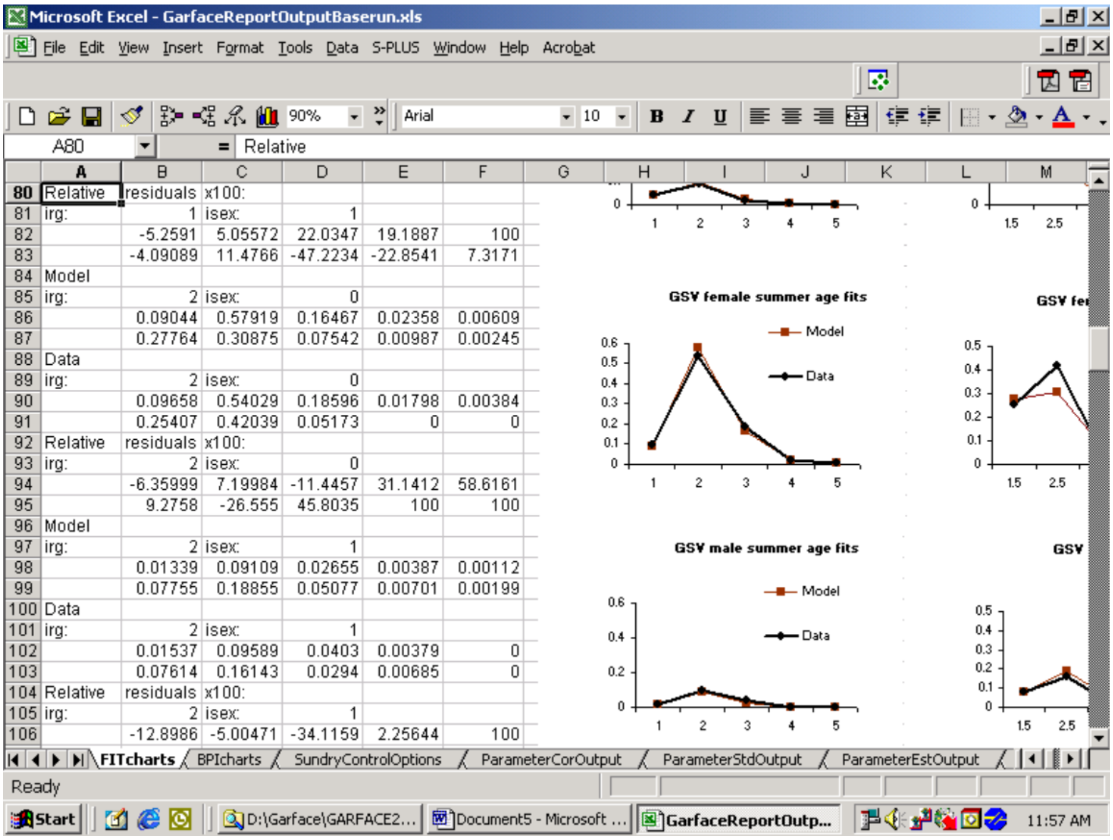
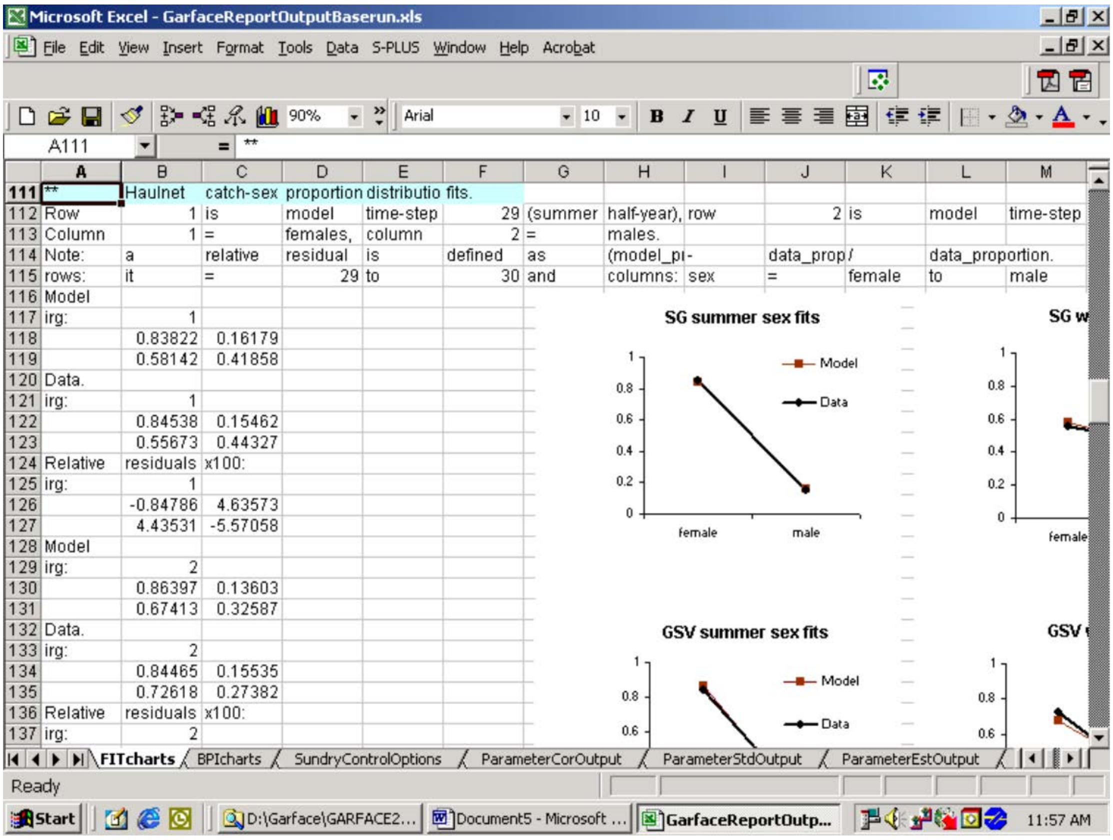
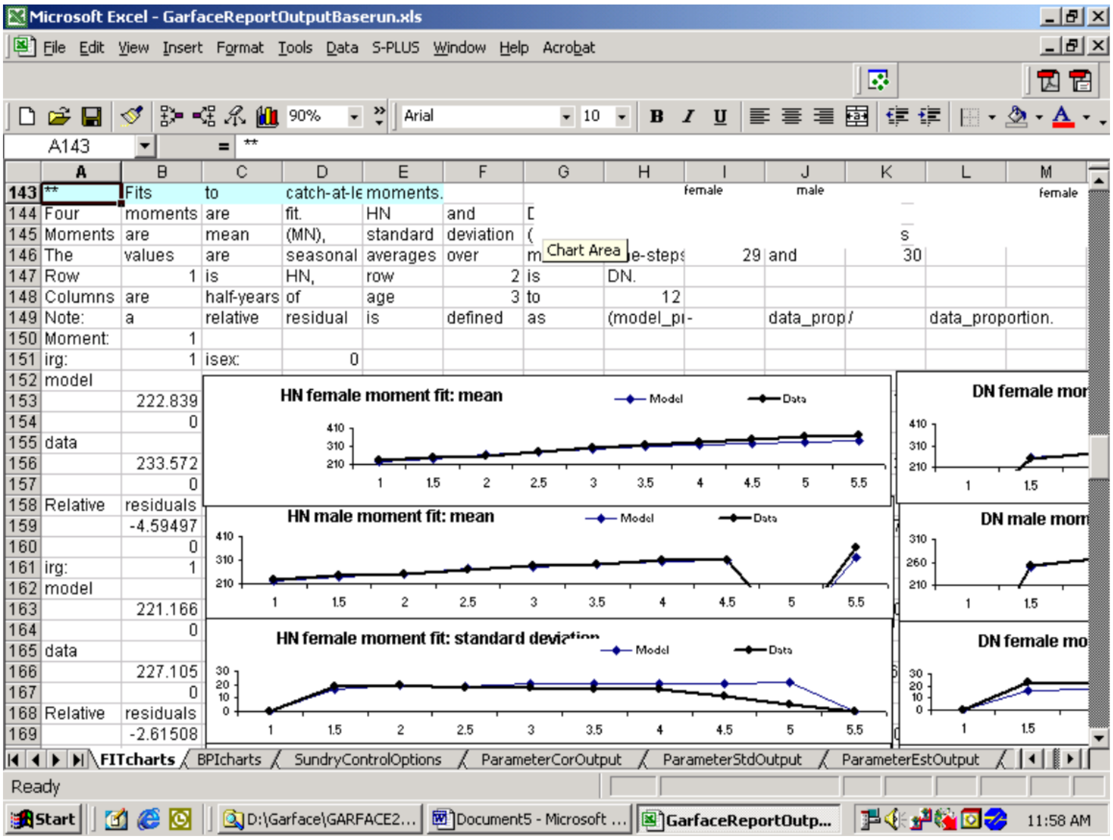



Microsoft Excel - GarfaceReportOutputBaserun.xls
A31 = Catch
30 Columns are model
31 Catch (kgs)
32 irg: SG
33 63324.4 59674.2 76302.6
34 37742.1 69278.7 35092.9
35 4100.13 4579.5 5342.84
36 9046.88 1784.76 10104.2
37 57128.3 75602.7 67379
38 38109.4 46575 34761
39 4351.36 2241 3068.2
40 14690.4 2015.29 14854
41 irg: GSV
42 49680.2 66489.1 61837.7
43 23208.5 32678.7 21798.7
44 12067.5 1.19E+04 8569.96
45 26264 4.27E+03 25798.4
46 35297 6.13E+04 56836.8
47 30159 2.59E+04 31168.6
48 8686.26 9.26E+03 8091.14
49 30950.8 7.79E+03 31295.4
56 ** Haulnet catch-at-a proportion distributio fits.
DN all target types SG catch fits
Model
Data
Catch (kg)
Time period
Recreational SG catch fits
FITcharts BPIcharts SundryControlOptions ParameterCorOutput ParameterStdOutput ParameterEstOutput
Ready
11:55 AM


Microsoft Excel - GarfaceReportOutputBaserun.xls
A56 = **
56 ** Haulnet catch-at-a proportion distributio fits.
57 Row 1 is model time-step 29 (summer half-year), row 2 is model time-step
58 Column 1 = age 1 year, column 2 = age 2 years, column
59 Note: a relative residual is defined as (model_pı- data_prop / data_proportion.
60 Model
61 irg: 1 isex: 0
62 0.25323 0.44073 0.11542 0.02391 0.00493
63 0.33022 0.19237 0.04733 0.00956 0.00195
64 Data
65 irg: 1 isex: 0
66 0.25147 0.45291 0.1123 0.02454 0.00417
67 0.33208 0.19469 0.02194 0.0072 0.00083
68 Relative residuals x100:
69 irg: 1 isex: 0
70 0.70086 -2.68811 2.77912 -2.59202 18.2192
71 -0.56121 -1.18949 100 32.829 100
72 Model
73 irg: 1 isex: 1
74 0.04201 0.09462 0.02092 0.00365 0.00058
75 0.22334 0.15565 0.03306 0.00565 0.00089
76 Data
77 irg: 1 isex: 1
78 0.04434 0.09007 0.01715 0.00306 0
79 0.23286 0.13962 0.06263 0.00732 0.00083
80 Relative residuals x100:
81 irg: 1 isex: 1
82 -5.2591 5.05572 22.0347 19.1887 100
SG female summer age fits
SG male summer age fits
Model
Data
FITcharts BPIcharts SundryControlOptions ParameterCorOutput ParameterStdOutput ParameterEstOutput
Ready
11:56 AM


Microsoft Excel - GarfaceReportOutputBaserun.xls
File Edit View Insert Format Tools Data S-PLUS Window Help Acrobat
A80 = Relative
80 Relative residuals x100:
81 irg: 1 isex: 1
82 -5.2591 5.05572 22.0347 19.1887 100
83 -4.09089 11.4766 -47.2234 -22.8541 7.3171
84 Model
85 irg: 2 isex: 0
86 0.09044 0.57919 0.16467 0.02358 0.00609
87 0.27764 0.30875 0.07542 0.00987 0.00245
88 Data
89 irg: 2 isex: 0
90 0.09658 0.54029 0.18596 0.01798 0.00384
91 0.25407 0.42039 0.05173 0 0
92 Relative residuals x100:
93 irg: 2 isex: 0
94 -6.35999 7.19984 -11.4457 31.1412 58.6161
95 9.2758 -26.555 45.8035 100 100
96 Model
97 irg: 2 isex: 1
98 0.01339 0.09109 0.02655 0.00387 0.00112
99 0.07755 0.18855 0.05077 0.00701 0.00199
100 Data
101 irg: 2 isex: 1
102 0.01537 0.09589 0.0403 0.00379 0
103 0.07614 0.16143 0.0294 0.00685 0
104 Relative residuals x100:
105 irg: 2 isex: 1
106 -12.8986 -5.00471 -34.1159 2.25644 100
GSV female summer age fits
Model
Data
GSV male summer age fits
FITcharts BPIcharts SundryControlOptions ParameterCorOutput ParameterStdOutput ParameterEstOutput
Ready
Start D:\Garface\GARFACE2... Document5 - Microsoft ... GarfaceReportOutp... 11:57 AM


Microsoft Excel - GarfaceReportOutputBaserun.xls
File Edit View Insert Format Tools Data S-PLUS Window Help Acrobat
A111 = **
111 ** Haulnet catch-sex proportion distributio fits.
112 Row 1 is model time-step 29 (summer half-year), row 2 is model time-step
113 Column 1 = females, column 2 = males.
114 Note: a relative residual is defined as (model_pi- data_prop)/ data_proportion.
115 rows: it = 29 to 30 and columns: sex = female to male
116 Model
117 irg: 1
118 0.83822 0.16179
119 0.58142 0.41858
120 Data.
121 irg: 1
122 0.84538 0.15462
123 0.55673 0.44327
124 Relative residuals x100:
125 irg: 1
126 -0.84786 4.63573
127 4.43531 -5.57058
128 Model
129 irg: 2
130 0.86397 0.13603
131 0.67413 0.32587
132 Data.
133 irg: 2
134 0.84465 0.15535
135 0.72618 0.27382
136 Relative residuals x100:
137 irg: 2
SG summer sex fits
Model
Data
female
male
GSV summer sex fits
FITcharts BPIcharts SundryControlOptions ParameterCorOutput ParameterStdOutput ParameterEstOutput
Ready
Start D:\Garface\GARFACE2... Document5 - Microsoft ... GarfaceReportOutp... 11:57 AM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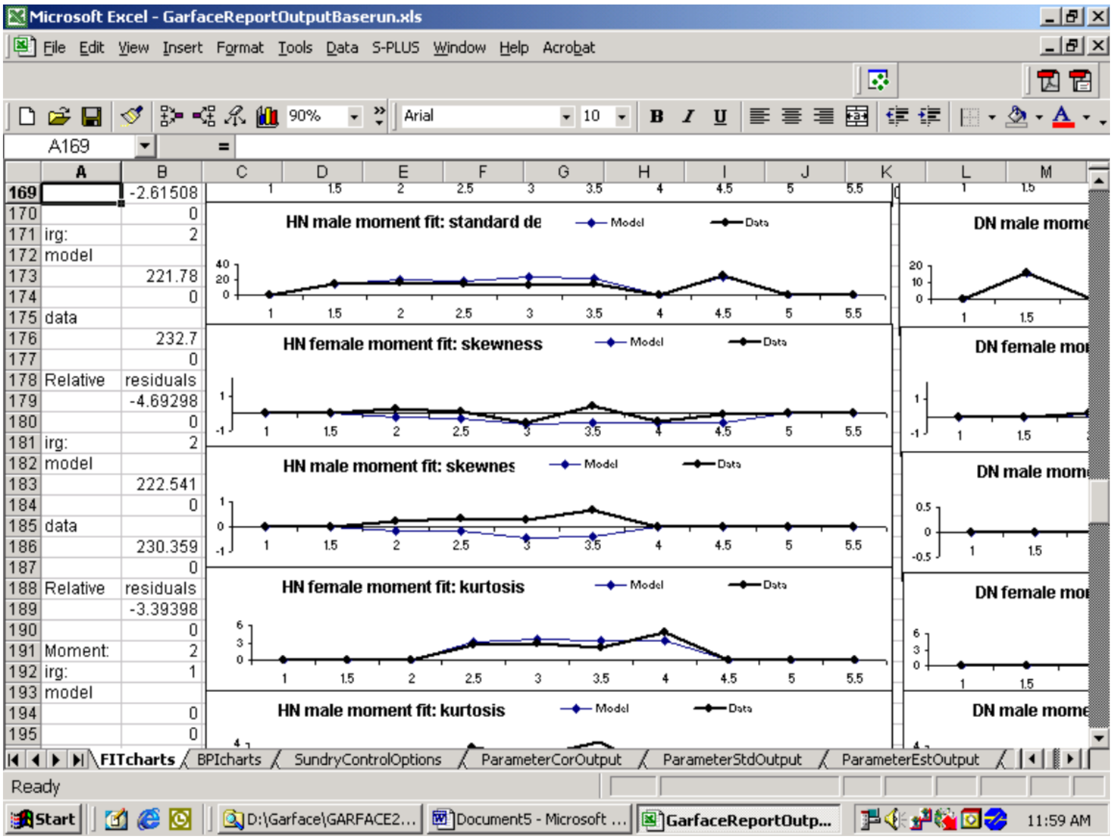
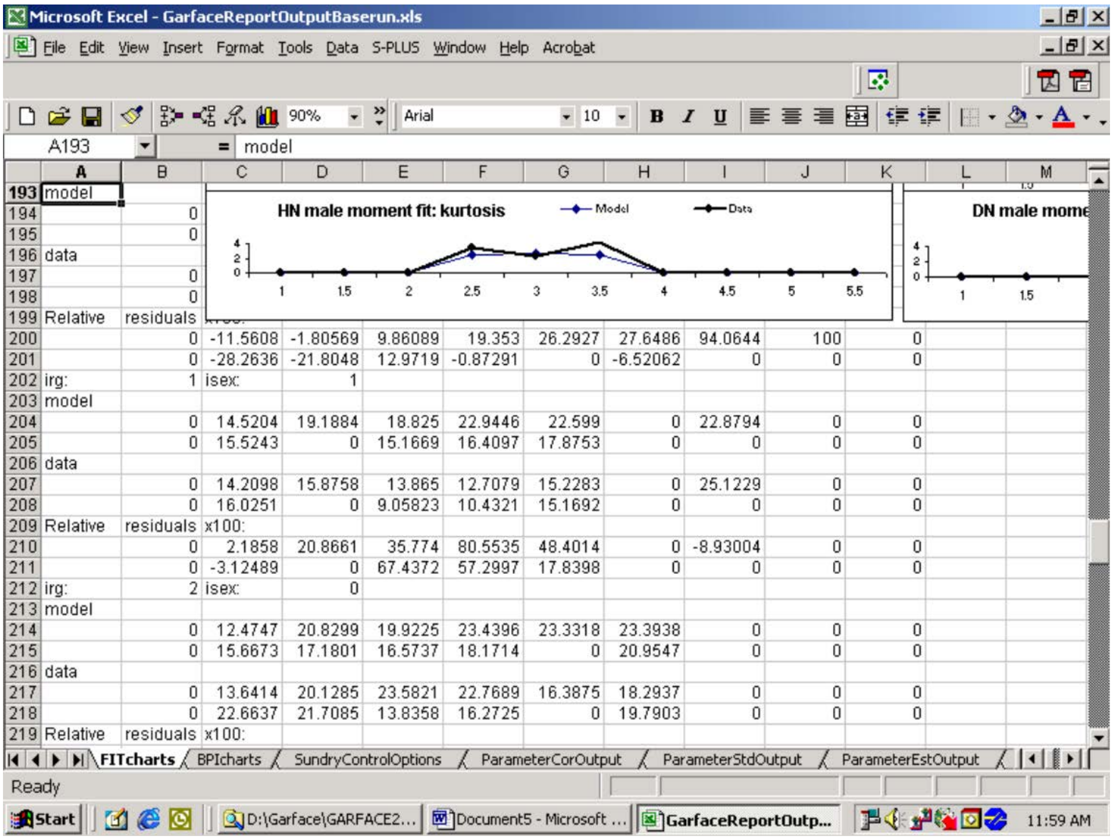
File Edit View Insert Format Tools Data S-PLUS Window Help Acrobat
A143
Fits to catch-at-le moments.
Four moments are fit. HN and
Moments are mean (MN), standard deviation
The values are seasonal averages over
Row 1 is HN, row 2 is DN.
Columns are half-years of age 3 to 12
Note: a relative residual is defined as (model_pr- data_prop)/ data_proportion.
Chart Area
HN female moment fit: mean
HN male moment fit: mean
HN female moment fit: standard deviation
Model
Data
FITcharts BPIcharts SundryControlOptions ParameterCorOutput ParameterStdOutput ParameterEstOutput
Ready
Start
11:58 AM


Microsoft Excel - GarfaceReportOutputBaserun.xls
File Edit View Insert Format Tools Data S-PLUS Window Help Acrobat
A169
HN male moment fit: standard de
HN female moment fit: skewness
HN male moment fit: skewnes
HN female moment fit: kurtosis
HN male moment fit: kurtosis
Model
Data
FITcharts BPIcharts SundryControlOptions ParameterCorOutput ParameterStdOutput ParameterEstOutput
Ready
Start
11:59 AM




# Benefits

The principal beneficiaries are the marine scale fishers, both commercial and recreational. The managers of these fisheries, and the fishers' peak bodies, have requested improved measures of changing stock abundance. These performance indicators should ideally be estimated using all available relevant data. The models developed fulfil this need. In addition, the stock assessment biologists here in South Australia can assist more directly in running the yearly stock assessments using the Excel user interface which permits biologists to run the estimation engine (coded in AD Model Builder) without detailed knowledge of the underlying model code. These assessments will then provide (1) relative indicators of changing biomass of snapper and garfish which incorporate and combine data from all gear and target types, and both sectors, (2) estimates of recruitment, absolute fishable biomass and exploitation rate, and (3) confidence intervals on all parameters derived.

The garfish and snapper models have been implemented for management and are used as the primary tools of gauging stock performance. Appendix 3 provides the cover letter summarising management-relevant outputs from the garfish model, provided at the request of the Marine Scalefish Fishery Management Committee. The snapper outputs form an important basis of the recent stock assessment report, and decisions on whether to continue closures in August and November, will be based, in part, in the model outputs.

Cost effectiveness is achieved in two ways: (1) Model components common to several species are developed once and applied to all. (2) The scientists currently engaged and familiar with the biology and data of each species will implement the stock assessment analyses, minimising on-going salaries and consulting fees to fishery modellers who remain in short supply. Modellers will continue to collaborate in their yearly use and will make future model modifications.

Cost savings may be estimated by comparison with the alternative for yearly assessment of these stocks in the absence of the software tools here proposed. Assuming the biologists supplied the data to a team of fisheries modellers and data analysts hired to carry out the estimation of stock indicators, this would need to be repeated yearly. Current marine scale licence fee funding allocation in South Australia is for 0.5 FTE to do stock assessment modelling. If the estimation were done by a team employed for that purpose, a requirement of a staff of 3 (a modeller and two data analysts) will be assumed. Thus the savings is a factor of roughly 6 times less in yearly stock assessment modelling licence fee research costs.

Additional costs are those of operating without employing data already gathered to generate fish stock performance indicators. Currently, in South Australia, the fishery is being restructured with effort and license reductions being considered. Decisions of how to carry out this restructure, and where, will benefit by generation of performance indicators as recommended by the external review.

# Further Development

In future, the principal outcome will be updates to the input data sets, by the addition of semi-yearly totals of catch and effort for snapper and garfish. Biologists can then implement these yearly up-dates as they are needed.

Current plans for future improvement to the underlying model estimator include (1) incorporating the results of the FRDC-sponsored National Recreational and Indigenous Fishing Survey (assigned a high priority by PIRSA managers and MSFMC), (2) incorporating knowledge of snapper movement obtained from a current FRDC Project analysing snapper otolith microchemistry (FRDC Project 2002/001), and (3) potentially, once measurements are made of release mortality, re-assessing the effect of the recent increase in legal minimum length of South Australian garfish.

# Planned Outcomes

Biological performance indicators annually generated from data with this estimation software will serve as the basis for stock assessment of two key marine scalefish stocks in South Australia, snapper and garfish.

As with the recently completed King George whiting model, the results will be provided to the Marine Scalefish Fishery Management Committee (MSFMC) in yearly stock assessment reports.

# Conclusions

**Objective 1.** To build a model estimation software structure, which will use (1) monthly catch and effort data, (2) aged catch samples, (3) life history information, and when available (4) recruitment indices, and (5) length-frequency samples to estimate yearly performance indicators, accessed through a graphical user interface, for use in marine scalefish stocks.

This objective was met as described in Non-Technical Summary, and in Chapters 1, 4 and 6. The two stock assessment models were developed which take as inputs all of the data sources numbered above, except recruitment indices. Recruitment is estimated as an output in both models. There is no recruitment index for South Australian garfish and no plans for one. For snapper, yearly spawning-season cruises sampling juveniles (year 1 or 0) have been undertaken for three years. In future, as the snapper time series becomes long enough, it will be incorporated in the model.

The graphical user interface makes the two model estimators available for use by stock assessment biologists.

**Objective 2.** To build two models for key marine scalefish species in South Australian waters for use in yearly stock assessment.

We believe that the two models make significant improvements on the methodology of statistical stock assessment estimation. Most notably, three features are new: (1) the dynamic formulation of slice-growth, first developed in static form for King George whiting, essentially removes all biases in growth and mortality that can result from a non-dynamic representation of length and of age in the model population array. It permits a rigorous description of the on-going growth of recruits to legal size. And it allows a clean separation of legal fish from non-legal sizes, and thus the differing rates of mortality are explicit. (2) The correction for non-representative subsampling for fish to be aged, from the usually much larger sample of fish measured for length, can add to the power of stock assessment in two ways: (2.1) When aged fish are obtained in a non-systematic fashion, so that subsampling is essentially random, the bias that this would cause can be avoided. (2.2) In future, strategies of age subsampling that give better information about mortality can be implemented to maximise the precision of stock assessment, in particular by ageing more older fish. (3) The moment method of fitting to length data, which allows length distributions to be fitted for individual ages and sexes, should reduce the loss of information that would normally occur in summing the numbers captured in each length bin over age and sex. Notably, more information about growth is retained, because the mean length of fish (along with the standard deviation, skewness and kurtosis) for each age and sex are explicit in the model likelihood.

**Objective 3.** To transfer model outcomes, notably yearly estimated biological performance indicators, to the Marine Scalefish Fishery Management Committee (MSFMC).

The models have now serve as a principal basis of fishery management decision making for snapper and garfish populations in South Australia. Although a garfish stock assessment report is not contracted for currently, Appendix 3 and Chapters 1-3 of this report were provided to the MSFMC, at their request, and formal presentation of these results was made to the committee in December 2003, providing stock assessment advice, notably on the projected effects of the recent increase in legal minimum length from 21 to 23 cm. The recent snapper stock assessment report (Fowler and McGarvey 2003) uses the model outputs as the basic overall measure of stock performance.

Per-recruit analyses (Chapters 3 and 5) also have been used to inform management decisions for both garfish and snapper, notably in analysing the change in legal size of garfish (Chapter 3), and in comparing two candidate management regulations under consideration for snapper (Chapter 5), maximum size and temporal closure. A two-part seasonal closure for snapper was recommended and adopted based on the model outputs.

# Appendix 1: Intellectual property

The FRDC's share of intellectual property, based on inputs, is 46%.

# Appendix 2: Project Staff.

| | |
|---|---|
| SARDI Aquatic Sciences: | Rick McGarvey |
| | John Feenstra |
| University of Washington and CSIRO: | André Punt (external reviewer) |

# Appendix 3: Cover Letter of Stock Assessment Results Provided to the South Australian Marine Scalefish Fishery Management Committee.

SARDI Aquatic Sciences
PO Box 120
Henley Beach SA 5022
tel: (08) 8200 2460
fax: (08) 8200 2481
email: mcgarvey.richard@saugov.sa.gov.au
3 February 2003

Mr. Maurie Vast
Chair, Marine Scalefish Fishery Management Committee
PO Box 6
Kent Town SA 5071

Dear Maurie,

Please find enclosed sections from the two FRDC reports relevant to garfish stock assessment and management, as requested at the last MSFMC meeting (6 December 2002).

As you know, SARDI is currently undertaking an FRDC project to develop marine scale stock assessment models (Project No. 1999/145, by McGarvey and Feenstra, project entitled, "Stock Assessment Models with Graphical User Interfaces for Key South Australian Marine Finfish Stocks"). The two fish stocks targeted for stock assessment model development were snapper and garfish.

This year, under funds available for core research, only snapper and King George whiting have been designated for stock assessment reports in South Australia. But under this cover we provide the outputs from the stock assessment model developed for garfish in the current FRDC project.

The garfish model of McGarvey and Feenstra is based on extensive data collection undertaken in a previous FRDC Project on garfish, notably on the samples for spawning seasonality and for sex, age and length population structure over one full year. That FRDC Project No. 97/133 was entitled, "Fisheries Biology and Habitat Ecology of Southern Sea Garfish (*Hyporhamphus melanochir*) in Southern Australian Waters", *eds.*, Jones, G.K., Ye, Q., Ayvazian, S., and Coutin, P.C.

These two FRDC final reports will be cited below as 'McGarvey and Feenstra' and 'Jones et al. (2002)'. We enclose Chapters 1, 2 and 3 of McGarvey and Feenstra, and those portions of Section 3.3 from Jones et al. that report summaries of South Australian garfish commercial catch and effort time series.

In the rest of this letter, we highlight results in these two FRDC Reports that may be of most relevance to garfish management in South Australia. Principally, this summary will list specific parts of the two reports that constitute stock assessment outcomes, notably (1) catch, effort and CPUE data time series up to 99/00 (Jones et al. 2002) and (2) model estimated yearly stock abundance indicators, including legal size garfish population biomass and exploitation rate (McGarvey and Feenstra). In addition, results were derived to estimate (3) egg-, yield-, and value-per-recruit at a range of different possible choices for legal minimum length (LML) (McGarvey and Feenstra).

The commercial catch and effort data summaries are found in Section 3.3 of Jones et al. (2002) and comprise data between 83/84 and 99/00. Notable results from Section 3.3 follow:

1. Two commercial gear types operate, haul net and dab net.
2. Average haul net catch has been largely unchanged through the length of the time series, since 1983 (Jones et al., Figure 3.3).
3. Dab net catch (Jones et al., Figure 3.3) and effort (Jones et al., Figure 3.4) rose to its current level in 92/93 and has been flat thereafter.
4. Targeted haul net effort declined substantially in the years 83/84 to 92/93 (Jones et al., Figure 3.4). Since then, it has been stable.

5. Catch per unit effort (CPUE), the catch by weight per fisher day of targeted effort has exhibited a general rising trend (Jones et al., Figure 3.5). Most of this increase for targeted haul net CPUE occurred from 83/84 to 89/90. Since then the rise has been more gradual. Dab net CPUE has shown a stronger rising trend over the full length of the time series.
6. The garfish haul net fishery exhibits a strong seasonality. Summer is the season of spawning when haul net effort targets principally female spawning aggregations inshore.
7. In the two main areas where haul netting occurs, Northern Spencer Gulf and Gulf St.Vincent, catch and effort peak in late summer/autumn at roughly double their winter levels (Jones et al., Figures 3.7 and 3.27). In winter, on the other hand, CPUE rises to a peak of roughly double that of summer (Jones et al., Figures 3.8 and 3.28).

The FRDC project to develop marine scale models extended the 'slice-growth' model formalism of King George whiting. The model results for garfish, broken down into the two gulfs up through September 2001, may be briefly summarised as follows:

8. Model estimated legal-size biomass has exhibited a general rising trend since October 1983, with a noticeably accelerated rise in the last two years. This inference is drawn primarily from the rising CPUE trend mentioned in point 5 above (McGarvey and Feenstra, Figure 1.11). This rising in population with time is stronger in GSV.
9. The model takes into consideration all, including untargeted, catch and effort data but assumes no rising effective effort over time. To test for the possible effect on these biomass estimates of any improvement in the catchability of the commercial gear over time, we have included a sensitivity analysis in Chapter 2. A yearly 1% rise in effective effort results in biomass being underestimated in the early years and overestimated in the later years, with the amount of error largest at the beginning and end of the time series (McGarvey and Feenstra, Figure 2.1, 2.2). This bias in biomass time trend is about half (0.5% per year) the corresponding rate in assumed rise of effective effort. Note that 'True' in these figures refers to the simulated fishery used to generate simulated data where effective effort was programmed to rise 1% per year, and does not describe the Chapter 1 estimates of the real garfish fishery whose biomass trends are shown in Figure 1.11.
10. Model-estimated recruitment in the two gulfs show similar high and low years (Figure 1.7). This suggests that environmental factors affecting yearly recruitment success are common to the two gulfs.
11. A sharp rise in the last year of estimated recruit numbers (recruiting 2000/01 as 1 year olds, therefore plotted as the October 1999 summer year class) is also evident for both gulfs, suggesting a favourable marine environment for garfish recruitment in that year. Thus the most recent recruitment year class (1999) was a notably strong one matching the other peak year of 1987.
12. It is worth noting that the most recent estimates in any stock assessment are generally the least reliable because the data for these is incomplete. Experience has shown that these most recent years' estimates are the most likely to change when more data becomes available in future years.
13. The average yearly recruit numbers, and thus also total population size are similar in the two gulfs.
14. The weight of evidence also suggests an asymmetric sex ratio, that is many more females than males at age of recruitment (age 1 year).

15. Estimated legal garfish population numbers averaged over the two model time steps from October 1999 through September 2000 are around 5.4 and 6.6 million for SG and GSV respectively.
16. Estimated legal-size biomass levels over that year are 420,000 and 480,000 kg for SG and GSV respectively.
17. Selectivity by length (Figure 1.8) leaves most garfish unexploited in winter, but with essentially all lengths above 210 being taken by haul nets in summers (when the catch is predominantly females). (The model estimates ended prior to the raising of LML to 230 mm in July 2001.)
18. Exploitation rate on garfish in the two gulfs (McGarvey and Feenstra, Figure 1.12) has also exhibited a declining trend over the length of the model time series. This would be due to both (1) declining commercial haul net effort, and (2) rising biomass.
19. Estimates of exploitation rate (and biomass) depended on the assumed rate of natural mortality. The model runs in half-yearly time steps, and we thus report exploitation rate as the proportion harvested per half year. Jones et al. in the Green Paper (1990) assumed three possible levels of M, of 0.4, 0.55 and 0.7. These yield exploitation rates in Oct 99-Sep 01 of 0.28 and 0.26 per half-year in SG and GSV respectively when M = 0.4, reducing to 0.23 and 0.21 for M = 0.55 and to 0.19 and 0.16 for M = 0.7. .
20. For M=0.55, estimated legal-size biomass levels over that year (Oct 99-Sep 01) are 500,000 and 590,000 kg for SG and GSV respectively; assuming M=0.7, these biomass estimates become 627,000 and 752,000 kg for SG and GSV respectively.

Lastly we summarise the per-recruit estimates of the expected impact of the recent increase in legal minimum length (LML) from 210 mm to 230. These are presented in Chapter 3 of McGarvey and Feenstra.

21. Average egg per recruit (Figure 3.1) showed an unexpectedly slow rise with increased model legal minimum length. This is probably due to both (1) lower selectivity of the gear at these low sizes of 210-230 mm, notably in winter for haul nets, and very low catches at all at these smaller sizes for other gear (dab nets and recreational hook and line).
22. Plotting the contributions to egg production by age (Figure 3.2), namely (female) population numbers and eggs per female, shows that the peak in egg production comes from age 2 garfish.
23. Yield per recruit (YPR) also rose relatively slowly with increased legal minimum length (Figure 3.3).
24. Value-per-recruit (VPR) however did show a significant rise with increased legal minimum length (Figure 3.4). This is due to the substantially higher price paid for larger garfish.
25. All per-recruit results assume a natural mortality of M = 0.4. If the higher two values assumed by Jones et al. (1990) were employed, of M = 0.55 and 0.7 in place of M= 0.4, then all three quantities, egg-, yield-, and value-per-recruit, would have risen more slowly (or, for YPR and VPR, possibly declined) with increasing LML, because greater numbers would have been lost from the fishery and from the population in the intervening growth period, from 210 to 230 mm.
26. Also, these per-recruit results ignore release mortality of fish that are captured and returned to the sea, thus implicitly assuming no release mortality. Since some, and especially for garfish, a potentially large percentage of fish do die when

released, the same effect would have been observed as for higher M, namely lower benefits of increased LML.

27. In addition, it is likely that the increase in LML would induce a shift of fishing effort from smaller to still-legal larger garfish, which is also not modelled, being beyond the capability of the data available, in the per-recruit estimates above.

In summary, the South Australian garfish stock has had (1) stable catches, (2) stable or rising CPUE, (3) rising model biomass, (4) declining exploitation rates. Thus all indicators show a stock that has been getting steadily healthier over the time period since 1983 for which data are available.

Estimated levels of exploitation rate appear highly dependent on the assumed level of natural mortality. The value of M = 0.4 assumed in Chapter 1 suggests a relatively highly exploited stock. The value of M = 0.55 assumed as the best estimate of Jones et al. yields a medium level of exploitation. The value of 0.7, taken as the high end of expected values by Jones et al. (1990) yields model estimates that imply a relatively lightly exploited garfish population.

In assessing the impact of the increase in LML from 210 to 230 mm, simulations indicate a unexpectedly modest benefit. And this is without considering any release mortality or shift of effort to larger sized garfish, both of which would reduce these sustainability benefits, perhaps very considerably. Previous studies (Jones et al. 1990; Morison and Presser 2002) also predicted a modest gain in yield per recruit with raised minimum size.

This garfish stock assessment estimation model has been extensively reviewed, specifically, by Dr. André Punt over the last three winters. Last winter's review, with our responses to his comments are enclosed (McGarvey and Feenstra, Appendix 1.1).

The most significant data lack is from the recreational sector. The results of the 2000/01 telephone-based National Recreational and Indigenous Fishing Survey will thus be of considerable value. However, regular updates of recreational catch and effort are also needed.

References

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Sincerely,

Richard McGarvey
Subprogram Leader, Fisheries and Ecosystems Modelling

and

Keith Jones,
Program Leader, Finfish

# Appendix 4: Summary of the workshop evaluating 'Garface', the model graphical user interface for garfish

by John Feenstra

Participants: Keith Jones, Qifeng Ye, Tony Fowler, Rick McGarvey, John Feenstra (convener).

Workshop was held on Thursday afternoon 5 June 2003 at SARDI Aquatic Sciences, West Beach.

<u>Purpose:</u>

The reason for the workshop was to give those scientists at SARDI who may be potential users of the software program Garface instruction in how to carry out an update to yearly garfish stock assessment parameter estimator model outputs using a new year of catch and effort data.

<u>Equipment:</u>

-> One computer for the person who talked, linked to an overhead projector projecting the PC's screen.
-> Two other computers around which the other participants gathered and carried out a mock-up yearly stock assessment update using Garface.

<u>Activities:</u>

* About 40 minutes: Rick McGarvey talked.
-> General description of the stock assessment parameter estimation model the implemented program (Garest) of which Garface interfaces to the user.
-> Data used.
-> Model limitations.
-> Results obtained.

* About 1 hour: John Feenstra talked and demonstrated Garface.
-> Showed on the overhead projector Garface's popup control form and gave a general description of features on it.
-> Demonstrated the link to the manual.
-> Demonstrated how to access a Garface worksheet and how to return to the control form.
-> Showed each Garface worksheet in turn, starting with the charted results sheets (linked with results in Rick's talk), and other output worksheets:
    -> main features and logic of each worksheet
    -> walk-through description of the estimated parameters along the way
    -> showed locations and briefly explained inputs of log-likelihood weights, parameter bounds, and the phase –1 feature.

-> Described the parameter initial input values and data input values worksheet features (including the data array structure).
-> Demonstrated by means of an example how to obtain and enter one new year of catch and effort data to the existing data input worksheet contents, as well as how to add one new cohort year value at the end of the cohort recruitment array in the initial parameters worksheet.
-> The button on the control form was then clicked to run the estimation program. (However in this demonstration the estimation program was not executed due to a gremlin of some kind!)

* About 20 minutes: The participants carried out an exercise consisting of adding one new year of catch-effort data, adjusting the initial parameter worksheet values, and then running the estimation program. This was done successfully.

<u>Comments on the workshop:</u>

* Written comments by Rick McGarvey during the workshop:
-> In the "ParameterStdOutput" and "ParameterCorOutput" worksheets, the label "std" could renamed to something like 'standard error of parameter confidence interval' and "value" renamed to 'parameter estimate'. That is, Rick suggested that these names were not informative enough.
-> For the long list of parameters in worksheets "ParameterStdOutput" and "ParameterCorOutput" perhaps list parameter category labels (e.g. SG females) in column A next to this list. Rick suggests this would make it easier when the user wants to study parameter uncertainty information, instead of having to go to the manual's appendix.
-> In appendix A of the manual it would helpful to give the symbol names used in Chapter 1 of the FRDC report for Project No. 1999/145 ("Stock assessment models with graphical user interfaces for key South Australian marine finfish stocks") that correspond to the parameter names used in Garface. Rick suggests this way it makes the link between Garface and the Garest model easier to bridge.
-> Put in an explicit log-likelihood weighting factor for catch-effort data along side the other log-likelihood weighting factors. Rick suggests that although it was not needed in Garest it will make it easier for the user to understand this feature of estimation that Garface enables for use.
-> Mention on the worksheet "DataInput", instead of just the manual, that catch is in kilograms.

* General comments by Keith Jones, Qifeng Ye, and Tony Fowler at end of workshop:
-> Remarks were very positive for the Garface software, AD Model Builder estimation software, and the associated marine finfish modelling work in general for the three key species.

* Keith Jones, Qifeng Ye, and Tony Fowler said that they would experiment with Garface and provide more feedback when they had time to do so.